Predicting Indian SME financial distress: an ex-ante approach

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Abstract

Purpose – The purpose of this study is to propose a financial distress prediction (FDP) model and method suitable for listed Indian small and medium enterprises (SMEs).

Design/methodology/approach – A three-part screening criteria similar to Platt and Platt (2006) was tested independently and jointly on Indian SMEs using statistically significant financial variables. Five stepwise multiple discriminant analysis (MDA) models were developed and the best-performing model was further compared against seminal models to check for robustness.

Findings – Model C2 developed under Criterion C which stated "if net income before special items is negative in any given year the firm is considered as 'unwell'" proved robust and effective.

Originality/value – The proposed model identifies the importance of profitability and efficiency ratios over leverage ratios in determining financial distress and therefore, has implications for SME owners/managers and shareholders.

Keywords Bankruptcy, Developing countries, Financial distress, Model, Small and medium enterprises (SMEs)

Paper type Research paper

1. Introduction

Financial distress continues to be the global interest of researchers since the 1930s (Bellovary, *et al.*, 2007) and a significant number of financial distress prediction (FDP) developers persist in constructing models ranging from Altman's *Z*-score model to Zmijewski's model (1984) (Durica *et al.*, 2019). Likewise, the initial FDP model for small and medium enterprises (SMEs) was proposed by Edmister in 1972, Abidin *et al.* (2021). The SME sector is regarded as a stimulus for socio-economic revolution but faces numerous challenges (Das, 2017). Consequently, the number of wholesale and retail trade SMEs registered under the insolvency and Bankruptcy Code (IBC) 2016, escalated from 526 cases in March 2022 to 657 as of March 2023 (Soni, 2023).

Therefore, this calls for contemplating techniques to detect and prevent SME bankruptcy. Although recent research in SME FDP has increased (Ciampi *et al.*, 2021), it unevenly

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concentrates on developed markets (Rosenbusch *et al.*, 2011) when SMEs in developing and under-developed countries are known for high failure rates (Page and Söderbom, 2015). Furthermore, the SME FDP literature largely proposes ex-post models that consider only failing firms while an ex-ante approach includes firms that file for bankruptcy and firms that fail to meet operational cash flows thereby facilitating reevaluation of financial health for all periods (Pindado *et al.*, 2008). Therefore, identifying and understanding failure symptoms before bankruptcy provides warning signs to forecast the potential threats to a firm (Saleh, 2016). Moreover, a new term and concept, such as the *zombie firm* has emerged in European research which describes a company that continues doing business, however, there are several measurable indicators that suggest that it must be "dead" and depart the market. There could be several internal and external factors responsible for its condition (Blažková and Dvouletý, 2020). Thus, through an ex-ante approach, a model and method suitable to the needs and economic features of SMEs is proposed to prevent financial distress. The study is organized as follows. Section 2 presents a review of literature on SME FDP models and hypothesis development. Section 3 details about the sample features, variables and techniques applied, Section 4 presents the results while Section 5 discusses about the model and method proposed. Section 6 and Section 7 present the implications and conclusion, respectively.

2. Literature review

Although bankruptcy is a dominant computation of financial distress in modern literature, delineating failure through financial distress in lieu of bankruptcy can help build models relevant to its situation and requirements (Sokka, 2020). Financial distress refers to a firm's feeble liquidity position to meet financial obligations (Dakhwani, 2019). Though a specific definition does not exist yet (Shi and Li, 2019), terms such as default, distress, liquidation, industrial sickness and bankruptcy is generally used in literature to define firm failure (Dakhwani, 2019).

Furthermore, due to the absence of a combined theory (Bandyopadhay, 2006), many SME FDP models in developing countries have been using various statistical and/or artificial intelligence (AI) techniques with diverse variables. For instance, Terdpaopong and Mihret (2011) proposed a six-variable multiple discriminant analysis (MDA) model for Thai SMEs which achieved an accuracy rate of 97.2%. Likewise, Bhunia (2012) developed a multiple linear regression model using the metrics of Alexander Bathory's model to evaluate financial risk of 513 Indian-listed BSE SMEs for the years 2001–2011, which proved robust. To examine the major components of Altman's Z' score model, Prakash, and Verma (2019) used sample data from non-listed Indian SMEs. The model achieved an accuracy between 89% and 99.8%. Likewise, ElBannan (2021) aimed to highlight factors affecting the probability of financial distress in a cross-country analysis of 11 countries in the Middle East and North Africa (MENA) region and further assessed the validity of life cycle theory. To measure the likelihood of firm distress, Altman's *Z*-score model, Asquith's criteria, and Taffler's *Z*-score model were used. The study identified firm age, liquidity, profitability, market-to-book, asset growth, firm size, and institutional variables as significant predictors of financial distress. Overall, the study concluded that firms in maturity stage and which are profitable, liquid and small in size with high market-to-book ratios and low asset growth have lower probabilities of experiencing financial distress.

Nevertheless, applying traditional models further decreases prediction power due to varied country economic conditions (Karas and Srbova, 2019) and lacks stability (Pindado *et al.*, 2008). Overall, though the literature on FDP is scant in case of emerging markets, it reveals that there are different variables, tools/techniques to employ when proposing a model. That said, this study utilizes financial ratios that reflect the liquidity, profitability, leverage and efficiency positions of Indian-listed SMEs based on data availability. Apparently, statistical techniques were preferred more often than AI techniques in extant literature. Nevertheless, MDA provides a better understanding of a full set of predictors simultaneously and the interaction of the same (Gerritsen, 2015). Therefore, MDA was used to propose an SME FDP model to differentiate between “unwell” and “well” Indian SMEs. The following research hypotheses were formulated:

RH1. There is no significant difference in the selected financial ratios between “unwell” and “well” Indian SMEs.

RH2. There is no significant difference between the classification results of the best performing proposed model and seminal models.

The first hypothesis enables to examine the mean differences between the financial variables of the classified groups while the second hypothesis relates to the comparison of the performance of the optimal proposed model with the seminal models derived from the literature.

3. Methodology

3.1 Sample features

As accounting data of unlisted SMEs is difficult to access and collect, this study obtained and used financial data from a convenient source. A population of 492 listed Indian SMEs were identified in NSE EMERGE (173) and BSE SME (285) and SMEs that were listed in both (34). As data were mostly available from the period 2017–2019, it was considered for analysis. However, issues such as lack of data, incomplete data/annual reports, repeated cases, or illegible annual reports occurred. Therefore, from 492 SMEs, 172 cases were eliminated from the list and remaining 320 SMEs with complete data were considered.

Since this study utilizes the ex ante approach of identifying firms experiencing financial distress, there is no one way to classify firms. There are several ways to classify firms or define the ‘event’ using proxies. The ex ante approach is imperative for tools/methods such as MDA, LR and neural networks (Min and Lee, 2008). Likewise, the firms were classified as “unwell” and “well”, coded as 1 and 0, respectively, based on the criteria used in Platt and Platt (2006) which were computed for the years 2018 and 2019. The “well” SMEs were randomly selected after identifying and separating “unwell” SMEs from the list for each criterion; an approach similar to Platt and Platt (2006). The screening criteria used to classify firms in any given year (i.e. 2018 and/or 2019) are presented below:

A. Earnings Before Interest, Taxes, Depreciation and Amortization (EBITDA) is lower than interest expense: when a firm is unable to generate sufficient funds from operational activities to cover its financial expenses. A total of 36 firms were identified as “unwell” while 284 were “well”.

B. Negative EBIT: negative operating income questions the long-term sustainability of business operations. A total of 40 firms were identified as “unwell” while 280 were “well”.

C. Negative net income before special items: unable to make sufficient funds to meet interest payments questions the long-term firms’ creditworthiness. A sum of 42 firms were classified as “unwell” while 278 were “well”.

D. Combined all conditions together (i.e. A to C). A total of 31 firms were identified as “unwell” and 289 firms were “well”.

The sample was apportioned into two samples under each criterion, namely, estimation sample (ES) and holdout sample (HS). Each sample set was distributed on an 80–20 basis. The estimation year for the model building was 2017 while the three-year data of the HS were considered for validating estimated models. The final sample data were an equal segregation of "well" and "unwell" SMEs for both ES and HS under each criterion. The total sample size was 72, 80, 84, and 62 for Criterion A to D, respectively. For instance, under Criterion A, ES and HS consisted of 58 and 14 SMEs, respectively, with equal binary groups. Furthermore, the study combined data (i.e. ES + HS) from 2017 to 2019 to validate the overall performance of the models, which was similar to Swaminathan's (2018) approach. To validate and select the ideal model and method, receiver operating characteristic (ROC) curve was estimated (see Gupta *et al.*, 2015) on the combined sample, as ROC must be estimated on a sample above 100 for reliable results (Hanczar *et al.*, 2010).

3.2 Data normalization

In social sciences research, normalizing data is crucial as abnormal data can yield ineffective estimates and the presence of outliers can lead to biased results. Consequently, transformation techniques such as the Box-Cox technique was used under each criterion to remove skewness, rectify normality, linearity and homoscedasticity (Malik *et al.*, 2021). Previous FDP studies such as Jones *et al.* (2017) highlighted that since models built using linear discriminant analysis, quadratic discriminant analysis and probit depend highly on normality assumptions, this technique helps improve the predictive performance of the sample.

3.3 Financial variables

A set of 28 financial variables were verified which included liquidity, turnover, profitability, and leverage ratios. These were selected based on frequency and/or significance in extant FDP literature (i.e. Abidin *et al.*, 2021; Platt and Platt, 2006; Terdpaopong and Mihret, 2011). The types of ratios used for analysis include: Liquidity: current ratio (CR), quick ratio (QR), current assets/total assets (CA/TA), quick assets/total assets (QA/TA), current liabilities/total liabilities (CL/TL), working capital/total assets (WC/TA), current liabilities/total assets (CL/TA), interest/net sales (Int./NS) and EBIT/interest (EBIT/Int.). Efficiency: asset turnover ratio (ATR), fixed assets turnover ratio (FATR), shareholders' fund/net sales (Sh.F./NS), quick assets/net sales (QA/NS), working capital turnover ratio (WCTR), current assets/net sales (CA/NS), debtors turnover ratio (DTR) were used. Profitability: earnings before interest and tax/net sales (operating profit margin-OPM), EBIT/TA (ROA1), net income(NI)/total assets (TA) (ROA2), profit after tax/net sales (PAT/NS), and return on net worth (RONW). Leverage: total liabilities/total assets (TL/TA), equity ratio (EQR), debt-equity ratio (DER), retained earnings/total assets (RE/TA), long-term liabilities to total assets (LTL/TA), long-term liabilities to equity (LTL/Equity) and fixed capital ratio (FCR) were assessed.

3.4 Robustness check with seminal models

To further confirm the robustness of the proposed optimal model, it is compared against three seminal models found in literature. In 1978, Springate constructed a stepwise MDA model on 40 Canadian firms. Thus, a discriminant score below 0.862 is deemed as a distressed firm (Swaminathan, 2018):

$$Z = 1.03X1 + 3.07X2 + 0.66X3 + 0.4X4$$

where,

$X1 =$ working capital/total assets
$X2 =$ net profit before interest and taxes/total assets
$X3 =$ net profit before taxes/current liabilities
$X4 =$ sales/total assets

Next, a modified *Z*-score model was developed for emerging markets by Altman, Hartzell, and Peck in 1995 with a cutoff score below 1.75 depicting firm failure (Altman, 2005):

$$Z'' = 3.25 + 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4$$

where,
X1 = working capital/total assets
*X*2 = retained earnings/total assets
X3 = operating income/total assets
X4 = book value of equity/total liabilities

Likewise, according to Terdpaopong and Mihret's (2011) Thai SME model, a discriminant score below the cutoff score of −1.956 is denoted as a distressed firm:

$$Z = -1.021 + 0.015CATA - 0.01LLTA + 0.007WCTA + 0.154DE + 0.001TITA + 0.011EBITTA$$

where,
CATA = current assets/total assets.
LLTA = long-term liability/total assets.
WCTA = working capital/total assets.
DE = debt to equity ratio.
TITA = total income/total assets
EBITTA = earnings before interest and tax expenses/total assets.

4. Results

4.1 Test of equality means in financial variables

A comparison of descriptive statistics was performed on 28 variables of the classified groups. The study verified the statistical significance of the mean differences between the predictors for the SME classified groups. The test results, considering all criteria together, revealed that 12 out of 28 variables (i.e. ATR, CA/TA, ROA1, WC/TR, ROA2, RONW, QA/TA, CL/TL, OPM, FA/TR, PAT/NS, and QA/NS) were found significant in discriminating between the groups at a 0.05 level of significance. Therefore, the results reveal that there are significant differences in liquidity, profitability, and efficiency variables of the binary groups except for leverage.

4.2 SME FDP models – estimation, validation, and robustness check

Subsequently, five stepwise MDA models (as shown Table 1) based on four different criteria were developed. An additional model was built for screening Criterion C as multicollinearity

Model	Discriminant function	Cut-off score
A	Z = 0.979ROA1 + 2.227CLTL − 1.884 (constant)	−0.0105
B	Z = 1.108ROA1 + 0.849QATA − 0.709 (constant)	0.0115
C1	Z = 0.853ROA1 + 0.003WCTR + 0.844QATA − 0.823 (constant)	−0.013
C2	Z = 0.415ATR + 0.987QATA + 10.943ROA2 − 1.350 (constant)	0.0125
D	Z = 1.098 ROA1 − 0.233 (constant)	0.012

Source: The authors

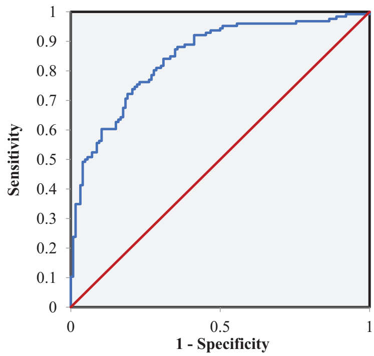
Table 1. Discriminant functions of screening criteria A to D

Table 2. Effectiveness of discriminant functions

Model	Eigen-value	Wilks' lambda	Estimated sample (2017)		Holdout Sample (2017–2019)		Combined sample - 2017–2019				
							Type 1 error		Type 2 error		
			Type 1 error	Type 2 error	Type 1 error	Type 2 error	Count	%	Count	%	ROC (%)
A	0.317	0.759	10 / 29	5 / 29	13 / 21	8 / 21	47 / 108	43.52	35 / 108	32.41	69.30
B	0.444	0.692	7 / 32	6 / 32	1 / 24	10 / 24	14 / 120	11.67	66 / 120	55.00	75.70
C1	0.613	0.620	11 / 33	6 / 33	0 / 27	20 / 27	12 / 126	9.52	80 / 126	63.49	73.70
C2	0.540	0.649	9 / 33	6 / 33	2 / 27	14 / 27	18 / 126	14.29	44 / 126	34.92	84.60
D	0.306	0.765	6 / 25	6 / 25	0 / 18	17 / 18	6 / 93	6.45	71 / 93	76.34	82.10

Source: The authors

issues appeared for ROA2 (i.e. variance inflation factor [VIF] = 12.483). Therefore, two models were developed: Model C1 (ROA2 was replaced with ROA1) and Model C2 (ROA1 was replaced with ROA2) which indicated VIF values below 10. Next, according to Table 2, models A, B and D reported eigenvalues below 0.5 and high Wilks' Lambda implying lower dissemination of group means and minimal discriminating ability. Furthermore, Model A misclassified more number of "unwell" SMEs (i.e. Type 1 error) than "well" SMEs (i.e. Type 2 error), which was reflected in the ROC estimate while Models B and D demonstrated



Source: The Author

Figure 1. Model C2 – ROC curve

	N			Mean rank			Asymp. Sig. (2-tailed)		
	SM	EMS	TM	SM	EMS	TM	SM	EMS	TM
(–) ranks	4[a]	0[a]	0[a]	19.00	0.00	0.00			
(+) ranks	33[b]	142[b]	151[b]	19.00	71.50	76.00			
Ties	215[c]	110[c]	101[c]						
Total	252	252	252						
							0.00	0.00	0.00

Notes: [a]SM/EMS/TM < MC2; [b]SM/EMS/TM > MC2; [c]SM/EMS/TM = MC2; SM – Springate's model, EMS = Altman's model for emerging markets; TM = Terdpaopong and Mihret's model; MC2 = Model C2; *N* = total sample; Z-score, Asymp. Sig. = Asymptotic significance level (*p* value)
Source: The authors

Table 3. Wilcoxon signed rank test statistics – SM, EMS, TM, and Model C2

Unwell (1)	Predicted group membership								
Well (0)	1				0				
Original count	MC2	SM	EMS	TM	MC2	SM	EMS	TM	Total
1	108	89	9	1	18	37	117	125	126
0	44	34	1	0	82	92	125	126	126

Notes: MC2 = Model C2; SM = Springate's model; EMS = Altman's model for emerging markets; TM = Terdpaopong and Mihret's model
Source: The authors

Table 4. Classification error test of SM, EMS, TM, and MC2

inconsistent predictive ability on all samples and therefore, ROC values are low. Although models under Criterion C demonstrated efficiency against other models, Model C2 classified the binary groups more efficiently than Model C1 which was reflected in its ROC estimates. This further implied that the approach used to compute ROA largely influenced the performance and classification of Indian SMEs under Criterion C.

Overall, Model C2 classified 75.40% firms accurately with the highest ROC value of 84.60% as shown in Table 2. Furthermore, Figure 1 illustrates that the curve bends closer to the top left-hand corner and farther away from the reference line indicating an improved predictive ability and that it is not random. The results further revealed that Criterion C emerged as a strongest criterion in classifying SMEs in the Indian context based on ROC estimates while Criterion A came forth as the weakest method to explain firm performance. Apparently, the discriminant model with measures of profitability, liquidity, and efficiency classified the SMEs in binary groups more effectively than a classification by probability. However, the robustness of Model C2 is compared against seminal models.

The proposed Model C2 was further compared against seminal models through Wilcoxon signed rank test as shown in Table 3. The *Z*-scores of the models were analyzed for a combined sample of 252 SMEs for 2017–2019. As the scores between each seminal and proposed model is statistically significant (p-value < 0.05), the null hypotheses were rejected. However, in comparison to Springate's model (SM), more than 80% (i.e. 215 / 252) of its data records were equal to Model C2, implying that SM performed much like the proposed model as opposed to Altman's model for emerging markets (EMS) (i.e. 110 / 252) and Terdpaopong and Mihret's model (TM) (i.e. 101 / 252). For further clarity, a classification error test was done as shown in Table 4. Evidently, Model C2 (i.e. MC2) reports the lowest misclassification error of "unwell" SMEs and correctly classifies 75.40% (i.e. 190 / 252) of SMEs against SM (i.e. 71.83%), EMS (i.e. 53.17%) and TM (i.e. 50.40%), implying that Model C2 performs better.

5. Discussion

Predicting SME financial distress is an indispensable exercise today and research in this area is gaining steady momentum. However, previously proposed FDP models were irrelevant, unstable, had limited focus on SME failure, and ex-ante models were largely developed using LR which is subject to non-normality. Therefore, this study contributes to the literature by proposing an SME FDP model through an improved ex-ante approach using MDA, as this is more resilient to the period as opposed to the FDP estimates based on existing models.

Several methods/criteria were used and verified to present a befitting method and model that accurately evaluates the financial distress of Indian SMEs. The study empirically found 12 significant variables differentiating between binary groups, thereby rejecting the first hypothesis. Then, of the five models developed, Model C2 developed under Criterion C emerged as the ideal model, further implicating the importance and computation of ROA. Finally, as Model C2 further performed significantly different from the seminal models in terms of Wilcoxon test and classification error test, the second hypothesis was also rejected. Interestingly, leverage was not commonly significant in MC2 and SM, likewise, in EMS and TM model, efficiency was not significant. Accordingly, this may indicate the importance of efficiency to Indian SME performance against leverage. Furthermore, differences in coefficients of variables and performance between MC2 and seminal models indicated the importance of profitability variables in explaining the performance of Indian SMEs while leverage demonstrated a low impact on performance.

Although Modina and Pietrovito (2014) in Ciampi *et al.* (2021) revealed leverage ratios as better predictors of SME financial distress than liquidity and profitability variables, our results were in line with Danso *et al.* (2021) which stated that the impact of financial leverage on small Indian firms is meager than in large Indian firms. Also, Chadha and Sharma (2015) revealed that financial leverage has no impact on the listed Indian firm financial performance variables such as ROA. Nevertheless, the significance of ATR in predicting financial distress in SMEs was supported by Abidin *et al.* (2021) and Zizi *et al.* (2020) while QATA was found significant in Karas (2022) and ROA was found significant in Abidin *et al.* (2021). Therefore, the findings of this study have implications for the concerned.

6. Implications for SMEs and policymakers

The proposed model implicates the need to maintain good efficiency, liquidity, and profitability levels, therefore, some actionable implications for SMEs are made. They must undertake cash budgeting to increase growth because it would ensure growth efficiency in their endeavors (Attayi *et al.*, 2022). Furthermore, Mungal and Garbharran (2014) emphasize negotiating with suppliers to extend payment due date thereby enabling SMEs to reduce cash management problems. Also, managing accounts payables effectively will help control cash outflow such that negative effects on firm's liquidity and profitability may be avoided (Uremadu *et al.*, 2012). While an ex ante approach implies the prevention of financial failure, ex post approach focuses on reacting to failure. Importantly, ex ante regulation is incapable of preventing all financial failures which implies that both such approaches have positive and negative effects to the financial regulatory policy and system. Therefore, balancing ex ante regulation and ex post regulation strategies is essential to offset the negative impacts of these approaches by supplementing each other in carrying out the goals of economic efficiency and financial strength (Anabtawi and Schwarcz, 2013).

7. Conclusion

Limited research is available on SME FDP models in developing countries especially when they are more prone to business failures than SMEs in advanced economies. Therefore, this study proposed a suitable method and model for listed Indian SMEs. Although the proposed model has implications for the concerned, this study is subjected to certain limitations. Data pertaining to COVID-19 years (2020–2021) were not considered as such turbulent events can change the influence of the factors of financial distress (Singh and Rastogi, 2022). Moreover, due to lack of and/or incomplete data during and post-COVID-19, model development was not possible. Furthermore, as assumptions of MDA needed to be satisfied, the data were normalized, however, in real-world scenarios, data are seldom normally distributed. Therefore, careful interpretation of the findings is necessary.

The results of this study further have implications for future research. For instance, the variables in the Thai SME model (TM) could not explain the performance of Indian SMEs but a Canadian non-SME FDP model (SM) performed similarly to the proposed model (MC2). Therefore, future studies must explore the relationship between SME characteristics and country-specific characteristics that determine financial distress in SMEs. Future FDP developers may also test additional explanatory variables, particularly, cashflow, corporate governance, macroeconomic, innovation-related, and bank-customer, which were identified in the literature as having a bearing on SME performance. Also, building and comparing models before, during, and post-COVID-19 period will help identify how different financial and/or non-financial variables impact SMEs' performance in different economic periods. Finally, examining significant indicators and model performance of firms in the "grey zone" and comparing with "well" and "unwell" firms' variables and model performance is another area to explore.

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