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Sensitivity of bankruptcy prediction models to the change in econometric methods

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Abstract. *Previous studies on bankruptcy prediction focused on identifying significant indicators to predict bankruptcy. Few studies analyzed the impact of the change in space and time but there are limited studies which attempted to investigate the sensitivity of these models to the change in econometric methods. The current study analyses the impact of the change in econometric methods on the predictive performance of Singh and Mishra (2016a) bankruptcy prediction model. A matched pair of 208 companies comprising distressed and non-distressed firms for the period 2006 to 2014 were selected randomly. The study utilises Multivariate Discriminant Analysis (MDA), logit and probit econometric techniques to model bankruptcy. Secondary sample, long range accuracy and Receiver Operating Characteristic (ROC) tests were used for the validation of bankruptcy prediction models. The major findings of the study suggest that accounting information's, namely, leverage, profitability and turnover ratio remained significant indicators to predict bankruptcy for Indian manufacturing firms. The study further concludes, if significant indicators of bankruptcy are identified, then there is no significant impact of the change in econometric methods on the predictive performance of the default prediction models.*

Keywords: bankruptcy prediction, Indian manufacturing companies, logit, probit, MDA.

JEL Classification: G33, G32.

1. Introduction

The change in the attitude towards financial leverage as a means of economic prosperity led to the credit explosion all over the world. Polonius, a character in Shakespeare's 17th century play Hamlet says, "Neither a borrower nor a lender be", but he was voicing perception of his time (Lamb, 2000). In modern times, since Schumpeter (1911), there is a longstanding debate on the role of finance contributing to economic growth. Some believe that finance promotes growth (Goldsmith, 1969; McKinnon, 1973; Shaw, 1973; King and Levine, 1993a, 1993b, 1993 c): few do not find it worth discussing (Lucas, 1988). Others assert that real sector development itself creates demand for financial development (Robinson, 1952; Singh and Mishra, 2014, 2015). In spite of the differences in the views of economists on the finance-growth nexus, all believe finance works as a facilitator in the economic system and reduces transaction and information cost. Earlier, being a borrower or debtor brought misery and shame. Now the perception of people has changed, and the debtor is seen as a person using financial leverage and entitlement. The use of credit has become a major factor in the economic prosperity of countries as well, and there is a significant increase in the leverage by individuals and corporations all over the world.

The Global Financial Crisis of 2008 made credit risk inescapable and Basel III Accord was the unanimous global response to address the problem of credit risk. Since, Beaver (1966) large number of bankruptcy prediction studies were conducted to identify important accounting and market based financial information to assess the credit worthiness of counterparty. Some studies analysed the impact of the change in space and time (Platt and Platt, 1990; Singh and Mishra, 2016a) but there are limited attempted to investigate the sensitivity of these models to the change in econometric methods. The current study analyses the impact of the change in econometric methods on Singh and Mishra (2016a) bankruptcy prediction model for Indian manufacturing firms. In the light of above discussion the major aim of the paper is to identify significant financial variables to predict bankruptcy and examine the sensitivity of bankruptcy prediction models for Indian manufacturing firms to the change in econometric methods. The current study is unique of its kind which exclusively examines the impact of the change in econometric methods on the predictive performance of default prediction model. The major findings of the study suggest that accounting information's, namely, leverage, profitability and turnover ratio and use of more recent financial information remained as important in default prediction. The study further concludes, if important indicators of bankruptcy are identified, then there is no significant impact of the change in econometric methods on the predictive performance of the bankruptcy prediction models.

The reminder of the paper is structured as follows. Section 2 gives an account of the survey of the literature. Data and methodology are covered in section 3.Section 4 give details of Singh and Mishra (2016a) bankruptcy prediction model. Details about the estimation of logit, probit and MDA models are provided in section 5. Empirical results are reported in section 6. The study concludes with section 7.

2. Survey of literature

Use of accounting information's is widely studied in the literature of default perdition. Initial default prediction studies were univariate in nature and single financial ratios were used to assess the financial position of the firms. Use of multiple financial ratios with the help of statistical tools such as Discriminant Analysis, logit, probit etc. revolutionized the literature of bankruptcy prediction. Some of the notable pioneered univariate studies are Smith and Winaker (1935), Chudson (1945) and Beaver (1966). In the past eight decades there is a substantial development in the literature of bankruptcy prediction. Broadly, default prediction models can be classified into two groups, namely, (a) parametric and (b) non-parametric models.

2.1. Parametric models

These models largely use accounting based financial information and sometimes use non-financial information to foretell bankruptcy. Such models can be categorized into accounting and market based models which can be univariate and multivariate in nature.

Beaver (1966) was pioneered to conduct bankruptcy prediction study on US firms with the help of single financial ratios. Later, Altman (1968) conducted a study on US firms using multivariate financial ratios. Altman et al. (1977) again conducted a study on US manufacturing and retail firms, and developed a bankruptcy prediction model with the help of MDA which had effective classifying power till 5 years prior to bankruptcy. Some of the notable bankruptcy prediction studies based on accounting information are Deakin (1972), Blum (1974), Springate (1978) and Fulmer (1984).

Ohlson (1980) introduced a logit model for bankruptcy prediction utilizing financial and non-financial information. Later, Abdullah et al. (2008) used a logit model to foretell the bankruptcy of Malaysian firms. Zmijewski (1984) developed a probit model to predict bankruptcy for US firms. Later, a large number of studies were conducted to examine the effectiveness of different default prediction models in different markets. Pongsatat et al. (2004) examined predictive accuracy of Altman (1968) and Ohlson (1980) model in case of Thailand and a similar study was conducted by Ugurlu and Aksoy (2006) on Turkish firms. In the Indian market, Bandyopadhyay (2006) developed a default prediction model for the Indian corporate bond sector using MDA and logit technique. Ramkrishnan (2005) developed a bankruptcy prediction model with the help of MDA and logit technique for Indian firms. Similarly, Bhunia and Sarkar (2011) developed a bankruptcy prediction model for Indian pharmaceutical companies using MDA technique. Singh and Mishra (2016a) developed a hybrid default prediction model for Indian manufacturing companies.

The second class of parametric models are market-based models which can be further classified into structural and reduced form models. Some of the notable structural models are Merton (1974); Agarwal and Taffler (2008); Wu et al. (2010); Hillegeist et al. (2004) and Bharath and Shumway (2008). However, some of the notably reduced form models are Jarrow and Turnbull (1995), Duffie and Singleton (1999) and Lando (1994). Agrawal and Maheshwari (2018) utilizing industry factor conducted a study to predict default of the Indian corporate sector. In the Indian market, some of the important studies conducted using market-based information are Varma and Raghunathan (2000), Kulkarni et al. (2005) and Singh and Mishra (2016 b).

2.2. Non-parametric models

Most of the non-parametric models are multivariate in nature and heavily dependent on high computing techniques. Some of the widely used non-parametric models are artificial neural networks (ANN), hazard models, fuzzy models, genetic algorithms (GA) and hybrid models. Kirkos (2015) conducted a default prediction study applying an artificial intelligence technique. Messier and Hansen (1988), Raghupathi et al. (1991), Coats and Fant (1993), Guan (1993), Tsukuda and Baba (1994), and Altman, Marco, and Varetto (1994) are some of the notable studies which applied ANN technique to foretell bankruptcy. Varetto (1998) applied GA, one of the prominent non-parametric technique to predict bankruptcy. Premachandra et al. (2009) in their study compared LR and DEA models. Verikas et al. (2010) examined hybrid and ensemble-based soft computing techniques to predict bankruptcy. Korol and Korodi (2011) applied the Fuzzy logic approach to study the bankruptcy of firms. The early warning system was developed by Shetty et al. (2012) for the Indian IT/ITES sector. Further, Kumar and Rao (2015) using Person Type-3 distribution developed non-linear new Z-score model. Hosaka (2019) developed a default prediction model using imaged financial ratios and co-evolutional neural networks.

3. Data and methodology

3.1. Data

The distressed companies are identified using the Board of Industrial and Financial Reconstruction (BIFR) reference from the list of the companies registered sick during the period 2006 to 2014. The same reference was used in the studies of Bandyopadhyay (2006), Ramkrishnan (2005), Kulkarni et al. (2005), Varma and Raghunathan (2000). The matched pair of non-defaulted companies are chosen randomly based on asset size and industry type. During 2006 to 2014 more than 600 companies were registered sick with BIFR. A matched pair of 208 companies encompassing bankrupt and non-bankrupt firms are selected for the study out of which 130 used for estimation and 78 hold-out for model validation. The balance sheet and income statements at the end of every year were used to collect financial information of the companies from their respective websites. Considering sectoral heterogeneities of the companies', estimated and hold-out sample was categorised into 14 industry category matching with National Industrial Classification Code (NIC) 3 digit classification of 2008 (See Table 1).

Table 1. *Distribution of Firms as per NIC Classification 2008*

NIC Code	Sector	Estimation Sample	Hold-out Sample	Total
107	Manufacturer of other food products	14	6	20
131	Spinning, weaving and finishing of textiles	34	16	50
170	Manufacturer of paper and paper products	4	10	14
201	Manufacturer of basic chemicals, fertilizer and nitrogen compounds, plastics, synthetic rubber in the primary form	18	6	24
210	Manufacturer of pharmaceuticals, medicinal chemical and botanical products	6	2	8
221	Manufacturer of rubber products	4	4	8
231	Manufacturer of glass and glass products	4	2	6

NIC Code	Sector	Estimation Sample	Hold-out Sample	Total
239	Manufacturer of non-metallic mineral products n.e.c.	2		2
243	Casting of metals	16	6	22
261	Manufacturer of electronic components	6	16	22
271	Manufacturer of electric motors, generators, transformers and electricity distribution and control apparatus	4		4
291	Manufacturer of motor vehicles	8	6	14
310	Manufacturer of furniture	4		4
492	Other land transport	6	4	10
	Total	130	78	208

Source: Singh and Mishra (2016a).

3.2. Methodology

The study utilizes MDA, logit and probit econometric techniques to model bankruptcy.

3.2.1. Multivariate Discriminant Analysis (MDA)

The vital assumption of MDA technique is that variance-covariance matrices of the two groups are statistically identical. The weights of the discriminant function are the difference of the mean vectors of the explanatory variables for the defaulted and non-defaulted groups. There are twofold objectives of the MDA technique: The first to look for predictors (financial ratios) that lead to lower misclassification rates within the sample and to get improved predictive accuracy in an un-estimated hold-out sample.

The discriminant analysis model involves linear combinations of the following form:

$$Z = \sum_{i=0}^{k} a_i x_i \quad (1)$$

Where,

Z= overall index (discriminate function)

a_0 = a constant

a_i's= the discriminate coefficients or the weight of that dependent variable

x_i's = the set of independently normally distributed random variables.

i = 1 to k

The weights can be defined as:

$$a = (\mu^1 - \mu^2)\Sigma^{-1} \quad (2)$$

Where μ^1 and μ^2 are the mean vectors of the explanatory variables of the two groups, in the current context distressed and non-distressed. Σ Signifies variance-covariance matrix of the two group which is assumed to be equal. More formally:

$x^1 \sim N(\mu_1, \Sigma)$

$x^2 \sim N(\mu_2, \Sigma)$

Meaning that x is a k*1 multivariate normally distributed random variables with parameter μ_1 and Σ for group one and parameter μ_2 and Σ for group two.

3.2.2. Probability models

If the dependent variable is binary and it is a function of a set of independent variables, the Linear Probability Model (LPM) can be written as:

$$P_i = E(Y = 1 | X_i) = \beta_1 + \beta_2 X_i \tag{3}$$

Where, Pi represents probability, X_i represents various financial ratios of the firms and Y is the dependent variable. When Y=1 then the firm is bankrupt and Y=0 means non-bankrupt firms, β_1 and β_2 are the slope coefficients.

The inherent defects of LPM led to the development of logit and probit models. In equation (3) the probability of LPM can exceed the limit of 0 and 1. The best way to solve this problem is to transform $X_i's$ and $\beta's$ in a way with probability density function F that probability value should be in a limit between 0 and 1. Mathematically,

$$prob(y_i) = F(X_i\beta) \tag{4}$$

Where, F is the cumulative density function.

Logit

Choice of F as a logistic distribution yields one of the ways to limit $prob(y_i)$ between 0 and 1. When logistic distribution is used in the place of cumulative density function to restrict the probabilistic value of response variable, it can be said logit model.

$$prob(y_i = 1) = \Lambda(X_i\beta) = \frac{expX_i\beta}{1+expX_i\beta} \tag{5}$$

In the context of bankruptcy prediction study, the logit model is used to classify whether a company is bankrupt or non-bankrupt by using accounting and non-accounting financial information's.

Probit

In equation (4), if cumulative normal distribution is used to limit the probabilistic value of the response variable in the range of 0 and 1, it can be said probit model.

$$prob(y_i) = \phi(X_i\beta) = \int_{-x}^{X_i\beta} \frac{1}{\sqrt{2\pi}} exp\left(\frac{-z^2}{z}\right) dz \tag{6}$$

The standard normal transformation $\phi(.)$ limit the probability to lie between 0 and 1.
or,

$$\lim_{z\to+\infty} \emptyset(z) = 1 \quad \text{and} \quad \lim_{z\to-\infty} \emptyset(z) = 0$$

4. New Bankruptcy Prediction Model for Indian Manufacturing Companies

Singh and Mishra (2016a) developed a four-step bankruptcy prediction model for Indian manufacturing companies. The study was conducted on the matched sample of 208 companies out of which 130 were included in the estimation sample and 78 were hold-out for the accuracy test.

In the first step 25 financial ratios were chosen based upon the past empirical literature. Subsequently, mean, standard deviation and their respective p-values were checked to test equality in means of between two groups. In the second step forward selection and backward elimination technique were applied with the combinations of statistically significant financial ratios which had a difference in mean between the two groups. Further, in the next step, sectoral heterogeneities of the companies' were considered and the data set has been categorised into 14 industry category matching with National Industrial Classification Code (NIC) 3 digit classification of 2008. For every industry 14 industrial dummies were included but none of them was found to be significant. The final profiles of financial ratios were chosen based upon the sign, statistical significance and classification power. The final profile of financial variables selected for the model are:

BVEBVD (Book Value of Equity/Book value of Total Liabilities): This financial ratio measures leverage of the companies.

SLTA (Sales/Total Assets): This indicator measures effectiveness and efficiency of the firm's assets to generate profit and widely used turnover ratio in the literature of default prediction.

NITA (Net Income/Total Assets): It is the financial indicator to measure the performance of the firm.

NITL (Net Income/Total Liabilities): This financial indicator measures return on an asset which is also the measure of companies' profitability and performance.

5. Estimation of logit, probit and MDA Models

This section covers estimation of bankruptcy prediction models under different econometric methods such as Singh and Mishra (2016a) logit model for Indian manufacturing firms, probit and MDA using the same final profile of financial ratios. The results of Singh and Mishra (2016a) logit model is reported in the second column of Table 2. Further, the results of probit and MDA models are also reported in the third and fourth column of Table 2 respectively. The results show the coefficients of all the variables under different econometric methods are statistically significant at 1, 5 and 10 per cent level of significance respectively.

Table 2. *Results of logit, probit and MDA models*

Statistic	Logit	Probit	MDA
BVEBVD	-13.859***	-7.364***	-13.859***
SLTA	-1.113*	-0.652*	-1.113***
NITA	-18.759**	-10.134**	-18.760***
NITL	-34.354**	-19.273**	-34.354**
Constant	-0.449	-0.215	-0.604
Wilks' lambda for the discriminant function			0.37
Chi-square test			125.435
LR	164.955	164.892	
P-value	0.00	0.00	0.00

Note: ***, ** and * represents the level of significance at 1 per cent, 5 per cent and 10 per cent respectively.
Source: Author's compilation.

The LR ratio tests for logit and probit shows the overall significance of the models. In the case of logit and probit model the LR ratio is found to be 164.955 and 164.892 respectively at 1 per cent level of significance. Hence, the empirical results show a change in econometric methods have no significant effect on the sign and level of significance of the coefficients of financial ratios.

In the next step, the total error minimization principle is adopted to determine cut-off values of logit, probit and MDA models. Table 3 reports cut-off values for logit, profit and MDA models which are taken as 0.6, 0.7 and 0.6 respectively.

Table 3. *Identification of Cut-off Value of different models*

Cut-off value	Overall correct prediction	Type I Error	Type II Error
Logit Model			
0.7	98.462	3.080	0.000
0.6	98.460	1.540	1.540
0.5	97.690	1.540	1.540
0.4	97.690	1.540	3.080
Probit Model			
0.7	98.461	3.077	0.000
0.6	97.692	1.538	3.077
0.5	97.692	1.538	3.077
0.4	96.923	1.538	4.615
MDA Model			
0.7	85.384	27.692	1.538
0.6	98.461	1.538	1.538
0.5	96.923	1.538	4.615
0.4	90.769	1.538	16.923

Source: Author’s compilation.

6. Results and discussion

This section covers the sensitivity of bankruptcy prediction models on their predictive accuracies to the change in econometric methods. Predictive accuracy of all the three models is tested using diagnostics tests such as secondary sample, long-range accuracy and ROC tests.

6.1. Predictive accuracy

Predictive accuracies of logit, probit and MDA models are reported in Table 4. For all the three models the overall predictive accuracy is found to be 98.461 per cent. Singh and Mishra (2016a) logit model with 98.461 per cent of overall correct prediction successfully classifies 96.923 per cent of distressed and 100 per cent of non-distressed firms respectively. Again with 98.461 per cent of overall correct prediction of the probit model it correctly classifies 96.923 per cent of distressed and 100 per cent of non-distressed firms respectively. In case of the MDA model with 98.461 per cent of overall correct prediction the model correctly classifies 98.461 per cent of distressed and non-distressed firms.

Table 4. *Comparison of Predictive Accuracy of the Models*

Models	Estimation Sample Overall	Distressed	Non-Distressed	Hold-out Sample Overall	Distressed	Non-Distressed
Logit	98.461	96.923	100	89.743	82.051	97.435
Probit	98.461	96.923	100	89.743	82.051	97.435
MDA	98.461	98.461	98.461	89.743	82.051	97.435

Source: Author's compilation

The results reported in Table 4 shows that there is no significant impact on the overall predictive accuracies and classification rate of different models towards change in econometric methods. Hence, change in econometric methods has neither significant impact on sign and significance of coefficients nor on the predictive performance of the models.

6.2. Diagnostics checks

This section deals with diagnostics tests such as secondary sample, long-range accuracy and ROC test on logit, probit and MDA models.

The results in Table 4 also reports the predictive performance of logit, probit and MDA models on the secondary sample. The overall predictive accuracy of logit, probit and MDA model on the hold-out sample is found to be 89.743 per cent. Further, all the models correctly classify 82.051 and 97.435 per cent of distressed and non-distressed firms respectively. The predictive performance of logit, probit and MDA models on the hold-out sample is found be the same. Hence, all the models have good secondary sample results and there is no impact of the change in econometric methods on the predictive performance of the models

Table 5 reports long-range accuracy results of logit, probit and MDA models on estimation and secondary sample. The overall predictive accuracy of logit model on the estimation sample is 98.461 and 83.076 per cent for one year and two years prior to bankruptcy respectively. On the hold-out sample, it is found to be 88.461 and 70.512 per cent for one year and two years prior to default respectively. In the case of probit model the overall predictive accuracy on the estimation sample is 98.461 and 83.846 per cent for one year and two years before bankruptcy. On the hold-out sample, it is found to be 89.743 and 64.102 per cent for one year and two years prior to bankruptcy respectively. Finally, in the case of the MDA model the overall predictive accuracy on the estimation sample is 98.153 and 76.153 per cent for one year and two years prior to default. The overall predictive accuracy on the hold-out sample is found to be 89.743 and 64.102 per cent for one year and two years before bankruptcy respectively.

Table 5. *Comparison of long range accuracy of the models*

Years before distress	Estimation Sample Overall	Distressed	Non-Distressed	Hold-out Sample Overall	Distressed	Non-Distressed
	Logit					
1	98.461	96.923	100	88.461	82.051	94.871
2	83.076	67.692	98.461	70.512	48.717	92.307
	Probit					
1	98.461	96.923	100	89.743	82.051	97.435
2	83.846	67.692	100	64.102	38.461	89.743
	MDA					
1	98.461	98.461	98.461	89.743	82.051	97.435
2	76.153	53.846	98.461	64.102	38.461	89.743

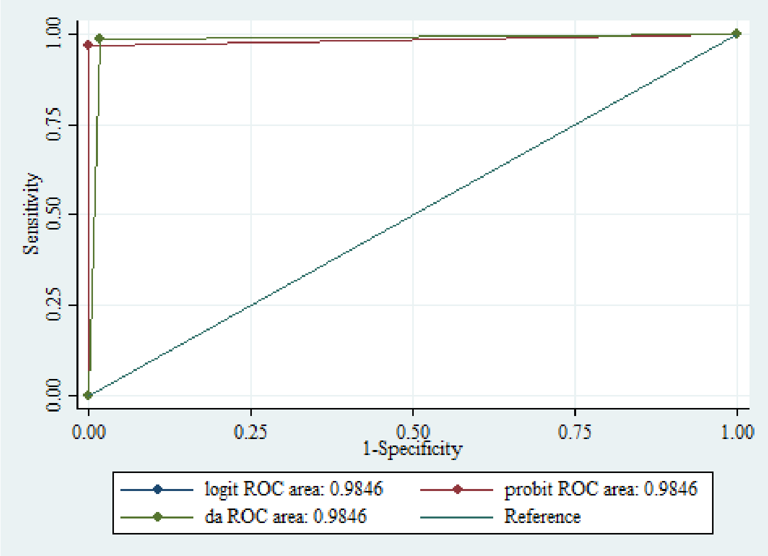
Source: Author's compilation.

The long range accuracy results are fairly good and satisfactory for logit, probit and MDA models. The predictive accuracy of all the models decreases on estimation and hold-out sample as we go more backward from the year of bankruptcy. Hence, the change in econometric methods has no significant impact on predictive accuracy and most recent information remained more helpful to predict bankruptcy with higher accuracy.

The Receiver Operating Characteristic (ROC) is a widely used performance test for a binary classifier. In a single number the Area under Receiver Operating Curve (AUROC) summarizes the performance of binary classifier model. The accurateness of the test depends on how accurately the model classifies between the two groups, namely, bankrupt and non-bankrupt. ROC with AUROC 1 for any model signifies a perfect model whereas AUROC with 0.5 signifies worthless model. Contrary to the misclassification matrix the ROC envisages all possible thresholds. In the test sensitivity is the proportion of the firm which is correctly identified whereas the specificity is the proportion of the firm having negative test results. The ROC curve represents a graph between specificity and 1-senstivity. Hence, an excellent test has a good balance between sensitivity and specificity.

Figure 1 shows AUROC for logit, probit and MDA models on the estimation sample for one year prior to distress. The result shows the AUROC is 0.984 which is same for all the models. Hence, the test results for all the models on estimation sample one year prior to distress is perfect which accurately classifies between bankrupt and non-bankrupt firms.

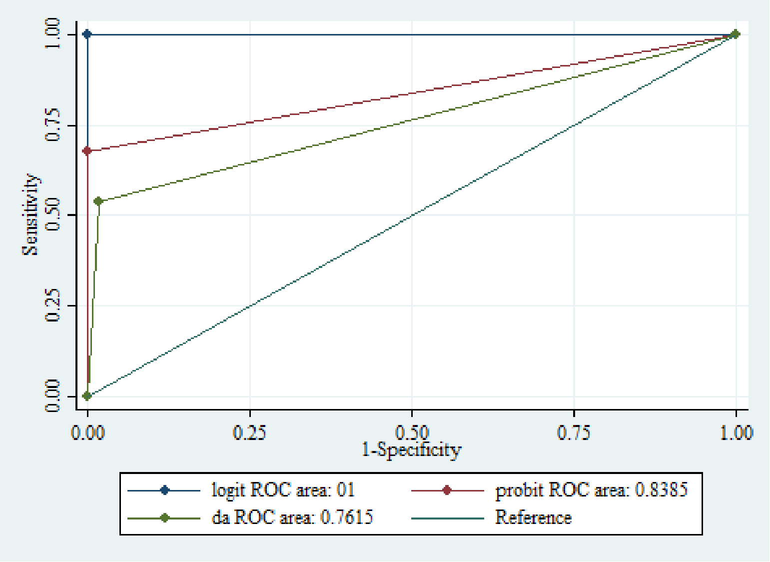
Figure 1. *Comparison of AUROC of different models on the estimation sample for one year prior to distress*



Source: Author's estimation.

Figure 2 reports AUROC for logit, probit and MDA models on the hold-out sample for one year before bankruptcy. The result shows the AUROC for logit, probit and MDA models are 1, 0.838 and 0.761 respectively. Hence, the test results for logit and probit models are perfect and good for MDA model for one year before bankruptcy which accurately classifies bankrupt and non-bankrupt firms.

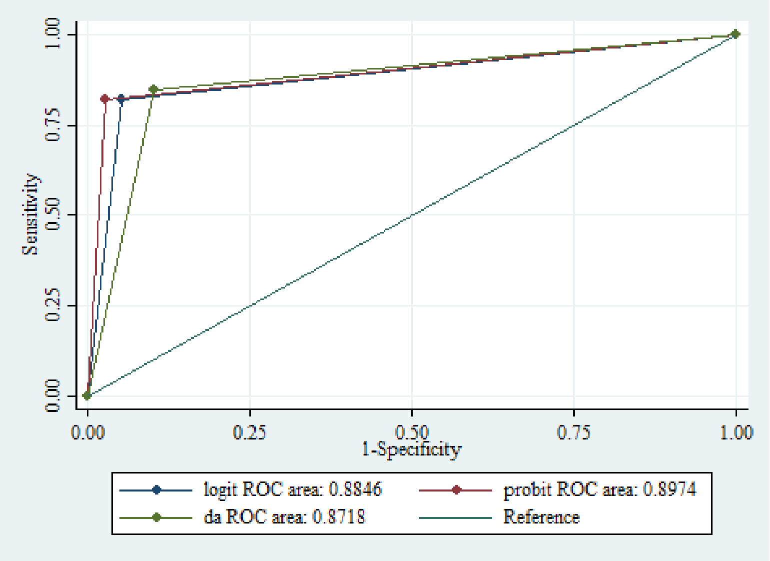
Figure 2. *Comparison of AUROC of the different model on the hold-out sample for one year prior to distress*



Source: Author's estimation.

Figure 3 reports AUROC for logit, probit and MDA models on the estimation sample for two years prior to default. AUROC for logit, probit and MDA model are found to be 0.884, 0.871 and 0.897 respectively. The test results for all the models are found to be perfect.

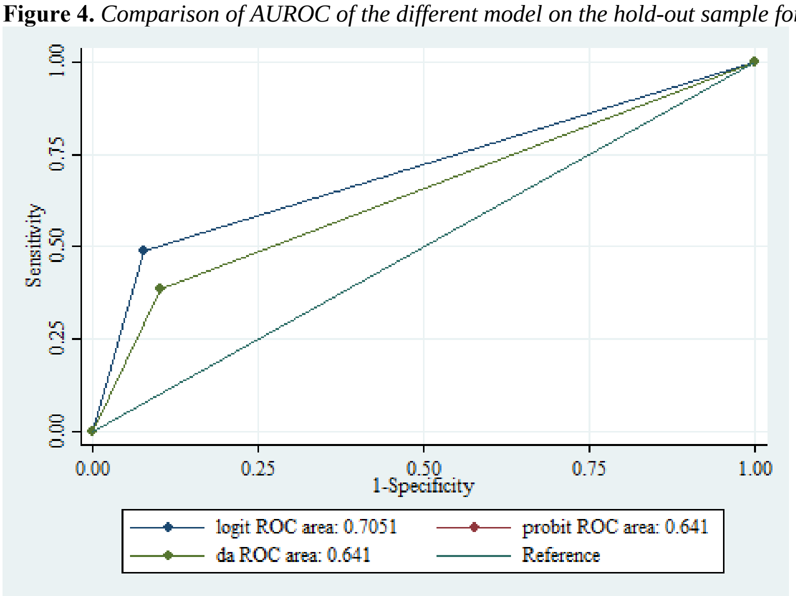
Figure 3. *Comparison of AUROC of different models on the estimation sample for two years prior to distress*



Source: Author's estimation.

Figure 4 reports AUROC for logit, probit and MDA models on the hold-out sample for two years prior to distress. AUROC for logit, probit and MDA model are 0.705, 0.641 and 0.641 respectively. The test results for all the models are found to be fairly good on the hold-out sample for two years prior to distress.

Figure 4. *Comparison of AUROC of the different model on the hold-out sample for two years prior to distress*



Source: Author's estimation.

The results of all the diagnostics tests on the predictive performance of binary classifier models confirms all the models are perfect and there is no significant difference in predictive performance of the models. Hence, the study empirically confirms in the Indian setting that there is no significant impact of the change in econometric methods on the predictive performance of the model if significant financial ratios are identified accurately.

7. Conclusion

The paper empirically investigated the impact of the change in econometric methods on the new bankruptcy prediction model for Indian manufacturing firms proposed by Singh and Mishra (2016a). The new bankruptcy prediction model utilized logit technique to model bankruptcy. In the current study probit and MDA econometric techniques were used to re-estimate the Singh and Mishra (2016a) model utilizing the same data set and financial ratios. The probit and MDA techniques are theoretically different from each other. The probit technique is similar to logit because both the econometric techniques are based on cumulative density function whereas MDA is based on discriminant function and widely used in the bankruptcy prediction literature.

The coefficient of probit and MDA models are found to be statistically significant. The predictive accuracy of logit, probit and MDA models on estimation sample is found to be same i.e. 98.461 per cent whereas predictive accuracy on the hold-out sample is 89.743 per cent which is also same for all the models. The results of all the diagnostics tests on the predictive performance of binary classifier models confirms all the models are perfect and there is no significant difference in predictive performance of the models. The major findings of the study suggest that accounting information's, namely, leverage, profitability and turnover ratio remained as significant indicators to predict bankruptcy for Indian manufacturing firms. The study further concludes, if significant indicators of bankruptcy are identified, then there is no major impact of the change in econometric methods on the performance of the bankruptcy prediction models. Further, the study provides empirical support for the proposition that the predictive accuracy of the bankruptcy prediction model is not sensitive towards change in econometric methods if significant financial variables are identified accurately. Hence, the results give empirical validation to the proposition that the selection of correct financial ratios and the use of more recent financial information are vital in the bankruptcy prediction. The major limitation of the study is that it can be applied to only manufacturing firms and larger data set can be applied to validate the results.

References

Altman, E.I., Haldeman, R. and Narayanan, P., 1977. ZETA analysis, a new model for bankruptcy classification, *Journal of Banking and Finance*, Vol. 1, No. 1, pp. 29-54.

Abdullah, N.A., Halim, A., Ahmad, H. and Russ, R.M., 2008. Predicting corporate failure of Malaysia's listed companies: comparing multiple Discriminant analysis, logistic regression and hazard model, *International research journal of finance and economics*, Vol. 15, pp. 201-217.

Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, *Journal of Finance*, Vol. 23, No. 4, pp. 189-209.

Agarwal, V., Taffler, R.J., 2008. Comparing the performance of market-based and accounting based bankruptcy prediction models, *Journal of Banking and Finance*, Vol. 32, No. 8, pp. 1541-1551.

Bharath, S.T. and Shumway, T., 2008. Forecasting default with the Merton distance to default model, *The Review of Financial Studies*, Vol. 21, No. 3, pp. 1339-1369.

Bhunia, A. and Sarkar, R., 2011. A study of financial distress based on MDA, *Journal of Management Research*, Vol. 3, No. 2, pp.1-11.

Bandyopadhya, A., 2006. Predicting probability of default of Indian corporate bonds: logistic and Z-score model approaches, *The Journal of Risk Finance*, Vol. 7, No. 3, pp. 255-272.

Blum, M., 1974. Failing company discriminant analysis, Journal of Accounting Research, Vol 12, No. 1, pp. 1-25.

Beaver, W.H., 1966. Financial ratios as predictors of failure, Journal of Accounting Research, Vol. 4, pp. 71-111.

Chudson, W., 1945. The Pattern of Corporate Financial Structure, National Bureau of Economic Research, New York.

Coats, P.K. and Fant, L.F., 1993. Recognizing financial distress patterns using a neural network tool, *Financial management,* Vol. 22, No. 3, pp. 142-155.

Duffie, D. and Singleton, K., 1999. Modelling term structures of defaultable bonds, *Review of Financial Studies*, Vol. 12, No. 4, pp. 197-226.

Deakin, E., 1972. A discriminant analysis of predictors of business failure, *Journal of Accounting Research*, Vol. 10, No. 1, pp. 167-179.

Fulmer, J., Moon, J., Gavin, T. and Erwin, M., 1984. A bankruptcy classification model for small firms, *Journal of Commercial Bank*, Vol. 66, No. 11, pp. 25-37.

Goldsmith, R.W., 1969. Financial Structure and Development, Yale University Press, New Haven and London.

Guan, Q., 1993. Development of optimal network structures for back-propagation trained neural networks. Ph.D. dissertation, University of Nebraska.

Hosaka, T., 2019. Bankruptcy prediction using imaged financial ratios and convolutional neural networks, *Expert Systems with Applications*, Vol. 117, pp. 287-299.

Hillegeist, S., Keating, E., Cram, D. and Lundstedt, K. (2004), Assessing the probability of bankruptcy, *Review of Accounting Studies*, Vol. 9, no. 1, pp. 5-34.

Jarrow, R. and Turnbull, S., 1995. Pricing derivatives on financial securities subject to credit risk, *Journal of Finance*, Vol. 50, No. 1, pp. 53-85.

King, R. and Levine, R., 1993a. Financial Intermediation and Economic Development, in Capital Markets and Financial Intermediation, Centre for Economic Policy Research, Colin Mayer and XavierVives, London.

King, R. and Levine, R., 1993b. Finance and growth: Schumpeter might be right, *Quarterly Journal of Economics*, Vol. 108, No. 3, pp. 717-738.

King, R. and Levine, R., 1993c. Finance, entrepreneurship and growth: theory and evidence, *Journal of Monetary Economics*, Vol. 32, No. 3, pp. 513-542.

Kirkos, E., 2015. Assessing methodologies for intelligent bankruptcy prediction, Artificial Intelligence Review, Vol. 43, No. 1, pp. 83-123.

Koro, T. and Korodi, A., 2011. An evaluation of effectiveness of Fuzzy logic model in predicting the business bankruptcy, *Romanian Journal of Economic Forecasting*, Vol 3, No. 1, pp. 92-107.

Kumar, M.N. and Rao, V.S.H., 2015. A New Methodology for Estimating Internal Credit Risk and Bankruptcy Prediction under Basel II Regime, *Computational Economics*, Vol. 46, No. 1, pp. 83-102.

Kulkarni, A., Mishra, A.K. and Thakker, J., 2005. How Good is Merton Model at Assessing Credit Risk? Evidence from India, National Institute of Bank Management, Pune.

Lando, D., 1994. Three essays on contingent claims pricing, Ph.D. dissertation, Cornell University.

Lucas, R.E., 1988. On the mechanics of economic development, *Journal of Monetary Economics*, Vol. 22 No. 1, pp. 3-42.

Lamb, S., 2000. *Shakespeare's Hamlet*, Hungry Minds, New York.

McKinnon, R.I., 1973. Money and Capital in Economic Development, Brookings Institution, Washington, DC.

Merton, R., 1974. On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance*, Vol. 29, No. 2, pp. 449-470.

Messier, Jr. W. and Hansen, J., 1988. Inducing rules for expert system development: an example using default and bankruptcy data, *Management Science*, Vol. 34, No.12, pp. 1403-1415.

Ohlson, J.A., 1980. Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research*, Vol. 18, No. 1, pp. 109-131.

Premachandra, I.M., Bhbra, G.S. and Sueyoshi, T., 2009. DEA as a tool for bankruptcy assessment: A comparative study with logistic regression technique, *European Journal of Operational Research*, Vol. 193, No. 2, pp. 412-424.

Pongsatat, S., Ramage, J. and Lawrence, H., 2004. Bankruptcy prediction for large and small firms in Asia: a comparison of Ohlson and Altman, *Journal of Accounting and Corporate Governance*, Vol. 1, No. 2, pp. 1-13.

Platt, D.H. and Platt, M.B., 1990. Development of a class of stable predictive variables: The case of bankruptcy prediction, *Journal of Business Finance and Accounting,* Vol. 17, No. 1, pp. 31-51.

Raghupathi, W., Schkade, L.L. and Raju, B.S., 1991. A neural network application for bankruptcy prediction. In System Sciences, Proceedings of the Twenty-Fourth Annual Hawaii International Conference IEEE, Vol. 4, pp. 147-155.

Ramakrishnan, P.R., 2005. Financial Distress Prediction Models: A Case of Potential Sick Companies in India, The ICFAI Journal of applied Finance, pp. 68-77.

Robinson, J., 1952. *The rate of interest and other essays*, MacMillan, London.

Singh, B.P. and Mishra, A.K., 2016a. Re-estimation and comparisons of alternative accounting based bankruptcy prediction models for Indian companies, *Financial Innovation*, Vol. *2*, No. 1, pp. 1-28.

Singh, B.P. and Mishra, A.K., 2016b. Predicting probability of default of Indian companies: A market based approach, *Theoretical and Applied Economics*, Vol. *23,* No. 3, pp. 197-204.

Schumpeter, J.A., 1911. The theory of economic development, Harvard University Press, Cambridge.

Shaw, E.S., 1973. Financial Development and Economic Deepening, Oxford University Press, New York.

Singh, B.P. and Mishra, A.K., 2015. Researching the relationship between Financial and Real sectors in India, *Indian Journal of Economics and Development*, Vol. 11, No. 4, pp. 861-868.

Singh, B.P. and Mishra, A.K., 2014. Nexus of financial development and economic growth in India: revisiting Schumpeter, *Indian Journal of Economics and Development*, Vol. 10, No. 3, pp. 246-255.

Smith, R. and Winakor, A., 1935. Changes in Financial Structure of Unsuccessful Industrial Corporations, Bureau of Business Research, Bulletin No. 51. Urbana: University of Illinois Press.

Springate, G.L.V., 1978. Predicting the Possibility of Failure in a Canadian Firm, Unpublished M.B.A. Research Project, Simon Fraser University.

Shetty, U., Pakkala, T.P.M. and Mallikarjunappa, T., 2012. A modified directional distance formulation of DEA to assess bankruptcy: An application to IT/ITES companies in India, *Expert Systems with Applications*, Vol. 39, No. 2, pp. 1988-1997.

Tsukuda J. and Baba, S.I., 1994. Predicting Japanese corporate bankruptcy in terms of financial data using neural network, *Computers & Industrial Engineering*, Vol. 27, No. 1, pp. 445-448.

Ugurlu, M. and Aksoy, H., 2006. Prediction of corporate financial distress in an emerging market: the case of Turkey, *Cross Cultural Management: An International Journal*, Vol. 13, No. 4, pp. 277-295.

Vareto, F., 1998. Genetic algorithms applications in the analysis of insolvency risk, *Journal of Banking and Finance,* Vol. 22, No. 10-11, pp. 1421-1439.

Verikas, A., Kalsyte, Z., Bacauskiene, M. and Gelzinis, A., 2010. Hybrid and ensemble-based soft computing techniques in bankruptcy prediction: a survey, *Soft Computing*, Vol. 14, No. 9, pp. 995-1010.

Varma, J.R. and Raghunathan, V., 2000. Modeling credit risk in Indian bond markets, *The ICFAI Journal of Applied Finance,* Vol. 6, No. 3, pp. 53-67

Wu, Y., Gaunt, C. and Gray, S., 2010. A comparison of alternative bankruptcy prediction models, *Journal of Contemporary Accounting and Economics,* Vol. 6, No. 1, pp. 35-45.

Maheshwari, Y., 2018.Efficacy of industry factors for corporate default prediction, *IIMB Management Review,* doi: https://doi.org/10.1016/j.iimb.2018.08.007

Zmijewski, M.E., 1984. Methodological issues related to the estimation of financial distress prediction models, *Journal of Accounting Research,* Vol. 22, pp. 59-82.