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Credit Risk Assessment and Analysis of Select Listed SMEs in India: A Comprehensive Study

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Abstract
Small and Medium Enterprises (SMEs) in India are found in various sectors and are crucial for economic growth, contributing around 40% to the GDP and employing 110 million people. However, they face obstacles in obtaining credit due to information gaps and complex processes. To address this, a study analyzes creditworthiness parameters in the capital goods and consumer durables sectors, using the MCDM model. This model assists financial institutions in making informed decisions. Digital technologies are also reshaping the financial industry, impacting payments, loans, insurance, and wealth management.

Keywords: Sustainability of SMEs, MCDM, Credit Analysis, Credit scoring, Fintech

I.Introduction

1.1 About SMEs in India

Over the past few decades, the Micro, Small, and Medium Enterprises (MSME) sector has grown to be a very vibrant and pulsing area of the Indian economy. Supporting private businesses and creating significant employment opportunities at comparatively lower investment costs than any other sector of the economy, except for agriculture, has significantly advanced the nation's economic and social development. The MSMEs are expanding the scope of their businesses into several economic sectors and providing a wide variety of goods and services to satisfy both domestic and global markets. (MSME- Annual Report, n.d.)

1.2 Hardships faced by SMEs to avail of loans.

1.2.1. Absence of Credit

One of the most difficult issues that SMEs must deal with is the lack of timely access to credit. Financial institutions require compliant paperwork, reliable collateral, a rigid payback schedule, and hefty interest rates in exchange for loans. These factors may make it difficult for SME owners to obtain the loans they need for the expansion of their companies and may stifle their drive to grow the business. (Charan Singh, 2016)

1.2.2. Lack of Knowledge of Technology

Rural and semi-urban SMEs face challenges due to limited awareness of modern software and hardware. A significant barrier is the lack of technical expertise. Implementing ERP, AI-driven tools, and inventory management software can boost productivity. However, affordability issues may hinder access to advanced technology, including accounting systems and AI-based solutions, due to the high costs of computers and software. (Charan Singh, 2016)

1.2.3. Inadequate Marketing

The third challenge faced by SMEs is effective marketing. While they may have innovative ideas, success often relies on the guidance of a skilled marketing agency to attract more customers. However, such services can be costly, and shortcuts may not sustain long-term growth. To overcome this, SMEs can consider taking a loan to hire employees. This approach allows them to manage working capital needs, pay salaries, and invest in professional marketing agencies as the business expands and becomes profitable. (Charan Singh, 2016)

1.3 MCDM techniques

Since the early 1970s, Multi-Criteria Decision Making (MCDM) has been an active research area with numerous publications on theory and application (Roy, 2005). MCDM aims to find the most favorable alternative, categorize options, or rank them based on subjective preferences. When dealing with multiple criteria, all decision-making techniques that aid preferences fall under MCDM (Ho, 2008). Essentially, MCDM is a method of breaking down complex issues into manageable parts, evaluating factors, and providing an overall

view to decision-makers after assessing and judging smaller components.
(MCDM*, n.d.)

II. Review of Literature

2.1 Can Credit Scoring Models Effectively Predict Small Enterprise Defaults? Statistical Evidence from Italian Firms. (Vallini C, January 2008)

The literature places a strong emphasis on large and medium-sized businesses. Small businesses typically have financial reports that communicate less effectively (and are consequently more difficult to comprehend), which limits the applicability of statistical methods. The lack of data affects the prediction model's success rate, creating a research gap for small business credit scoring.

2.2 **Modelling Credit Risk for SMEs: Evidence from the U.S. Market, 2007** (Edward I. Altman, 29 April 2008) The authors created a one-year default prediction strategy using a logit regression method using sample data from over 2,000 U.S. companies (with sales less than $65 million) between 1994 and 2002. Compared to a general corporate structure, this method has about 30% more out-of-sample prediction power.

2.3 **Bank Involvement with SMEs: Beyond Relationship Lending.** (Augusto de la Torre, September 2010)

This study elucidates the discrepancy between this viewpoint and banking procedures. According to the report, banks view SMEs as a crucial strategic sector and are in a position to strengthen their relationships with SMEs.

2.4 **A Novel Big-data-driven Credit Reporting Framework for SMEs in China.** (Sun, Li, & et.al, A Novel Big-Data-Driven Credit Reporting Framework for SMEs in China, 20-21 October 2016) In traditional SMEs, this article has identified three opportunities for improvement: a one-dimensional information approach constrained business coverage, and report production delays. There is a need for more systematic approaches to combine hard and soft data when evaluating creditworthiness since this would increase effectiveness, quality, and timeliness.

2.5 A multicriteria credit scoring model for SMEs using hybrid BWM and TOPSIS (Roy, 2021) The best-worst method (BWM) and the Technique for Order of Preference by Similarity to the Ideal Solution were combined to create the model that the researchers utilized (TOPSIS). The BWM establishes the initial weight criterion, and TOPSIS is then used to grade SMEs. An actual case study was looked at to show how successful the suggested model is, and a sensitivity analysis was done to determine how robust the model is to unforeseen financial circumstances. Incorporating other nonfinancial factor indicators and revealing the kind of SMEs chosen for the study would close the research gap

III. Research Gap

Financial institutions employ a credit scoring methodology that determines the probability of default risk, or how likely a borrower is to default on a loan in the future, to assess the creditworthiness of SMEs.

Financial companies employ mathematical models called credit scorecards to quantitatively determine whether a borrower is likely to exhibit bad credit behavior like loan default, bankruptcy, or delinquency to aid in improved decision-making. By comparing the borrower's score with the cut-off score in the scorecard, financial institutions determine whether to grant a loan or not.

The traditional approach, known as financial modeling, relies primarily on various financial ratios and financial structures based on data gathered from the borrower's financial records to statistically identify the important predictors of default.

IV. Research Problem

The following research questions were identified from the problem statements:

1. What are the many industries into which SMEs can be categorized?
2. What financial and non-financial information affects the creditworthiness of SMEs?
3. What weights should be given to the variables when applying the model for credit analysis?

V. Objectives

The paper attempts to find the results with the following objectives

1. Assessing the elements to determine the SME's credit risk score.

2. To determine the weights for each parameter through identified credit scoring model.
3. To arrive at the SME's credit scoring using the weights as determined.

VI. Research Methodology

6.1 Type of research

The paper is an empirical study based on quantitative and qualitative data of capital goods and consumer durables sectors listed SMEs in India.

6.2 Data for the credit analysis process.

Financial data (such as cash flow data) and non-financial data are the two main categories of data that have been categorized for analysis (e.g. company credit analysis reports.

6.3 Classification of financial data for creditworthiness assessment

The conventional technique makes use of financial data, particularly ratios that are computed according to the major categories below:

In the below table Main criteria have been coded as X1, X2….X,4, and Sub criteria are coded as R1, R2, R3……R6.

Table 1: Table showing the main criteria of Ratios

Main Criteria	**Sub criteria**	
Liquidity (X1)	Current ratio = Current Assets/ Current Liabilities	R1
	Liquidity ratios = Liquid Assets / Current Liabilities	R2
	Cash Ratio = (cash + marketable securities)/Current liabilities	R3
Solvency (X2)	Debt / Equity (Shareholder's funds)	R4
	Total Assets/ Long term debt	R5
	Net profit before interest and tax/ Interest on long-term funds	R6
Activity (X3)	Cost of goods sold/Average Inventory	R7
	Net credit sales/Average trade receivables	R8
	Net credit Purchases/ Average trade payables	R9
	Revenue from operations/ working capital	R10
	Gross profit/Turnover	R11
Profitability (X4)	Earning after Tax/ Turnover	R12
	Earning before interest, tax, and dividend (EBITDA)/ Capital Employed	R13
	EPS	R14

Source: (Roy, 2021)

The traditional method of credit scoring frequently makes predictions about potential loan defaults within one to three years using financial ratios obtained from financial statements and other third-party data. Although this method is effective for large businesses, it cannot be used to evaluate SMEs because there is not enough accurate financial information to make a prediction. To address this issue, the ability of SMEs to repay their loans can be evaluated using various information indicators. "Non-financial data" refers to these information indicators. Lenders are given a better understanding of SMEs' creditworthiness using non-financial data. Non-financial data can be used to produce supporting information that may give lenders a competitive edge when making judgments about lending to SMEs, in addition to conventional credit scoring data.

6.4 Classification of non-financial data for Evaluation of Creditworthiness

The records of commercial transactions between a company and its clients are referred to as non-financial data. Business, payment history, and behavioral attributes make up the non-financial data categories.

In addition, non-financial data might provide insights that help determine a company's creditworthiness. Transactional data are showing promise for credit scoring as trend analysis and default prediction is now being done using machine learning approaches.

The Classification of non-financial data is depicted below. In the below table, the Main criteria are continued with codes from Figure 1.1 as NX5,

NX6….NX8 and Sub criteria are continued with codes R14, R15, R16……R31.

Table 2: Table showing Classification of Non-Financial Data

Main Criteria	Sub Criteria	
Business Analysis (NX5)	Production as compared to the industry average	R17
	Sales trend – Increasing/decreasing	R18
	Impact of marketing strategies on turnover	R19
	Bank cashflow activity profiles	R20
	Number of years in business	R21
Management Analysis (NX6)	Type of enterprise	R22
	Education and experience	R23
	Future expansion plans	R24
	Angel investors/external funding	R25
	Financial flexibility	R26
Third-Party Analysis (NX7)	Company's credit analysis reports	R27
	Personal credit reports	R28
	Quality of customers	R29
	Target customer profile	R30
	Quality of transactions	R31
Behavioral traits (NX8)	Psychometric test	R32
	Sentimental Analysis	R33
	Risk Characteristics	R34

Source: (Roy, 2021)

6.5 Source for collection of data

Financial data is sourced from secondary sources, including the Bombay Stock Exchange, research articles, published thesis, and annual reports. Non-financial data is collected from secondary and primary sources via scheduled interviews with financial institution officials. The SME sectors covered include capital goods, consumer durables, construction, consumer services, items with short shelf life, financial services, healthcare, IT, media, entertainment, publications, real estate, services, and textiles. Five listed SMEs from two sectors, capital goods, and consumer durables, are chosen: Affordable Robotics and Automation Ltd, Benara Bearings and Pistons Ltd, Jigar Cables Ltd, Goblin India Ltd, and Inflame Application Ltd.

6.6 Sampling method and analysis

Selected SMEs considered for this study are Listed on BSE SMEs. The financial and non-financial data have been collected for 3 years from 31.3.2019 to 31.3.2022.

6.7 Process of BWM

Dr. Jafar Rezaei proposed the Best Worst Method (BWM), a multi-criteria decision-making (MCDM) technique, in 2015. The technique is used to assess several options about several choice criteria. A thorough pairwise comparison of the choice criteria serves as the foundation for the BWM. In other words, the decision-maker (DM) chooses two criteria after determining the decision: the best and worst. The best criterion is the one that is used most heavily in the decision-making process, whereas the worst criterion is used least heavily. The DM then uses the criteria to express his or her preferences for the best criterion over all other criteria as well as for all criteria over the worst criterion. (Best - worst Scaling, n.d.)

6.8 The process of BWM to calculate the credit scores.

The 4 main criteria in financial data are Liquidity (X1), solvency (X2), Activity (X3), and Profitability (X4), and each main criterion has 3-4 sub-criteria. The data analysis tool used for this analysis is Microsoft Excel. Using BWM Excel solver the sub-criteria weights are calculated. Based on the number of criteria the respective Excel solver has been chosen. An example for 4 criteria sheet C=4 is taken for calculation of the weights for the criteria of Activity (X3).

The sub-criteria are as follows the cost of goods sold/ Average Inventory (R7), Net credit sales/ Average trade receivables (R8), Net credit purchases/Average trade payables (R9), and Revenue from operations/ working capital (R10). Among the sub-criteria as per the expert view (Managers from Bank of SBI, APEX, and Canara Bank), Revenue from operations (R10) is selected as best, and Cost of goods sold / Average Inventory (R7) is selected as the worst.

Extract of Table 1

Activity (X3)	Cost of goods sold/Average Inventory	R7
	Net credit sales/Average trade receivables	R8
	Net credit Purchases/ Average trade payables	R9
	Revenue from operations/ working capital	R10

Source: (Roy, 2021)

Next, the ranking is done from best to worst criteria- in this case, the ranking is based on a scale of 1-9. The best criteria (R10, R10) are ranked as 1 and the rest of the criteria are assigned from the ranking nearest to the best criteria. So (R10, R7) is ranked as 2, which is the next best, (R10, R8) is ranked as 3, and (R 10, R9) is ranked as 4. Similarly, the worst to best criteria is calculated. Here the cost of goods sold/Average Inventory (R7), being the worst criteria (R7, R7) is assigned rank 1 and others based on the range from the worst criteria the rank is given. So (R8, R7) is ranked 5, R9, R7) is ranked as 6 and (R10, R7) is ranked as 7. The same is shown in Figure 1.6, an extract of the Excel document. After assigning the ranks the weights were calculated by using the Excel solver on the data tab. The Excel solver outputs the weight for each criterion along with that, gives the threshold limit and input-based CR, this helps in the acceptance of the pair-wise comparison or not. Figure 2: shows an extract of the BWM Excel solver, the weights for R7- R10 have been calculated as explained above by taking the best criteria as R10 (Revenue from operations/ working capital) and the Worst criteria as R7 (Cost of goods sold/Average Inventory). The pairwise comparison of best to others and others to Worst has been made. The final weights of R7 to R10 have been arrived by the Excel solver.

Figure 2: Extract of BWM Excel Solver Source: Self-generated in an Excel sheet

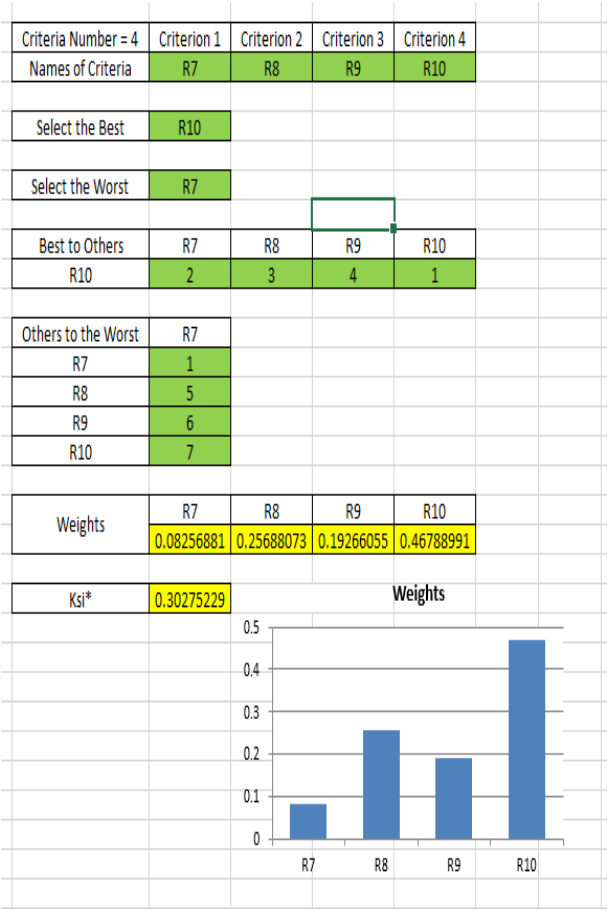

Table 2: Weights of sub-criteria R7 to R10

Cost of goods sold/Average Inventory	R7	0.0825
Net credit sales/Average trade receivables	R8	0.2568
Net credit Purchases/ Average trade payables	R9	0.1926
Revenue from operations/ working capital	R10	0.4678

Source: Self-Generated

It can be observed that the Revenue from operations/ working capital (R10) is assigned a maximum weight of 0.4678, as it is selected as best and the Cost of goods sold/Average Inventory (R7) is assigned with a minimum weight of 0.0825, as it is selected as the worst.

The above procedure has been followed to find out the weights of all the sub-criteria from R 1 to R 15, for financial data, then R 16 – R 34, for non-financial

data. Figure 1.8 gives the detailed calculation of weights for all the sub-criteria.

Similarly, the main, criteria weights of financial data (X1 to X4) and Non-financial data (NX5 to NX 8) have been ascertained. Further after calculating the weights of the main criteria and weights of the sub-criteria, combined weights are calculated by multiplying the weights of the sub-criteria with the weights of the main criteria. The total of all weight should be equal to 1.

6.9 Results and Discussion

After finding out the combined weights, the data from three years of financials are collated. The weighted average of three years of data is calculated by assigning weights 1,2,3, Recent year is assigned the maximum weight. Further, these financial figures are normalized using the normalization formula (X- X min/ X max- X min). The normalized values are then multiplied with the weights for each criterion to arrive at the total score.

Depending on the final credit score the rating is awarded, if the credit score is 61 and above it will be considered adequate for high safety. If the credit score falls below 50 it is considered a high-risk category.

According to the information gathered from banks and other financial institutions, the following slabs for the overall scores are considered for credit score rating.

Rating Awarded		
61 to 70	SIB A	*Adequate*
71 to 80	SIB AA	*High Safety*
Above 80	SIB AAA	*Highest Safety*
46 to 50	SIB B	*High Risk*
51 to 55	SIB BB	*Inadequate safety*
56 to 60	SIB BBB	*Moderate Risk*
40 to 45	SIB C	*Substantial Risk*
Less than 40	SIB D	*Default*

Table: 3 Rating awarded based on the credit score

Source: Table as per SBI bank norms

Source: SBI Bank

6.10 Sector-wise details of credit scores of all the Companies

The credit scores of the selected SMEs were determined based on detailed financial and non-financial data from the last three years (from 31.3.2000 to 31.3.2022). The BWM procedure was followed for each company to calculate Main and Sub criteria weights, which were then multiplied with the normalized figures. The final credit scores are displayed in Figure 4. During the COVID period, all SMEs were impacted, but Benara Bearings and Pistons Ltd showed a decent credit score of 0.67. Although Affordable Robotic and Automation Ltd had a credit score of less than 0.50, it secured additional term loans based on good collateral. The company's business in Robotic Welding Cells, Indexing & Rotary type Welding fixtures, and automatic car parking systems experienced increased demand, leading to a comeback from losses in 2021 to a profit of Rs 236.92 in 2022. Considering the demand and positive financials, granting a loan is recommended. Jigar Cables received a credit score of 0.49 through the BWM process, and their turnover reduced in 2022 compared to the previous year. While they managed to repay their loan balance, there was no significant increase in EBITDA and PAT in recent years. In the Consumer durables sector, Goblin India Ltd, despite being a low performer with losses in the last two years, was granted a loan of Rs 9,42,62,100 from NBFCs as unsecured loans. The promising non-financial score and the good reputation of the directors and key personnel in the industry make Goblin Ltd a likely candidate for the loan. They have secured a niche market locally and globally, with clients in France and Paris. Inflame Appliance Ltd witnessed an increase in turnover from Rs 19,86,8,840 in FY 2021 to Rs 39,61,70,520 in FY 2022. The loss in the current year reduced significantly, from 33 crores in FY 2021 to 16 crores in FY 2022, indicating an improving trend that facilitated obtaining loans amounting to Rs 51 crores from financial institutions.

Figure 4: Final Credit scores

Sector	Capital goods			Consumer durables	
Companies	Affordable Robotic & Automation Ltd	Benara Bearings and Pistons Ltd	Jigar Cables Ltd	Goblin India Ltd	Inflame Appliances Ltd
Combined weights	0.37	0.67	0.49	0.45	0.49

Source: Self-generated in an Excel sheet.

6.11 Summary of Findings

Traditional credit scoring models relied more on financial data for analyzing the creditworthiness of SMEs. Non-financial data were not given emphasis. Financial Institutions can give equal weightage to both financial and non-financial data by using the BWM process as under this method 34 parameters have been identified and weightage for each parameter is calculated logically. Through the BWM process, both financial data and non-financial data have been given importance in arriving at credit scoring and ascertaining the creditworthiness of SMEs. Further from the above findings it has been observed that Benara Bearings and Pistons Ltd have a reasonably good credit score, despite suffering major setbacks during the covid period. Other SMEs may not have fared well, but few have given good collaterals for additional loans, which can be one of the factors for granting the loan. BWM can generally be used by all institutions as it can reduce information asymmetry.

VIII. Scope for Further Research

Financial Institutions typically process credit proposals in 14 to 22 days. Weights can be assigned to various parameters to make the analysis more systematic and speed up the process. The TOPSIS model facilitates score normalization for ordering performance based on similarity to the ideal solution. It allows manual criteria extraction and employs a compensatory aggregation approach to compare alternatives. The geometric distance from the ideal alternative is measured. Weights for criteria can be determined using various methods. methods. https://en.wikipedia.org/wiki/ By assigning weights to different parameters, the analysis becomes more systematic, reducing the time frame. Conventional SME credit reporting models have limitations in terms of a unidimensional approach, limited business coverage, and delays in report generation. To overcome these drawbacks, the proposed credit analysis in the paper involves attaching weights through the BWM model to financial and non-financial parameters to assess SME credit accuracy. The process takes approximately 2 days and can be further expedited by using the TOPSIS model for score normalization. https://en.wikipedia.org/wiki/TOPSIS

IX. Conclusion

The credit scoring model used gives results of the combined weights for each SME in that particular sector. This helps in analyzing the performance of each sector. Further few parameters are affected because of the covid period where most of the companies were running under loss during the FY 2000- 2022. The sectoral analysis gives a wider perspective in terms of the performance of each SME. Collectively the SME industry is reviving after the covid period. A few SMEs taken for this research have obtained loans with good collateral and increased turnover and EBITDA margin. The BWM process may be used in general to find the weights for all SMEs, it can act as a recommendatory mechanism in reducing the information asymmetry. Since each SME is unique and manufactures products that are not similar, the decision can be taken to grant a loan based on specific factors taking into consideration the non-financial data as a whole.

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