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Predictive analysis of corporate default in Indian Manufacturing BSE listed companies using Altman's Z-Score Model

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Abstract
This study investigates the cogency and accuracy of Altman's Z model in predicting default or financial distress in manufacturing companies in India. The study uses a balanced sample of 40 manufacturing firms of 20 firms are defaulting and 20 non-defaulting firms listed on BSE over a period of five years from 2015-2019. The study utilize listed manufacturing firm's data across 5 years composed a balance default and non-default (20 each) firms. The findings of research suggest that Altman model is still effective with an accuracy of 81% even after dramatic changes in manufacturing sector across globe in general and India in particular help stakeholders to make more sound decision and 81% classification accuracy demonstrate model's robustness.

Keyword: Altman z-score model, default, bankruptcy, financial distress, insolvency

Introduction

It is very common for companies to face financial distress and many companies don't succeed to overcome the situation of financial distress and tend to default eventually and experiences financial failure. Companies are said to be in financial distress when they, find it very difficult to service their debts and meet current financial obligations. Financial distress is directly in proportionate to the firm's leverage decision. Presence of high leverage is prime causes of financial distress. And when these firms have to undergo a legal process of either liquidation of assets or winding up, it is said to be the situation of bankruptcy.

The situation of financial distress, default or bankruptcy is unfavorable for banking and financial sector as the failure of companies in servicing their debt culminated in NPA which eventually have negatively affect the banking sector leading to financial pressure on public exchequer. According to Beaver (1966) [11], the inability to honor the financial obligations may largely be driven by events such as bankruptcy, bond default, an overdrawn bank account, or non-payment of a preferred stock dividend. The bankruptcy, is not a one-time event it also embedded the indirect cost (Altman, 1984) [5]. Prediction of credit risk or defaults is imperative for an economy particularly for the firms, regulators, investors, and bankers to know about the probable defaults for making prudent decisions, examining the growth of any debt instrument, pricing the risky bonds, establishing the default savvy policies. Basel accords have made it mandatory for the banks, to incorporate an internal risk management system using various prediction models. It is imperative that the default prediction methods should be simple yet with precision and applicable across industries and consistent in prediction. Prior information about defaults events provide the lead time to the firms and also to the banks to take corrective actions leading to restructuring and required adjustments to the realities and if required get out from in time.

There are various prediction methods and models that can be used by Indian corporate to practice internal risk management and predict potential defaults. The majorly used methods is consisting of either statistical methods or firm's specific structural models along with machine and artificial intelligence based models that are being used to assess creditworthiness of firms. The history of default prediction models dates back to 1966 with Beaver developing a univariate default prediction model using financial ratios. Later on, most the statistical models used financial ratios to predict default and bankruptcy.

The initially multivariate model for default prediction was introduced by Altman (1968) [4], known as Altman Z-Score. This model has used five ratios for bankruptcy prediction of a company. Altman model helps in identifying whether a firm is financially distressed. Several other models have been introduced to predict bankruptcy such as Springate (1978) [34] which uses 4 ratios; Ohlson (1980) [24] used 9 ratios; Zmijewski (1983) [37] used 3 ratios; & Grover (2001) that uses 3 ratios to predict bankruptcy. The similarity of the Z score and O score is that both of these functions are predominantly based upon accounting ratios, unlike the structural model. The structural model has also been used to explain the expected default frequency (EDF). This model is based upon the distance to default measure using the Black Scholes option pricing model. The default prediction studies based on structural model conducted so far have provided better results relative to Altman (1968) [4] and Ohlson (1980) [24]. However, there are some studies that have found other models performing better than structural model.

SEBI disclosed the defaulted amount of 60 listed firms i.e. 75000 crores as of Dec 31, 2019. The majority of the defaults have been reported from the Anil Ambani Group firms namely Reliance Communications, Reliance Naval & Engineering, Reliance Infrastructure and Reliance Power have defaulted. The defaulted amount consists of bank loans, loans from NBFCs and unlisted debt securities. Such defaults might be triggered caused by collapse of IL&FS Group in 2018 that had reduced the economic growth to 5% i.e. the lowest in the last 6 financial years. Lots of companies in recent times is disclosing themselves as willful defaulter because of mandate issued by SEBI in November 2019 under which the firms must disclose their defaults within 7 days after closing of the quarter (Economics Times, 2021).

According to CRISIL, the firms that have issued debt instruments are likely to default on the obligation of their debt holders. However, the report of CRISIL demonstrated only 2% default rates in the Financial-Year 2021 against 4.5% default rate in the Financial Year 2020 owning to the measures taken by RBI during lockdown period of 2020 such as moratorium period, credit line guarantee scheme, and deferment of asset classification and relaxed norms of default recognition adopted by SEBI for public ltd firms. CRISIL reported that the 2 firms rated as AA category one from aviation and another from textile defaulted during the pandemic. Around 16% of risky corporate debt is expected to default in the next 3 years that will account for a further 10.52 trillion of bad loans. (CRISIL, 2022) [13].

Lately, Suzlon Energy, Jaypee Infratech, Ansal Housing, Aban Offshore, ISMT, Religare Enterprises, Bedmutha Industries, Hindustan Construction and Bombay Rayon Fashions failed to oblige its debts. The rating agencies have given a warning about the forthcoming huge wave of corporate defaults. That is why it would be prudent for the lenders, investors to predict the corporate defaults in advance. Further, the most debt-ridden Indian firms are Power Finance Corporation, Reliance Industries, HDFC, Rural Electrification Corporation, LIC Housing Finance, Power Grid, Vodafone, Larsen and Turbo, Bharti Airtel. (Economics Times, 2021). GMR Warora make a default on interest payment on loan and debts, total 2913 crore (Economic times 2022) [15]. The MSP Metallics owned more than 1500 crore from its lenders and SBI have 32.2% voting right in company management (Economic times 2022) [15]. The names add every year in the list, need an effective solution which can be helped by statistical model who help in prediction of distress situation prior to it happen.

The mounting growth of NPA and willful defaults has made it imperative to predict defaults before it actually happens. Indian banks have taken multiple measures to combat the corporate defaults in order to narrow down NPA for instance SARFAESI Act 2002, Corporate Debt Restructuring, Asset Reconstruction Company, Debt Recovery tribunal, Insolvency & Bankruptcy Code (IBC) 2016& Lok Adalats but it eludes the effective results. The credit defaults of Indian corporate are the real cause climbing NPA in banks, for all that other factors also contributing to the growth of NPA such as global recession, political interference, corruption, and fraud. RBI grouped the defaulters into willful defaulter*s* & others. The willful defaulters are the borrowers, who, despite having the capacity to pay, fail to pay by taking unfair benefits of the weak governance framework of the banks. (RBI, 2022) [28].

Review of Literature

Over the era, various approaches for prediction of default have been evolve by using different methods and assumptions so that financial health of various industries could be estimated prior to defaults so that corrective measures can be taken in time by the stakeholders with the purpose to avoid huge economic costs that firms and economies have to bear due to defaults by the firms.

Recent default prediction studies conducted so far have provided better results relative to Altman (1968) [4] MDA model and Ohlson (1980) [24] O-score model. Logit model validates the existence and applicability of these functions in contemporary studies in order for default prediction and to rate the debt instruments by the rating agencies. The multiple discriminant analysis (MDA) classifies a firm into good and bad categories based upon its score which is computed using accounting ratios. Whereas, logistic regression computes the probability of a firm that it would default. Both of these functions are static that is basically used by various studies for forecasting of single-period default events. Although, the structural model presumes that firm defaults when the values of its assets drizzled to a sufficiently low level than to its liabilities. A key implication is that, the distance to default is the only key variable, that a firm's conditional default probability is completely determined by, which is closely connected with firm's annual asset growth, accounting for its levels of liabilities and volatilities.

MDA

Chijoriga (2010) [12] shows that liquidity & leverage ratios combinedly used in MDA improves prediction of loan applicants' defaults and provides easy way to access credit risk. The study also conclude that quantitative CSM's(Credit Scoring Model) help in making good management decision rather than subjective assessment method and a blending of qualitative and quantitative approach should be apply in credit assessment (Chijoriga, 2010) [12]. Hybrid default estimate models incorporating BSM parameters can prove better and incorporates credit approach and various pricing decision by banks and financial institution (Bandyopadhyay A, 2007) [9]. There is minimal or negligible difference in prediction capability of MDA and Ohlson models. However, discrimination model is comparatively more accurate for large sample (Upadhyay, 2019) [35].

Bandyopadhyay (2006) [8] develop a model for predicting corporate default of the Indian market using 104 listed corporations. The study applies Multiple Discriminate Analysis (MDA) in order to construct Z-score models and logistic regression for directly estimating the probability of default (PD), for this study using both financial and non-financial variable. The classification power of the model within the sample have high, 91% accuracy rate achieving. Furthermore, model have strong prediction power with accuracy rate 92% & 88% in detecting bad firm in holdout samples. Additionally, Z-model shows ability in forecasting bankruptcy prior 2 years to financial distress, with accuracy 97.5% & 96.3% respectively. The new developed model surpasses the Altman’s 1968 [4] model and emerging market score model 1995.

Panda and Behera (2015) [26] focuses on predicting financial distress of the pharmaceutical industry using Altman's Z-Score model. The study inspected the financial health of pharmaceutical companies over 11-year period (2001-2012) and scrutinized their vulnerability to bankruptcy. The study wraps up that there are significant differences in the variables while used Altman's Z-Score model between financially distressed and non-distressed companies. The findings advocated various methods such as effective financial management, sales revenue enhancement, and consideration carefully of various financial ratios are essential for preventing bankruptcy. Various tools used to prediction bankruptcy and distress level of corporates, in this study Altman’s Z-score model employed to prediction the distress level of 6 BSE and NSE listed corporates of manufacture and non-manufacture sector over 5years. Study reveals that Altman model prove a good indicator in prediction of default and identify that distress level is spreading over these 5 years (Sajjan, 2016) [29].

A study was conducted by Marvadi (2016) [22] on steel companies in India and apply Z model along with parameters such as profitability, liquidity etc. and suggest that Z model is effective in prediction of default along with these parameters.

Singh and Mishra (2016) [33], study focus on Indian Manufacturing companies and develop a bankruptcy prediction model by introduce a risk-neutral indicator of credit risk derived from the Black-Scholes-Merton (BSM) framework, utilizing data sample of 208 firms, including both defaulted and non-defaulted entities. The study re-estimates accounting-based bankruptcy prediction models, specifically Altman's Z-Score, Ohlson's Y-Score, and Zmijewski's X-Score models. MDA, PROBIT and Logit models were used for estimation and validation purposes. A variety of tests were used to evaluate the model, including predictive accuracy, statistical significance, long-term accuracy, secondary models, and receiver operating characteristic (ROC) tests. Study shows that re-estimating coefficients increases a model's prediction accuracy. It is reported that the new business forecasting model surpass other models. Observed results indicate that the average probability of failure (PD) predicted by BSM for distressed companies is higher (10.43%) than the standard benchmark probability of failure (PD) estimates for non-stressed companies (0.75%). The results revels that the model is succeed and doesn’t differentiate among those companies facing negative risk.

Nandi, Sengupta, and Dutta (2019) [23] focused on financial analysis problems of the Indian oil drilling industry. This study examined 12 large companies over 5 years using Altman's Z-score. For instance, the accounting ratios such as working capital to total assets (WC/TA), net income to total assets (NI/TA), EBIT to total assets(EBIT/TA), operating expenses to liabilities, & total assets sold immediately. This study applies Altman's model through discriminant analysis and provides acumen into the forecast ensemble and the overall economy. More specifically, 75% of companies are in good financial health and have significant Z-scores for Working Capital/Total Assets.

Logistic regression (LR)

Altman and Sabato (2005) [6] prospect the credit risk for Small and Medium-sized Enterprises (SMEs) in US market, the study employ logistic regression analysis to a sample data of SMEs to investigate the most prominent factors of credit risk, as measured by default. The sample consists of 1,000 private US firms that have issued bonds between 1984 and 2014. The study concludes that the most prominent factors of credit risk for SMEs are liquidity, profitability, & leverage. Additionally, the study found that the Altman Z-score, a well-known credit risk model for larger firms, is also effective for predicting credit risk for SMEs. However, the study also highlights the need for SME-specific credit risk models, as smaller firms have unique characteristics that may not be captured by models developed for larger firms. The study's findings have notable inference for credit risk assessment and lending practices for SMEs.

Hauser and Booth (2011) [17] argue that traditional logistic regression models can be sensitive to outliers and influential observations, which can negatively impact model performance. Hauser and Booth propose the use of robust logistic regression, which is less sensitive to outliers and provides more reliable estimates of coefficients. The study collate the performance of conventional logistic regression model with robust logistic model by using a dataset of bankrupt and non-bankrupt US firms 2008-09. The findings suggest that the use of robust logistic regression can improve the accuracy about 33.33% and reliability in prediction bankruptcy.

This study applies LR (Logistic regression) for predicting the probability of default of 90 BSE listed company and study conclude that model seems to be best fit for identify the defaulting capability of corporates during 2010-2014. The study accesses the impact of sensitivity variable for industrial factors on firm default probability. The study estimate industry beta use LR and MDA and concluded that sensitivity variable is significant in default prediction and suggest that by constantly monitor the firm sensitivity towards changes help in identify the default risk (Verma 2019) [36].

Other models

Study reveals that discriminant ratio model proved too much accurate in predict the bankruptcy with a accuracy of 94-95% for public manufacturing corporates. Study based on 16 US hospitality firms between 1999-2004 which went bankrupt and 16 non-bankrupt firms and predict bankruptcy in advance prior 2 years and result shows that if a firm have low operating cash flow & total liabilities high then more chances to go bankruptcy and correctly predict 91%-81% of bankruptcy in 1 and 2 year earlier (Kim & GU, 2010) [19].

Study based on Tehran stock exchange (2001-2008) of 304 corporates, use distress score along with financial ratios and ROC curve analysis as a predictor variable and conclude that prediction accuracy can be enhanced by using distress score. (Sheikhi, Sham, & Sheikhi, 2012) [31].

The study provides a comprehensive analysis for consideration of corporate default using Bayesian Model Averaging (BMA) methodology. The study applies a dataset of Spanish non-financial firms between 2001 and 2010, which includes information on default status, financial and non-financial variables. The study employs BMA approach, which allows for the identification of the significant determinants of corporate default while accounting for model uncertainty. The study finds that the most significant determinants of corporate default are the firm's profitability, leverage, size, liquidity, and growth opportunities. Specifically, the study finds that firms with low profitability, high leverage, low liquidity, and small size are more likely to default. On contrary, those firms having high growth opportunities they are less likely to default. Additionally, the study explores significant role of macroeconomic factors, such as GDP growth and inflation, in predicting corporate default. Finding shows that these factors are not significant determinants of corporate default on their own, but they do have an indirect effect through their impact on the firm-specific variables. The BMA approach provides a more robust analysis of the corporate default determinants by accounting for model uncertainty and identifying the significant predictors (Aguado and Benito, 2012) [3].

The study flashes a light on default probabilities of 47 Indian firms from the period of 2007 to 2013. The study utilizes an options-based method that utilizes the Black, Scholes, and Merton model to predict the probability of default of these firms. By estimating the asset volatility, current market value of asset, risk-neutral default probability, and real default probability of firms, the study aims to determine the factors that have an impact on default probabilities. Finding shows that options based models can effectively predict the default probability and also reveal that when the distance to default is < 1 (less than 1), the occurrence of default increases significantly. The current market value of assets and asset volatility have an inverse relationship with default probability, and the distance to default has an inverse relationship with default probability. On the other hand, asset volatility and probability of default have a positive relationship. However, study suggests that default is not solely determined by the current market value of assets and liquidity position of firms, but by other factors as well. Despite predictions of default, companies such as Kingfisher, Varun Industries, Suzlon Energy, and Electrotherm (India) continued to operate for years. The industry in which companies operate also seems to be crucial in determining the availability of debt capital, which has an impact on default (Sharma, *et al*. 2017) [30].

Study based on sugar mills in Pakistan and focus on leverage, growth & liquidness of the firms to locate the probability to default and use financial ratios as an indicator for probability default, conclude that the main reason for probability default are external factors during study period (Islam & Nabi, 2015) [18].

Indian textile industry is a huge industry also face soundness problem as conclude in the study. On the sample data of 11 textile firms, the study apply Enyi's relative solvency ratio and a solvency management model, suggest that these models more helpful in finding overall liquidity position rather than general individual financial ratios. (Pai & Dam, 2017) [25].

The study is empirical & make a comparison between five default prediction models i.e. Ohlson, Altman, Grover, Zmijewski and Springate & finding shows that Springate and Zmijewski models are more accurate in prior prediction of probability of default (Agarwal & Patni, 2019) [1].

The study use two learning algorithm model i.e. decision tree and random forest in conducive to predict credit risk & probability to default. The result revels that both methods give accuracy about 73% to 80% but random forest models seems to be better (Madan, Kumar, Keshri, Jain, & Nagrath, 2020) [21].

However, numerous studies based on financial ratios like Altman and Sabato (2005) [6], Chijoriga (2010) [12], Islam and Nabi (2015) [18], Nandi, Sengupta, and Dutta (2019) [23], Panda and Behera (2015) [26], and succeed in default prediction. Although the accounting ratios form a based and alone are sufficient in prediction bankruptcy of a firm as supported by the above listed studies. Financial ratios are incorporated with other independent variables such as market and economic variables provide a more comprehensive result as suggested by Bandyopadhyay (2006) [8], Singh and Mishra (2016) [33], and Upadhyay (2019) [35].

Objectives

- In conducive to predict bankruptcy in Manufacturing Sector BSE listed company from 2015-2019.
- Predict the default probability prior 2 years.

Research methodology

The study conducted in conducive to investigate the cogency of Altman Z model in default prediction or financial distress situation in manufacturing companies in India listed in BSE. The sample consist a balance of default and non-default firms so that the classification accuracy can be accurately justify. The sample data is filtered in excel by removing the missing cases. The clean data processed with the Altman Z-score model in excel so that the classification accuracy identify for these particular sample case.

Altman Z-Score Model

$$Z=1.2z1+1.4z2+3.3z3+0.6z4+1.0z5$$

- Z=Altman Z-Score
- z1=WC/TA Ratio (higher the ratio good financial situation of company, or vice versa)
- z2=RE/TA Ratio (lower ratio indicate company going

to bankruptcy in near future, or vice versa)

- z3=EBIT/TA Ratio (demonstrate company generate revenue, which is enough to make debt payment and stay profitable, or vice versa)
- z4=MVE/TL ratio (higher ratio interpreted higher investor confidence in company, or vice versa)
- z5=TS/TA ratio (higher ratio indicate that little investment required to generate sales and increase overall profitability, or vice versa)
- WC=Working Capital, this variable indicate difference between current asset and current liability of a company, depict short term financial health. Positive means company is in good financial situation.
  - TA=Total Asset
  - TL=Total Liability
  - TS=Total Sales
  - EBIT=Earnings before Interest & Tax
  - MVE=Current Market Value of the Equity

Zones of Discrimination

1) Z > 3.0 Safe
2) 1.80< Z < 3.0 Grey
3) Z < 1.80 Financial distress

Source of data

Secondary data used, data has been collected from the BSE website and annual report, balance sheet and P/L extract from individual manufacturing firm website. Data has been analyzed and apply the Z-Score Altman Model in conducive to predict the probability of default. In the z-score model various variables such as working capital, total assets, EBIT, total sales, market value of equity, total liability employ to predict Bankruptcy.

Findings

This study conducted on 20 non-defaulting and 20 defaulting firms from the manufacturing sector listed in BSE over the time period of 2015-2019. After using the Original Altman Model's coefficients on this sample, the overall accuracy of model is 81% with Type I error of 9.9% and Type II error of 25.2%. The overall accuracy here, Altman model is comparable to many previous studies. However, high Type II error somehow makes the model less accurate. The matter of concern here is Type II error i.e. 25.2% cases the model fails to predict those firms which are actually defaulted firms but model suggest them and categorized them as non-default while Type I error suggest that firms are non-defaulted but models predict them as default firms. So here, the rate of Type II error is not at a lower side. Several studies found that Altman Z model is one of the best statistical models in prediction firms forthcoming bankruptcy situation. Altman use discrimination ratio which give 94-95% accuracy in manufacturing sector (Djamaluddin, Putridan, & Ali, 2017) [14] revels 60.71% accuracy in prediction bankruptcy in Japanese electronic manufacturing companies with Altman model (Sajjan, 2016) [29]. Use Z model and conclude that during 2011-16 most of the Indian firms are in distress zone. Z score model which help in prediction accurately one year prior the bond defaulting (Bandyopadhyay A, 2006) [8]. The analysis of the current study shows that type I error comes out to be 9.9% which is not a concern matter but Type II error concern more as it come out as 25.2%, but still the overall accuracy rate of the model is 81% which again prove as a benchmark model in prediction of accuracy of that much high rate. The Z model is an effective tool in analyze and predict accurately the bankruptcy rate.

Table 1: Classification accuracy

Classification Table			
	Default	**No Default**	**Total**
Default	73	8	81
No Default	30	89	119
Overall Accuracy			81.0%
Type I error			9.9%
Type II error			25.2%

Source: Based on sample data result assess in excel

The Z-Score Model is applying to predict defaults by companies in servicing their external debts in coming years. The lower is the Z-Score, higher is the possibility of default by the company. Accordant to the Altman's Z-Score, the Z-score lower than 1.8 (Z<1.8) signifies that company is facing financial problems or in financial trouble and is in financial distress stage with higher possibilities of default. The Z-score above 3 is observed to be in safe zone with very low possibility of default. The Z-score between 1.8 and 3 (1.8<Z<3), considered in grey area with moderate chances of default.

Table 2: Firms categorization

Z-Score	Category	No of Cases
Less than 1.8	Default Zone	103
1.8-3	Distress Zone	28
More than 3	Safe Zone	69

Source: Sample data analyzed in excel

In the analyzed sample, there are 103 cases, which have Z-score lower than 1.8. There are 28 cases which have Z-score lower in the range of 1.8-3 categorizing these in distress zone. There are 69 cases which Z-score higher than 3 making these cases to be safe. The finding suggests that the Altman Z-score model is quite significant predict the default firms with an accuracy of 81% of Indian manufacturing sector firms. The model is efficiently categorized the firms under different categories as demonstrated above in Table 2.

Conclusion

The bankruptcy is not just an event but has embedded indirect cost (Altman, 1984). It not only negatively impacts the firm in the question but the whole financial system and economy. From the above study, it is concluding that Altman model prove to be an effective model which can predict default probabilities accurately prior to 2 years. The current study applies Altman Z-Score Model on a sample of 20 defaulting and 20 non-defaulting manufacturing firms listed on BSE over the period of 2015-2019. The study reveals that prediction of default using the Altman's Original Z-Score Model has an accuracy of 81%. On 200 cases analyzed, the study finds 103 cases in default zone and

28 cases are in distress zone and rest 69 cases in safe zone. The analysis of the current study shows that type I error is 9.9% but Type II error is 25.5% which a cause of concern and indicates that model needs to be either recalibrated or new model needs to be developed. However, on comparing with many other studies on different countries and samples, the overall accuracy rate of the model which is 81% is at par making the Altman's Original Z-Score Model still relevant in changed economic environment. However, the present study suggests that Altman Z-score model is still significant in context of Indian manufacturing firms, but based on only financial ratios is limitation too. Further this limitation overcome through incorporation of market and economic variables and employ MDA, PBOBIT, BSM models etc. models for better default prediction.

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