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Do Traditional Financial Distress Prediction Models Predict the Early Warning Signs of Financial Distress?

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Abstract: Purpose: This study aims to compare the prediction accuracy of traditional distress prediction models for the firms which are at an early and advanced stage of distress in an emerging market, Pakistan, during 2001–2015. **Design/methodology/approach:** The methodology involves constructing model scores for financially distressed and stable firms and then comparing the prediction accuracy of the models with the original position. In addition to the testing for the whole sample period, comparison of the accuracy of the distress prediction models before, during, and after the financial crisis was also done. **Findings:** The results indicate that the three-variable probit model has the highest overall prediction accuracy for our sample, while the Z-score model more accurately predicts insolvency for both types of firms, i.e., those that are at an early stage as well as those that are at an advanced stage of financial distress. Furthermore, the study concludes that the predictive ability of all the traditional financial distress prediction models declines during the period of the financial crisis. **Originality/value:** An important contribution is the widening of the definition of financially distressed firms to consider the early warning signs related to failure in dividend/bonus declaration, quotation of face value, annual general meeting, and listing fee. Further, the results suggest that there is a need to develop a model by identifying variables which will have a higher impact on the financial distress of firms operating in both developed and developing markets.

Keywords: financial distress; emerging market; prediction models; Z-score; logit analysis; probit model

JEL Classification: G01; G11; G17; G32; G33

1. Introduction

Financial distress is a company's inability to fulfill their debt requirements—that is, going into bankruptcy, experiencing liquidation and another form of asset seizure and distribution (Sun et al. 2014). Because a company facing financial distress will experience huge losses, being able to predict financial distress before it occurs is paramount to a business's success. The debt of a company tends to negatively affect all its stakeholders—its employees, shareholders, managers, investors, and creditors alike (Chen and Merville 1999). Pindado and Rodrigues (2005) argued that companies both locally and internationally have experienced damaging consequences, because of ignoring the warning signs of financial distress and the effects it has on a business's stability and growth. With the use of business failure prediction models, many companies have seen a significant difference in their financial stability and have even been able to lower their chances of going into bankruptcy. Bankruptcy prevention not only prolongs a firm's economic life and augments its financial performance, it also serves to improve a country's overall economic well-being.

Over the most recent two decades, many organizations in all economies have suffered financial distress, so there is a need to recognize a model which may help investors to evaluate firms' financial issues and make judgments about their future. This can shield them from misfortunes arising out of the failure of organizations. Commonly used bankruptcy prediction models have been specially constructed for developed markets; as such, their relevance and prediction accuracy are questionable for emerging markets like Pakistan, with a large industrial manufacturing base[1].

In the context of Pakistan, there is a very limited number of studies conducted on financial distress prediction; nonetheless, these studies are limited to a small sample size, specific industrial sectors, and statistical techniques. For instance, Rashid and Abbas (2011) employed multiple discriminant analysis (MDA) on the data of 52 firms; Ijaz et al. (2013) focused only on sugar sector with a sample size of 35 firms; Ammar-ud-din and Aziz (2016) took only 48 firms of textile sector; Wagan et al. (2016) employed MDA on a sample size of 38 firms and Jaffari and Ghafoor (2017) compared MDA and logit analysis using a sample of 70 firms. The objective of this study is to fill the gap in the literature by comparing the prediction accuracy of five well-known distress prediction models by using the large sample size of 422 companies listed on a Pakistan Stock Exchange from 2001 to 2015. We aim to answer three questions in this paper:

(a) Do traditional distress prediction models have the ability to predict financial distress of firms with early warning signs of bankruptcy?
(b) Which traditional distress prediction model (Altman (1968), Z-score; Ohlson (1980), O-score; Zmijewski (1984), probit model; Shumway (2001), hazard model, and Blums (2003), D-score model) can predict financial distress of Pakistani companies more accurately? and
(c) What are the differences in the predictive ability of the models before, during and after the financial crisis?

A firm does not enter the state of financial distress at once; analysis of UK firms shows that a firm takes up to three years to enter the state of bankruptcy (Tinoco and Wilson 2013). The case is the same for US firms, which tend to, on average, stop providing financial statements two years before bankruptcy (Theodossiou 1993). Our study contributes to the literature by extending the definition of financial distress to apply also to firms that show early warning signs of financial failure, that is, not only firms that are well in the middle of financial distress. Our contention is that real benefit lies in identifying the signs of financial distress well before the ultimate disaster of liquidation sets in. Analyzing a firm's financial statements just before it goes into bankruptcy or having a detailed investigation into what went wrong serve little purpose for the investors or the economy at large. The material utility of financial distress prediction models is to pick up the signs early enough in order to start the financial reconstruction in good time. In addition to the other commonly available and applied definitions of financial distress, we selected those firms for our sample which have failed to pay a listing fee, conduct an annual general meeting, and whose shares are quoted at less than 50% of book value. We then tested the generalizability of the commonly used distress prediction models for the emerging market firms, which are at an early and advanced stage of distress. The manufacturing sector firms listed on the Pakistan Stock Exchange from 2001 to 2015 were selected for this purpose. Further, the differences in the predictability of the models were tested before, during, and after the financial crisis period. Additionally, a robustness test was conducted to check the differences in the predictive ability of models with respect to early-distressed firms.

Our overall results indicate that all five models are applicable for the emerging markets, but their prediction accuracy is slightly different than that of original studies in developed markets. The results

[1] Many developed markets are witnessing the hollowing out of their manufacturing base, which raises concerns of the applicability of financial distress models in emerging markets (Paolone and Rangone 2015).

show that the probit model has the highest overall prediction accuracy, while the Z-score model more accurately predicts all the stages of the deterioration of a firm's financial position for the emerging market. A robustness test for each model also reflects the same results with respect to the early warning signs of financial distress. With this detailed evidence on the predictability of traditional distress prediction models, the current study suggests practitioners in an emerging market like Pakistan, with a large manufacturing base, can rely on the accounting-based distress prediction models, Altman (1968) and Zmijewski (1984), to check the stage of firm's financial position and take decisions accordingly. Moreover, the empirical results suggest that there is a need to develop a model by identifying variables which will have a higher impact on the financial distress of firms operating in both developed and developing markets and increases the overall prediction accuracy of the model.

The rest of the paper is organized as follows. The following section gives an overview of the previous literature in the area of distress prediction. Section 3 describes the data, sample, and methodology followed by empirical results in Section 4. The last section covers the conclusion and discussion of the result outcomes.

2. Literature Review

Over the last five decades, financial distress prediction has been an interesting topic for researchers because of its incredible significance to companies, the economy, and all other concerned parties (Wanke et al. 2015). To dissect the extensive literature on financial distress prediction, we divide our literature review into three parts. The first part covers the traditional bankruptcy prediction models, the second part analyzes the comparative studies on the distress prediction model, and the third part elaborates on the criterion used to define financially distressed and stable firms.

2.1. Traditional Distress Prediction Models

The empirical literature on financial distress prediction is large and varied, in terms of explanatory variables and methodological techniques. Since Beaver's seminal work (Beaver 1966) using a univariate discriminant analysis to compare the ratios of failed and nonfailed firms, a number of bankruptcy prediction models have been developed and tested by researchers. Altman (1968) extended the work of Beaver (1966) by employing multiple discriminant analysis (MDA) to identify a group of distress prediction ratios. Later, MDA was used by many researchers, including Deakin (1972), Grice and Ingram (2001), and Agarwal and Taffler (2007). Most recently, Rim and Roy (2014) tested the performance of the original Altman Z-score model for manufacturing companies operating in Lebanon and found that it is still a valuable tool to predict financial distress of the Lebanese manufacturing sector. The findings of the study are consistent with those of Li and Rahgozar (2012) and Ilahi et al. (2015). On the other hand, Almamy et al. (2016) found that the prediction accuracy of the original Z-score model declined with the passage of time for the UK market, especially during the global financial crisis.

Since 1968, the Altman model has been widely used in the distress prediction literature, but the MDA technique is sharply criticized because of its restrictive assumptions about multivariate normality and the independence of explanatory variables (Ohlson 1980). To overcome these limitations, Ohlson (1980) proposed a new model based on logit analysis with a set of nine accounting ratios. This resulted in the proliferation of studies using logit analysis and an improvement of financial distress predictability (Campbell et al. 2008; Sun et al. 2014; Jones et al. 2015, 2017). Furthermore, Zmijewski (1984) employed probit analysis and developed a three-variable distress prediction model, which was further tested by many researchers, including Wu et al. (2010) and Kleinert (2014).

Shumway (2001) presented a further extension of financial prediction models, who criticized the static bankruptcy prediction techniques and developed a discrete hazard model with the addition of market-based variables, which led to increases in the overall classification accuracy of a model. His model was further tested by a number of researchers, including Campbell et al. (2008) and Bonfim (2009). Later on, researchers including Chava and Jarrow (2004) and Agarwal and Taffler (2008) articulated that market-based variables reflecting both internal and external information increase the overall predictability of distress prediction models. Further, Trujillo-Ponce et al. (2014) suggested that a combined model with both accounting and market-based variables is the best option, as both types of information are important for distress prediction.

A major drawback of previous distress prediction models is the lack of strong theoretical framework—for example, one of the most widely used studies of Altman (1968) was developed with limited data and by searching for the right variable (Wilcox 1971; Blum 1974; Scott 1981). To address this problem in the literature, Blums (2003) proposed a D-score model, based on the accounting and market-based variables with the strong conceptual framework. After that, researchers continued to add new variables to the distress prediction literature with a strong theoretical background. For instance, Tykvová and Borell (2012) employed a set of liquidity, profitability, and solvency ratios; moreover, Korol (2013) used a set of profitability, liquidity, and activity ratios with a strong theoretical background. In addition to the statistical-based techniques, several artificial intelligence modeling techniques, including support vector machines, genetic algorithms, decision trees, and neural networks, have been largely developed in the recent years. Much of the financial distress literature has relied on quite simpler prediction accuracy methods, as they are a better predictor of financial distress (Jones et al. 2017); therefore, we also restricted our study to the statistical-based techniques.

2.2. Comparative Position

The plethora of financial prediction models in terms of variables and techniques warrants research to investigate which variables and models perform the best at financial distress prediction. Begley et al. (1996) demonstrated that both the Z-score and O-score models did not perform well for US firms with data belonging to the 1980s. By contrast, Pongsatat et al. (2004) found that both models significantly predict defaulter firms operating in Thailand. Abdullah et al. (2008) found that the hazard model outperforms MDA and the logit model for Malaysian firms. Nam et al. (2008) found similar results and reported that the hazard model has a higher accuracy level than the static logit model for the Korean firms. On the other hand, Kordlar and Nikbakht (2011) proved that the O-score more accurately predicts financial distress for Iranian firms when compared with the Z-score, probit, and hazard models. Further, Imanzadeh et al. (2011) compared the performance of the Springate (1978) and Zmijewski (1984) models for firms on the Tehran Stock Exchange and found that Zmijewski (1984) model is the most accurate predictor of bankruptcy.

Recently, Tinoco and Wilson (2013) tested the performance of the Altman (1968) Z-score model for UK firms and noticed a significant decrease in the prediction accuracy of the model than the original study. On the other hand, Roomi et al. (2015) reported that the Z-score model is a good predictor for predicting financial distress of Pakistani firms. Moreover, Jaffari and Ghafoor (2017) found that the logit model is better than MDA, but the prediction accuracy of the models declines when applied to the Pakistani market. More recently, researchers including Mselmi et al. (2017) and Jones et al. (2017) reported that the logit analysis is the most accurate predictor for a French and US market. In sum, the literature reports mixed results with respect to the predictive ability of the traditional distress prediction models when applied to different economies of the world.

2.3. Definition of Financial Distress

Most of the previous studies on default prediction models differentiate financial distress in two ways—legal state (Altman 1968; Shumway 2001; Wu et al. 2010; Almamy et al. 2016) and doorway to distress state (Lau 1987; Hill et al. 1996; Cheng and Li 2003; Hensher et al. 2007). Financial distress is the state wherein the firm has insufficient cash flows to meet its debt obligations (Wruck 1990). The effects of financial distress can be detected in advance by witnessing a decrease in firm value before the actual default of the firm (Whitaker 1999). A number of researchers make use of different states of financial distress based on the prewarning signs. Foster (1978), for instance, defines four stages of financial distress based on debt payments, dividend payments, products power, and bond default. Chen (1983) categorized companies based on three states—financial distress, financial imbalance, and bankruptcy.

He defined financial distress as the state of power revenue, delayed debts, and the shortage of cash flows. Furthermore, Lau (1987) defined five states of financial distress based on stability, missing or decrease in the dividend, loan payment default, protection under the bankruptcy act, and finally bankruptcy filing. Moreover, Cheng and Li (2003) modified the financial administration stages of the Lau (1987) model and broadly defined them based on financial distress and financial stability with the four states of financial distress used in the original model. Later, Cheng et al. (2006) used this modified version of the model to develop a prewarning model based on fuzzy regression.

If the net worth of the company's shares is less than its book value, then the firm is in the stage of financial distress (Wang and Deng 2006). Similarly, we define a firm as in the early stage of distress if the quotation of its shares is less than 50% of the book value for three consecutive years. In addition, akin to the previous literature (see, e.g., Foster 1978; Lau 1987; Cheng et al. 2006), we also classify financial distress as the reduction or omission of dividend payments for five consecutive years. Theodossiou (1993) articulated that firms that stop publishing financial statements at least two years before filing for bankruptcy. If the firm is not publishing final accounts, it will not conduct an annual general meeting. Therefore, we argue that firms which do not publish their financial statements for at least three consecutive years are in the early stages of financial distress[2]. It is widely understood that the financially distressed firm faces difficulties to meet its obligations, and if the firm is not paying a listing fee of the Stock Exchange, it is in a state of distress. Hence, firms that failed to pay the annual listing fee for two consecutive years are in the early stages of distress and were categorized as early distressed firms in our study.

Tinoco and Wilson (2013) argued that financial distress is costly for the creditors of the firm, and they want to minimize the cost of it by taking necessary actions. Therefore, a reliable financial distress prediction model should have the capability to predict all the stages of a firm's financial position, the early stage of distress, and the advanced stage of financial distress. We contribute to the literature by testing the predictive ability of five well-known traditional distress prediction models by including early distressed firms in our sample. Moreover, existing studies on the financial distress literature suffered from a few limitations for emerging markets. The first issue is related to the selection criteria for the distressed firms because there are no databases available with financial information pertaining to these companies. The current study addresses this problem by selecting companies based on the financial criteria used for developed markets from popular databases along with the fact that we extended the definition of financial distress and included early distressed firms in our sample. The second issue has been limited availability of financial distress data for emerging markets; previous studies primarily compared the performance of two models with a limited time frame. There was a need to collect more historical data with a large time frame and sample, to comment better on the predictive ability of traditional distress prediction models. The extant study addresses this issue by using the large time frame of fifteen years for all the companies listed on one of the emerging markets to test the applicability of the models. Thirdly, according to the best of our knowledge, none of the studies focused on the differences in the predictive ability of the models with respect to the financial crisis for emerging markets. The current study checks the difference by dividing the sample into three periods—pre-crisis period (2001–2006), financial crisis period (2007–2009) and post-crisis period (2010—-2015).

[2] It should be noted that this study covers data relating to financial years up to FY 2015 when the new Companies Act 2017 had not come into force, which entails provisions for the automatic delisting of companies that fail to file annual accounts or hold annual general body meetings within the prescribed time limits.

3. Sample and Methodology

3.1. Construction of Sample

Our sample first met the following inclusion criteria: (1) The company is listed on the Pakistan Stock Exchange (PSE) from 2001 to 2015, (2) the company belongs to the nonfinancial sector, (3) financial statement data are available in the annual reports published by the State Bank of Pakistan from 1998 to 2015. Using these criteria, a sample of 422 companies was selected, which were further classified based on their financial position. This study used two criteria to classify firms to compare the results with those from previous studies; (i) Common death types used in the literature by many researchers (Taffler 1982; Appiah and Abor 2009; Christidis and Gregory 2010; Almamy et al. 2016), and (ii) an additional criterion which includes defaulter firms which did not fulfill their listing requirements and obligations (see Table 1).

Table 1. Definition of financial distress stages.

Stages of Financial Position	Description	Degree of Financial Position
State 0	Financial stability	Stable
State 1	Defaulter firms with below reasons for default: (i) Less than 50% quotation of book value for consecutive 3 years (ii) Failure of dividend/bonus declaration from continuous 5 years (iii) Failed to conduct AGM for consecutive 3 years (iv) Failed to pay the yearly listing fee for 2 years. Delisted/Suspended/Liquidation/Winding up/Bankruptcy	Financial distress

Using the above criterion, 154 companies were classified as distressed from 2001 to 2015. The study uses an unpaired sampling technique frequently employed in the distress prediction literature by many researchers (Ohlson 1980; Taffler 1982; Zmijewski 1984; Begley et al. 1996; Wu et al. 2010; Almamy et al. 2016), and includes 268 remaining manufacturing sector companies listed on the Pakistan Stock Exchange during any year from 2001 to 2015 as financially stable firms. The total listed companies of PSE differ every year which gives us the sample of total 5139 observations for both distressed and stable firms from ten[3] major industrial sectors.

Secondary data were collected from different sources: Balance sheet analysis published by the State bank of Pakistan; analysis reports published by the Pakistan Stock Exchange; Business Recorder (BR); Yahoo Finance; and indices published by the World Bank.

3.2. Distress Prediction Models

Over the last four decades, several distress prediction models have been developed by various researchers. The most commonly used are:

(a) Altman (1968), Z-Score Model

$$Z = 1.2WCTA + 1.4RETA + 3.3EBITTA + 0.6MCTL + 1.0STA \tag{1}$$

[3] Textile; Sugar; Food Products; Chemicals and Pharmaceuticals; Other Manufacturing; Cement; Motor Vehicles, Trailers and Autoparts; Fuel and Energy; Coke and Refined Petroleum Products; Paper, Paperboard, and Products; Electrical Machinery and Apparatus.

(b) Ohlson (1980), O-Score Model

$$O = \left\{ 1 + exp\left(-\begin{bmatrix} -1.3 - 0.4OSIZE + 6.0TLTA - 1.4WCTA \\ +0.1CLCA - 2.4OENEG - 1.8NITA \\ +0.3FUTL - 1.7INTWO - 0.5CHIN \end{bmatrix} \right) \right\}^{-1} \tag{2}$$

(c) Zmijewski (1984), Probit Model

$$P = \Phi(-4.336 - 4.513NITA + 5.679TLTA + 0.004CACL) \tag{3}$$

(d) Shumway (2001), Hazard Model

$$H = \left\{ 1 + exp\left(-\begin{bmatrix} 13.303 - 1.982NITL + 3.593TLTA \\ -0.467RSIZE - 1.809LExReturn \\ +5.791LSigma \end{bmatrix} \right) \right\}^{-1} \tag{4}$$

(e) Blums (2003), D-Score Model

$$D = -4.907 - 2.11NITA + 0.0006TDTE - 1.734TETA - 0.016\Delta P + 0.005\Delta S + 5.885CLTA \tag{5}$$

Table 2 shows a summary of the variables and analysis technique for each model. Using an up-to-date data set from the emerging market, we compared the prediction accuracy of these models.

Table 2. Summary of distress prediction models and variables employed.

Model	Analysis Techniques	Variables	Description
Altman (1968) Z-Score Model	Multiple Discriminant Analysis	*WCTA*	Working capital/Total assets
		RETA	Retained earnings/Total assets
		EBITTA	Earnings before interest & taxes/Total assets
		MCTL	Market value of equity/Book value of total liabilities
		STA	Sales/Total assets
Ohlson (1980) O-Score Model	Logit	*OSIZE*	Log (Total assets/GNP price-level index)
		TLTA	Total liabilities/Total assets.
		WCTA	Working capital/Total assets
		CLCA	Current liabilities/Current assets.
		OENEG	One if total liabilities exceed total assets, zero otherwise
		NITA	Net income/Total assets
		FUTL	Funds provided by operations/Total liabilities
		INTWO	One if net income was negative for the last two years, zero otherwise
		CHIN	$\frac{\text{NIt}-\text{NIt\_1}}{\lvert\text{NIt}\rvert+\lvert\text{NIt\_1}\rvert}$ where NI_t and $\text{NI}_\text{t\_1}$ is the net income for the most recent and the preceding year respectively. The variable measures the change in net income.
Zmijewski (1984) Probit Model	Probit	*NITA*	Net income/Total assets
		TLTA	Total liabilities/Total assets
		CACL	Current assets/Current liabilities
Shumway (2001) Hazard Model	Hazard	*NITL*	Net income/Total liabilities
		TLTA	Total liabilities/Total assets
		RSIZE	Log (the number of outstanding shares multiplied by year-end share price then divided by total market value)
		LExReturn	Cumulative return of Company in year $t-1$ less cumulative return of PSE in year $t-1$
		LSigma	Standard deviation of residual derived from regressing monthly stock returns of company on market return in year $t-1$
Blums (2003) D-Score Model	Logit	*NITA*	Net income/Total assets
		TDME	Total Debt/Market equity
		META	Market Equity/Total assets
		ΔP	6-month Stock Price change
		ΔS	3-year Sales Growth
		CLTA	Current liabilities/Total assets

The methodology involves constructing model scores for both financially distressed and stable firms and then comparing the prediction accuracy of the models with the original position. To check the prediction accuracy of models, we used original cut-off points of the models—2.67 for Z-score, 0.038 for O-score, and 0.5 for the remaining three models. The predictive ability of the models was evaluated based on overall precision accuracy together with Type I and Type II error. Table 3 shows Type I and Type II errors along with different types of costs linked with each.

Table 3. Type of errors.

Actual Position	Model's Prediction	
	Distressed	**Stable**
Distressed	Correctly predicted	Type I Error
Stable	Type II Error	Correctly predicted

4. Empirical Results

4.1. Descriptive Statistics

The descriptive statistics of variables from all five models are shown in Table 4. The variables from all models are categorized into five groups: Profitability; liquidity; leverage; company size; and market-based variables. The table lists mean, median, and standard deviation for both distressed and stable firms. There are clear differences in the mean value of distressed and stable firms. The average mean of *profitability* variable, *sales growth* (ΔS) is quite low (0.00) for distressed firms compared to stable firms, indicating the declining sales of distressed firms. The distressed firm's ability to pay short-term debts is indicated by the *liquidity ratio* (*WCTA*), which is quite low for distressed firms (-0.45) than the stable firms (0.03). The mean of the *leverage ratio*, *total liabilities to total assets* (*TLTA*) for distressed firms (1.22) is quite higher than that for stable firms (0.61). Similarly, the *relative size (RSIZE)* of stable firms has a higher mean of -1.81 than that of distressed firms with the mean of -2.69. The table also lists the two-sided *t*-test values, which shows that the mean of both groups is significantly different for most variables, at 1% level.

4.2. Prediction Accuracy of Models

We compared the overall accurateness of all five models, along with Type I and Type II error. Type I is the incorrect classification of distressed companies, while Type II error is the incorrect classification of stable companies. As shown in Table 5, the prediction accuracy of the D-score model is higher (86.7%) for the distressed companies than for the stable ones (only 22.7%), indicating that the model overestimates the sample companies as distressed and shows only 42.8% overall prediction accuracy. The overall prediction accuracy of the O-score and hazard models is 68% and 70.7%, respectively, but the Type I error is higher for both models with a value of 98% and 92.3%, which indicates that the models overestimate the companies as financially strong. According to Hsieh (1993), the cost linked with Type I error is higher than that linked with Type II error, so the best model should have the lowest Type I error. The remaining two models, Z-score and probit, perform well for the Pakistani equity market, with an overall prediction accuracy rate of 66.3% and 73.4%, with a Type I error of 22.1% and 37.2%, respectively. The results indicate that the overall prediction accuracy of the models decreases compared to that in the original studies—Blums (2003) D-score model from 71.8% to only 42.8%, Ohlson (1980) O-score from 96.4% to 68%, Altman (1968) Z-score 95% to 66.3%, Shumway (2001) hazard model 96.5% to 70.7%, and Zmijewski (1984) probit model 98.2% to 73.4%.

Table 4. Descriptive statistics of distressed and stable firms.

Independent Variables	Distressed N = 1612			Stable N = 3527			t-Test [a]
	Mean	Med	SD	Mean	Med	SD	
Profitability							
EBITTA	−0.00	0.00	0.31	0.10	0.09	0.20	0.00 **
STA	0.74	0.57	0.79	1.26	1.12	0.83	0.00 **
NITA	−0.05	−0.03	0.32	0.04	0.03	0.19	0.00 **
CHIN	0.34	0.00	0.43	0.17	0.03	0.23	0.72
ΔS	−0.00	0.00	0.68	0.14	0.11	0.48	0.00 **
Liquidity							
WCTA	−0.45	−0.16	1.22	0.03	0.03	0.29	0.00 **
CLCA	3.03	1.57	5.39	1.21	0.94	1.63	0.00 **
FUTL	0.03	0.00	1.31	0.10	0.09	0.20	0.00 **
INTWO	0.37	0.00	0.48	0.10	0.00	0.30	0.00 **
OENEG	0.36	0.00	0.48	0.04	0.00	0.19	0.00 **
CACL	2.41	0.64	0.79	1.48	1.07	3.28	0.00 **
CLTA	0.96	0.56	2.24	0.45	0.44	0.25	0.00 **
Leverage							
RETA	−0.68	−0.05	2.42	0.23	0.26	0.37	0.00 **
MCTL	2.63	0.12	0.81	1.57	0.42	0.25	0.11
TLTA	1.22	0.84	1.58	0.61	0.61	0.29	0.00 **
NITL	−0.18	−0.03	0.82	0.12	0.06	0.80	0.60
META	0.31	0.12	0.70	0.44	0.25	0.54	0.00 **
Company Size							
OSIZE	1.39	1.43	0.38	1.79	1.76	0.35	0.00 **
RSIZE	−2.69	−2.87	0.80	−1.81	−1.67	1.37	0.00 **
Market							
LExReturn	−0.23	−0.28	0.56	−0.12	−0.15	0.48	0.00 **
LSigma	0.17	0.14	0.16	0.14	0.12	0.13	0.00 **
ΔP	0.21	0.00	1.01	0.28	0.07	0.89	0.01 **

[a] P-Value of two-sided t-test to check the mean differences between distressed and stable firms; ** indicating significance at 1%.

Table 5. Prediction accuracy of models.

Model Prediction	Distressed		Stable		Overall
	Distressed	Type I Error	Stable	Type II Error	
Z-Score	1255 77.9%	357 22.1%	2154 61.1%	1373 38.9%	3409 66.3%
O-Score	33 2.0%	1579 98.0%	3460 98.1%	67 1.9%	3493 68.0%
Hazard	124 7.7%	1488 92.3%	3508 99.5%	19 0.5%	3632 70.7%
Probit	1012 62.8%	600 37.2%	2761 78.3%	766 21.7%	3773 73.4%
D-Score	1398 86.7%	214 13.3%	799 22.7%	2728 77.3%	2197 42.8%

This table presents the overall prediction accuracy of models along with type I and type II error. Results are displayed in both numeric and percentage form for each model. The first column is the list of models, second and third column reports classification results for distressed firms, third and fourth column reports the classification results for stable firms and the final column shows overall classification accuracy of models.

Our results showed that the probit model of Zmijewski (1984) has the higher overall prediction accuracy for the Pakistani equity market than all other models in the study. The findings of our study are consistent with those of Avenhuis (2013), who tested the prediction accuracy of the Altman (1968), Ohlson (1980), and Zmijewski (1984) models for Dutch firms. Similar results were reported by Wu et al. (2010), who compared five distress prediction models for US firms using data from 1980 to 2006. While doing the comparison of the Ohlson (1980) and Altman (1968) model, we found that the Ohlson model performs worse than the Altman model. Our results are consistent for the UK and Malaysian markets as reported by the studies of Agarwal and Taffler (2007) and Abdullah et al. (2008), respectively. The opposite results were found by Begley et al. (1996) and Jaffari and Ghafoor (2017) for the US and Pakistani market, respectively. Our results also showed that the prediction accuracy of the Shumway (2001) model is quite lower for the Pakistani Equity Market, inconsistent with the findings of Wu et al. (2010) and Kordlar and Nikbakht (2011) for the US and Irani markets, respectively. The results of this study with market-based variables confirm the findings of Liu et al. (2010) and Charalambakis and Garrett (2016), who proved that the models with market-based variables are insignificant predictors of financial distress for developing countries—China, Taiwan, and India, respectively.

4.2.1. Pre-Crisis (2001–2006)

In addition to the prediction accuracy of the model for the whole sample period from 2001 to 2015, we also tested the prediction accuracy of the models before, during, and after the financial crisis.

Table 6 indicates that the results of the models before the financial crisis are consistent with the overall time period results. D-score leads to higher Type I errors, while the O-score and hazard model show higher rates of Type II errors. The probit model has the highest overall prediction accuracy (75.3%), while the Z-score prediction accuracy is slightly lower (66.5%).

Table 6. Prediction accuracy of models before financial crisis.

PRE-CRISIS					
Model Prediction	**Distressed**		**Stable**		**Overall**
	Distressed	**Type I Error**	**Stable**	**Type II Error**	
Z-Score	611 74.9%	205 25.1%	846 61.5%	530 38.5%	1457 66.5%
O-Score	21 2.6%	795 97.4%	1348 98.0%	28 2.0%	1369 62.5%
Hazard	60 7.4%	756 92.6%	1372 99.7%	4 0.3%	1432 65.3%
Probit	528 64.7%	288 35.3%	1122 81.5%	254 18.5%	1650 75.3%
D-Score	730 89.5%	86 10.5%	280 20.3%	1096 79.7%	1010 46.1%

This table presents the prediction accuracy of models before the financial crisis in numeric and percentage form.

4.2.2. During Crisis (2007–2009)

A large number of companies around the world faced difficulties in survival during the financial crisis (Duchin et al. 2010; Vermoesen et al. 2013). According to the Economic Survey 2009–2010 published by the Government of Pakistan, there was a 33% decrease in the after-tax profits of the listed companies at PSE. The study uses 2007 to 2009 as the crisis years as considered by Dietrich and Wanzenried (2011). As shown in Table 7, the overall prediction accuracy of the probit model is higher (68.8%) than that of the Z-score model, while the Z-score more accurately (81.1%) predicts distress during the crisis time period. There was a significant decrease in the prediction accuracy of both models at the time of financial crisis; Z-score decreased from 66.5% to 62.0% and the probit model from 75.3% to 68.8%.

Table 7. Prediction accuracy of models during financial crisis.

DURING CRISIS					
Model Prediction	**Distressed**		**Stable**		**Overall**
	Distressed	**Type I Error**	**Stable**	**Type II Error**	
Z-Score	284 81.1%	66 18.9%	355 52.2%	325 47.8%	639 62.0%
O-Score	8 2.3%	342 97.7%	669 98.4%	11 1.6%	677 65.7%
Hazard	24 6.9%	326 93.1%	677 99.6%	3 0.4%	701 68.1%
Probit	223 63.7%	127 36.3%	486 71.5%	194 28.5%	709 68.8%
D-Score	313 89.4%	37 10.6%	138 20.3%	542 79.7%	451 43.8%

This table presents the prediction accuracy of models during the financial crisis (2007 to 2009) in numeric and percentage form.

4.2.3. After Crisis (2010–2015)

There was a significant increase in the number of companies with financial difficulties which lead to the downward trend in Pakistan Stock Exchange after the global financial crisis (Hameed et al. 2013). The comparison of performance in Table 8 depicted that Type I error is quite lower (19.3%) for the Z-score model than for the probit model (41.5%) after the financial crisis, which indicates that the Z-score more accurately predicts financially distressed companies.

Table 8. Prediction accuracy of models after financial crisis.

AFTER CRISIS					
Model Prediction	**Distressed**		**Stable**		**Overall**
	Distressed	**Type I Error**	**Stable**	**Type II Error**	
Z-Score	360 80.7%	86 19.3%	953 64.8%	518 35.2%	1313 68.5%
O-Score	4 0.9%	442 99.1%	1443 98.1%	28 1.9%	1447 75.5%
Hazard	40 9.0%	406 91.0%	1459 99.2%	12 0.8%	1499 78.2%
Probit	261 58.5%	185 41.5%	1153 78.4%	318 21.6%	1414 73.8%
D-Score	355 79.6%	91 20.4%	381 25.9%	1090 74.1%	736 38.4%

This table presents the prediction accuracy of models after the financial crisis in numeric and percentage form.

When we compared the differences in the prediction accuracy of traditional distress prediction models before, during, and after the financial crisis, results indicated that the prediction accuracy of the models decreases during the period of crisis. Similar results of the decrease in the prediction accuracy of discriminant analysis during the period of the financial crisis were reported for the Italian and UK markets by Teti et al. (2012) and Almamy et al. (2016), respectively. Moreover, Fahlenbrach et al. (2012) and Dietrich and Wanzenried (2011) reported the same effect of a crisis on the performance of accounting ratios for US and Swiss banks.

5. Robustness Test

The characteristics of a firm experiencing financial problems differ from those of healthy firms, and the signals of the firm's deteriorating condition are produced successively for many years before failure (Theodossiou 1993). Therefore, a more accurate distress prediction model should have the ability to predict such shifts in the financial positions of firms as soon as they begin. To test the robustness of the models with respect to the early warning signs of financial distress, we reclassified firms into three stages based on the degree of their financial position—stable (financially stable firms), early-distressed (an additional criterion to represent firms which are at an early stages of distress), and distressed (common death types used in the literature to classify distressed firms). The description of the different stages is presented in Table 9.

Table 9. Stages of financial distress.

Stages of Financial Position	Description	Degree of Financial Position
State 0	Financial stability	Stable
State 1	Defaulter firms with below reasons for default: (i) Less than 50% quotation of book value for consecutive 3 years (ii) Failure of dividend/bonus declaration from continuous 5 years (iii) Failed to conduct AGM for consecutive 3 years (iv) Failed to pay the yearly listing fee for 2 years.	Early distressed
State 2	Delisted/Suspended /Liquidation/Winding up/Bankruptcy	Distressed

Using the above criteria, 176 companies with 1605 firm year observations were in the state of distress from 2001 to 2015. As there are two states of distressed firms in our study, we further classified these observations into early distressed and distressed states, which gave us 1056 observations for the early distressed firms and 549 observations for the distressed firms. After dividing the financial position of firms into three states, we compared the prediction accuracies of all five models. Table 10 presents the overall classification accuracies of models along with Type I (incorrect classification of early distressed and distressed firms) and Type II error (incorrect classification of stable firms). The classification accuracy results in Table 10 are robust after dividing the sample into three stages of financial distress. The results indicate that the overall classification accuracy of the probit model is higher (73.6%) compared to those of the other four models. The D-score overestimates the early distressed and distressed firms, while the O-score and hazard models overestimate the stable firms. Furthermore, the Z-score has a higher prediction accuracy of 77.4% for distressed and early distressed firms, along with 66.7% overall prediction accuracy.

Table 10. Prediction accuracy of models with three stages of financial distress.

Model Prediction	Distressed		Early Distressed		Stable		Overall
	Distressed	Type I Error	Early Distressed	Type I Error	Stable	Type II Error	
Z-Score	425 77.4%	124 22.6%	817 77.4%	239 22.6%	2186 61.9%	1348 38.1%	3428 66.7%
O-Score	9 1.6%	540 98.4%	24 2.3%	1032 97.7%	3475 98.3%	59 1.7%	3508 68.3%
Hazard	31 5.6%	518 94.4%	63 6.0%	993 94.0%	3519 99.6%	15 0.4%	3613 70.3%
Probit	326 59.4%	223 40.6%	675 63.9%	381 36.1%	2783 78.7%	751 21.3%	3784 73.6%
D-Score	442 80.5%	107 19.5%	941 89.1%	115 10.9%	848 24.0%	2686 76.0%	2231 43.4%

This table presents the overall prediction accuracy of models for all three states of companies. Results are displayed in both numeric and percentage form for each model. The first column is the list of models, the second and third column report classification results for distressed firms, the third and fourth column report the classification results for early distressed firms, the fifth and sixth column show the classification results for stable firms, and the final column shows the overall classification accuracy of models.

6. Conclusions

Empirical researchers and practitioners frequently use traditional financial distress prediction models constructed using data from developed markets. This poses a potential problem for the reliability of the models for emerging markets because traditional models were developed using economically advanced countries' data. In this paper, the empirical performance of five financial distress prediction models constructed particularly with the data from developed markets was tested on the emerging market with up-to-date data from 2001 to 2015. Many companies were financially distressed and filed for bankruptcy during the recent global financial crisis (Li and Zhong 2013). Recent studies by Teti et al. (2012) and Almamy et al. (2016) proved that the accuracy of the discriminant model decreases during a period of financial crisis. This poses a question of the applicability and the prediction accuracy of distress prediction models during a period of crisis. In addition to the testing of distress prediction models for the whole sample period, we also compared the accuracy of the distress prediction models before, during, and after the financial crisis to check the differences in the prediction accuracy of the models with regard to the financial crisis. Detection of a firm's movement towards failure at the early enough stage is beneficial for all stakeholders of the business; researchers developed several distress prediction models by keeping this purpose in mind (Theodossiou 1993). To capture the predictive ability of traditional distress prediction models for the firms that are at an early stage of financial distress, we classified them as a separate state in the robust test and compared the prediction accuracy of all five models.

Our results indicated that all five models are applicable to the Pakistani equity market, but their prediction accuracy decreases with the passage of time. The D-score model of Blums (2003), logit model of Ohlson (1980), and hazard model of Shumway (2001) performed poorly relative to other two models, with an overall prediction accuracy of 42.8%, 68%, and 70.7%, respectively. The results also showed that the D-score model overestimates financially distressed companies, while the other two models overestimate companies as financially strong, indicating the poor ability of the models to discriminate between financially strong and weak firms. The models with market-based variables are based on the assumption that the market is efficient, which is not the case for the Pakistani stock market. That is why the models with market-based variables do not perform as well as theoretically expected. The reason behind this inefficient performance of models with market-based variables could be the assumption of efficient and mature securities market, which is not the case for developing economies as theoretically expected (Liu et al. 2010).

Both the Z-score and probit model perform well for the emerging market. When we look at the overall prediction accuracy of the models, the probit model of Zmijewski (1984) more accurately predicted companies than the other four models during the whole time period of the study, whereas the prediction of Z-score is the best for firms at an early and advanced stage of distress, with a minimum Type I error of 22.6%. If Type I error is considered costlier, then the Z-score model would be more ideal than the probit model.

Our overall conclusion is that both conventional accounting-based models by Altman (1968) and Zmijewski (1984) are still valuable for predicting the financial distress of emerging markets and can be used by businessmen, financial specialists, administrators, and other concerned parties who are thinking about investing in an organization and/or want to enhance their organization performance. When we look at the differences in the prediction accuracy of traditional distress prediction models before, during, and after the financial crisis, the results indicate that the prediction accuracy of these traditional models decreases during the period of crisis, consistent with the findings of Almamy et al. (2016).

Results of this study on the accounting-based models confirm the finding of Agarwal and Taffler (2008), who found that despite extensive criticism, traditional accounting-based models are robust compared to the market-based models. The superior performance of accounting-based models could be due to many reasons. First, a firm does not suddenly file for bankruptcy: It is the result of several years of adverse performance; hence, it will be largely captured in the accounting statements of firms. Second, a double entry system ensures the minimal effect of window dressing and change in accounting policies in different aspects of accounting information. Third, loan agreements are based on numbers and are most likely to be a part of accounting-based models.

This study contributes to the literature by finding the most accurate predictor of financial distress for emerging markets after conducting a more comprehensive and detailed comparison of traditional distress prediction models, constructed primarily for developed markets. There are no available financial databases for the Pakistani equity market which indicate the financial status of the companies based on the company's performance. The study added to the literature by utilizing various information sources to classify companies based on liquidation, suspension, default, delisting, and winding up of companies. We contribute to the literature by extending the definition of financial distress by adding firms which failed to quote, pay a dividend/bonus, listing fee, and to conduct an annual general meeting. Our study used a long-time frame of fifteen years to check the differences in the predictive ability of the models with respect to the financial crisis for the emerging markets. We also provided evidence on the predictive ability of models with respect to the early warning signs of financial distress.

Even though our sample includes all companies listed on the Stock Exchange of the emerging market with the large time span of fifteen years, it has certain limitations. Including more emerging markets would help to comment better on the generalizability of the financial distress prediction models with respect to the early warning signs of financial distress. In addition, there is a need for the financial distress prediction model with the most accurate ratios, which are stable and increase the overall prediction accuracy of models for both developed and developing markets.

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