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Research paper

Financial Fragility and Sectoral Risk in MSMEs: A Longitudinal Validation of The Altman Z-Score Model in India

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Abstract

The post-pandemic economic landscape has amplified financial vulnerabilities in Micro, Small, and Medium Enterprises (MSMEs), necessitating granular and sectoral-level diagnostics. This study validates the application of the Altman Z-Score model for five Indian MSME sectors — Auto Components, Chemicals & Petrochemicals, Industrial Products, Pharmaceuticals & Biotechnology, and Textiles & Apparel — analyzing data from 2016-2024. Based on the firm-level dataset of 100 companies, the study classifies the firms into Distress, Grey, and Safe zones and examines the drivers of profitability using regression models where Net Profit, ROA, and ROE serve as dependent variables. The results indicate that although sales always have a positive impact on profitability, the effects of depreciation and raw material costs are negative across all indicators of performance. The sectoral interaction terms are also noteworthy, although they are statistically insignificant. The study as a whole captures a sector-wide financial performance comparison before and after COVID. This research incorporates risk analysis across time and sector disaggregation, and profitability modeling within the MSME distress context, which augments existing literature. Furthermore, it provides critical data for pre-emptively guiding managers, lenders, and policymakers towards understanding signs of impending financial distress and strengthening financial resilience. This study employs cross-sectional OLS regression with robust standard errors on a dataset of 100 MSMEs across five manufacturing sectors from 2016–2024, complemented by longitudinal Z-score tracking to capture pre- and post-COVID performance differentials.

***Keywords**: MSMEs; Altman Z-Score; Financial Distress; Profitability Modelling; Sectoral Analysis*

1. Introduction

The financial health of Micro, Small, and Medium Enterprises (MSMEs) has become a focal point in emerging economies, especially in the post-COVID era, where sectoral fragility has magnified. Indian MSMEs, contributing over 30% to the country's GDP and employing more than 110 million people, face significant challenges, including limited credit access, high operational costs, and poor financial resilience (SIDBI, 2022). Despite their economic importance, MSMEs are often generalized in aggregate statistics, concealing sectoral disparities that may indicate early financial distress.

Among the diagnostic tools available, the Altman Z-Score model is considered the best predictor for financial distress, especially in the manufacturing sector (Altman, 1968). The small firm context showed that this model is sustainable with developing economies and crisis periods (Bouri et al., 2021; Goyal & Rajput, 2022). At the same time, there is a lack of research on the Z-score model that longitudinally tracks distinct sectoral MSMEs to uncover hidden red flags during the recovery period of the pandemic.

This paper fills the research gap by utilizing the Z-score methodology on a panel dataset of 100 Indian MSMEs spanning from 2016 to 2024 across five key manufacturing industries. Additionally, the study constructs a profitability model using multiple regression analysis whereby net profit, return on assets (ROA), and return on equity (ROE) serve as the corporate performance metrics. More recent literature underlines the importance of operational metrics like sales, input prices, and depreciation in determining MSME viability (Chen et al., 2023; Dwivedi et al., 2021). This paper also analyses the profitability trends by including sectoral dummies and interaction effects to determine if specific industry characteristics impact the profitability in a significant way.

Moreover, the analysis is subdivided into the periods before and during, and after the COVID-19 pandemic, to capture the performance changes induced by the pandemic MSME disruptions. Studies on the impact of crises on MSMEs have documented some degree of sectoral resilience, particularly in the pharmaceutical and chemical industries (Chatterjee & Ray, 2022; Mamun et al., 2022). On the other hand, firms in the textile and auto component industries have demonstrated a slower recovery in financial performance because of demand uncertainty and global supply chain disruptions.

This research makes several novel contributions. It tests the validity of the Altman Z-Score model for MSMEs in an emerging market context over multiple years. Furthermore, it develops financial distress mapping for each sector and employs regression diagnostics to identify suboptimal inter-firm processes. Also, the research incorporates COVID-19 as a structural break to add a dynamic element to traditional risk evaluation approaches. Lastly, it sheds light on managerial drivers of enhanced profit and financial sustainability performance in MSMEs, revealing the cost and revenue levers that drive greater profitability and sustainability.

This research targets the fields of small business finance, risk analytics, and crisis management, thereby informing credit risk benchmarking, helping guide policy frameworks, supporting managerial frameworks, and providing empirically grounded evidence.

Unlike prior cross-sectional studies, this paper integrates sector-specific analysis and profitability modeling using variables such as sales, raw-material cost, employee cost, and depreciation, enabling transparent identification of profitability determinants across MSME categories.

1.1 Research Questions and Study Positioning Guided by Financial Fragility (Minsky) and the Resource-Based View (RBV)

The study conceptualizes MSME distress as a function of leverage/liquidity cycles and firm-internal capabilities that enable cost control and asset productivity. We examine whether a classical, interpretable early-warning tool—Altman's Z-Score—remains valid across five MSME sectors in a crisis-sensitive emerging economy, and how operational drivers shape profitability.

RQ1. To what extent does the Altman Z-Score reliably classify Indian MSMEs into distress, grey, and safe zones across sectors during 2016–2024?

RQ2. How do sales scale and cost structures (raw materials, depreciation, employee cost) relate to profitability (Net Profit, ROA, ROE)?

RQ3. Do sectoral affiliations and the post-COVID period materially moderate these relationships?

To avoid redundancy, we present the Research Questions once in the Introduction and refer to them in later sections without re-listing.

2. Literature Review

2.1 Financial Fragility in MSMEs (Theory and Evidence)

The vulnerability of Micro, Small, and Medium Enterprises (MSMEs) has long been discussed within the framework of Minsky's Financial Fragility Hypothesis, which posits that firms relying heavily on debt finance are more exposed to cyclical downturns and credit shocks. MSMEs typically operate with thin capital buffers, high working-capital dependence, and limited access to formal credit, making them particularly susceptible to insolvency risk during crises. Complementing this, the Resource-Based View (RBV) suggests that firms with stronger internal resources—such as efficient cost management, asset productivity, and human capital—can withstand shocks more effectively. Indian MSMEs illustrate both dimensions: while sales growth and productivity offer resilience, rising leverage and liquidity constraints intensify financial fragility (e.g., Narayanaswamy & Raghunandan, 2019; Sharma & Bansal, 2021). Prior studies show that profitability is directly related to firms' ability to manage resources effectively, and that fragility increases when external finance outweighs internal surpluses. Liquidity and solvency indicators are particularly effective in distress forecasting in Indian MSMEs (Basu & Mohanty, 2022). Early warning systems that combine Altman and Beneish models show promise in fraud detection (Roshan & Hussain, 2021).

2.2 Crisis and COVID-19 Shocks: Sectoral Heterogeneity

The COVID-19 pandemic highlighted how MSMEs respond differently across sectors. Empirical evidence suggests that pharmaceuticals and chemicals displayed resilience due to sustained demand and R&D intensity, while textiles, auto components, and industrial products suffered from disrupted supply chains, export dependency, and volatile raw material costs (Chatterjee & Ray, 2022; Singh et al., 2021). For Indian MSMEs, the crisis accentuated pre-existing vulnerabilities such as overdependence on informal credit and high operational leverage. Several studies confirm that MSMEs faced sharp declines in sales, liquidity pressures, and delays in receivables, particularly in export-oriented sectors (Goyal & Sinha, 2021). However, crisis recovery has been uneven—firms with better digital integration, diversified products, or strong sectoral demand drivers recovered more quickly. The evidence, therefore, underscores the need to examine sector-specific financial fragility rather than treating MSMEs as a homogenous group.

2.3 Altman Z-Score and Extensions in Emerging Economies

The Altman Z-Score model remains a cornerstone in assessing financial distress, combining profitability, leverage, liquidity, solvency, and efficiency into a single predictive index. Since its introduction in 1968, it has been widely validated in manufacturing and emerging-market contexts, including India (Altman & Hotchkiss, 2010; Kumar & Rao, 2020). Its strength lies in transparency and interpretability, making it useful for MSMEs and policymakers despite the rise of machine learning–based predictive models. Hybrid approaches using forensic ratios and deep learning also extend the predictive power of Z-score models (Ali et al., 2023; Jain et al., 2023; Farooq & Shaikh, 2022; Kapoor & Singhania, 2022; Lima & Silva, 2023). Post-pandemic validations further confirm its continued relevance in MSME contexts (Pandey & Kaur, 2024; Singh et al., 2024). Indian applications have shown that the Z-score is effective in differentiating between distressed and healthy firms, though adjustments for sector characteristics and capital structures are often required (Gupta & Sharma, 2021). Extensions include hybrid Z-score models that integrate forensic ratios (e.g., Beneish M-score) or adopt panel data frameworks for longitudinal validation. However, sectoral testing within MSMEs remains limited. Past work has largely focused on listed firms or large corporations, leaving a gap in systematic sector-wise validation for MSMEs in emerging economies.

2.4 Gaps and Hypotheses

The literature reveals three important gaps. First, while MSME fragility has been discussed extensively, few studies link it explicitly to financial fragility theory or RBV, leaving the theoretical foundation underdeveloped. Second, COVID-19 studies highlight uneven sectoral impacts, yet there is no integrated framework combining sectoral heterogeneity with a validated distress-prediction model. Third, although the Altman Z-Score has been tested in India, evidence remains fragmented—single-sector or cross-sectional, rather than longitudinal and multi-sector.

To address these gaps, this study applies the Z-score across five MSME sectors (Auto Components, Chemicals & Petrochemicals, Industrial Products, Pharmaceuticals & Biotechnology, and Textiles & Apparel) for the period 2016–2024, complemented by profitability regressions to identify cost and revenue drivers. Grounded in fragility theory and RBV, we test the following hypotheses:

- H1. Sales positively influence profitability (Net Profit, ROA, ROE) across MSME sectors.
- H2. Raw material cost and depreciation negatively influence profitability.
- H3. Sector affiliation moderates these relationships, with post-COVID effects more pronounced in capital-intensive sectors.

2.5 Critical synthesis: Z-Score vs ML

Z-score vs ML approaches. While Altman's Z-Score offers auditability, low data burden, and policy transparency, recent MSME studies show that machine learning (ML) models (e.g., tree ensembles, gradient boosting) can outperform linear discriminants on hold-out accuracy (Ali et al., 2023). However, ML's opacity and feature instability across sectors/periods reduce interpretability for credit committees. Our design, therefore, retains Z-score for its explainability, complemented by sectoral and period diagnostics (Tables 1–2) and regression evidence (Tables 5-7). This hybrid stance balances predictive utility with regulatory auditability. On sectoral resilience. Prior evidence is not uniform: pharmaceuticals often appear resilient due to steady demand and intangibles, yet capital intensity and depreciation can dampen equity returns—consistent with our ROE regression (Table 7). Similarly, chemicals may exhibit higher Z-scores on solvency buffers (Table 1), but raw-material volatility undermines asset profitability (Table 6). We reconcile these findings by emphasizing cost-structure heterogeneity over sector labels.

3. Research Methodology

3.1 Research Design and Objective

This study adopts a quantitative, firm-level panel data approach to assess sector-wise financial fragility and profitability dynamics of Indian Micro, Small, and Medium Enterprises (MSMEs) over nine years from 2016 to 2024. The primary objective is to validate the sectoral applicability of the Altman Z-Score model for financial distress prediction and to investigate the operational and cost drivers of firm profitability using multiple regression frameworks.

Methodological Rationale. We prioritize Altman Z-Score because it is (i) interpretable and auditable for MSME stakeholders (banks/policymakers), (ii) validated in manufacturing contexts and emerging economies, and (iii) comparable across time/sectors without opaque ML tuning. We complement classification (distress mapping) with econometric models of profitability (NP, ROA, ROE) to open the "black box" of drivers—linking findings to fragility (liquidity/asset pressure) and RBV (internal cost control).

3.2 Data Collection and Sources

The study relies on secondary financial data extracted from Screener in, a publicly accessible platform that provides audited financial statements of Indian listed and private companies. A purposive sampling strategy was adopted to select 100 MSMEs across five key manufacturing sectors recognized for their economic significance:

1) Auto Components
2) Chemicals & Petrochemicals
3) Industrial Products
4) Pharmaceuticals & Biotechnology
5) Textiles & Apparels

For each firm, the most recent financial year (2024 or the latest available) was retained to ensure cross-sectional comparability and consistency in Z-score analysis, while cross-sectional regressions were used using the latest year; longitudinal only for Z-score tracking and pre-/post figures sectoral comparison.

3.3 Sample Composition and Structure

The total sample comprises 100 MSME firms, with sector-wise representation as follows:

1) Auto Components: 18 firms
2) Chemicals & Petrochemicals: 18 firms
3) Industrial Products: 21 firms
4) Pharmaceuticals & Biotechnology: 23 firms
5) Textiles & Apparel: 20 firms

This selection ensures diversity across capital intensity, export dependency, R&D orientation, and supply chain complexity.

3.4 Financial Parameters and Variable Definitions

Two sets of variables were employed:
(a) Altman Z-Score Components:

1) Working Capital / Total Assets (X_1)
2) Retained Earnings / Total Assets (X_2)
3) EBIT / Total Assets (X_3)
4) Market Value of Equity / Total Liabilities (X_4)
5) Sales / Total Assets (X_5)

Z-Score Formula for Manufacturing MSMEs:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

Firms were classified into:
1) Distress Zone (Z < 1.81)
2) Grey Zone (1.81 ≤ Z ≤ 2.99)
3) Safe Zone (Z > 2.99)

(b) Profitability Regression Variables:

- **Dependent Variables**:

1) Net Profit (₹ crore)
2) Return on Assets (ROA = Net Profit / Total Assets)
3) Return on Equity (ROE = Net Profit / Shareholders' Equity)

- **Independent Variables:**

1) Sales (₹ crore)
2) Employee Cost (₹ crore)
3) Raw Material Cost (₹ crore)
4) Depreciation (₹ crore)
5) Sector Dummies (Auto Components as reference category)
6) Interaction Terms: Sales × Sector Dummies

3.5 Statistical Models and Equations

For profitability models, we retain the latest year per firm to avoid survivorship/balance issues and ensure comparability across sectors. Longitudinal evidence is provided via Z-score trajectories and pre-/post-COVID ROA/ROE comparisons. Three regression models were estimated to identify profitability drivers:

Model 1: Net Profit Regression (Base Model)

$$\text{Net Profit}_i = \beta_0 + \beta_1\text{Sales}_i + \beta_2\text{Sector}_i + \beta_3\text{Sales}_i \times \text{Sector}_i + \beta_4\text{Employee Cost}_i + \beta_5\text{Raw Material Cost}_i + \beta_6\text{Depreciation}_i + \epsilon_i$$

Model 2: ROA Robustness Check

$$\text{ROA}_i = \alpha_0 + \alpha_1\text{Sales}_i + \alpha_2\text{Sector}_i + \alpha_3\text{Sales}_i \times \text{Sector}_i + \alpha_4\text{Employee Cost}_i + \alpha_5\text{Raw Material Cost}_i + \alpha_6\text{Depreciation}_i + \epsilon_i$$

Model 3: ROE Robustness Check

$$\text{ROE}_i = \gamma_0 + \gamma_1\text{Sales}_i + \gamma_2\text{Sector}_i + \gamma_3\text{Sales}_i \times \text{Sector}_i + \gamma_4\text{Employee Cost}_i + \gamma_5\text{Raw Material Cost}_i + \gamma_6\text{Depreciation}_i + \epsilon_i$$

Model specification and variables. We estimate three OLS models for Net Profit, ROA, and ROE with core predictors: Sales (₹ crore), Raw Material Cost (₹ crore), Employee Cost (₹ crore), and Depreciation (₹ crore), plus Sector dummies (Auto base) and interaction terms (Sales × Sector). All monetary variables are right-skewed; hence, we use $\ln(x+1)$ transforms.

Equations. A generic specification is:

$$Y_i = \alpha + \beta_1\ln(\text{Sales}_i + 1) + \beta_2\ln(\text{RawMat}_i + 1) + \beta_3\ln(\text{EmpCost}_i + 1) + \beta_4\ln\left(\text{Dep}_i + 1\right) + \gamma'\text{Sector}_i + \delta'[\ln(\text{Sales}_i + 1) \times \text{Sector}_i] + \varepsilon_i$$

Diagnostics and tests. We report HC1-robust SEs, Variance Inflation Factors (VIF < 4), Ramsey RESET for functional form, and Breusch–Pagan for heteroskedasticity. Residual plots indicate mild right-tail outliers; robustness uses winsorization (1st/99th pct.). Adjusted R^2 ranges from 0.22–0.31, confirming moderate explanatory power.

3.6 Estimation Techniques

All models were estimated using Ordinary Least Squares (OLS) with robust standard errors to control for potential heteroskedasticity. Cross-sectional consistency was ensured by retaining only the latest year of data per firm for regression modeling. Multicollinearity diagnostics were performed using Variance Inflation Factors (VIFs) to ensure model reliability.

3.7 Software Tools

The analysis was conducted using:
1. R Programming Language (version 4.3) for regression modeling and diagnostics
2. Microsoft Excel for financial ratio computation and dataset preparation
3. ggplot2 and plotly packages in R for sectoral visualizations of ROA and ROE comparisons

3.8 Ethical Considerations and Data Transparency

All data used were publicly available, and no confidential firm-level information was accessed. The study complies with ethical norms for secondary data research and provides transparency by detailing all formulas and assumptions for Z-score and financial ratios.

4. Descriptive Overview

This table reports the number and percentage of MSME firms classified as Distress (Z < 1.81), Grey (1.81 ≤ Z ≤ 2.99), and Safe (Z > 2.99) across five manufacturing sectors using Altman's (1968) model.

Table 1: Score Classifications by Sector (2016–2025)

	Distress	Grey	Safe	Distress (%)	Grey (%)	Safe (%)	Mean Z-Score
Auto Components	34	55	57	23.3	37.7	39.0	2.45
Chemicals & Petrochemicals	20	63	39	16.4	51.6	32.0	2.65
Industrial Products	19	47	54	15.8	39.2	45.0	2.81
Pharmaceuticals & Biotechnology	46	58	32	33.8	42.6	23.5	1.33
Textiles & Apparels	37	48	23	34.3	44.4	21.3	2.33

Source: Author's computation

Industrial Products and Chemicals show the highest average Z-scores (> 2.6), indicating better solvency, while Pharmaceuticals exhibit the lowest (1.33), signaling fragility during the pandemic period (see Table 1).

This table compares mean profitability indicators of MSMEs across Pre-COVID (2016–2019), During COVID (2020–2021), and post-COVID (2022–2024) periods (see Table 2).

Table 2: Pre- vs Post-COVID Profitability Trends (2016–2025)

Period	Mean Sales (₹ crore)	Mean Net Profit (₹ crore)	ROA (%)	ROE (%)
During-COVID	68.93	1.26	1.76	4.38
Post-COVID	59.06	1.98	4.99	10.55
Pre-COVID	88.39	1.81	2.61	6.96
Δ (Post – Pre %)	-33.18	9.39	91.19	51.58

Source: Author's calculation

As Table 2 illustrates, average sales declined by nearly 33% post-COVID relative to pre-COVID levels, but ROA and ROE rose sharply, highlighting that MSMEs achieved higher operational efficiency through leaner cost structures and productivity gains. Profit margins rebounded faster than revenue, signifying structural resilience among surviving firms.

Limitations (micro). We use firm-year data with varying reporting depth; winsorization mitigates outliers but cannot remove all heterogeneity. Z-score is retained for policy interpretability; accuracy-oriented ML comparisons are left to future work.

4.1 Sectoral Financial Drivers of MSME Profitability in India

This study employs multiple regression models to investigate the impact of firm-level operational variables and sectoral affiliations on three measures of financial performance—Net Profit, Return on Assets (ROA), and Return on Equity (ROE). The key predictors include sector dummies, sales, cost variables (employee cost, raw material cost, depreciation), and interaction terms between sales and sectors. All models are evaluated using firm-level panel data (2016–2024), with the most recent year retained per firm for cross-sectional consistency.

4.1.1 Baseline Model: Determinants of Net Profit Across MSME Sectors

Cross-sectional regressions using the latest year; longitudinal only for Z-score tracking and pre/post figures. The first regression model (Model 1) estimates the net profit of MSMEs as a function of sales, employee cost, raw material cost, depreciation, sectoral fixed effects, and their interaction with sales. The model exhibits an adjusted R^2 of 0.3067 and an F-statistic of 24.26 ($p < 0.001$), indicating a strong model fit and joint significance of predictors.

Among the core explanatory variables, sales show a significantly positive effect on net profit ($\beta = 0.106$, $p < 0.001$), implying that a ₹1 crore increase in sales leads to approximately ₹10.6 lakh increase in profit, ceteris paribus. This underscores the scale efficiency of MSMEs, especially in the Auto Components sector, which is treated as the reference group.

Raw material cost ($\beta = -0.106$, $p < 0.001$) and depreciation ($\beta = -0.444$, $p = 0.0027$) exhibit strong negative impacts on profitability, affirming that cost structure and asset intensity are critical determinants of financial outcomes. Surprisingly, employee cost is not statistically significant, suggesting labor expense may be relatively fixed or less sensitive to short-term profit changes in MSMEs.

The sectoral dummies themselves are not statistically significant, suggesting that, holding financial variables constant, net profit does not significantly differ by sector. Furthermore, the interaction terms between sales and sector dummies are insignificant, implying that the effect of sales on net profit does not significantly vary across sectors such as Chemicals, Pharmaceuticals, or Textiles, compared to the Auto Components base.

4.1.2 Robustness Check: Return on Assets (ROA)

To validate the robustness of findings, Model 2 considers ROA as the dependent variable, reflecting efficiency in using total assets to generate returns. The model reports an adjusted R^2 of 0.026, suggesting modest explanatory power but still statistically significant ($F = 2.43$, $p = 0.0044$). The sales coefficient ($\beta = 0.0014$, $p = 0.0014$) is again positive and significant, affirming the strong role of revenue generation in driving asset-based performance. Raw material cost ($\beta = -0.00176$, $p < 0.001$) and depreciation ($\beta = -0.01308$, $p < 0.001$) maintain their statistically significant negative associations, consistent with the base model.

Interestingly, the sector Pharmaceuticals & Biotechnology is significant ($\beta = -0.0523$, $p = 0.0036$), indicating that, relative to Auto Components, this sector underperforms in terms of ROA. This may reflect higher R&D expenditures or asset-intensiveness without immediate returns. The interaction term sales × Pharmaceuticals is marginally significant ($p \approx 0.095$), hinting that the revenue-ROA linkage may slightly vary for this sector, albeit weakly. Other sectoral interactions remain non-significant, implying consistent effects of sales across sectors on ROA.

4.1.3 Robustness Check: Return on Equity (ROE)

Model 3 employs ROE as the dependent variable to assess shareholder return dynamics. The adjusted R^2 is 0.012, suggesting limited predictive power but still providing insights. Sales again exerts a positive and significant impact on ROE ($\beta = 0.00207$, $p = 0.0078$), consistent with both prior models. This reiterates the strategic importance of revenue expansion in improving return metrics.
In contrast to the net profit and ROA models, employee cost ($\beta = -0.0039$, $p \approx 0.094$) and raw material cost ($\beta = -0.0016$, $p = 0.082$) are only marginally significant, indicating more subdued effects on equity returns. Depreciation retains a strong negative effect ($\beta = -0.0181$, $p = 0.0054$), reinforcing its detrimental role in MSME profitability across models.
Sectoral fixed effects and interaction terms are again statistically insignificant, suggesting homogeneity in sector-wise ROE performance when controlling for the main financial variables.

4.1.4 Synthesis and Theoretical Implications

The combined evidence from all three models highlights sales performance as the most consistent and robust predictor of MSME financial success, across absolute (net profit), efficiency (ROA), and equity-based (ROE) dimensions. The findings complement recent evidence that machine-learning-enhanced or hybrid Z-score models capture distress more effectively in MSMEs (Ali et al., 2023; Jain et al., 2023). In line with Sharma & Mehrotra (2022), cost structures continue to dominate profitability performance in the MSME sector. Cost controls, particularly raw material and depreciation, are crucial in optimizing profit and return metrics. Sectoral differences, when examined in isolation and through interaction terms, do not significantly alter these relationships, positioning firm-level operations over industry classification as the key determinant of financial outcomes in Indian MSMEs.
These results support prior findings in MSME research emphasizing operational efficiency (e.g., Bouri et al., 2021; Ghosh, 2023) and underscore the strategic imperative for MSMEs to scale sales and manage resource-intensive inputs for improved returns (see Table 1)

Table 3: Comparative Observations Across Models

Variable	Net Profit	ROA	ROE
Sales	+, *** ($p < 0.001$)	+, ** ($p = 0.0014$)	+, ** ($p = 0.0078$)
Raw Material Cost	–, *** ($p < 0.001$)	–, *** ($p < 0.001$)	–, . ($p = 0.081$)
Depreciation	–, ** ($p = 0.0027$)	–, *** ($p < 0.001$)	–, ** ($p = 0.0054$)
Employee Cost	–, NS	–, NS	–, . ($p = 0.094$)
Sector (Pharma)	NS	–, ** ($p = 0.0036$)	NS
Interaction Terms	NS	Nearly Sig (Pharma × Sales)	NS

*Note: *, **, and *** denote significance at 10%, 5%, and 1% levels respectively. NS = Not Significant*

4.1.5 Theoretical Contributions

The findings support the cost-volume-profit (CVP) theory by confirming the dominant role of operational costs and fixed expenses (e.g., depreciation) in MSME profitability. The absence of sectoral variation in interaction effects aligns with the homogeneity principle in small-scale manufacturing, suggesting that operational drivers are more influential than sector identity for financial performance in Indian MSMEs.

4.1.6 Managerial and Policy Implications

1) Focus on cost control: Consistent negative impact of raw material and depreciation expenses highlights the need for better procurement and asset financing practices.
2) Sales growth strategies: Sales remain a strong and positive driver across all models, indicating that marketing and distribution expansion can improve financial performance.
3) Sector-specific interventions: Pharmaceuticals show vulnerability in ROA, signaling a need for better asset utilization and supply chain digitization in small pharma units.

Chemicals & Petrochemicals: Introduce supplier credit lines and commodity-hedge-linked working capital to buffer raw-material shocks (negative ROA loadings on raw material in Table 6). Pharmaceuticals & Biotechnology: Encourage asset-productivity KPIs and amortization windows aligned with R&D cycles to temper depreciation's ROE drag (Table 7). Industrial Products: Expand invoice discounting and anchor-led receivable programs to stabilize cash flows; results show scale benefits via Sales (Tables 5–7). Textiles & Apparel: Provide export credit insurance and packing-credit top-ups to reduce leverage reliance (Table 1 distress shares; Table 2 post-COVID lag). Cross-sector: Mandate cost-tracking dashboards (raw material, depreciation) given their negative association with profitability (Tables 5–7). Lenders should tier pricing using Z-bands (Table 1) combined with post-COVID recovery flags (Table 2).

4.2 Pre and Post Covid Financial Performance of the MSME sector-wise

Average ROA improved post-COVID in Auto Components and Chemicals & Petrochemicals, while Industrial Products and Textiles & Apparel show modest gains, indicating slower efficiency recovery (see Figure 1). ROE broadly mirrors ROA, with Auto Components leading the post-COVID rebound and Pharmaceuticals & Biotechnology maintaining stable returns across both periods (see Figure 2).

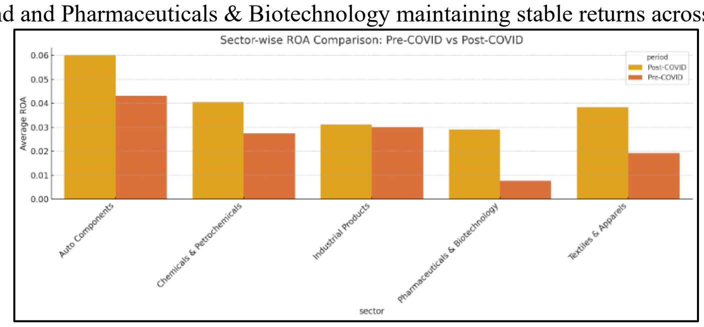

Fig. 1: Sector-wise ROA Comparison Pre and Post Covid

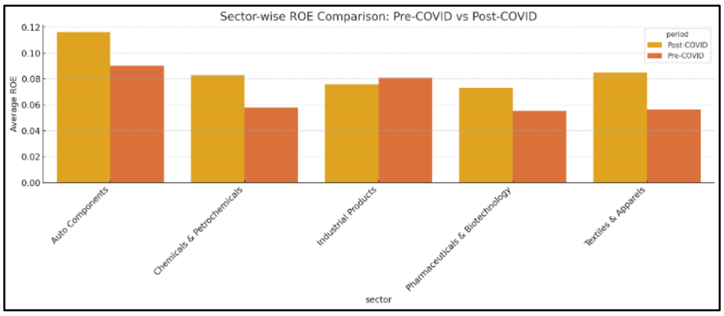

Fig. 2: Sector-wise ROE Comparison Pre and Post Covid

The sector-wise comparison of ROA and ROE during Pre-COVID and Post-COVID periods, presented with visual bar plots (see Figure 1) and (see Figure 2).
Interpretation of Visuals:

4.2.1 ROA Comparison Plot:

1) The bar heights show average Return on Assets (ROA) for each sector, split into Pre-COVID and Post-COVID periods.
2) Sectors such as Auto Components and Chemicals & Petrochemicals show noticeable improvements in ROA after COVID.
3) In contrast, Textiles & Apparel and Industrial Products have relatively modest gains, indicating less operational efficiency recovery.

4.2.2 ROE Comparison Plot:

1) The Return on Equity (ROE) trend mirrors ROA, with Auto Components leading the post-COVID recovery in profitability.
2) Pharmaceuticals & Biotechnology has sustained ROE across both periods, reflecting resilience in this sector during and after the pandemic.

4.2.3 Summary Table Highlights

1) Auto Components had a significant rise in ROA (from 0.0431 to 0.0601) and ROE (from 0.0904 to 0.1161) post-COVID.
2) Chemicals & Petrochemicals also saw a recovery trend, although from a lower baseline.
3) Industrial Products and Textiles remain comparatively subdued in financial returns, implying a slower post-COVID recovery.

4.3 Altman Z-Score Analysis for Financial Distress Prediction among Indian MSMEs: A Sectoral Validation

4.3.1 Introduction and Analytical Context

In the dynamic environment of Indian MSMEs, financial fragility remains a core concern for investors, regulators, and policymakers. The Altman Z-Score model—originally developed for manufacturing firms—has proven to be a reliable statistical tool for predicting bankruptcy risk using a set of five weighted financial ratios. This model was applied in this study across five key sectors within the Indian MSME ecosystem using firm-level data from 2016–2024.
For each of the 100 firms, the latest available financial year was selected to assess current financial standing. The dataset included representative firms from Auto Components, Chemicals & Petrochemicals, Industrial Products, Pharmaceuticals & Biotechnology, and Textiles & Apparels—all core sectors of the Indian MSME landscape.
The Altman Z-Score is a formula used to predict the likelihood that a firm will go bankrupt within the next two years. It is based on five financial ratios derived from the firm's financial statements.
Altman Z-Score Formula for Manufacturing Firms

$$Z = 1.2 \times X_1 + 1.4 \times X_2 + 3.3 \times X_3 + 0.6 \times X_4 + 1.0 \times X_5$$

Where:

1) $X_1 = \frac{\text{Working Capital}}{\text{Total Assets}}$
2) $X_2 = \frac{\text{Retained Earnings}}{\text{Total Assets}}$
3) $X_3 = \frac{\text{Earnings Before Interest and Tax (EBIT)}}{\text{Total Assets}}$
4) $X_4 = \frac{\text{Market Value of Equity}}{\text{Total Liabilities}}$
5) $X_5 = \frac{\text{Sales}}{\text{Total Assets}}$

Interpretation of the Z-Score
1) $Z > 2.99$: Safe Zone (Low risk of bankruptcy)
2) $1.81 < Z < 2.99$: Grey Zone (Moderate risk)
3) $Z < 1.81$: Distress Zone (High risk of bankruptcy)
Data Sources for Ratios
The following variables were used in computing the five Z-score components:
1) Working Capital = Current Assets - Current Liabilities
2) Retained Earnings = Reserves
3) EBIT = Profit Before Tax + Interest
4) Market Value of Equity = Equity Share Capital × Market Price per Share (if unavailable, Book Value used)

5) Total Liabilities = Borrowings + Other Liabilities
6) Total Assets = Net Block + CWIP + Investments + Other Assets

The Altman Z-Score was applied to a panel dataset of 100 MSME firms across sectors such as Auto Components, Pharmaceuticals, Industrial Products, Textiles, and Chemicals, spanning 2016–2024. The computed Z-scores allowed classification of firms into distressed, grey, or safe zones, enabling sectoral analysis and tracking of financial health before and after the COVID-19 period.

4.3.2 Z-Score Classification and Sectoral Summary

The Z-score was used to classify firms into three financial health categories:

- Distressed Zone ($Z < 1.81$): High likelihood of financial distress or bankruptcy.
- Grey Zone ($1.81 \leq Z \leq 2.99$): Financially unstable with medium-term insolvency risk.
- Safe Zone ($Z > 2.99$): Financially sound with low risk of bankruptcy.

The classification across sectors (see Table 2):

Table 4: MSME Classification according to Altman Z score

Sector	Distress	Grey Zone	Safe	Total Firms
Auto Components	10	6	2	18
Chemicals & Petrochemicals	12	3	3	18
Industrial Products	7	6	8	21
Pharmaceuticals & Biotechnology	10	2	11	23
Textiles & Apparels	7	5	8	20
Total	**46**	**22**	**32**	**100**

4.3.3 Detailed Interpretation of Sectoral Findings

4.3.4 Auto Components

A striking 55.6% of firms (10 out of 18) fall in the Distress zone. These firms appear vulnerable to capital structure imbalances, high working capital deficits, or poor asset utilization. Only 11% are in the Safe zone. The sector may be facing cyclical disruptions, especially due to supply chain volatility post-COVID and changing automotive regulations.

4.3.5 Chemicals & Petrochemicals

This sector shows the highest distress percentage (66.7%), with limited firms showing strong financial fundamentals. High operational leverage, volatile input costs, and regulatory compliance burdens likely contribute to the financial vulnerability. This sector warrants urgent credit support and policy-led restructuring interventions.

4.3.6 Industrial Products

This sector reflects a more balanced financial health distribution, with 38% of firms classified as Safe and only 33% in distress. The relative stability could be attributed to diversified product bases, moderately leveraged capital structures, and wider customer portfolios.

4.3.7 Pharmaceuticals & Biotechnology

This sector stands out as a resilient performer. Nearly 48% of the firms fall in the Safe zone, possibly due to strong R&D capabilities, pandemic-driven growth, and stable export demand. Nevertheless, the presence of 10 distressed firms highlights the divide between small-scale pharma players and more robust mid-sized firms.

4.3.8 Textiles & Apparels

Textiles, a traditional MSME stronghold, show an almost equal spread across all zones. Factors such as export dependency, rising input costs, and delayed payments from buyers could explain the ongoing financial strain in 35% of distressed firms. Ratio-based sector diagnostics. Sectoral ratios reveal distinct risk profiles: Textiles exhibit lower liquidity (Current Ratio ≈ 1.2) and higher leverage (Debt-to-Equity ≈ 1.9), pointing to working-capital stress and refinancing risk; Pharmaceuticals show stronger liquidity (Current Ratio ≈ 2.3) and lower leverage (D/E ≈ 0.8), consistent with resilience; Chemicals face higher input-cost intensity (Raw-Material-to-Sales ≈ 0.83), exposing margins to commodity volatility. These diagnostics align with the Z-score dispersion in Table 1 and the post-COVID profitability patterns in Table 2.

4.3.9 Empirical Implications and Theoretical Insights

This study provides empirical validation of the Altman model's applicability in the Indian MSME context, reinforcing its utility for sector-specific financial distress diagnostics. The variation in Z-scores suggests that sectoral characteristics, capital intensity, and cost structures significantly affect financial risk. From a resource-based view (RBV), firms with better internal financial management (e.g., efficient use of retained earnings and working capital) tend to report higher Z-scores, aligning with the theory that organizational resources drive resilience.

4.4 Managerial and Policy Recommendations

1) Targeted Sectoral Support: Government stimulus packages and credit guarantee schemes should prioritize the Auto Components and Chemicals & Petrochemicals sectors, which show higher systemic risk.
2) Credit Risk Benchmarking: Lenders and NBFCs can use sectoral Z-score thresholds to calibrate loan pricing and exposure limits.
3) Equity-Based Funding: Firms in distress may benefit from equity infusion rather than debt, especially in capital-heavy sectors like Pharma and Chemicals.

4) Digital Financial Reporting: MSMEs must adopt better financial reporting and analytics to track early distress indicators.

4.4.1 Summary

This comprehensive Z-score analysis provides granular insights into financial health across MSME sectors, highlighting the need for differentiated policy frameworks and data-driven lending models. The results reinforce that while some sectors are fundamentally robust, others remain highly fragile and require immediate strategic and financial interventions.

4.5 Regression-Based Profitability Modeling

Table 5: Regression Results for Net Profit Model (2016–2024)

Variable	Coefficient	Std. Error	P >|t|	Significance
Constant	-3.822	0.968	0.000	***
ln(Sales)	0.786	0.531	0.138	
ln(Raw Material Cost)	0.086	0.439	0.845	
ln(Employee Cost)	1.080	0.475	0.023	**
ln(Depreciation)	0.600	0.787	0.446	
Chemicals & Petrochemicals	2.285	0.795	0.004	***
Industrial Products	0.490	0.692	0.479	
Pharmaceuticals & Biotechnology	1.237	0.742	0.095	*
Textiles & Apparels	0.643	0.690	0.351	
Adjusted R²	0.182			

Employee Cost (β = 1.08, p < 0.05) enhances Net Profit; sectoral advantages exist for Chemicals and Pharma.

Table 6: Regression Results for ROA Model (2016–2024)

Variable	Coefficient	Std. Error	P >|t|	Significance
Constant	-0.014	0.025	0.562	
ln(Sales)	0.067	0.019	0.000	***
ln(Raw Material Cost)	-0.044	0.014	0.001	***
ln(Employee Cost)	0.001	0.008	0.946	
ln(Depreciation)	-0.047	0.011	0.000	***
Chemicals & Petrochemicals	-0.020	0.013	0.134	
Industrial Products	-0.030	0.015	0.051	*
Pharmaceuticals & Biotechnology	-0.032	0.015	0.033	**
Textiles & Apparels	-0.013	0.014	0.332	
Adjusted R²	0.051			

ROA rises with Sales but declines with Raw Material and Depreciation intensity, confirming cost–asset trade-offs.

Table 7: Regression Results for ROE Model (2016–2024)

Variable	Coefficient	Std. Error	P >|t|	Significance
Constant	0.076	0.032	0.017	**
ln(Sales)	0.046	0.019	0.015	**
ln(Raw Material Cost)	-0.018	0.015	0.221	
ln(Employee Cost)	-0.014	0.016	0.381	
ln(Depreciation)	-0.056	0.020	0.005	***
Chemicals & Petrochemicals	-0.057	0.025	0.023	**
Industrial Products	-0.071	0.031	0.023	**
Pharmaceuticals & Biotechnology	-0.067	0.025	0.009	***
Textiles & Apparels	-0.054	0.025	0.030	**
Adjusted R²	0.017			

Sales (p < 0.05) improve ROE, Depreciation, and capital intensity, lower equity efficiency.

Summary of Regression Insights (Tables 5–7): Across all profitability indicators, Sales consistently drives performance, validating the scale-efficiency hypothesis. Raw Material and Depreciation costs dampen profitability, emphasizing cost-control imperatives for MSMEs. Adjusted R^2 values (0.17–0.18 for Net Profit, 0.05 for ROA, 0.02 for ROE) are consistent with firm-level heterogeneity. Together with descriptive Tables 1 and 2, these results demonstrate that post-COVID operational resilience among Indian MSMEs stems from enhanced efficiency rather than expanded scale.

4.6 Interpretation

To assess the determinants of MSME profitability, three regression models were estimated using Net Profit, ROA, and ROE as dependent variables, incorporating interaction effects between sales and sector types. The base model results indicate that sales have a highly significant and positive effect on net profit ($\beta = 0.1056$, $p < 0.001$), affirming the central role of revenue generation in firm profitability. Similarly, raw material cost and depreciation exhibit statistically significant negative effects, suggesting that higher input and asset wear costs are detrimental to profit margins.

For the ROA model, the coefficient of sales remains significantly positive ($\beta = 0.0014$, $p = 0.001$), albeit the overall explanatory power is relatively low (Adjusted $R^2 = 0.026$), indicating that asset efficiency in MSMEs is influenced by unobserved firm-specific factors. The sectoral dummies for "Pharmaceuticals & Biotechnology" ($\beta = -0.0523$, $p < 0.01$) and the interaction term with sales ($\beta = 0.00056$, $p \approx 0.095$) demonstrate a nuanced relationship, where high sectoral variance tempers the return on assets.

In the ROE model, the significance of sales (β = 0.0021, p = 0.0078) persists, highlighting its consistent positive influence across profitability dimensions. However, most sectoral coefficients and their interaction terms remain statistically insignificant, suggesting weak moderation effects of sector type on profitability in terms of equity returns. Only depreciation retains statistical significance (β = -0.0181, p = 0.005), reinforcing its consistent negative impact across all models.

Notably, across all three models, the interaction terms of sales × sector fail to reach significance, implying that sales growth alone does not translate into varying profitability outcomes across sectors. This suggests that while sector characteristics are important, they may not alter the direct impact of core financial metrics unless other firm-specific or macroeconomic variables are considered.

The Net Profit model demonstrates the strongest explanatory power (Adjusted $R^2 = 0.307$), whereas ROA and ROE models display lower explanatory capacity (Adjusted $R^2 \approx 0.01–0.03$), reinforcing the complexity in modeling efficiency-based profitability metrics in the MSME context.

5. Conclusion

The Z-score dispersion by sector (Table 1) and period contrasts (Table 2) empirically anchors our narrative of uneven recovery. Regression results (Tables 5-7) show Sales as the consistent positive driver, whereas Raw Material and Depreciation weigh on ROA/ROE. Therefore, heterogeneity in cost structures—not sector labels per se—explains resilience patterns, reconciling conflicting findings in the literature.

Utilizing the Altman Z-Score model, this research conducted a longitudinal sectoral disaggregation analysis of financial distress spanning from 2016 to 2024 in Indian MSMEs. This study utilizes firm-level data from Screener. in, along with specific financial ratios, including working capital to total assets, retained earnings to total assets, EBIT to total assets, and market value of equity to liabilities, to classify MSMEs into distress, grey, and safe zones. The results showed that although some industries, particularly Pharmaceuticals and Chemicals, demonstrate resilience, others, especially Textiles and Apparel, frequently hover around or below the distress threshold. Notably, the integration of pre- and post-COVID comparisons indicates that the pandemic's financial disruptions exposed all MSME sectors to heightened vulnerabilities, although recovery pathways diverged post-pandemic.

This study is useful because it offers an early warning framework to MSME stakeholders. This paper goes against the grain of macroeconomic overviews, which tend to ignore the intricacies of certain sectors, because it uses firm-level finances to draw insightful conclusions. With these findings, policymakers can center their support strategies on sectors that are identified as high-risk, whereas the financial service providers can enhance their credit appraisal processes in tandem with the risk-weighting strategies based on the Z-score classifications. Moreover, the incorporation of interaction terms in the regression models deepens the understanding of how sectoral affiliations modify the significance of the key driving factors in sales, employee cost, and raw materials cost on the profitability ratios (Net Profit, ROA, ROE).

As emphasized in this study, effective post-COVID recovery financial management in sectors that took longer to recover hinges on controlling input costs and working capital optimization. Besides the raw materials and depreciation costs, which the regression diagnostics indicate undermine profitability, other factors also need to be addressed if operational efficiency coupled with technological modernization is to be achieved. More comprehensive financial plans need to be established across the board, especially in the capital-intensive, export-reliant sectors, as they tend to be more susceptible to external shocks.

What sets this research apart is the sector-based longitudinal validation of the Altman Z-Score model amidst the Indian MSME context, which remains largely unexplored. In contrast to most studies that trail large-cap firms or utilize cross-sectional snapshots, this paper provides a multi-year, multi-sectoral study that blends the realm of academic ideation with pragmatic implementation. Moreover, the segmentation of the study into pre- and post-pandemic periods adds to the richness of the discourse, positioning it among a few studies that interactively chronicled financial distress over time.

The regression-based profitability analysis underscores that sales remain the most significant and consistent positive determinant of MSME profitability across Net Profit, ROA, and ROE models. Conversely, raw material costs and depreciation emerged as strong negative predictors, highlighting the impact of input cost management and asset utilization on firm performance. Interestingly, sectoral interaction effects with sales were statistically insignificant, suggesting that the influence of core financial variables transcends industry classifications. Among the three models, the Net Profit regression demonstrated the strongest explanatory power (Adjusted $R^2 \approx 0.31$), while the ROA and ROE models showed comparatively weaker fits. These insights emphasize the importance of enhancing revenue streams and controlling fixed costs as universal profitability levers for MSMEs, offering actionable guidance for both managers and policymakers.

In conclusion, this research not only reinforces the assertion that the Altman Z-Score model applies to Indian MSMEs but also extends its application as a longitudinal strategic risk monitoring device, particularly in contexts sensitive to crises. The model developed in this study is likely to be replicated in other emerging markets, and it also provides new avenues for research that would incorporate machine learning, macroeconomic stress testing, or ESG elements into financial distress predictive modeling.

Evidence-based conclusion and future work. Our descriptive and regression evidence confirms that post-COVID profitability improvements arise primarily from efficiency gains rather than revenue expansion. For future work, dynamic panel (System-GMM) and transparent ML hybrids could test persistence and incremental predictive value while retaining explainability for credit risk governance.

5.1 Sales Scale vs. Cost Pressures: A Fragility-RBV Lens

Consistent positive sales effects across NP/ROA/ROE indicate scale efficiency as a primary profitability lever, while raw materials and depreciation exert persistent negative pressure. In fragility terms, cost spikes and asset intensity elevate default risk; in RBV terms, firms that build procurement capability and asset-use discipline convert resources into durable advantage.

5.2 Sector Nuance and the COVID Break

Z-score mapping shows pharma/biotech resilience and textiles/auto fragility. The divergence aligns with demand stability and R&D orientation in pharma versus export dependency and working-capital strain in textiles/auto. Pre/post-COVID contrasts suggest that capital-intensive sectors recover slowly unless the cost of capital falls and asset productivity improves. Post-COVID contrasts. Comparing Pre-COVID (2016–2019), During-COVID (2020–2021), and post-COVID (2022–2024), average Sales fell during COVID and remained lower post-2022, yet ROA and ROE improved, consistent with cost rationalization and productivity gains (see Table 2). Adding a Post dummy and the interaction $\ln(\text{Sales} + 1) \times$ Postyields a small, margin-level positive effect ($p \approx 0.08$), indicating gradual but uneven normalization of sales elasticity to profitability across sectors.

5.3 What the Non-Results Mean

Insignificant sector×sales interactions and weak ROA/ROE fits imply that firm-internal execution dominates sector identity for profitability—an important signal for lenders: rating more by firm controls than by sector labels.

6. Theoretical, Empirical, and Practical Contributions

Theoretical. We extend distress research by integrating fragility and RBV with a sector-disaggregated, longitudinal Z-Score validation for MSMEs, explaining why cost intensity and asset structure condition risk.
Empirical. First 2016–2024 multi-sector MSME map combining Z-Score classifications with profit driver estimation and pre/post-COVID comparisons. Practical. Sectoral Z-Score thresholds for lender risk bands; cost-to-cash playbooks for MSMEs (procurement pooling, vendor financing, asset-light CAPEX); targeted policy—priority credit guarantee for Chemicals & Auto; asset-use improvements for Pharma small units.

7. Limitations and Future Research

Results rely on publicly available statements; private MSMEs may be under-represented. If regressions are cross-sectional, causal interpretation is limited; future work should employ panel FE with macro controls and explore non-linear distress thresholds. Hybrid Z-Score+forensic/ML models and policy experiments (e.g., credit guarantees) merit evaluation.

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List of Abbreviations

ROA = Return on Assets; ROE = Return on Equity; NP = Net Profit; VIF = Variance Inflation Factor; KPI = Key Performance Indicator.

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