IMPROVING CORPORATE DEFAULT PREDICTION AT PAKISTAN STOCK EXCHANGE (PSX) THROUGH FORMATION OF THE COMPOSITE DEFAULT INDEX (CDI)

***Khalid Mumtaz Khan**

Assistant Professor, Bahria Business School, Bahria University Islamabad
Email: khalid@bahria.edu.pk

Naeem Ullah

Faculty of Management Sciences, Foundation University Islamabad

Nida Aman

Management Studies Department, Bahria University Islamabad

ABSTRACT

Corporate default prediction has been of great importance to the stake holders in the financial markets, especially, to the investors and the regulators. Pakistan Stock Exchange (PSX), despite economic, political, and geographical turbulence, has quadrupled it market index in last decade, showing an impressive growth, attracting bigger investors. These investors expect the corporate regulators, i.e., Securities and Exchange Commission of Pakistan (SECP), and the State Bank of Pakistan (SBP) to shield their interest in the market against unexpected events, including unanticipated corporate default(s). This study aims at improving upon the Altman (1968) Z-Score's ability to identify the financially distressed firms, listed at PSX, which are likely to default. The improvement has been brought through incorporation of Corporate Governance (CG), and Corporate Social Responsibility (CSR) into the Z-Score algorithm using additive index methodology. The resultant index, called the Composite Default Index (CDI), has proven to be superior than the Z-Score Default Index (ZDI), as it results in significantly lesser number of type-I and type-II errors in classifying the firms, as prone to default, or otherwise. SBP's Balance Sheet Analysis of 161 publicly listed firms at PSX has been used over a period of 2010-2016 for the purpose of this study. The findings support the use of CDI at PSX by the SECP for forewarning the stakeholders about financially distressed firms, in order for stakeholders to reposition their stake in such firms.

Key words: *Financial Distress, Corporate Default, Altman Z-Score, type-I & type II errors.*

INTRODUCTION

Unanticipated corporate default brings an end to a firm's life. Such events take the stakeholders by surprise, and also expose the corporate regulators such as Securities and Exchange Commissions (SEC) and Central Banks, in an exposed position to protect the interest of the stakeholders. It hurts the interests of the key stakeholders in the financial markets, and also erode their confidence in the corporate regulators' ability to protect the same (Ahmed et al., 2020). The corporate regulators are mandated primarily with protecting the interests of stakeholders in a market (du Jardin et al.,2019). An inability on part of the corporate regulators to do so, leads to a deterioration in investors' confidence in corporate regulators' ability to protect their interest. The corporate regulators, on the other hand, need a reliable and an effective mechanism to foresee such defaults. Pertinent to mention that financial distress, default, and bankruptcy is a sequential process, while in layman's understanding these terms are often used interchangeably. Financial distress refers to a situation where a firm foresees it inability to retire its liability on its due date. Default refers to the event of inability to meet its liability hon its due date. While the bankruptcy refers to initiation of a legal process of liquidating firms' assets in order to settle the lenders' claims (Habib et al., 2020).

Pre-empting the occurrence of a corporate default requires a holistic understanding of the financial environment, and its connection with economic, political, and social developments (Li and Faff, 2019). However, the precision in estimation of two elements i.e., probability of default, and distance to default, play critical role in predicting the corporate default. Probability of Default (PD) refers to likelihood of a firm default, while the Distance to Default (DD) refers to how far is the event of default from today, i.e., td – t0, where td is the expected calendar date of default, and t0 refers to the present calendar date. Difference between the both may be referred as the reaction time 'tr' which stakeholders have to re-think their stake in the firm, being considered for its default possibility. This time function may be stated in the form of following equation

$$tr = td - t0 \qquad (1)$$

Considering the criticality of PD and DD in Corporate Default Prediction, the importance of both factors can be illustrated in the form of following equation

$$CDP = f\,(PD, DD) \qquad (2)$$

Wrong estimation of either of the factors of CDP is consequential, at least on two accounts. First, wrong estimation of the PD leads to misclassification of a ‘to be default’ firm as a ‘to be survive’, or vice versa. Such a misclassification leads to type-I and type-II errors in corporate default prediction. Type-I error is where a defaulting firm is classified as a surviving, while the type-II error is where a surviving firm is classified as a defaulting one (Coser.et.al, 2019). Second, a wrong estimation of DD may not allow enough time to the stakeholders for the repositioning of their stake in the defaulting firm, or the stakeholders may pre-maturely reposition their stake from a firm expected to default. Furthermore, the precision in PD and accuracy in the DD needs to algorithmized into a model, for the stakeholders to be able to use it in practice.

Keeping the same in view, the corporate default research community has come up with a portfolio of corporate default prediction models. An array of such models in use. These models are based on different schools of thought (Datta.et.al., 2020) The ones relevant with the field of inquiry in this study are presented in the next section.

REVIEW OF LITERATURE

The terms ‘default’ and ‘bankruptcy’, though carrying different legal meaning, have interchangeably been used in the literature. The expression "bankruptcy" begins from the combination of *bancus* and *ruptus*, Latin words for "seat or table" and "broken" individually (Fernando.et.al., 2019). This is, said to emerge from the failure of a broker, who before all else executed his business in the commercial center on a workbench, to meet his legally binding commitments. Emblematically, his seat is, thought about broken (New Generation Research, Undated). The term is, likewise accepted to have establishes in *banco rotto*, from the archaic Italy, generally meant signify "broken bank." Similar theory on the inception word is, credited to the French articulation *banque* highway, an allegorical act of leaving a sign at the site of a neglected financier's table (Abatecola, 2019).

Summary of the Corporate Bankruptcy Theories

S. No.	Bankruptcy Theory	Key features	Inference for this study
1	Maximization of Social Welfare (MSW)	Social welfare is maximized when economically distressed firms are liquidated while financially distressed firms are allowed to continue.	It is of a great social value that the firms continue to exist, rather than the ones filing bankruptcy. It is only possible when financially distressed firm, which are likely to default are identified well in time
2	Absolute Priority Rule (APR)	Equitable distribution of the disposal proceeds from the firm's assets among the claimants	To protect the interests of stakeholders, the firm must not go bankrupt, hence should not default, therefore making it imperative to identify the financially distressed firms far earlier then they default.
3	Creditors Bargain Theory (CBT)	Bankruptcy costs may be minimized if creditors can sit and negotiate firm's capital structure with the firm.	Bankruptcy costs must be avoided by early detection of the financially distressed firms.
4	Risk Sharing Theory (RST)	Seeks to maximize the value of debtors' assets by compelling the stakeholders participate in risk sharing, especially related to the business failure.	Creditors must be seen as risk bearing stakeholders, rather than the ones secured against firms' assets for recovery of their stake in the firm.
5	Value Based Theory (VBT)	Just like human debtor, firms' resources available for distribution are imbued with social, political, and oral characteristics. They change with time and circumstances.	The phenomenon of corporate default needs to be seen holistically, including qualitative factors in addition of the mere accounting figures.
6	Bankruptcy Policy	Offers an alteration to parties non bankruptcy rights, because	Previous theirs have been addressing bankruptcy as a post

	Theory (BPT)	bankruptcy and non-bankruptcy laws deal with different kinds of defaults.	default event where a distributional mechanism of the firm assets among the creditors needs to be in place for maximizing the judicious distribution and value protection for the creditors

Prevailing models in Corporate Default Prediction

At present, the corporate analysts and regulators use an array of models to identify the defaulting firm(s). These models can broadly be categorized in three categories, the Statistical Models, the Artificially Intelligent Expert System Models (AIES), and the Theoretical Models (Ghio & Verona, 2020).

The statistical models include Uivariate models. These model prove a linear reationship of the elemens of the default algorithm with the default itself (Kisman & Krisandi, 2019) . Linear Probability Models (LPM), Logit Models, Probit Model, Cumulative Sums (CUSUM) Model and Partial Adjustment Processes, are the few examples of such models (Paharia, 2020). The Accounting Based Models (ABMs) fall within the same category, of which Altman Z-Score has been selected for the propose of this study.

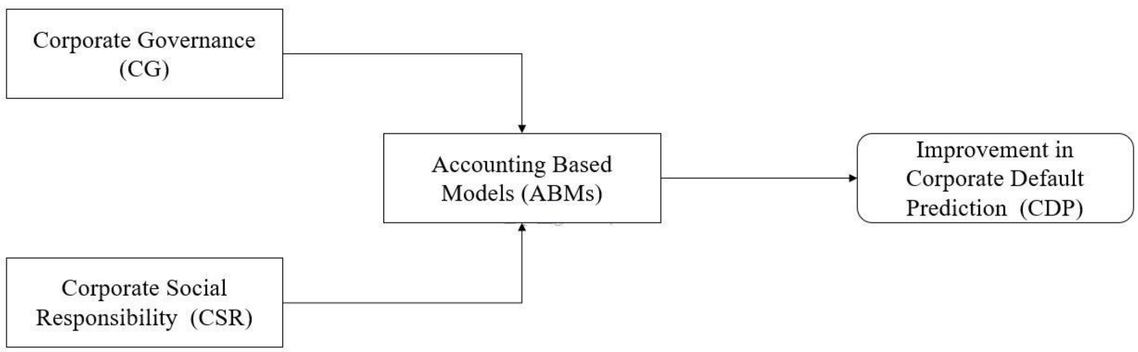
The AIES Models include Recursively Partitioned Decision Trees, Case Based Reasoning (CBR) Models, Neural Networks (NN), Genetic Algorithms (GA), and Rough Sets Model (RSM). These models may imply Artificial Intelligence (AI) into their algorithms (Vidal & Barbon, 2019; Menicucci, 2020).

Theoretical Models include Balance Sheet Decomposition Measures (BSDM) / entropy theory, Gambler Ruin Theory, Cash Management Theory, and Credit Risk Theories, and McKinney's Credit Portfolio View (Tang, 2019), (Jericevich & McKechnie, 2020; Nguyen, A. H., 2019).

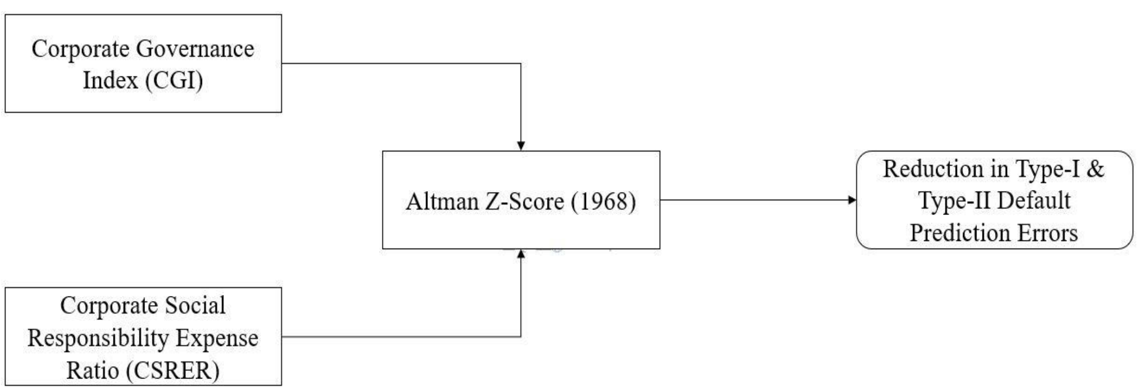
Such a wide range and generations of models make it difficult for the analysts, practitioners, and researchers to choose one model to make it better for identifying financially distressed firms (Munoz et.al., 2020), (PSX, 2018). This study adopts logistic regression model as the representative of our accounting-based financial distress detection model for comparison with the option-based model. Later both models are integrated to see if the financially distressed firms listed at PSX may be identified with a better precision. This study has taken up Altman Z-Score for the reason of its extensive use at present with the PSX analysts, ease of use & understanding, and of the shelf availability of technical expertise for use.

Research Frame Work

The research framework comprises of the n Accounting Based Model (ABM), i.e., Altman Z-Score, Corporate Governance (CG), and the Corporate Social Responsibility (CSR). The CG, and CSR, when enclosed into algorithm of the ABM is expected to improve the existing Corporate Default Prediction (CDP) of the ABM. The framework is laid down as follows.



The research framework has been operationalized as follows, where ABM has been measured as Altman Z-Score, CG as the Corporate Governance Index (CGI), and CSR as the CSR Expense Ratio (CSRER) with net profit.



METHODOLOGY

Data and Variables

The data

The State Bank of Pakistan (SBP) publishes extensively on economic data of Pakistan in form of an array of publications. One of those publication is the annual Handbook of Statistics on Pakistan Economy (Tahir et al., 2019). It presents financial statements analysis of all the companies in Pakistan listed on PSX. In addition, this economic data is periodically updated on SBP's website www.sbp.org/stats-pub.asp. The data set presents an extensive picture of corporate settings of Pakistan, and contains validated information on all dimensions of economy. One of those dimensions is the financial statements analysis of the companies in Pakistan. The data for the ratios within the Altman Z-Score has been taken from the Financial Statements Analysis Section of the SBP annual Hand Book of Statistics on Pakistan Economy. While the data for CG and CSR has been obtained for the financial statements of the companies along with the accompanied notes to the financial statements. Pertinent to mention that the data for the financial ratios is available for all the listed companies at PSX, as preparing and reporting the financial statements is a mandatory requirement for all the public listed companies in Pakistan. But same mandate does not exist when it comes to reporting for Corporate Governance (CG), and Corporate Social Responsibility (CSR) (Tahir.et.al., 2020). The CG and CSR information was available for the 161 publicly listed companies, hence forming the sample. The list is separately attached as annexure. These insights have been taken from the notes to the financial statements of the companies in sample.

The time horizon is kept as six years from 2010 to 2015 (both years inclusive). Thus, we have 966 (161 firms X 6 years) firm year observations for every variable of the study. This allows a reasonable canvas to analyze the impact of enclosing CG and CSR into the ABMs and evaluate whether the limitations in the existing accounting information based corporate default prediction models and delimitated, and the corporate default prediction of the ABMs gets refined.

The period of 2010-2015 has been selected because the Pakistani economy in particular and world economy in general went through different phases of economic cycle (for example, European Banking Crises 2011).

A sample of 161 manufacturing and services companies out of the 558 listed companies listed on PSX has been taken. These 161 companies are spread over different sectors. These companies pertain to sugar, pharmaceutical, cement, textiles, fabric, agriculture, energy, Autos, auto parts, refinery, airlines, apparel, shoes, castings, paints, chemicals, fibre, paper, jute, FMCGs, packaging, motors, fertilizers, gases, ceramics, food processing, oil exploration, telecom, oil fields, plastic & PVC, services, healthcare, hospitality, engineering, glass, data, films, and distribution sectors.

The availability of valid and authentic data is critical for any study to meet its objectives. Availability of the same in developing countries like Pakistan has limitation. Therefore, only those companies made it to the data sample that contained valid and authentic data for all the variables in this study. These firms were selected because they fulfilled two criteria. firstly, these firms had data for all variables of the study. Secondly, they did not belong to financial sector.

As expressed in the outset, that these 161 companies represent the manufacturing and service sector public listed on the PSX. However, the financial sector has been omitted for its well-regulated governance structure, stringent check and balance by the SBP, negligible default rate in the sector, and high degree of compliance by banks to the rules and regulations outlined by SBP. Thus, the financial sector firms have been omitted as this study seeks to analyse and test the efficacy of proposed default index in an environment that is not bound by legal constraints. This non-binding becomes even more compelling in the context of Pakistan's turbulent economic, financial, governance, and social environment, where obtaining the valid and accurate data becomes even more challenging.

Keeping the same challenge in view, obtaining the data for the variables of this study from the most trusted, reliable, valid and updated source remained pivotal. Therefore, the same has been obtained from balance sheet analysis published by the State Bank of Pakistan (SBP), annual reports published by the firms under reporting compliance towards the International Financial Reporting Standards (IFRS), and the regulatory compliance towards the Corporate Governance Code to the Securities and Exchange Commission of Pakistan (SECP). SBP's published Balance Sheet Analysis has been the source for accounting data required to compute Z-Score while data for the variables of CG and CSR has been obtained from the annual reports published by the companies.

These sources have been used for their authenticity, validity, and recency. SBP and SECP represent institution having autonomy yet drawing government sovereign support for the same. While the published annual reports are audited before being published and follow IFRS, and stand validated by the accounting bodies in the country.

The Variables

The study has taken three variables into account, namely, the Altman Z-Score, the Corporate Governance (CG), and the Corporate Social Responsibility (CSR). The construction of each of these three variables is explained in the following para.

The Altman Z-Score

The Altman algorithm for computing Z-Score is as follows;

Z= 1.2X1+1.4X2+3.3X3+0.4X4+1X5

Where;

X1 = Working Capital / Total Assets

X2= Retained Earnings / Total Assets

X3= Earnings Before Interest & Tax (EBIT) / Total Assets

X4= Market Capitalization / Total liabilities

X5= Sales / Total Assets

The resultant score determines the probability of default, as the score of 1.8 or below means the firm in in default, 1.8 to 2.7 means a grey area, above 2.7 is survival, while a score above 4 means a healthy firm.

Keeping the same in view a sample of 161 public limited listed companies at PSX has been taken. These companies consist of manufacturing and service sector firms. The business sectors of these firms include sugar, pharmaceutical, cement, textiles, fabric, agriculture, energy, Autos, auto parts, refinery, airlines, apparel, shoes, castings, paints, chemicals, fibre, paper, jute, FMCGs, packaging, motors, fertilizers, gases, ceramics, food processing, oil exploration, telecom, oil fields, plastic & PVC, services, healthcare, hospitality, engineering, glass, data, films, and distribution sectors. Financial data for these firms over a period 2010-2015 has been collected. Altman's Z-Score has been computed for these firms and financially distressed firms have been identified. This identification has been matched with the ground reality, i.e., type I and type II errors in these models where the firms expected to default has sustained, or a firm classified as financially healthy has defaulted. The extent and degree of both types of errors in both the models has been compared. The extent of errors sets the limitation to both the models for their reliability and foresight.

The Corporate Governance (CG)

This study has measured the Corporate Governance (CG) in form of the Corporate Governance Index (CGI). CGI is an additive index constructed by employing methodology of Aggarwal et al.(2009) and Amman et al. (2011) that converts firm level corporate governance attributes to ordinal variables ranging from 1 to 5. These firm level corporate governance attributes have been taken from shah (2009) for two reasons. Firstly, the robustness for these attributes, in both developed (U.S) and developing country (Pakistan). Secondly, it is parsimonious, as it contains all the variables that are present in every index used to study corporate governance quality. Thus, parsimony and stability are ensured by adopting these measures of corporate governance. The final index score ranges for 0 to 1. A higher score on the index indicates good corporate governance and vice versa. The governance attributes used in CGI are outlined in following table.

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 No. of Board members.
Board Independence	BI	Non-Executive Directors/ Total No. of Directors in Board
Audit Committee Independence	ACI	Non-Executive directors in Audit committee/ Total number of directors in Audit Committee
CEO Duality	CEOD	Whether CEO and Chairman are the same person.

The CGI was constructed by first converting all firm level governance variables in to 5 quintiles. In case of CEO Duality, if it had value of "0", it was assigned "quintile 1" and if it has value of "1", it was assigned "quintile 5". All quintiles were added for every firm year observation for every firm and index was obtained by using following formula

$$CGI = \frac{(Sum - Min)}{Range}$$

where "Min" was lowest value of sum across a single year in the sample and "Range" is difference between Maximum value of sum across a single year and minimum.

The Corporate Social Responsibility (CSR)

CSR reduces the corporate default risk, significantly. Review of relevant literature suggests the CSR accrues Social Capital that buffers the default risk for the firm. Firms having prior history of positive CSR engagement are less likely to file for bankruptcy, even when such firms are deeply in financial distress, and are more likely to experience an accelerated recovery for financial distress, instead of experience default.

Though the literature hints of further classification of Social Capital in to moral capital and exchange capital, where the moral capital reduces the likelihood of default when a firm grows larger, while the exchange capital does the same when a firm relies on intangible assets. But the issue of measurability remains unaddressed, which is critical for this study. Therefore, the ratio of CSR expense to Net profit has been adopted as the mean to measure a firm commitment towards CSR. This has been done for two reasons; First, its ability to quantify the firm's commitment towards CSR, second, the recognition of such commitment on face of the firm's income statement. Any amount booked on the face of financial statements is subject to IFRS compliance and verification in independent audit. This allows [CSR/Net Profit] ratio to qualify for inclusion into the issue under discussion.

In the ratio of CSR expense to Net Profit, the CSR expense represents the spending made by a firm as its commitment towards CSR activities, while the Net Profit represents profit after tax.

Composite Default Index (CDI)

The objective of this research is to enhance the corporate default prediction ability of the existing ABM, i.e., Altman's Z-Score, by enclosing Corporate Governance (CG) and Corporate Social Responsibility (CSR) information. The enhancement of the corporate default prediction ability would mean lesser errors of type-I and type-II errors, while identifying the financially distressed firms, likely to default. The incorporation of CG and CSR into the ABMs would delimit the ABMs, which largely pertains to the conservatism and prudence in the way with which accounting information in collected, classified, audited, and presented. The reduction in type-I and type-II errors would mean that delimiting the ABM improves their ability to identify the financially distressed firms, and anticipate the corporate default well before it occurs. The timely anticipation allows enough time to the stakeholders to reposition their stake in the defaulting firms, hence keeping the stakeholders' trust in the financial markets, and confidence in corporate regulators' ability to safe guard their interest.

Predictive research method has been adopted for this study. It is mainly concerned with predicting outcomes. These outcomes may be further translated into the consequences and allied effects. Predictive research analyses the existing phenomenon to extrapolate something that has not been tried, tested, or proposed before. This study has analysed the existing phenomenon of corporate default prediction and found out that accounting information-based default prediction models are the most reliable ones yet having limitation to being futuristic in foresight and accurate in the hindsight. These limitations have been addressed by incorporating Corporate Governance (CG) and Corporate Social Responsibility (CSR) information into the Altman's Z-Score, to timely identify the financially distressed firm, likely to default.

Composite default index is an additive index that uses quintiles of Z-score, CG Index and CSR. Z-score is converted in to quintile 1 and 5 with firms in quintile 1 having Z-score less than 1.8. CG Index and CSR are converted in to 5 quintiles. Firms having CG Index and CSR scores in first two quintiles were considered as firms with lower governance and low expenditure on CSR. However, firms in upper quintiles (such as quintile 4 and 5) were considered to be good governance firms that spend high sums on CSR. The additive index thus obtained ranged from 0 to 1 and was named as composite default index constructed using following relationship

$$CDI = \frac{(Sum - Minimum)}{Range}$$

Where, sum is addition of quintiles of Z-score, CG Index and CSR for every firm year observation, Minimum is the lowest score of sum across each year of the study and Range is difference between minimum and maximum score of sum across each year for every firm year observation. The CDI ranges from 0 to 1. Firms in lower quintiles of CDI have highest probability of default while firms in higher quintiles of CDI are firms that will survive.

Success Ratio

Success ratio is calculated by employing CDI and ZDI. For robustness purposes, firm year observations that fell in 1^{st} and 2^{nd} quintiles of CDI were assigned "0" while firm year observations that were in 3^{rd}, 4^{th} and 5^{th} quintiles of CDI were assigned "1". Similarly, for ZDI, firm-year observations that had value less than 1.8 were assigned 0 while others were assigned 1. Then for every firm in the sample, means were calculated for estimation period by adding respective values and dividing them by number of observations. Regarding means, we obtained two extreme ends namely mean of "0" and mean of "1". Those firms that had mean of "0" indicated that models in questions have declared them as being in default but in reality, they were on PSX and model failed. However, firms with mean of "1" indicated that model assigned the firm as being survivor and firm did survive as it was listed on PSX during estimation period. This indicated that model has successfully predicted firm's state of affairs. The values between zero and one are values where model gave mixed results. They can be thought of as grey areas.

ANALYSIS, RESULTS & FINDINGS

The Analysis

The analysis consists of comparison between the accuracy of prediction made by the Altman Z-Score in form of Z-Score Index (ZDI), and the Composite Default Index (CDI) comprising of Z-Score, Corporate Governance (CG), and the Corporate Social Responsibility (CSR).

The Results

Summary Statistics of CDI

Table1 indicates summary statistics of Composite default index. The summary statistics indicate CDI has total of 966 firm year observations. The means in 1st and 2nd quintiles indicates firm year observations where the index predicts failure while 4th and 5th quintile indicates firm year observations where it predicts survival.

Table 1: Summary Statistics of CDI by Quintiles

Q	Count	Mean	Sd	Min	Max
1	262	.164	.094	0	.273
2	253	.330	.043	.250	.364
3	127	.440	.018	.417	.454
4	179	.571	.051	.500	.637
5	145	.776	.115	.583	1
N	**966**				

Z-Score's correlation with CGI and CSR

Table 2 represents correlation matrix of CGI and CSR with Z-Score. Since it is mandatory to include those variables in index that have some correlation with each other, this table indicates that all the components of our Index are significantly correlated with one another and can be embedded to form a default index. An interesting insight from the correlation table is that all variables are positively correlated with one another. As Higher Z-score is associated with low default, similarly firms with higher governance scores and higher CSR expenditures are less likely to default.

Table 2: Z-Score's correlation with CGI and CSR

	Zscore	CGI	CSR
Zscore	1.00		
CGI	0.08^{**}	1.00	
CSR	0.07^{**}	0.14^{***}	1.00

**** p-value<0.05 *** p-value<0.01**

Comparative Success Ratio of the CDI and ZDI

The key finding of the study has been exhibited in table 3, where comparative mean of the success ration of each of the CDI and ZDI have computed. The success mean analysis has been categorized in four classes. The table exhibits that the out of 161 firms the Z-Score has been correct in identifying the survived firms for 32/161 or 19.87%, while CDI correctly identifies 65/161 or 40.37%, exhibiting a twice improvement in correctly identifying the successful firms. this may also be interpreted as the 50% reduction in the type-I errors, which is a significant improvement resulting in improving the corporate default prediction.

Table 3: Comparative Success Ratio of the CDI and ZDI

	(CDI)	(ZDI)
Success Mean	**Count**	**Count**
0	36	99
m>0<0.5	39	24
0.5	21	6
> 0.5	65	32
N	161	161

Similarly, the identification of firms failed has correctly been predicted by CDI by 39/161 or 24.22%, while the ZDI predicts it correctly by 14.91%, exhibiting a more than 60% reduction in type-II errors. This exhibits a significant improvement in correctly predicting the failed firms on the part of CDI.

Also, success mean of “0” represents that model predicted the firms to have been in default but in reality, they survived. This error in prediction is significantly less by using CDI. Out of 161 firms, it incorrectly predicted 33 firms to have defaulted while ZDI made wrong prediction about 99 firms. Thus CDI failure rate is 22% while ZDI failure rate is 61%. Thus there is reduction in failure in prediction by 39% using CDI.

These findings reveal that the Composite Default Index (CDI) predicts the success or failure of the firms correctly twice as compared to the Z-Score Default Index (ZDI)

Paired Sample T-Test of Success Ratios of CDI and ZDI

Table 4 represents results of paired sample t-test assuming unequal variance. The default prediction success ratio mean of CDI is compared with default prediction success mean of ZDI under assumption of Un-equal variance.

The results of paired sample t-test indicates that there is significant improvement in prediction of default by CDI as compared to ZDI. The success mean of CDI is statistically significant than the mean of ZDI. Thus CDI has improved prediction of default as compared to ZDI. These results are in line with the findings presented in table 3.

Table 4: Paired Sample T-Test Of Success Ratio of CDI and ZDI

	CDI	ZDI
Mean	0.467	0.226
Variance	0.130	0.126
Observations	161	161
Hypothesized Mean Difference	0	
Df	320	
t Stat	6.041	
P(T<=t) one-tail	0.000	
t Critical one-tail	1.649	
P(T<=t) two-tail	0.000	
t Critical two-tail	1.967	

CONCLUSION, RECOMMENDATION, & LIMITATION

The findings lead to the conclusion that the Composite Default Index (CDI) yields significantly lesser number of type-I and type-II errors, hence substantially improving upon the accuracy in identifying the financially distressed firms listed at PSX, which are likely to default. This improvement in the corporate default prediction at PSX is likely to improve the stakeholder's confidence in the markets for secondary financial instruments in Pakistan.

The study recommends that the corporate default predictions mechanism be seen in holistic manner where hindsight and foresight are combined to develop a mechanism, which is not only reliable, hut also has a futuristic outlook. this study has restricted itself to the incorporation of only CG and CSR only, into one of the ABMSs, i.e. Altman Z-Score. future studies may consider more futuristic elements for incorporation into different ABMs to consolidate the corporate reduction into a more holistic mechanism, which may bring markets to a more stable, yet rewarding investing platform for the stakeholders.

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