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EVALUATING THE ACCURACY OF PREDICTION IN ACCOUNTING-BASED MODELS FOR COMPANIES IN INDIA UNDER IBC

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Abstract *The objective of this research study is to compare the performance of and test the reliability of four accounting-based models on a sample of 30 companies under the Insolvency and Bankruptcy Code in India and a matched sample of 30 solvent companies. The solvent companies are identified as those with highest and high safety, denoted with credit ratings 'AAA' and 'AA', respectively, and are matched on size (market capitalisation), year, and sector. The four models chosen are: Altman original Z-score, Altman Z-score for emerging markets, Ohlson model, and Zmijewski model. The scores are computed for T−1, T−2, and T−5 years, where T is the year the company filed under the IBC. The research findings reveal that all the models are able to predict default accurately for one and two years prior to bankruptcy, but fail to do so accurately for T−5 years. The predictive ability of the models is evaluated by ROC curves and the Gini coefficient. It is observed that the Ohlson model has the highest predictive ability, followed by the Zmijewski model and the Altman Z-score. In the next stage of our analysis, we compare the four accounting-based models with the Merton (market-based) model and the logit model to assess if the models, in their original form, are more accurate than these two models for the Indian markets. It is observed that the Merton model has the highest predictive accuracy, followed by Ohlson, Zmijewski and Altman Z-score. We conclude that neither the accounting nor the market models in themselves are sufficient; the models need to be reassessed based on specific regions and industries, and the scores need to be re-computed for better accuracy. We recommend that for accurate and early prediction, we need to look beyond financial statements to qualitative and other quantitative variables, so that defaults can be preempted and lenders be forewarned against impending distress.*

Keywords: *Accounting-Based, Bankruptcy, Predictive, Default, Accuracy*

INTRODUCTION

Credit risk is the uncertainty of the probability of loss that emerges when the borrower is unwilling or unable to make a successful repayment to the lender, which leads to an economic loss to the bank. According to Ruziqa (2013), credit risk is measured by the rate of bad debts. As stated by Kou, Peng and Lu (2014), loans are the main type of bank credit risk. The bank's inability to assess the borrower's ability and willingness to cause a default can lead to considerable losses to the bank, thereby affecting its financial health, leading to a systemic crisis. Prudent management of credit risk has benefits for all stakeholders: lenders, investors, management, shareholders, and regulators (Gepp & Kumar, 2012). Therefore, a proper method to address the credit risk and appropriate risk mitigation measures for the same play an essential role for banks and other lenders. The global financial crisis of 2008 and its aftermath led to corporate bankruptcies and advocated that bankruptcy prediction is vital for the survival of an economy in the long run, and the models developed for the same are to be close to reality. Post the financial crisis, there has been considerable change in the various methodologies used to identify and mitigate risk prevalent in the firms and financial institutions. Credit risk modelling has grown significantly over the past few years and is attracting strong interest from all market participants, financial institutions (commercial banks, investment banks, and hedge funds), and regulators.

The Indian financial sector has been plagued with non-performing assets of the banking sector over the last few years. With an aim to mitigate the rising NPAs, several measures were introduced by the regulators, the Sick Industrial Companies Act (1985), Corporate Debt Restructuring (2001), Strategic Debt Restructuring (2015), Securitisation and Reconstruction of Financial Assets, and Enforcement of Security Interest (SARFAESI, 2002)

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Companies Act (Amended) 2013. However, none of them could successfully resolve the problem of rising NPAs.

To manage the resolution and recovery of stressed assets, the Insolvency and Bankruptcy Code, 2016 (IBC), was introduced in November 2016. This is the bankruptcy law of India that seeks to consolidate the existing framework by creating a single law. It outlines separate resolution proceedings for individuals, companies, and partnership firms. The Code was enacted in December 2016. It improves the time taken to resolve failure and provides a clear exit option to investors and increases recovery value. It is recommended that it would be appropriate to notify a higher default threshold of INR 50 lakhs for calculating default.

We pay close attention to predictions of bankruptcy as it is important from the point of view of creditors, employees, and other entities around the affected company that would feel the effect the bankruptcy brings (Štefko et al., 2012). By taking early remedial measures, businesses can prevent future bankruptcy events (Gundová, 2015).

There have been numerous examinations in the past with respect to the proficiency of the expectation models. Endeavours to discover the best expectation model have been plenty, yet none have been extremely fruitful. Further, the greater part of these examinations have been on a worldwide scale and focus more on firms that are gigantic multinationals. The motivation behind our exploration is to consider the reasonableness of significant insolvency expectation models by applying them to companies under IBC. Against this backdrop, the objective of this study is to identify 30 companies under IBC and 30 solvent companies, and to evaluate the predictive ability of the models one, two, and five years prior to insolvency and bankruptcy, and to compare the accuracy in prediction across models. More specifically, the objectives are:

- To know the bankruptcy status of the companies using different models.
- To know the accuracy of these models in predicting the bankruptcy status.
- To compare the predictive ability of accounting-based and market-based models.

The original models so tested are compared with the Merton and logit model to evaluate and compare the predictive ability. These models when applied to bankrupt companies will help in evaluating the financial distress in future. It would also help in identifying if the accounting-based and market-based models can be used in the Indian context to predict financial distress and default.

The rest of the paper is structured as follows. Section 2 discusses the relevant literature on accounting-based models, while section 3 discusses research design and methodology. Section 4 gives the results and discussion, and section 5 concludes, along with the limitations of our study.

REVIEW OF LITERATURE

The pioneers for the accounting-based bankruptcy models are Beaver (1966, 1968) and Altman (1968). Altman, Haldeman and Narayanan (1977) constructed a second-generation model with several enhancements to the original Z-score approach. Subsequently, Altman, Hartzell and Peck (1995) modified the Z-score model in the context of corporations in emerging markets. Ohlson's O-score model (1980) selected nine ratios or terms which he thought should be useful in predicting bankruptcy. Jaydev (2006) analysed the power of financial risk factors in predicting default of companies. Bandyopadhyay (2006) compared three models: (i) the original Z-score model; (ii) the Z-score model for emerging markets; and (iii) logistic regressions, to predict the probability of default. Further extended work done on accounting-based models has been by Taffler (1983, 1984); Bhatia (1998); Sahoo et al. (1996); Zmijewski (1984); Agarwal and Taffler (2007); Kumar and Kumar (2012); Hussain et al. (2014); and Altman et al. (2017).

Poongavanam and Babu (2012) applied the Z-score model to assess the financial health of BHEL. The empirical findings revealed the financial health of the company and financial viability.

Ahmed et al. (2018), in their study, assessed the effectiveness of Altman's Z-score for Canadian listed companies and confirmed that the cut-off regions and the coefficients used by Altman should be time-varying.

Manaseer et al. (2018) also saw the strong predictive power of Altman Z-score model when used to predict financial failure in insurance companies listed on the Amman Stock Exchange (ASE).

Ali and Dhiman (2019) tried to explore the empirical association between credit risk management and public sector banks' financial performance. The research focused on ten PSU banks on the basis of total assets, and the results of the research reveal that credit risk management indicators have a significant influence on the financial performance of selected public sector banks in India.

Kapil and Agarwal (2019) focused on Altman Z-score and its correlation to the various financial performance indicators and compared the traditional models with new methods like decision tree framework and neural network framework to predict bankruptcy.

Kittur (2019) attempted to measure the effectiveness of Altman's Z-score model using non-performing assets (NPA) as a benchmark stability indicator. The results suggested that during the distress period, the Z-scores only marginally capture the distress caused by the NPAs; however, the Z-scores do not have the predictive ability to capture the future NPAs.

Kaur (2019) assessed the financial performance of the banking sector in India using Altman (1968) Z-score model for the period 2012-2017, using Tobin's Q as the performance measure. The results revealed that distressed stocks outperform non-distressed stocks during the market upturns.

Tung and Phung (2019) applied the Altman model on firms in Vietnam. The empirical findings revealed the significance of both financial and non-financial factors in predicting bankruptcy.

Agarwal and Patni (2019) considered the fundamentals of companies using financial ratios, by choosing companies of PSU index listed on the Bombay Stock Exchange across different sectors, over a period of six years, from 2013-2018. The finding reveals that Altman's Z-score model has a remarkable degree of accuracy in predicting distress using financial ratios.

Patel et al. (2021) evaluated the financial distress in the automobile sector in India. Their study applied Altman, Grover, Springate, and Zmijewski models to find distress scores results, to confirm if there is any change in the financial performance of companies. Their findings were that distress levels predicted for the selected automobile firms are significantly the same.

Thus, this study tests the accounting-based models, coupled with the structural Merton model, on companies in India under IBC, with a matched sample of solvent companies to evaluate their predictive ability.

RESEARCH DESIGN AND METHODOLOGY

Objectives of this Study

- To know the bankruptcy status of the companies using different models for T−1, T−2, and T−5 years, where T is the year in which the firm enters insolvency.
- To evaluate and compare the predictive ability of the models and compare the original models with the market-based Merton model and logit model developed by us.

Scope of the Study

The scope of the study is 30 companies which are filed under the Insolvency and Bankruptcy Code, and a matched sample of 30 companies taken as being solvent. The solvent companies are matched based on sector, year, and market capitalisation. The definition of 'solvent' considered by us are companies that were assigned a credit rating of 'AAA'/'AA' in the year T0, where T0 is defined as the year in which the companies were included under IBC. Sector classification is taken on the basis of The Refinitiv Business Classifications (TRBC) of the industry. Companies were filtered such that all publicly available financial data for all firms and ratings for solvent companies from T0 to T−5 years was available.

Models Used for the Study

The present study has identified four original accounting-based models, a market model, and a logit model for further analysis. The models chosen by us are:

- Altman Z-Score Model
- Emerging Market Scoring Model
- Zmijewski Score Model
- Ohlson O-Score Model
- Merton Model
- Logit Model

Altman Original Z-Score Model

Altman's Z-score model (1968) is an application of multivariate discriminant analysis (MDA) in credit risk modelling. Altman drew on a sample containing 66 manufacturing firms (33 that filed a bankruptcy petition during the period 1946-1965 and 33 that did not fail). Altman examined 22 potentially helpful financial ratios and ended up selecting five as providing, in combination, the best overall prediction of corporate bankruptcy. This model was proved to be accurate in predicting the bankruptcy at a rate of 94%.

The result is a credit score for each new loan application, with a high score indicating a better performance of the borrower, and thus, a lower probability of default.

Altman's statistically derived discriminant function is:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5$$

Where:

X1 = Working Capital / Total Assets

X2 = Retained Earnings / Total Assets

X3 = EBIT / Total Assets

X4 = Market Capitalisation / Book Value of Total Liability

X5 = Sales / Total Assets

The firm is classified as:

'Financially Sound' if $Z > 2.99$, and

'Financially Distressed' or 'Bankrupt' if $Z < 1.81$,

$1.81 < Z < 2.99$ = Grey Zone

Altman Emerging Market Scoring Model (EMS)

The original Z-score has two attributes that make it inappropriate for emerging markets: (1) it requires the firm to have publicly traded equity and (2) it is primarily for manufacturers. While the EMS model originated from the original Z-score model, this is a more enhanced version of the Altman Z-score in that it can be applied to non-manufacturing companies, and other factors like firm vulnerability to currency devaluation, industry affiliation, and competitive position in the industry are considered. Since the values of the sales / total assets ratio appear to change significantly in different productive sectors, a version of the Z-score model most suitable for private non-manufacturing firms and emerging markets was proposed, which excludes such a variable.

EM score = $6.56X1 + 3.26X2 + 6.72X3 + 1.05X4 + 3.25$

X1 = Working Capital / Total Assets

X2 = Retained Earnings / Total Assets

X3 = EBIT / Total Assets

X4 = Book Value of Equity / Book Value of Total Liability

The constant term enables us to standardise the analysis, so that a default equivalent zones of discrimination may be stated.

$Z > 2.6$ = Safe Zone

$1.1 < Z < 2.6$ = Grey Zone

$Z < 1.1$ = Distress Zone

Ohlson O-Score Model

Ohlson O-Score model was introduced by James Ohlson in 1980. He used the logit model, where the practical benefits are that it does not require the restrictive assumptions of MDA and allows one to work with disproportional samples. The estimated model consisted of 105 bankrupt and 2,058 non-bankrupt industrial firms for the period 1970-1976.

Ohlson O-Score = $-1.32 - 0.407X1 + 6.03X2 - 1.43X3 + 0.757X4 - 1.72X5 - 2.37X6 - 1.83X7 + 0.285X8 - 0.521X9$

Where:

X1 = Log (Total Assets / Gross National Product Price Index Level)

X2 = Total Liability / Total Assets

X3 = Working Capital / Total Assets

X4 = Current Liability / Current Assets

X5 = 1 if Total Liability > Total Assets, otherwise 0

X6 = Net Income / Total Assets

X7 = Funds from Operations / Total Liabilities

X8 = 1 if Net Income was negative from last two years, otherwise 0

X9 = $(\text{Net Income}(t) - \text{Net Income}(t-1))/(|\text{Net Income}(t)| + |\text{Net Income}(t-1)|)$

If O-Score > 0.5, the firm will default within two years.

If O-Score < 0.5, the firm is healthy.

Zmijewski Score

Zmijewski (1984) score is a model which is used to predict bankruptcy of a company in two years. The model was based on probit analysis for bankruptcy prediction, where the financial variables were selected based on prior works. The model uses 40 bankrupt and 800 non-bankrupt industrial firms' data for the period 1972-1978. The formula is written as follows:

Zmijewski's score = $-4.336 - 4.513X1 + 5.679X2 - 0.004X3$

Where,

X1 = Net Income / Total Assets

X2 = Total Liabilities / Total Assets

X3 = Current Assets / Current Liabilities

The cut-off point = 0.

- If the X-score is below the cut-off point, the company is healthy.
- However, if the X-score is above the cut-off point, the company is in financial distress.

Merton Model (1974)

Merton (1974) applied the option pricing methodology developed by Black and Scholes (1973). According to this model, the firm's equity can be seen as a European call option on the firm's assets, with a strike price equal to the book value of the firm's liabilities. It is based on the assumption that all liabilities are due on the same date, namely, at the maturity of the option. If the market value of the firm's assets is greater than the book value of liabilities at maturity, then the shareholders exercise their option on the assets. In this case, the shareholders pay off the debt-holders and the firm continues to exist. The general equation of the model is:

$$Ve = Va^*(d1) - e^{-r(T-t)} * D * N(d2)$$

Ve = value of equity

Va = value of the firm

D = debt of the firm

N(d1) and N(d2) = normal distribution variable

Here, d2 is the distance to default and N(d1) is the delta which is also the hedge ratio, while N(d2) is the probability that the option is in the money. Hence, N(d2) can be considered the probability that the firm will pay off its debts, while 1−N(d2) can be considered the probability of it defaulting on its payments.

Logit Model

Logistic regression is used for predicting the outcome of a categorical criterion variable based on one or more predictor variables. Logistic regression can be bi- or multi-nomial. The outcome is coded as '0' and '1' in binary logistic regression, as it leads to the most straightforward interpretation. Logit model takes an S shape and is stated as:

$$\frac{1}{1+e^{-value}}$$

Where, e is the base of natural logarithms.

Testing the Predictive Ability of the Models

The predictive ability of the models is tested by plotting the Receiver Operating Characteristics (ROC) curve. The area under the ROC curve (herein referred to as AUC) measures the model's performance in predicting actual defaults. The ROC reports the percentage of defaults that the model correctly classified as defaults on the y-axis and the percentage of non-defaults that the model incorrectly classified as defaults on the x-axis. A perfect model will have an area under curve (AUC) of 1, while a perfectly naïve model will have a score of 0.5.

Accuracy ratio is a linear transformation of AUROC (area under ROC). It is calculated as (2 * AUC) − 1. This is also called as the Gini coefficient. The higher the AR, the more robust the model.

EMPIRICAL FINDINGS

Altman Z-Score

Table 1 shows the number of firms falling under the Z-scores for T−1, T−2, and T−5 years. An average of 85-90 per cent of the companies are correctly predicted to be in the distress zone for T−1 and T−2 years, but for T−5 years, it reduces to 80 per cent. The Z-score shows robust results in predicting default up to two years most accurately, and for up to five years moderately.

Table 1: Companies under IBC under Zones from Altman Z-Score

	T−5	T−2	T−1
Distress Zone < 1.88	24	26	27
Grey Zone 1.88-2.99	4	2	1
Safe Zone > 2.99	2	2	2

Source: Compiled by author.

From Table 2, it can be inferred that one year prior to bankruptcy, only 14 out of the 30 companies are in the safe zone and are unlikely to default. Six companies are in the grey zone; the remaining companies are in the distress zone and have a high probability of going bankrupt in the next two to five years. Thus, more than 50 per cent of the firms are in distress and in the grey zone for all the years, implying that the lenders need to be vigilant about these companies even though they enjoy high credit ratings.

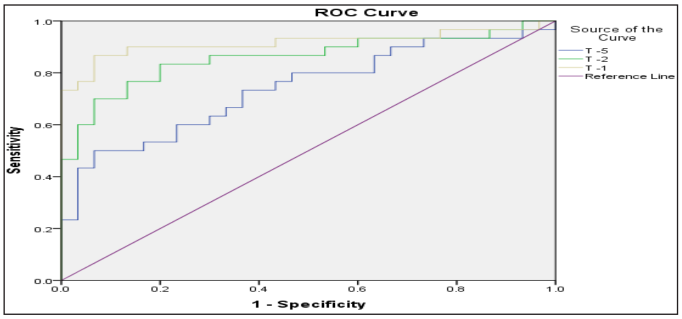
Table 2: Altman A-Score for Solvent Companies

	T−5	T−2	T−1
Distress Zone < 1.88	16	11	10
Grey Zone 1.88-2.99	7	8	6
Safe Zone > 2.99	7	11	14

Source: Compiled by author.

Predictive Ability of Model

We compute the probability of default (PDs) for all 60 companies and plot the ROC curves for the same. It is observed from the AUC and Gini coefficient that the predictive ability of the model is highest one year prior to default, followed by T−2 and T−5. However, even for T−5, the accuracy is almost 74 per cent; therefore, the model exhibits moderate accuracy.



Source: Extracted from SPSS.

Fig. 1: ROC Curve for Altman Z-Score Model

Table 3: Performance Metrics for Altman Z-Score

Year	AUC	Gini Coefficient
T−5	.739	47.8
T−2	.859	71.8
T−1	.916	83.2

Source: Compiled by author.

Emerging Market Score Model

Table 4 shows that for IBC companies, the maximum companies in the distress zone were seen in T−1 years and the least in T−5 years. Around 47 per cent of the firms were classified under the distress zone one year prior to bankruptcy, while it declined to 3.33 per cent five years prior to bankruptcy. This shows that the model is not accurate in classifying firms under financial distress.

Table 4: Altman Z (EMS) for Companies under IBC

	T−5	T−2	T−1
Distress Zone < 1.1	1	5	14
Grey Zone 1.1-2.6	4	4	2
Safe Zone > 2.6	25	21	14

Source: Compiled by author.

From Table 5, it is seen that the EMS model is correctly able to predict the financial status of solvent companies, with the accuracy of classifying more than 90 per cent of the companies correctly in the safe zone.

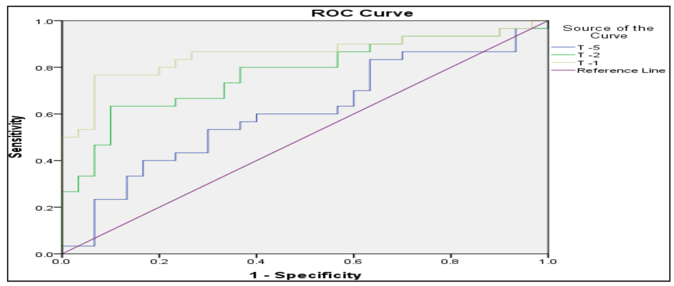
Table 5: Altman (EMS) Score for Companies that are Solvent

	T−5	T−2	T−1
Distress Zone < 1.1	1	0	0
Grey Zone 1.1-2.6	1	1	2
Safe Zone > 2.6	28	29	28

Source: Compiled by author.

Predictive Ability of the Model

It can be seen from Table 6 that the robustness of the model is maximum for T−1 years, with an AUC of 85.6 and Gini coefficient (AR) of 71.2 per cent. The model is not robust for T−2 and T−5 years.



Source: Extracted from SPSS.

Fig. 2: ROC Curve for Altman EMS

Table 6: Performance Metrics for EMS Model

Year	AUC	Gini Coefficient
T−5	.606	21.2
T−2	.772	54.4
T−1	.856	71.2

Source: Compiled by author.

Zmijewski Score

Table 7 shows the Zmijewski score of the companies for the three time horizons. Around 83.3 per cent of the companies are correctly classified as being in the distress zone for T−1 years, and 66.6 per cent in T−2 years. However, the accuracy declines sharply in classifying companies correctly for T−5 years, with only 40 per cent falling in the distress zone.

Table 7: Score for Companies under IBC

	T−5	T−2	T−1
Distress Zone > 0	13	20	25
Safe Zone < 0	17	10	5

Source: Compiled by author.

From Table 8, we see that the companies that are in the safe zone remain constant for T−1 and T−2 years, with a value of 83.3 per cent; however, even in T−5 years, the companies in the safe zone remain at almost 80 per cent, showing that the model has good predictive power of classification for healthy companies.

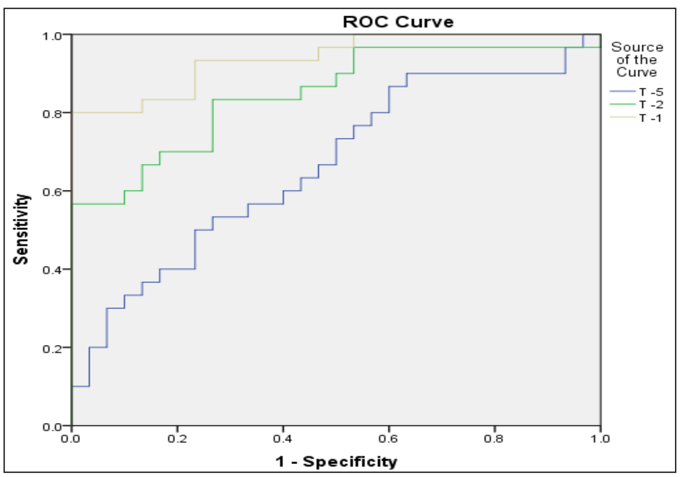
Table 8: Zmijewski Score for Solvent Companies

	T−5	T−2	T−1
Distress Zone > 0	7	5	5
Safe Zone < 0	23	25	25

Source: Compiled by author.

Predictive Ability of the Model

The model exhibits a strong predictive ability, as can be seen from the ROC and Gini coefficient, at 93.9 per cent and 87.8 per cent, respectively, for T−1 years. It shows moderate robustness for T−2 years, with AUC at 85 per cent and a Gini coefficient of 69.4 per cent. However, the model is not robust for T−5 years.



Source: Extracted from SPSS.

Fig. 3: ROC Curve for Zmijewski Model

Table 9: Performance Metrics for Zmijewski Model

Years	AUC	Gini Coefficient
T−5	.664	32.8
T−2	.847	69.4
T−1	.939	87.8

Source: Compiled by author.

Ohlson's O Score

Table 10 shows that the Ohlson's O score of all companies under IBC are below the cut-off, which shows that the companies are under financial stress and the chances of going bankrupt are very high. It shows strong accuracy in classifying firms under the distress zone.

Table 10: O-Score for Companies under IBC

	T−5	T−2	T−1
Safe Zone < 0.5	3	0	0
Distress Zone > 0.5	27	30	30

Source: Compiled by author.

If we analyse solvent companies from Table 10, a majority of the companies have a very high probability of default according to the Ohlson O-score. Though these companies enjoy high ratings, findings from the model indicate a warning sign for up to five years prior to our base year.

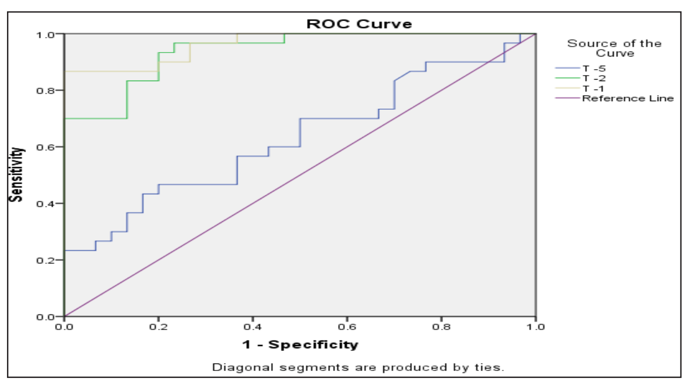
Table 11: O-Score for Solvent Companies

	T−5	T−2	T−1
Safe Zone < 0.5	3	6	5
Distress Zone > 0.5	27	24	25

Source: Compiled by author.

Predictive Ability of the Model

It can be seen from the ROC curve and Gini coefficient given in Table 12 that the model shows maximum predictive ability at 96 per cent at T−1 years, followed by almost 94 per cent at T−2 years. We also observe that the model is not robust at T−5 years. The Gini coefficient is 92 per cent and 88 per cent, respectively, with the model demonstrating high predictive ability.



Source: Extracted from SPSS.

Fig. 4: ROC Curve for Ohlson Model

Table 12: Performance Metrics for Ohlson Model

Year	AUC	Gini Coefficient
T−5	.631	26.2
T−2	.939	87.8
T−1	.963	92.6

Source: Compiled by author.

The four accounting-based models showed high predictive ability for one year prior to bankruptcy. Thus, in the next stage of analysis, we compare the performance of these four models with Merton and logit models for T−1 years.

Findings from Merton Model

Merton model was run for T−1 years. Distance to default is the probability that the company will not default, and likewise, PD, i.e., probability to default, states that the company is likely to default. Findings from the model show that for almost all the insolvent companies, the distance to default is very small and its probability of default is around 98-99 per cent, while for most of the solvent companies, the distance to default is large, and hence, the probability of default varies between 0 to 99 per cent. We observe that most of the solvent companies have PDs in the range of 0-10 per cent, while for insolvent companies, we see that the PDs are higher, i.e., 80-100 per cent. Hence, we observe that the Merton model is a good predictor of solvency.

Findings from Logit Model

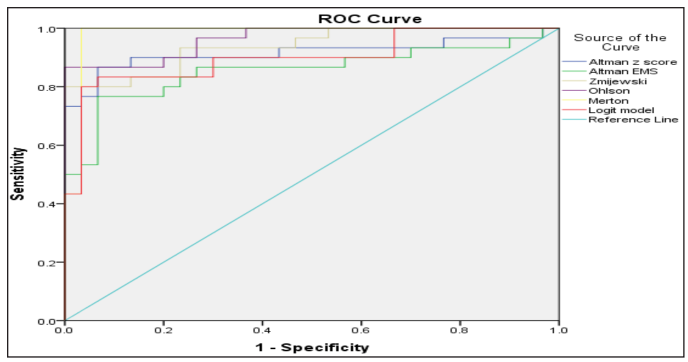
We ran binary logistic regression for T−1 years, taking the dependent variable coded '0' for solvent companies and '1' for companies in IBC. We considered Altman ratios, debt/equity, interest coverage, current and quick ratio, and net profit/total assets as our independent variables. Our empirical findings were that the current ratio and book value of equity/total liabilities were statistically significant, and the classification accuracy of the model with no predictors was 50 per cent and improved to 81.7 per cent when the variables were added.

Evaluating Predictive Ability of All Models

The accuracy of classification of companies as identified by us is maximum for T−1 years. We thus extended our analysis and included the Merton model and logit model and their findings for further comparison. The performance evaluation metrics used by us for evaluation was the ROC curve and the Gini coefficient.

When we compare the ROC curves of all six models, it is observed that the Merton model exhibits the strongest predictive accuracy, followed by Ohlson, Zmijewski, and Altman Z-score. The logit model shows better predictive ability compared to the Altman EMS model.

The predictive ability of the models shows that both accounting-based and market-based models are robust. While Z-score does not directly compute probability of default, the logit model and the Merton model compute the PD for companies. The classification accuracy test on the secondary data shows that our model is capable of predicting bankruptcy with reasonable accuracy. These findings strengthen result testing and help in identifying the best model in terms of its predictive ability. Since both accounting-based and market-based models show high predictive ability, we infer that neither model is sufficient in itself, and that a hybrid form of credit risk model which factors in market variables coupled with financial data can forewarn against corporate distress.



Source: Extracted from SPSS.

Fig. 5: ROC Curve for All Models

Table 13: Performance Metrics for All Models

Models	AUC	Gini Coefficient
Altman Z-score	.916	83.2
Altman EMS	.856	71.2
Zmijewski	.939	87.8
Ohlson	.963	92.6
Merton	.981	96.2
Logit model	.899	79.8

Source: Compiled from SPSS.

CONCLUSION

The objective of this study is to compare four accounting-based models for accuracy in predicting financial distress for companies one, two, and five years prior to them filing for insolvency and bankruptcy. The analysis indicates that the models are able to predict bankruptcy most accurately one year prior to bankruptcy, and the accuracy declines for all models progressively and consistently for the earlier years, till five years prior to bankruptcy (year T−5). This indicates that the most recent data prior to the bankruptcy plays an important role in business crisis prediction and the importance diminishes progressively, which is in line with the research findings of Beaver (1966) and Altman (1968). This study also proved empirically that financial ratio is an effective tool for predicting corporate distress. On comparing the accounting-based models, we see maximum predictive ability of the Ohlson model, followed by Zmijewski and Altman original Z-score. We extend our analysis to compare the accounting-based models in their original form with Merton market-based and logit model. It is seen that the predictive ability is maximum for the Merton model, followed by Ohlson, Zmijewski, Altman Z-score, and logit.

The conclusion drawn from the research findings are that though accounting-based models are not sufficient in themselves, they can identify financially distressed companies from the information disclosed in the financial statements. These findings strengthen result testing and help in identifying the best model in terms of its predictive ability, and conclude that a credit risk model which factors financial data can complement the role of external rating agencies. All in all, the four models under consideration show uniform results, with a high average default probability for IBC companies and low average default probability for solvent companies.

These models help in effective risk identification, risk monitoring, and measurement. They can be used by lenders in determining the solvency status of firms based on the financial information available in the public domain. Early identification of financial distress would help lenders in better CRM and management in undertaking strategies to tide over from being bankrupt in the near future.

However, the limitations of these models are that, in themselves, they are inflexible, backwards-looking, and incorporate information in the financial statement which are based on the historical past. Moreover, they do not cover the qualitative factors which can have a bearing on the research. In most of the IBC companies, we see that they were profit-making companies which entered into IBC due to factors like lack of management competency and professional management of the company, and other factors like creative accounting practices and strong promoters' shareholdings, which have led to some companies going from healthy to bankrupt over the years covered in the research work. A wider study with a bigger sample size and other factors would allow us to identify and create a more robust model.

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