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RESEARCH PAPER

Identification of the Financially Distressed Firms through Enclosure of Corporate Governance Information into the Altman Z-Score

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ABSTRACT

Timely and accurate identification of the financially distressed firms helps safeguarding the interests of the stakeholders, and brings stability to the financial markets. Accounting based models are widely used to identify financially distressed firms, which may default and face subsequent bankruptcy. These models use accounting information from the published financial statements of the firms. Based on the accounting conventions of prudence and conservatism, this information is considered reliable and authentic. Despite reliability and authenticity, the accounting-based models yield type-I and type-II corporate default prediction errors. To reduce the quantum of these errors, this study has enclosed the corporate governance (a foresighted market information) into the Altman Z-Score (a hind-sighted accounting-based information). 161 non-financial firms listed at Pakistan Stock Exchange during the period of 2010-2016, have been taken as the study sample. Additive index methodology has been used to create two distinct indices, i.e., the Z-Score Default Index, and the Composite Default Index. Z-Score Default Index comprises of Z-Score, while the Composite Default Index comprises of the Z-Score and the Corporate Governance information in form of Corporate Governance Index. The results reveal that the Composite Default Index yields significantly lesser number of type-I and type-II corporate default prediction errors in comparison with the Z-Score Default Index. This study concludes that the enclosure of Corporate Governance into the Altman Z-Score improves the Z-Score's ability to identify the financially distressed firms. While concluding this study acknowledges the limitation in terms of the selecting the accounting-based model, and the market information. The study recommends considering different accounting-based models, market information, and the financial market for the future studies.

KEYWORDS Corporate Governance, Financial Distress, Type-I and Type-Ii Errors, Z-Score

Introduction

Corporations are legal entities, recognized artificial persons, where owners have limited liability towards settlement of business debts, i.e., only to the extent of their investment in these firms, as equity. These entities are often known as the Limited Liability Company (Bowie, 2019). These corporations are stringently regulated for safeguarding the interest of stakeholders. Securities & Exchange Commission (SEC), in every country, is mandated to safeguard the stakeholders' interests in these firms (Gebrayel, et.al., 2018). SECs usually deploy the Code of Corporate Governance to regulate firms and businesses (Herbert & Agwor, 2021).

Though the list of stakeholders is long, nevertheless, the investors, lenders, vendors, creditors, suppliers, employees, and customers are the significant ones. The degree of risk exposure varies for these stakeholders in case a firm ceases to exist on account of inability to meet its financial obligations, i.e., theoretical default (Ciampi, et.al., 2021). It is a scenario where the current liabilities of firm exceed its current assets. If left unchecked, the theoretical default may lead to corporate bankruptcy, and subsequent foreclosure (Shetty & Vincent, 2021). Does it happen as simply as stated? It does not. The journey from financial distress to bankruptcy consists of a series of financial events, where the likelihood of averting bankruptcy increases with late identification of the of financial distress within the firm (Sehgal, et.al., 2021).

The corporate default and the subsequent bankruptcy may be averted, provided the financial distress within firms, and financially distressed firms within the financial market are identified in a timely and accurate manner (Li, et.al., 2021). Such identification is not only expected to avert defaults and bankruptcies, but also consolidate stakeholders' trust in the corporate regulators' ability to safeguard their stakes in the firms and financial markets.

Financial distress is the first step towards corporate default and subsequent bankruptcy. Timely and accurate identification of the financial distress is important for the stability of financial markets (Sun & Lei, 2021). Corporate regulators, business analysts, and researchers use many models to identify the financial distress. The timely dentification allows enough time to the stakeholders for repositioning their stake in the firm (Chen & Svirydzenka, 2021). Similarly, accurate identification is critical to avoid disseminating the wrong signal about financial health of the firm. This yields type-I and type-II errors, i.e., a firm classified as the one prone to default actually survives in the future, and a firm classified as the one prone to survive actually defaults in future, respectively.

Among these models, the Accounting Based Models (ABMs) are frequently used (Verdet & Sanchez, 2021). Their frequent use is attributable to the elements of authenticity, prudence, and conservatism within the accounting information (Biddle, Ma, & Song, 2022). Moreover, the ease in access to financial information, extent of its disclosure, and its user friendliness makes it widely used by the analysts, researchers, and corporate regulators. Therefore, the models based on accounting information tend to be frequently used by the stakeholders.

The use ABMs started with the first model proposed by Beaver in 1966, followed by Altman Z-Score (1968), and Ohlson O-Score (1980) (Arora & Saurabh, 2022). These models tend to have improved over the period, nevertheless the hind-sightedness, prudence, and conservatism within the accounting information limits the futuristic outlook of these models. This limitation is grounded in the argument that corporate default prediction is foresighted, while the accounting information is compiled in hind sight (Bryce, Ali, & Mather, 2021). Therefore, ABMs yield type-I and type-II errors, when used to identify the financially distressed firms. Hence this study argues that infusion of a foresighted information into the ABMS, is likely to decrease the quantum of these errors, and improve the identification of financially distressed firms.

This study has used Corporate Governance Index (CGI) as the foresighted information for its enclosure into the widely used ABM, i.e., the Altman Z-Score. Pakistan Stock Exchange (PSX) has been chosen at the unit of analysis. 161 non-financial sector listed firms have been used as sample. The study period of year 2010-2016 has been selected for representativeness of Pakistan's economic and financial state. Two separate default indices have been formed. First consisting of Altman Z-Score, named as the Z-Score Default Index (ZDI), and the second comprising of Altman Z-Score and CGI, named as the Composite Default Index (CDI). Both indices have been compared for their quantum of type-I and type-II errors.

The findings reveal that the enclosure of CGI into the Altman Z-Score, significantly reduces the quantum of type-I and type-II errors, hence improving upon the Z-Score existing ability to identify the financially distressed firms. These findings are of significant value to the stakeholders and the corporate regulators, including the Securities and Exchange Commission of Pakistan (SECP), State Bank of Pakistan (SBP), in addition of the analysts, stockbrokers, and researchers. Timely and accurate identification of the financially distressed firms allows enough reaction time to the stakeholders for repositioning their stakes in the financial markets.

Literature Review

Separation of ownership, and control within a business entity determines the extent of owners' financial liability towards the business debts, i.e., the limited liability (Pires & Moreira, 2021). This development has staggering implications on the birth the corporatocracy, where a larger portion of global wealth is owned by corporations, rather than humans (Gare, 2021). The financial size and annual turnover of many of such corporations is bigger than the economies and foreign reserves of many countries (Young & Pagliari, 2022). Such financial presence of these corporations on the global economic canvas may be a celebrated consequence of separating ownership from control, but it surely needs a stringent corporate regulatory framework for protecting the stakeholders. ENRON and WORLDCON are the examples from recent past where both these global corporations filed for bankruptcy, despite having an unqualified audit opinion in their year of default. Such unexpected defaults and bankruptcies erode stakeholders' confidence in the corporate regulators' ability to protect their stakes in the financial markets (Din, et.al., 2021). Therefore, an effective mechanism to identify the financially distressed firms in an accurate and timely manner, is important.

Pertinent to mention that the corporate default and subsequent bankruptcy is not a point-in-time event without a forewarning mechanism (AlRawashdeh, 2021). Corporate default is a state where the current liabilities of firm exceed its current asset, while the corporate bankruptcy is a firm's failure to settle down its current liabilities on their maturity date (Jabeur, et.al., 2021). It means, keeping all other factors constant, a default would occur prior to bankruptcy. Before a firm gets into a default stage, it shows visible signs of financial distress. These signs are characterized by early impairment, deterioration in performance, failure, and insolvency. Identify financially distressed firms at the stage of early impairment improves their likelihood of avoiding default and subsequent bankruptcy. It allows enough reaction time to the corporate regulators and stake holders for taking appropriate measures for averting default and subsequent bankruptcy.

Early signs of financial distress include early impairment in profitability, deterioration in financial performance, operational failure, and insolvency (Bandyopadhyay, 2022). A close synthesis of the factors of financial distress narrows down to profitability and liquidity of the firm. Keeping these factors in view Professor Edward Altman proposed the Altman Z-Score with the following algorithm.

$$\text{Z-Score} = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \qquad \text{(eq-2.1)}$$

Where:

Z = overall index or score.

X_1 = Ratio of working capital to total assets, i.e., Working Capital / Total Assets.

X_2 = Ratio of retained earnings to total assets, i.e., Retained Earnings / Total Assets.

X_3 = Ratio of earnings before interest and taxes to total assets, i.e., EBIT / Total Assets.

X_4 = Ratio of market value of equity to book value of total liabilities.

X_5 = Ratio of sales to total assets, i.e., Sales / Total Assets.

The Z-Score algorithm results into a numeric score, where a score of 1.8 or below indicates a high level of financial distress, 1.8 to 2.7 represents a tolerable level financial distress, while 2.7 and above indicates a financially healthy firm (Divekar & Sukhari, 2021).

A close synthesis of the Z-Score reveals its underpinning elements of operational performance, liquidity, working capital, and asset turnover (Cındık & Armutlulu, 2021). The result is consequential to the managerial decisions at various levels along with the way in which corporations are governed. For enhancing visibility and transparency of these managerial decisions the SECs issue code of corporate governance. This code acts as a bench mark for the firms to operate in manner where the interests of all stakeholders are protected (Goforth, 2021). The code of corporate governance has been substantially improved of ENRON, WORLDCON, and many other such firms (Huang & Ho, 2022).

The corporate governance, earlier exercised as a best practice, now exists as Corporate Governance Index (CGI). This index is constituted around the elements of board structure, board procedures, adequate disclosure, ownership structure, and minority shareholding. Each of these elements have subcomponents, comprising of subindices. The CGI aims at measuring the efficiency of the way firm is being governed. The governance mechanism influences the decision making, may it be at the strategic, operational, and tactical level (Nsour & Al-Rjoub, 2022). Meaning thereby that the elements of corporate governance should be given due weightage, while identifying the financially distress within a firm and financially distressed firms within a market.

Keeping the same in view, this study has proposed the enclosure of CG into the Altman Z-Score to improve the Z-Score's existing ability to identify financially distressed firms at the PSX. Improvement is proposed to be measured through reduction in the existing quantum of the type-I and type-II errors presently being yielded by the Z-Score, in its standalone capacity. The CGI used for the purpose of this study has been presented below, followed by the methodology to enclose CG into the Altman Z-Score.

Table 1
Elements of the Corporate Governance Index (CGI)

Elements	Abb	Explanation
Ownership Structure	OS	Shares held by board of directors/ Total number of outstanding shares
Ownership Concentration	OC	Shares owned by top-10 shareholders/ Total number of outstanding shares
Institutional Ownership	IO	Shares held by institutional owners/ Total number of outstanding shares
Board Size	BS	Ln. of total number of the board members.
Board Independence	BI	Non-Executive Directors/ Total number of Directors in the Board
Audit Committee Independence	ACI	Non-Executive directors in the Audit committee/ Total number of directors in Audit Committee
CEO Duality	CEOD	Whether CEO and Chairman are the same person.

Material and Methods

Altman Z-Score is measured as a numeric score with a cutoff point at 1.8, while the CG information is measured in form of a Corporate Governance Index (CGI). For enclosure of an indexed information into numeric score, this study has adopted additive index methodology by converting both information existing in different measurement scales, into distinctive indices to create a set of measurable indices. Two separate default indices have been created using additive indexation, i.e., Z-Score Default Index (ZDI), and the Composite Default Index (CDI). ZDI is based on the default index based on the default scores achieved from computing Z-Scores for the 966 firm-year observations, while CDI has been computed on the basis of scores achieved from additive index created through addition of the scores achieved from Z-Score and CGI.

Non-financial firms listed at the PSX during the period of years 2010-2016 has been taken as the population, filtered on two criteria. First, the firms remained listed for all the years of the study period. Second, the availability published data related to the elements of Altman Z-Score and the CGI. A total of 161 firms qualified the criteria resulting in 966 firm-year observations to perform the statistical and mathematical procedures for accepting / rejecting the hypothesis stated below.

H1: The CDI yields lesser number of type-I and type-II errors as compared to the ZDI while identifying the financially distressed firms listed at PSX.

H2**:** The ZDI yields lesser number of type-I and type-II errors as compared to the CDI while identifying the financially distressed firms listed at PSX.

Data

The time period of year 2010-2016 has been chosen for two reasons. First, its representativeness of Pakistan's economic and financial state. Second, having minimal effects of abnormal events such as internal security, political turbulence, natural calamities, economic emergency, and financial crises within the country. Published annual reports of the 161 firms in sample over the period 2010-2016 have been used to extract the data elements for this study.

Comparative analysis between the ZDI and CDI has been drawn on the basis of comparing the respective number of corporate defaults predicted by either of the indices, in foresight, with that of the actual number of corporate defaults occurring during the analysis period, i.e., 2010-2016, in hindsight. Referring back to the first criteria applied to draw the sample firms, i.e., the firms staying listed on PSX over the study period, means only survived firms have been taken as sample. Meaning there by that any default predicted either by the ZDI or the CDI, would be a type-I prediction error. Hence either of the ZDI or CDI which yields lesser number of errors, proves to be a better identifier of the financially distressed firms at PSX.

To assess the impact of enclosing CGI into the Z-Score to construct the CDI for improving its ability to identify the financially distressed firms, the corporate distress score prediction of the firm has been proxied by the Z-Score, using the following dynamic panel data model estimated under the Generalized Methods of Moments (GMM) environment.

$\text{Z-Score}_{i,t} = \alpha_{i+}\ \beta 1(\text{Z-Score})_{i,t-1} + \beta 2(\text{CGI})_{i,t} + \text{Year Effect} + \text{Industry Effect} + \acute{\varepsilon}_{i,t\ldots}$ (eq. 3.1)

This study has developed a Composite Default Index (CDI) comprising of the Altman Z-Score and the CGI. The index has been constructed in four steps. First, the Z-Score computed has been converted into two quintiles, i.e., quintile 1, and quintile 5, where the firms having a Z-score of 1.8 or below have been assigned to the quintile 1, and quintile 5 has been assigned to the firms having a score above 1.8. Second, the Corporate Governance Index (CGI) has been converted into 5 quintiles. The 4^{th} and 5^{th} quintiles represent the firms complying to the code of corporate governance and consequently experiencing lower level of financial distress, while the 1^{st} and 2^{nd} quintiles indicate lower compliance and high financial distress levels. Whereas the 3^{rd} quintile refers to observations of CG that has median score. Third, the yearly minimum and maximum values have been estimated to determine the Range of the CDI, i.e., Range = Maximum value – Minimum value. Fourth, all quintiles have been yearly for each firm to obtain the aggregate sum, and compute the composite default as; CDI = [Sum – Minimum] / Range

The resulting index ranges from 0 to 1. Firms falling within the higher quintiles, i.e., 3^{rd} 4^{th} and 5^{th} have lesser degree of financial distress and are not likely to default in the foreseeable future. While the firms falling within lower quintiles, i.e., 1^{st} and 2^{nd} have higher degree of financial distress and are more likely to default in the foreseeable future.

Data Analysis

STATA has been used to analyze to 966 firm-year observations, which is product of 161 non-financial sector firms observed over a period of six years. Accounting ratios within Altman Z-Score, and the CGI of the firms in sample are the key data components for this study. The data has been analyzed both statistically and arithmetically. The statistical analyses include summary statistics, component summary, correlation matrix, regression analysis, estat-abond Arellano Bond test, and paired sample t-test. While the arithmetical analysis includes computation of the success ratio, i.e., which of the indices, either ZDI or CDI, has higher success ratios of identifying the financially distressed firms. Higher success ratio means yielding lesser quantum of the type-I and type-II errors.

Results and Discussion

Table 2
Summary statistics for the Z-Score and CGI

	Count	Mean	Stand Dev	Min	Max
Z-Score	966	1.298	0.771	-0.011	4.932
CGI	966	0.445	0.186	0	1
N	966				

Table 2 presents the summary statistics for the Altman Z-Score and the CGI. The values present the firm-year observations count, maximum value, minimum value, mean value, and standard deviation. The negative minimum value for Z-Score is attributable to negative working capital and retained earnings for a few firms.

Table 3
Altman Z-Score's component' summary statistics

	Count	Mean	Stand Dev	Min	Max
WC	966	0.298	0.337	-1.141	0.999
RE	966	0.012	0.127	-2.836	0.558
EBIT	966	0.065	0.139	-1.240	0.998
MV/TL	966	2.731	9.586	0.0032	200.248
Sales	966	1.188	0.811	3.836	6.484
N	966				

Table 3 presents the component summary statistics for the elements / ratios within the algorithm of the Altman Z-Score. The arithmetic mean, standard deviation, minimum value, and the maximum value for 966 firm year observations have been computed. The negative minimum values for the Earnings Before Interest and Tax (EBIT), Retained Earnings (RE), and the Working Capital (WC) are attributable to the reported annual losses, and excess of current liabilities over the current assets, respectively.

Table 4
Correlation matrix for Altman Z-Score and CGI

	Z-Score	CGI
Z-Score	1.00	
CGI	0.86**	1.00

Table 4 presents the correlation between the Altman Z-Score and the CGI. The result exhibits a strong positive correlation between the CGI and the Z-Score.

Table 5 - Regression analysis for the Altman Z-Score and CGI

	Z-Score
Z-Score	0.610***
	(0.157)

CGI	0.260*
	(0.149)
Intercept	-0.381
	(0.341)

Table 5 presents the regression analysis for the Altman Z-Score and the CGI. The results exhibit a strong association between the two, hence making it case for the enclosure to improve the ability of the Z-Score for timely identification of the financially distressed firms at PSX.

Table 6
estat abond Arellano Bond test results for Z-Score

Order	Z	Prob > z
1	-3.4292	0.0006
2	-1.4339	0.1516

The results above report in table 6, the extent of serial correlation in the first-differenced errors. It is based on the residuals of the estimation. This test, by default, is caried out with the standard covariance matrix of the coefficients. The results show that autocorrelation does not exist within the first order and second order testing for identifying any serial correlation. This makes the enclosure of the CGI viable, into the Altman Z-Score.

Table 7
CDI Summary stats

Quintiles	Count	Mean	Stand dev	Min	Max
1	247	0.009	0.0317	0	0.125
2	195	0.213	0.057	0.125	0.25
3	191	0.399	0.050	0.375	0.5
4	180	0.506	0.027	0.5	0.625
5	153	0.828	0.127	0.625	1
N	966				

Table 7 exhibits the summary statistics for the Composite Default Index (CDI). The first two quintiles, i.e., 1st and the 2nd quintile, represent firms with a high level of financial distress under which the firms are likely to default. The total count of such firm-year observations is 472 out of the total of 966. firms-year observations. The differential between the results of CDI's classification of the firm-year observation compared with that of the one presented by the ZDI may be observed from the results in table 4.7, where comparative supremacy of the means has been presented.

Table 8
CDI: Paired sample t-test

T-test CDI = ZDI mean						
Variable	**Observ.**	**Mean**	**Std. Err.**	**Std. Dev.**	**[95% Conf.**	**Interval]**
CDI	161	0.542	0.031	0.397	0.481	0.604
ZDI	161	0.226	0.028	0.355	0.170	0.281
Diff	161	0.317	0.030	0.378	0.258	0.376
mean(diff)	= Mean (CDI-1A mean - ZDI mean)				t = 7.096	
Ho: mean(diff) = 0				degree of freedom = 160		
Ha: mean(diff) < 0		Ha: mean(diff) = 0			Ha: mean(diff) > 0	
Pr (T < t) = 1.0000		Pr (|T| > |t|) = 0.0000			Pr (T > t) = 0.0000	

Table 8 presents the paired sample t-test between the means of the ZDI and the CDI. The t-value of 7.096 representing the mean difference the CDI and ZDI, exhibits the supremacy in accuracy of the CDI over the ZDI in rightly identifying the financially distressed firms listed at the PSX. To warrant the same, an alternate, in the form of success ratio has been presented in the following table.

Table 9
Comparative success ratio of CDI and ZDI

Success Mean		**CDI**		**ZDI**		**Differential**		**Error**
Mean	D / S	Firms	Count	Firms	Count	Diff	% Diff	Type
0	D	39	**73**	24	**123**	50	41%	I
1	D	34		99				
2	S	11	**88**	6	**38**	50	132%	II
3	S	77		32				
N		161	**161**	161	**161**			

Table 9 presents the comparative success ratio of the CDI with the ZDI. The results exhibit that a total of 50 firms have been reclassified as the ones not likely to default. This represents a reduction of 41% in the type-I, and 132% in type-II errors. which is a significant improvement in identification of the financially distressed firms.

Discussion

Based on results presented in the previous section through table 2 to table 9, the enclosure of CGI into the Altman Z-Sore has significantly improved the Z-Score's ability to identify the financially distressed firms, listed at the PSX. This improvement is evident from the results presented in table 8 where the mean accuracy of the CDI constructed through the enclosure of CGI into the Altman Z-Score is significantly higher than that of the ZDI. The t-value of 7.096 exhibits the comparative supremacy which the CDI has over the ZDI in identifying the financially distressed firms.

The findings based on statistical results, discussed in the previous para, are strengthened by the results presented in table 9, which exhibits the finding based on a simple arithmetic percentage. Before discussing the results exhibited in table 4.8, it is imperative to refer back to first conditionality for selecting the sample, i.e., that the firm stays listed for the study period. Meaning that it did not default, hence classifying it as a to-default firm is a type-I error. Any on the default indices, either ZDI or CDI, yielding lesser number of these errors, would be a better identifier of the financially distressed firms. The CDI identified 73 financially distressed firms out of the 161, which are likely to default, while the ZDI identified 123. Meaning there by that moving 50 firms out from a wrongly classified bracket of to-be-defaulted firms. This correction reduces the quantum of type-I errors by 41% and the type-II errors 132%, respectively. This reduction in errors leads to a significant improvement in the Altman Z-Score's ability to identify the financially distressed firms, once it is enclosed with the CGI.

Conclusion

Based on the findings presented in the previous section, it may be concluded that Z-Score's ability to identify the financially distressed firms improves significantly, once it is enclosed with the CGI. It may further be concluded that the elements prudence and conservatism within the accounting information, limits its ability to identify financially distressed firms, timely and accurately. This limitation yields a higher quantum of type-I and type-II errors, which may be addressed through the enclosure of a foresighted information into the existing algorithm of Z-Score. The significant decrease in the quantum of these errors after the enclosure of CGI into the Z-Score supports the hypothesis that this enclosure has significantly improved the Z-Score as an identifier of the financially distressed firms.

Limitations

This study has been kept limited to the non-financial firms listed at the PSX. The financial sector firms have not been included within the scope for their distinct nature, and stringent regulation by the State Bank of Pakistan (SBP). Nevertheless, this does not rule out the likelihood of these firms getting into the financial distress. Therefore, future studies may include or have a separate analysis carried out for the financial sector firms at PSX.

Further, this study has taken PSX as the unit of analysis, keeping in view the need of such studies for the stakeholders. Nevertheless, future studies may extend the same to other stock exchanges in the region. Dubai International Financial Exchange (DIFX) may be one of the considerations in this regard, given the portfolio of global firms, trading volume, and stability of the exchange. Other stock exchanges within the South Asian Association for Regional Cooperation (SAARC) may also offer prospects for a good study on the same subject.

In addition, this study has been kept limited to only one ABM, and single element of the market information i.e., Altman Z-Score, and Corporate Governance respectively. This limitation has been kept for the reason to establish a baseline study for such enclosures. Future studies may include other ABMs along with additional elements of market information. For accounting-based models, Ohlson O-Score may be considered, while for fore-sighted information, Corporate Social Responsibility (CSR) may be considered.

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