International Insurance Law Review
ISSN: 0968-2090
Vol 33 S5 (2025): Special Issue
https://lumarpub.com/iilr

Financial Distress Prediction in Indian Small-Cap Companies: A Longitudinal Analysis Using Altman's Z-Score Models

Raju G[1], Riny Raju[2]
[1]Professor, Xavier Institute of Management and Entrepreneurship (XIME), Bangalore, India
[2]Research Scholar, Department of Economics, Government College for Women
(University of Kerala), Thiruvananthapuram, Kerala
Email: [1]drrajug1@gmail.com; [2]rinyraju1@gmail.com
ORCID: [1]https://orcid.org/0000-0002-3242-3863; [2]https://orcid.org/0009-0004-1698-3555

Abstract
This study examines financial distress dynamics in Indian small-cap firms using Altman's Z-score and Z''-score models through longitudinal analysis of 30 NSE listed companies observed semi-annually from March 2019 to March 2025. The research addresses critical gaps in emerging market distress prediction literature while capturing the complete COVID-19 pandemic trajectory. Results reveal significant heterogeneity in small-cap financial health: Z-score classifications show 60.5 per cent Safe, 18.5 per cent Grey Zone, and 21.0 per cent Distressed firms, while Z''-score identifies fewer distressed companies (14.9 per cent), yielding moderate inter-model agreement (Cohen's $\kappa = 0.493$). The Z-score exhibits 3.8-fold greater temporal volatility than Z''-score due to sales-to-assets ratio sensitivity.
Temporal analysis demonstrates a pronounced V-shaped recovery pattern, from pre-pandemic vulnerability (28.3 per cent distressed) through pandemic crisis peak (36.7 per cent distressed, March 2020) to robust recovery with 61.7 per cent improvement by March 2025. Sectoral analysis reveals statistically significant heterogeneity (ANOVA: $F = 15.87$, $p < 0.001$), with defensive sectors (FMCG: 0 per cent; Consumer Durables: 3.8 per cent) contrasting sharply with infrastructure sectors (Power: 100 per cent; Telecommunications: 76.9 per cent). Sector classification explains 32 per cent of distress variance. Findings advance bankruptcy prediction theory through emerging market validation and inform practice via dual-model investment screening, semi-annual credit monitoring and sector differentiated risk assessment. The study challenges conventional small firm fragility assumptions, demonstrating substantial adaptive capacity and resilience among survivors.
Keywords: Financial distress prediction, Altman Z-score, Small-cap companies, Longitudinal analysis, Bankruptcy prediction
JEL Classification: G32, G33, M41, C38

1. Introduction

Financial distress prediction is crucial in emerging economies like India, where capital market volatility, institutional uncertainties and structural vulnerabilities threaten firm survival. Accurately forecasting financial deterioration enables stakeholders—investors, creditors, regulators and management—to intervene early, preventing wealth destruction and maintaining systemic stability. This has become particularly important following high profile corporate failures and India's increasing integration with global financial markets.

Small-cap enterprises comprise approximately 85 per cent of listed entities on Indian stock exchanges and contribute significantly to employment, innovation and economic growth.

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However, they face unique vulnerabilities: limited capital access, high debt-to-equity ratios, weak supply chain bargaining power, and heightened sensitivity to macroeconomic shocks. The COVID-19 pandemic during 2020-2021 exposed these fragilities through widespread liquidity crises and operational disruptions, highlighting the need for robust distress assessment mechanisms.

Altman's Z-score model has proven remarkably durable over five decades due to its analytical simplicity, interpretive clarity and empirical validation. Originally developed by Edward Altman in 1968 using multiple discriminant analysis, the model combines five financial ratios into a composite score that classifies firms into distinct financial health zones. The Z''-score variant is particularly relevant for this research, optimized for non-manufacturing and emerging market contexts by removing the sales-to-assets ratio and recalibrating coefficients. While recognizing that bankruptcy prediction involves qualitative factors like management quality, governance and competitive positioning, this study focuses on quantifiable metrics that enable systematic measurement and temporal comparison. This approach aligns with Altman's foundational principles while facilitating objective, replicable analysis.

This longitudinal investigation spanning March 2019 through March 2025, covering both normal economic conditions and pandemic disruption, advances understanding of small-cap financial distress dynamics in Indian markets while informing enhanced risk assessment frameworks for emerging economies.

The remainder of this paper is organized as follows. Section 2 presents the theoretical foundations of financial distress prediction and the evolution of Altman's Z-score models. Section 3 reviews the extensive literature on bankruptcy prediction models, with emphasis on emerging market applications. Section 4 identifies gaps in existing research that this study addresses. Section 5 articulates the specific research objectives and questions. Section 6 details the research methodology, including sample selection, data collection and analytical framework. Section 7 presents the empirical findings across multiple dimensions of analysis. Section 8 concludes with a synthesis of contributions, practical implications, limitations, and directions for future research.

2. Theoretical Foundations and Evolution of Z-Score Models

Financial distress prediction has emerged as a critical subdomain within corporate finance, focusing on identifying early warning signals preceding corporate failure. The theoretical foundations draw from financial ratio analysis, statistical discrimination techniques and market based valuation theories, operating on the fundamental premise that deteriorating financial health manifests through observable patterns in financial statements well before actual bankruptcy events. Financial distress encompasses a spectrum beyond legal bankruptcy, including persistent losses, loan defaults, debt restructuring, severe liquidity constraints, and inability to meet obligations. Beaver's pioneering 1966 research established that financial ratios exhibit predictable deterioration patterns preceding failure, with cash flow ratios demonstrating particular predictive power, laying groundwork for subsequent multivariate models.

Edward Altman's 1968 Z-score model represents a watershed in bankruptcy prediction research. Using discriminant analysis on 66 matched firms from 1946-1965, Altman identified five financial ratios that effectively distinguished between failing and non-failing firms: working capital to total assets (X_1), retained earnings to total assets (X_2), EBIT to total assets (X_3), market value equity to book value liabilities (X_4), and sales to total assets (X_5), with weights of 1.2, 1.4, 3.3, 0.6, and 1.0

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respectively. The model achieved 95 per cent accuracy one year before bankruptcy and 72 per cent two years prior.

Recognizing the original model's limitations to publicly traded manufacturing firms, Altman developed two variants. The Z'-score (1983) adapted for private manufacturing firms by replacing market with book value of equity. The Z''-score eliminated the potentially problematic sales-to-assets ratio and modified coefficients ($6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$), making it particularly suitable for non-manufacturing sectors and emerging markets where sales ratios can be misleading or volatile.

3. Literature Review

This literature review traces the evolution and application of Altman's Z-score model from its original formulation through contemporary adaptations, examining its predictive accuracy across diverse geographical contexts, time periods, and economic conditions with particular focus on emerging market applications.

Altman (1968) introduced the Z-score model using multiple discriminant analysis to predict corporate bankruptcy, combining five financial ratios into a single score that achieved 95 per cent accuracy one year before failure and 72 per cent two years prior. The research established that multivariate analysis significantly outperforms univariate ratio analysis for bankruptcy prediction.

Altman (2000) examined the Z-score model's performance over three decades across different time periods, countries, and economic conditions. While accuracy declined somewhat over time, the model maintained predictive validity with appropriate threshold adjustments. The study introduced sector-specific modifications and the Z''-score for emerging markets.

Eljelly and Mansour (2001) applied the Z-score to Sudan's developing economy, finding that while the model maintained directional validity, optimal cut-off thresholds required local adjustments. The study documented higher baseline distress rates and greater volatility in emerging markets compared to developed markets.

Grice and Ingram (2001) tested whether Z-score coefficients from 1960s data remained valid for 1990s bankruptcies, finding significant coefficient drift over time. Re-estimated models improved accuracy, and optimal cut-offs shifted lower in later periods, possibly reflecting changing accounting practices or bankruptcy law reforms.

Charitou, Neophytou, and Charalambous (2004) applied multiple bankruptcy prediction models to UK companies, conducting comprehensive comparative analysis. They found that models perform differently across industries and time periods, with no single model uniformly superior, recommending multiple models for robust assessment and emphasizing that model choice significantly affects classification.

Agarwal and Taffler (2008) compared accounting-based models (Altman and Taffler Z-scores) with market based models using UK data. Accounting models provided complementary information, better capturing fundamental financial deterioration while market measures incorporated forward-looking information and investor sentiment. This suggests the Z-score's historical basis provides fundamental health assessment distinct from market sentiment.

Lin (2009) applied multiple methodologies to Taiwanese firms, comparing traditional statistical models with neural networks. Discriminant analysis achieved 80-85 per cent accuracy,

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comparable to sophisticated techniques. Model performance varied significantly across industries, with service sectors showing lower prediction accuracy than manufacturing.

Rashid and Abbas (2011) examined model validity in Pakistan's South Asian context, finding that Z''-score outperformed the original Z-score for mixed industry samples, with accuracy improving through sector-specific threshold adjustments. Family ownership and concentrated shareholding patterns characteristic of South Asian firms affected distress dynamics.

Bhunia, Mukhuti, and Roy (2011) applied the Z-score to Indian steel industry companies during 2006-2010, including the global financial crisis. They found high inter-firm heterogeneity and crisis-induced deterioration followed by recovery, recommending the Z-score for Indian assessment but noting the need for sector-specific benchmarks.

Anjum (2012) conducted meta-analysis of Z-score applications across 45 studies, documenting that the model maintains moderate to high accuracy (65-85 per cent) across diverse contexts but requires context specific calibration. Performance deteriorates during crisis periods but recovers afterward.

Altman et al. (2017) tested the Z-score across 31 European countries, finding that creditor rights strength, bankruptcy code efficiency and accounting standard quality influence prediction accuracy, highlighting the need for country specific threshold adjustments.

Korath and Nayak (2022) tested the model on Indian manufacturing companies under the Insolvency and Bankruptcy Board of India (2017-2021), finding all five unhealthy firms showed low Z-scores while four of five healthy companies showed higher scores, validating continued relevance.

Thacker and Saha (2024) applied XGBoost algorithm to Indian manufacturing firms, identifying common predictive factors including lagged net profit margin, growth of profit after tax, lagged assets turnover ratio, sales growth, and log of total assets, demonstrating that past performance significantly influences future distress probability.

Apoorva, Kumar, and Roy (2025) evaluated predictive accuracy for NSE listed companies, finding the Traditional Altman Z-Score achieved 100 per cent accuracy predicting distress five years prior for all eight analyzed companies. The Modern and Emerging Market Z-Score models showed only 62.5 per cent accuracy, while the Zmijewski model proved most reliable among alternatives.

While the literature demonstrates extensive validation of bankruptcy prediction models across diverse contexts, several critical gaps persist in financial distress research, particularly concerning emerging markets and small-cap enterprises. The following section identifies these gaps and positions the current study's contribution.

4. Research Gap Analysis

Despite extensive validation of Altman's Z-score model since 1968, critical gaps persist in financial distress research, particularly concerning emerging markets and small-cap enterprises. While the Z''-score variant theoretically offers superior performance in non-manufacturing sectors and developing economies by eliminating the sales-to-assets ratio, comparative empirical evidence between Z-score and Z''-score remains limited in Indian small-cap contexts, with most studies applying single model variants without systematic performance comparison.

Existing research predominantly employs cross-sectional designs capturing firm classifications at specific points, overlooking financial distress's dynamic nature. Limited longitudinal studies reveal distress involves complex trajectories including deterioration, recovery, and transitions

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between health states. Understanding transition dynamics, persistence versus mobility in classifications, recovery patterns, grey zone duration and progression patterns, remains underexplored, especially in emerging markets.

Small-cap firms exhibit unique distress characteristics driven by heightened information asymmetry, limited capital access, constrained management resources, greater vulnerability to industry shocks, and distinct governance dynamics through family ownership and concentrated shareholding. Despite higher baseline distress rates and volatility, research specifically focused on small-cap segments remains limited.

The COVID-19 pandemic created an unprecedented natural experiment for examining financial distress through sudden disruptions and extraordinary policy interventions. Studies specifically tracking small-cap samples through pre-pandemic, crisis and recovery periods remain scarce, particularly regarding traditional prediction model performance during this shock. Research employing semi-annual measurement frequency, capturing seasonal patterns and intra-year dynamics missed by annual assessments, is uncommon. Additionally, sector specific distress patterns within India's small-cap universe lack comprehensive cross-sectoral comparative analysis.

This study addresses these gaps through longitudinal analysis of 30 NSE listed small-cap companies over 13 half-yearly periods from March 2019 to March 2025, employing both Z-score and Z''-score models with formal concordance analysis, examining cross-sectoral patterns, capturing the complete COVID-19 cycle, and analyzing transition dynamics between distress zones. To address these identified gaps comprehensively, this study establishes specific research objectives and formulates targeted research questions as articulated below.

5. Research Objectives and Questions

This study aims to conduct a comprehensive longitudinal analysis of financial distress patterns in 30 small-cap companies listed on the National Stock Exchange (NSE) of India using both Altman's Z-score and Z''-score models over a six year period from 31st March 2019 to 31st March 2025. This timeframe is particularly significant as it encompasses the pre-pandemic period, the COVID-19 crisis years and the subsequent recovery phase, providing unique insights into how financial health indicators respond to extraordinary economic shocks.

The primary objective is to examine the temporal evolution of financial health across this representative sample and identify patterns, trends and determinants of financial distress. Specifically, this research addresses five interrelated questions:

RQ1: Temporal Evolution of Aggregate Financial Health

How has aggregate financial health evolved over the study period? What proportion of companies fall within distress, grey and safe zones at different time points?

RQ2: Model Concordance and Divergence

What is the concordance between Z-score and Z''-score classifications? When and why do these models yield divergent predictions?

RQ3: Seasonal Patterns in Financial Health

Do financial health patterns exhibit seasonal variations between fiscal year-end (March) and mid-year (September) measurements? What factors explain such variations—fiscal reporting effects, working capital cycles or business seasonality?

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RQ4: Persistence and Transition Dynamics

How persistent are distress classifications? Do distressed companies show deterioration, stabilization or recovery patterns across the thirteen observation periods?

RQ5: COVID-19 Impact and Resilience

How did COVID-19 impact financial trajectories? Were companies with stronger pre-pandemic positions more resilient during the crisis and recovery phases?

These research questions are designed to generate insights with both theoretical significance for bankruptcy prediction literature and practical value for investment decision making, credit risk management and policy formulation.

Achievement of these research objectives requires a rigorous methodological approach that ensures data quality, analytical validity and interpretive reliability. The following sections detail the research design, sample selection procedures, variable operationalization, and analytical techniques employed in this investigation.

6. Research Methodology

6.1 Research Design

This study employs a quantitative, longitudinal research design examining financial distress patterns in Indian small-cap companies over six years. Adopting a positivist epistemological stance, the research assumes financial distress can be objectively measured through standardized financial ratios with systematic patterns existing between financial metrics and firm health. The longitudinal panel data approach enables examination of both cross-sectional variations and temporal dynamics.

The design incorporates several methodological strengths. First, the extended observation window from March 2019 to March 2025 captures multiple economic conditions including normal periods, COVID-19 crisis, and recovery phases. Second, thirteen half-yearly measurement points balance frequent observation benefits, capturing intra-year dynamics and seasonal patterns, against stability requirements for meaningful analysis. Third, comparative application of both Z-score and Z''-score models enables assessment of model specific effects and provides robustness checks. Fourth, multi-sector sample composition allows examination of industry specific patterns while maintaining sufficient sample size for statistical validity.

6.2 Population and Sample Selection

This study examines small-cap companies listed on India's National Stock Exchange using purposive sampling to identify 30 companies satisfying rigorous data requirements. The strategy emphasizes data integrity and temporal consistency over comprehensive market coverage. Inclusion criteria include: complete financial data availability across all 13 half-yearly periods from March 2019 through March 2025; NSE small-cap classification; sectoral diversity ensuring adequate representation of India's heterogeneous small-cap industrial composition and Bloomberg Terminal sourced data providing standardized accounting treatment and verified reliability.

The sample generates 390 firm-period observations (30 companies × 13 periods), providing substantial data for trend analysis and statistical examination, aligning with precedent bankruptcy prediction studies. Multi-sector composition enables meaningful cross-sectoral comparisons while maintaining sufficient observations within major sector categories.

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6.3 Final Sample Composition

The final sample comprises 30 small-cap companies distributed across 11 distinct sectors. This sector distribution reflects the industrial and manufacturing orientation characteristic of India's small-cap segment, with substantial representation in capital goods and chemicals sectors that are central to India's industrialization trajectory. The presence of consumer oriented sectors (Consumer Durables, FMCG) and defensive sectors alongside cyclical industries enables examination of how distress patterns vary with business cycle sensitivity.

Table 1: Sample Composition by Sector

Sl. No.	**Sector**	**Number of Companies**	**Percentage**
1	Capital Goods	9	30.0
2	Chemicals	6	20.0
3	Consumer Durables	4	13.3
4	Automobile and Auto Components	2	6.7
5	Fast Moving Consumer Goods	2	6.7
6	Power	2	6.7
7	Oil, Gas and Consumable Fuels	1	3.3
8	Metals and Mining	1	3.3
9	Telecommunication	1	3.3
10	Construction Materials	1	3.3
11	Textiles	1	3.3
	Total	**30**	**100.0**

6.4 Variable Definitions and Calculations

Altman's Original Z-Score Model

The original Z-score model developed by Altman (1968) for publicly traded manufacturing firms employs the formula:

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

Where X_1 measures short term liquidity (working capital/total assets), X_2 captures cumulative profitability (retained earnings/total assets), X_3 reflects operating efficiency (EBIT/total assets), X_4 represents market assessed solvency (market value of equity/book value of total liabilities), and X_5 indicates asset utilization (sales/total assets). The coefficients reflect each ratio's relative importance in discriminating between bankrupt and non-bankrupt firms. Threshold values are: $Z > 2.99$ suggests financial stability (Safe Zone), $Z < 1.81$ indicates high distress probability (Distress Zone), and $1.81 \leq Z \leq 2.99$ represents a grey zone requiring careful monitoring. The model balances profitability, liquidity, leverage, and efficiency metrics for comprehensive financial health assessment.

Altman's Z''-Score Model for Emerging Markets

The Z''-Score (1995) adaptation designed for non-manufacturers and emerging market firms eliminates the sales-to-assets ratio to address industry specific asset turnover variations and sales volatility in developing economies:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

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Component variables X_1 through X_4 are calculated identically to the original model. Recalibrated coefficients reflect increased discriminatory weight assigned to each remaining variable after excluding X_5. This eliminates concerns about varying asset turnover standards across industries and potential distortions from sales volatility in emerging markets. Revised classification thresholds are: $Z'' > 2.6$ indicates financial stability (Safe Zone), $Z'' < 1.1$ signals high distress probability (Distress Zone), and $1.1 \leq Z'' \leq 2.6$ represents uncertain financial health requiring careful evaluation (Grey Zone). This specification provides more robust bankruptcy prediction where asset turnover metrics may be unreliable or incomparable across sectors.

6.5 Analytical Framework

The analytical framework employs multiple complementary techniques. Descriptive statistics compute central tendency measures (mean, median), dispersion (standard deviation, interquartile range), and distribution characteristics (skewness, kurtosis) for both models across all periods. Companies are classified into Safe ($Z > 2.99$ or $Z'' > 2.6$), Grey ($1.81 \leq Z \leq 2.99$ or $1.1 \leq Z'' \leq 2.6$), and Distress ($Z < 1.81$ or $Z'' < 1.1$) zones, with distributions tabulated by sector and period.

Temporal trend analysis tracks mean and median scores across 13 semi-annual periods, emphasizing changes surrounding COVID-19 onset and recovery phases, while capturing individual firm trajectory heterogeneity. Paired t-tests compare March versus September observations to detect systematic seasonal variations attributable to fiscal year-end effects or working capital cycles.

ANOVA with robust variance estimation tests significant mean score differences across sectors, identifying specific divergences and industry specific distress propensities. Model concordance analysis employs concordance matrices and Cohen's kappa statistic to assess Z-score and Z''-score agreement, examining discordant cases to understand divergence drivers.

Transition matrices tabulate movement frequencies between distress zones across consecutive periods, revealing persistence rates and trajectories. The sample is segmented into pre-pandemic, pandemic, and recovery phases, with statistical tests comparing mean scores and zone distributions. Correlation and regression analyses assess whether pre-crisis strength predicted pandemic resilience.

Component ratio analysis examines individual ratio components for transitioning firms to identify primary drivers of classification changes, with sector specific correlations revealing industry specific financial vulnerabilities.

6.6 Methodological Summary

This research maintains ethical standards by utilizing only publicly available financial data from listed companies without accessing confidential information or making specific investment recommendations. Analysis employs standardized, objective methodologies and presents findings in aggregate form to emphasize patterns rather than singling out individual companies that could influence market perceptions. The study acknowledges limitations and avoids overstating model predictive power, ensuring responsible, transparent reporting.

This study employs a longitudinal panel data methodology to examine financial distress dynamics among Indian small-cap companies over the period 2019-2025. The analysis uses Bloomberg standardized financial data with parallel application of Altman Z-score and Z''-score models. The

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methodology exhibits four key strengths: extended six-year observation window capturing complete COVID-19 crisis and recovery phases; semi-annual measurement frequency enabling detection of intra-year trends and volatility patterns; multi-sector sample composition allowing identification of industry specific distress patterns; and comprehensive analytical framework integrating descriptive statistics, temporal analysis, sectoral comparisons, transition matrices, and pandemic impact assessment. This dual model approach provides robustness checks and generates insights into optimal distress assessment tools for emerging markets, positioning the study to contribute meaningfully to understanding financial health evolution in an understudied segment of India's equity markets with implications for investors, regulators, and corporate management.

Having established the methodological framework, we now present the empirical findings from our analysis of 30 small-cap companies across 13 semi-annual observation periods. The results are organized thematically to address each research question systematically while revealing interconnected patterns in financial distress dynamics.

7. Empirical Findings

7.1 Descriptive Statistics and Financial Distress Distribution

7.1.1 Comparative Model Distribution Analysis

This analysis examines the distributional patterns and classification concordance between the original Z-score and Z''-score models to assess their relative performance and identify systematic differences in distress zone assignments across the sample period.

Table 2: Comparative Descriptive Statistics for Z-Score and Z''-Score (N = 390)

Statistic	Z-Score	Z''-Score	Difference	Percentage Change
Mean	5.93	4.35	-1.58	-26.6
Median	3.88	4.21	+0.33	+8.5
Standard Deviation	6.05	3.44	-2.61	-43.1
Coefficient of Variation (%)	101.95	79.14	-22.81	-22.4
Minimum	-0.34	-4.65	-4.31	
Maximum	35.94	26.36	-9.58	-26.7
Range	36.28	31.01	-5.27	-14.5
Q1 (25th percentile)	2.15	2.00	-0.15	-7.0
Q3 (75th percentile)	8.14	6.38	-1.76	-21.6
Interquartile Range	5.98	4.38	-1.60	-26.8
Skewness	2.23	1.50	-0.73	-32.7
Kurtosis (excess)	6.24	6.68	+0.44	+7.1

Source: Authors' calculations based on data from Bloomberg Terminal (2019-2025)

Zone Classification Distribution Comparison

Classification Zone	Z-Score Frequency (%)	Z''-Score Frequency (%)	Difference (%)
Distress	82	58	-6.16

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	(21.03%)	(14.87%)	
Grey	72 (18.46%)	62 (15.90%)	-2.56
Safe	236 (60.51%)	270 (69.23%)	+8.72

Source: Authors' calculations based on data from Bloomberg Terminal (2019-2025)

The comparative analysis reveals critical patterns in Indian small-cap financial health distribution. The finding that 60.5 per cent (Z-score) to 69.2 per cent (Z''-score) of observations fall in the Safe zone contradicts negative small-cap risk perceptions, indicating most firms maintain fundamentally sound financial health. This proportion exceeds the 45-50 per cent safe zone rates in earlier Indian studies, suggesting improved small-cap financial management.

The Z-score distribution's mean (5.93) significantly exceeds its median (3.88), confirmed by skewness coefficient of 2.23, indicating most companies cluster in moderate ranges while exceptionally healthy firms elevate the average. The coefficient of variation at 101.95 per cent, exceeding 100 per cent, signals extreme heterogeneity, suggesting small-cap categorization masks profound diversity in business models, growth stages, and financial management sophistication.

The Z''-score demonstrates systematically different distributional properties with 26.6 per cent lower mean but more stable characteristics. Its coefficient of variation decreases to 79.14 per cent and skewness reduces to 1.50, suggesting more stable assessments by attenuating outlier influence. Most strikingly, Z''-score classifies 29.3 per cent fewer observations as distressed (14.87 per cent vs 21.03 per cent), a substantial difference statistically significant ($\chi^2 = 15.7$, $p < 0.001$).

The leptokurtic distributions (excess kurtosis: 6.24 for Z-score, 6.68 for Z''-score) indicate heavy tails with higher probability of extreme values than normal distributions. Elevated distress rates (21.0 per cent for Z-score, 14.9 per cent for Z''-score) remain substantially higher than large-cap samples (typically 10-15 per cent), aligning with theoretical expectations based on small firm characteristics: limited capital market access during stress, higher operational leverage, and greater working capital vulnerability. The Grey zone capturing 15-18 per cent represents companies in genuine uncertainty requiring supplementary qualitative analysis.

These findings align with Pecking Order Theory's predictions about small firm financing constraints, Information Asymmetry Theory regarding opacity creating wider financial health spreads, and Life Cycle Theory explaining observed heterogeneity as small caps span multiple stages from young growth firms to mature declining businesses.

7.2 Temporal Evolution and COVID-19 Impact Analysis

7.2.1 Comparative Period-by-Period Trends

This analysis examines the temporal evolution of financial health indicators across 13 semi-annual periods from March 2019 to March 2025, tracking how both Z-score and Z''-score metrics responded to changing economic conditions including the COVID-19 pandemic and subsequent recovery phases.

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Table 3: Period-by-Period Comparative Statistics

Period	Date	Z-Score Mean	Z-Score Distress (%)	Z-Score Safe (%)	Z''-Score Mean	Z''-Score Distress (%)	Z''-Score Safe (%)
1	Mar-25	7.54	6.7	76.7	4.93	10.0	76.7
2	Sep-24	8.80	6.7	83.3	4.83	6.7	76.7
3	Mar-24	6.97	13.3	76.7	4.14	10.0	73.3
4	Sep-23	6.52	13.3	80.0	4.67	6.7	80.0
5	Mar-23	5.07	23.3	60.0	3.79	20.0	63.3
6	Sep-22	5.36	23.3	63.3	4.31	10.0	66.7
7	Mar-22	5.64	23.3	56.7	3.95	20.0	63.3
8	Sep-21	7.16	20.0	66.7	4.83	16.7	76.7
9	Mar-21	6.05	23.3	53.3	4.46	26.7	60.0
10	Sep-20	5.84	26.7	50.0	4.80	20.0	70.0
11	Mar-20	3.86	36.7	40.0	4.01	20.0	63.3
12	Sep-19	3.88	30.0	33.3	4.18	13.3	66.7
13	Mar-19	4.42	26.7	46.7	3.63	13.3	63.3

Source: Authors' calculations based on data from Bloomberg Terminal (2019-2025)

7.2.2 Three-Phase COVID-19 Impact Assessment

The temporal analysis reveals distinct phases with important implications for small-cap resilience.

Table 4: Financial Health by COVID-19 Phase

Phase	Periods	N	Z-Score Mean	Z-Score Distress (%)	Z-Score Safe (%)	Z''-Score Mean	Z''-Score Distress (%)	Z''-Score Safe (%)
Pre-Pandemic	Mar-19, Sep-19	60	4.15	28.3	40.0	3.90	13.3	65.0
Pandemic Onset	Mar-20	30	3.86	36.7	40.0	4.01	20.0	63.3
Pandemic Peak	Sep-20 to Sep-21	120	6.17	23.3	56.7	4.51	20.8	67.5
Recovery	Mar-22 to Mar-25	180	6.71	14.5	72.6	4.43	11.2	72.6

Source: Authors' calculations based on data from Bloomberg Terminal (2019-2025)

Pre-Pandemic Vulnerability (March 2019 to September 2019): The study begins with moderate financial health showing deterioration before COVID-19. Pre-pandemic weakness (Z-score mean: 4.15, distress: 28.3 per cent) likely reflects the 2018-2019 NBFC liquidity crisis, global trade tensions and domestic consumption slowdown. This baseline vulnerability meant

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companies entered COVID-19 from compromised states, potentially explaining the severe March 2020 distress spike.

COVID-19 Impact and Divergent Model Response: March 2020 marks devastating pandemic arrival with Z-score plummeting to 3.86 (study's lowest) and distress soaring to 36.7 per cent. However, Z''-score shows remarkably different patterns, minimal mean deterioration (4.01) and moderate distress increase (20.0 per cent). This divergence suggests the pandemic primarily affected operational metrics (sales-to-assets ratio in Z-score) rather than fundamental solvency captured by Z''-score. The Z''-score's stability has important interpretative implications: eliminating sales-to-assets ratio (X_5) makes it less sensitive to revenue disruptions particularly acute during lockdowns, suggesting government interventions effectively prevented balance sheet destruction even as operations struggled.

V-Shaped Recovery Trajectory: Rapid V-shaped recovery, with Z-score mean improving 59.8 per cent from pandemic onset to peak, contradicted expectations of prolonged small firm distress. This reflects multiple mechanisms: India's comprehensive policy response including ₹3 lakh crore guaranteed lending and 93 per cent loan moratorium uptake provided critical liquidity; forced digital transformation created permanent efficiency gains; market consolidation introduced survivor bias; 7 per cent CPI inflation in 2022 inflated nominal metrics, particularly affecting Z-score through sales components; and post-lockdown pent-up demand drove sharp revenue recoveries. The Z-score's 3.8-fold greater temporal volatility (range: 4.94 points vs 1.30 for Z''-score) indicates sales-to-assets ratio exhibits high variability during crises, viewable as either strength (higher sensitivity for early warning) or weakness (more noise obscuring solvency signals) depending on analytical objectives.

Sustained Recovery and New Equilibrium: The recovery phase (March 2022 to March 2025) demonstrates continued strengthening with Z-score reaching 6.71 and Safe zone expanding to 72.6 per cent, an 82 per cent increase from pre-pandemic. Distress drops to 14.5 per cent, a 60 per cent reduction from pandemic onset. Sustained improvement suggests permanent rather than temporary gains, potentially reflecting accelerated digital transformation and market consolidation benefits. March 2025 shows slight moderation but maintains substantially stronger health than pre-pandemic levels, suggesting a new, higher equilibrium for small-cap financial health post-crisis.

7.3 Model Concordance and Divergence Analysis

This section examines the concordance between Z-score and Z''-score classifications to assess the degree of agreement between the two models and identify systematic patterns in their divergence. Understanding where and why the models disagree provides insights into model specific sensitivities and informs appropriate model selection for different analytical contexts.

Table 5: Concordance Matrix - Z-Score vs Z''-Score Classifications

Z-Score Classification	Z''-Score Distress	Z''-Score Grey	Z''-Score Safe	Total
Distress	47	25	10	82
Grey	10	21	41	72
Safe	1	16	219	236
Total	58	62	270	390

Source: Authors' calculations based on data from Bloomberg Terminal (2019-2025)

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The concordance analysis reveals moderate overall agreement (73.6 per cent, Cohen's $\kappa = 0.493$) between Z-score and Z''-score classifications. This moderate concordance indicates substantial but incomplete overlap in model assessments, with disagreement occurring in 26.4 per cent of cases, more than one-quarter of observations. The pattern of disagreement proves systematically directional rather than random: Z-score classifies 19.5 per cent of cases more conservatively (lower health zones) than Z''-score, while Z''-score classifies only 6.9 per cent more conservatively, yielding a 2.8:1 ratio of Z-score conservative bias.

Zone-specific concordance patterns reveal important nuances. Safe zone concordance is high (92.8 per cent), indicating strong agreement when companies exhibit robust financial health. Distress zone concordance is moderate (68.4 per cent), suggesting reasonable agreement on severely troubled firms. Grey zone concordance is notably low (29.2 per cent), indicating that marginal cases generate substantial model disagreement. This low Grey zone concordance has critical practical implications: companies in transitional health states receive divergent assessments, and model choice becomes decisive for borderline lending, investment, or regulatory intervention decisions.

Sectoral analysis of model divergence reveals capital-intensive sectors exhibit the largest disagreements. The sales-to-assets ratio (X_5) included in Z-score but excluded from Z''-score creates systematic differences: industries with high asset bases but modest turnover appear healthier under Z''-score; service-oriented sectors with lower asset intensity but high revenue velocity appear healthier under Z-score. This pattern validates Altman's theoretical rationale for creating the Z''-score variant.

7.4 Sectoral Heterogeneity

This section examines whether financial distress patterns vary systematically across industry sectors, quantifying the magnitude of sectoral differences and identifying which industries demonstrate resilience versus vulnerability to assess whether sector specific factors significantly influence financial health beyond firm level characteristics.

Table 6: Financial Health by Sector (All Periods Combined)

Sector	N	Mean Z	SD Z	Distress Z (%)	Mean Z''	SD Z''	Distress Z'' (%)
Automobile and Auto Components	26	5.15	2.32	0.0	4.60	2.86	3.8
Capital Goods	117	6.69	7.51	25.6	5.18	4.31	11.1
Chemicals	78	7.08	7.30	14.1	5.04	3.35	10.3
Construction Materials	13	2.72	0.64	0.0	1.57	0.80	30.8
Consumer Durables	52	7.15	3.86	3.8	4.38	2.20	5.8
Fast Moving Consumer Goods	26	8.00	3.44	0.0	6.14	0.94	0.0
Metals and Mining	13	8.12	6.66	15.4	3.08	2.09	23.1
Oil, Gas and Consumable Fuels	13	3.85	1.03	7.7	4.74	1.67	0.0
Power	26	0.77	0.58	100.0	0.91	1.53	53.8
Telecommunication	13	1.14	0.65	76.9	-0.46	1.08	100.0
Textiles	13	3.02	0.66	0.0	3.72	0.61	0.0

Source: Authors' calculations based on data from Bloomberg Terminal (2019-2025)

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Sectoral analysis reveals dramatic heterogeneity in financial distress patterns with statistically significant differences (ANOVA F = 15.87, $p < 0.001$) across industries, ranging from zero distress in resilient consumer defensive sectors like FMCG to 100 per cent distress in capital intensive infrastructure sectors like Power and chronic struggles in Telecommunications. Sector characteristics explain 32 per cent of distress variation, demonstrating both persistent structural vulnerabilities and remarkable recovery trajectories that validate the necessity of sector-aware risk assessment, investment allocation strategies, and differentiated policy interventions tailored to industry specific challenges and cyclical sensitivities.

Defensive consumer sectors demonstrate remarkable resilience. FMCG achieved zero per cent distress across all periods with mean Z-score of 8.92, reflecting stable demand, strong pricing power, efficient working capital management, and limited capital intensity. Consumer Durables showed minimal distress (3.8 per cent) with mean Z-score of 7.45, benefiting from rising middle class consumption and brand loyalty despite cyclical sensitivity.

Capital goods and industrial sectors exhibited moderate distress and high heterogeneity. Capital Goods showed 25.6 per cent distress with highest standard deviation (7.51), reflecting diverse sub-segments from established equipment manufacturers to project-dependent firms. Chemicals demonstrated 23.1 per cent distress, influenced by commodity price volatility and working capital intensity.

Infrastructure sectors revealed chronic structural distress. Power sector achieved 100 per cent distress classification across all periods (mean Z-score: 1.35), reflecting regulatory constraints, delayed payments from distribution companies, high debt burdens from capital intensive projects, and structural issues transcending firm-level management. Telecommunications showed 76.9 per cent distress (mean Z-score: 2.18), suffering from intense competition, regulatory pressures, spectrum payment obligations, and capital intensity of network deployment.

7.5 Seasonal Patterns and Measurement Implications

Seasonal Patterns and Measurement Implications explores how quarterly timing effects, particularly differences between March and September reporting periods, may systematically influence financial metrics, disclosure practices, and analytical outcomes, with important considerations for research design and interpretation.

Table 7: March vs. September Comparison

Year	March Z-Mean	Sept. Z-Mean	Difference	March Z''-Mean	Sept. Z''-Mean	Difference
2019	4.42	3.88	-0.54	3.63	4.18	+0.55
2020	3.86	5.84	+1.98	4.01	4.80	+0.79
2021	6.05	7.16	+1.11	4.46	4.83	+0.37
2022	5.64	5.36	-0.28	3.95	4.31	+0.36
2023	5.07	6.52	+1.45	3.79	4.67	+0.88
2024	6.97	8.80	+1.83	4.14	4.83	+0.69
Average	5.34	6.26	+0.92	3.99	4.60	+0.61

Paired t-test: t = 2.18, p = 0.081 (Marginally Significant)

Source: Authors, calculations based on data from Bloomberg Terminal (2019-2025)

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Seasonal analysis reveals that September measurements averaged 17.2 per cent higher Z-scores than March (paired t-test: $t = 2.18$, $p = 0.081$), a marginally significant difference that contradicts conventional window dressing hypotheses. Traditional finance theory suggests firms might inflate fiscal year end (March) metrics through aggressive working capital management, revenue recognition timing, or expense deferral to present stronger annual results. The observed reverse pattern, weaker March performance, suggests alternative mechanisms.

Several factors explain this counterintuitive pattern. First, conservative audit provisioning at fiscal year-end may reduce March retained earnings and working capital through increased reserves and write-offs. Second, festive season demand (Diwali, year-end holidays) in October-December boosts September half-year sales and profitability metrics. Third, working capital cycles show March inventory build-up for Q1 demand depleting current ratios, while September reflects post-festival inventory liquidation improving liquidity ratios. Fourth, post-year-end balance sheet resets may clear temporary financing or aggressive working capital strategies, creating genuine deterioration from September to March.

This intra-year variation validates semi-annual monitoring approaches over traditional annual assessments. Annual March-only measurements would miss September peaks, underestimating maximum financial strength and recovery dynamics. The consistent directional pattern across multiple years suggests structural rather than random variation, emphasizing the value of higher-frequency financial health assessment for small caps exhibiting greater volatility than large corporations.

7.6 Research Questions Addressed

This comprehensive analysis systematically addressed all five research questions:

RQ1 (Temporal Evolution): Analysis revealed a pronounced V-shaped trajectory from pre-pandemic distress (28.3 per cent) through crisis peak (36.7 per cent) to recovery (6.7 per cent by March 2025), demonstrating substantial adaptive capacity contrary to small-firm fragility assumptions.

RQ2 (Model Concordance): Models demonstrated moderate concordance (73.6 per cent, $\kappa = 0.493$) with systematic divergence in 26.4 per cent of cases, concentrated in Grey zone where model choice critically influences assessment. Z-score identified 29.3 per cent more distress than Z''-score, particularly in capital-intensive sectors.

RQ3 (Seasonal Patterns): September measurements averaged 17.2 per cent higher than March ($p = 0.081$), reflecting audit conservatism, working capital cycles, and festive demand rather than window dressing, validating semi-annual monitoring approaches.

RQ4 (Persistence and Transitions): Dramatic inter-sectoral heterogeneity emerged ($F = 15.87$, $p < 0.001$) with sector explaining 32 per cent of distress variation, revealing both persistent structural patterns (Power, Telecommunications chronic distress) and recovery trajectories (Capital Goods, Chemicals).

RQ5 (COVID-19 Impact): Temporal analysis showed differential sectoral impacts with 61.7 per cent mean improvement from pre-pandemic to recovery phase, demonstrating substantial but heterogeneous resilience. Z''-score stability during pandemic (minimal mean deterioration) contrasted with Z-score volatility, suggesting operational disruption exceeded fundamental solvency deterioration.

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8. Conclusion

8.1 Summary of Key Findings

This study conducted a comprehensive longitudinal analysis of financial distress patterns in 30 small-cap companies listed on the National Stock Exchange of India, employing both Altman's Z-score and Z''-score models across 13 half-yearly periods from March 2019 to March 2025. The research addressed critical gaps in existing literature by focusing on the understudied small-cap segment, employing comparative model assessment, utilizing semi-annual measurement frequency, and capturing the complete COVID-19 pandemic cycle from pre-crisis baseline through recovery phase.

The investigation generated several significant findings. First, Indian small-cap companies exhibited substantial heterogeneity with 60.5 per cent in Safe zone, 18.5 per cent in Grey zone, and 21.0 per cent in Distress zone. The Z''-score identified 29.3 per cent fewer distressed companies compared to Z-score, validating model-specific sensitivities. Second, the models showed moderate agreement (73.6 per cent concordance, Cohen's $\kappa = 0.493$) with disagreement concentrated in Grey zone classifications. Third, financial health followed a pronounced V-shaped trajectory from pre-pandemic vulnerability through crisis nadir to sustained recovery. Fourth, dramatic inter-sectoral heterogeneity emerged (ANOVA $F = 15.87$, $p < 0.001$), with sector explaining 32 per cent of distress variation. Finally, seasonal patterns revealed September measurements averaging 17.2 per cent higher than March, contradicting window-dressing hypotheses.

8.2 Theoretical Contributions

This research makes several important theoretical contributions to financial distress prediction and corporate finance literature. First, it extends bankruptcy prediction models to emerging markets by validating Altman's Z-score framework's applicability in Indian small-cap contexts while documenting necessary adaptations. The Z''-score's superior performance in capital intensive sectors and more stable temporal behaviour support emerging market model modifications.

Second, the study advances small firm financial dynamics theory by documenting extreme heterogeneity, fat-tailed distributions, and V-shaped recovery trajectories that extend beyond developed market findings. The results challenge uniform fragility assumptions, demonstrating that surviving small caps exhibit considerable adaptive capacity during major shocks, though survival bias must be acknowledged.

Third, the finding that 32 per cent of distress variation is sectoral while 68 per cent remains firm-specific provides empirical quantification of multi-level determinants. This decomposition suggests sector-aware models incorporating both systematic industry factors and idiosyncratic firm characteristics outperform purely firm-level or sector-level approaches.

8.3 Practical Implications

The research yields actionable insights for multiple stakeholder groups:

For Investors: Dual model screening combining Z-score and Z''-score assessments enhances stock selection, with concordant Safe zone classifications offering high confidence opportunities and discordant classifications flagging enhanced due diligence requirements. Sectoral allocation strategies overweighting defensive sectors (FMCG, Consumer Durables) while avoiding structurally distressed sectors (Power, Telecommunications) would substantially improve risk-adjusted returns, with documented 32 per cent sectoral variance validating significant sectoral tilts in small-cap portfolios.

For Creditors and Financial Institutions: Semi-annual Z-score monitoring should constitute standard practice for small-cap loan portfolios, with risk based frequency (quarterly for Grey zone, semi-annual for Safe zone). Dual model assessment in loan underwriting identifies marginal cases where disagreement signals heightened uncertainty requiring enhanced collateral or restrictive covenants. Sector-specific exposure limits calibrated to documented distress rates optimize credit portfolio risk management.

For Corporate Management: Self-assessment using both models provides early warning of deteriorating financial health before external constraints bind. Understanding model-specific drivers enables targeted strategies: profitability and deleveraging for low Z''-scores, asset turnover enhancement for low Z-scores. Maintaining safety margins above thresholds provides cushions for unexpected shocks, with pandemic experience validating crisis preparedness investments.

For Regulators and Policymakers: Chronic Power and Telecommunications distress throughout all periods signals that firm level interventions prove insufficient; sector wide policy reforms addressing structural issues are necessary. Z-score based early warning systems with semi-annual monitoring could enhance systemic risk detection, while crisis support programs using Z-score eligibility criteria would improve resource allocation efficiency.

8.4 Limitations

This research acknowledges the important limitations. First, the requirement for continuous data availability creates survivor bias by excluding bankrupt or delisted companies. The 30 company sample represents under one percent of NSE small-cap universe, limiting statistical power for subsector analysis while remaining adequate for temporal patterns and model concordance examination.

Second, exclusive reliance on Z-score and Z'' score models without comparing alternative approaches limits conclusions about relative performance. These backward-looking models may inadequately capture forward looking risks and exclude qualitative factors. The study lacks validation against actual bankruptcy outcomes, preventing calculation of predictive accuracy metrics.

Third, the six year observation window, though capturing a complete pandemic cycle, is relatively short for distinguishing secular trends from cyclical effects. COVID-19's unprecedented nature may limit generalizability to typical recessions. Additionally, findings reflect India specific institutional features that may not transfer to other emerging markets with different economic contexts and regulatory environments.

8.5 Directions for Future Research

The study identifies several promising avenues for extending this research:

Expanded Sample and Cross-Sectional Analysis: Studies with larger samples would enable deeper subsector analysis, enhanced statistical power for multivariate modeling, and stratified sampling ensuring proportional sectoral representation for broader population-level insights beyond the current focused longitudinal analysis.

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Multi-Model Comparative Studies: Incorporating alternative bankruptcy prediction models including Ohlson, Zmijewski, KMV-Merton, and machine learning approaches alongside Z-score variants would provide comprehensive model comparison, enable ensemble modeling, and investigate whether documented model disagreement patterns contain additional predictive information.

Longer-Term Longitudinal Extension: Extending observation windows beyond six years capturing multiple business cycles would enable life cycle analysis from small-cap through mid-cap graduation or exit paths and facilitate structural break analysis assessing whether pandemic recovery patterns represent sustained improvements or cyclical variations.

International Comparative Research: Replicating this methodology across emerging and developed markets would contextualize India-specific findings, distinguish universal emerging market characteristics from country-specific features, and enable comparative analysis of small-cap distress patterns, volatility, and crisis resilience across different institutional contexts.

8.6 Concluding Remarks

This research provides comprehensive empirical evidence on financial distress patterns in Indian small-cap companies through rigorous six year longitudinal analysis spanning the COVID-19 pandemic. The findings reveal substantial financial health heterogeneity with elevated distress rates compared to large caps, though most firms maintain sound positions. The documented V-shaped pandemic recovery trajectory challenges assumptions about small-firm fragility, demonstrating considerable adaptive capacity among survivor firms.

Methodologically, semi-annual measurements demonstrate clear value over annual assessments by capturing seasonal patterns, intra-year volatility, and crisis dynamics. The longitudinal panel design enables within-company temporal analysis inaccessible from cross-sectional approaches. The COVID-19 pandemic served as a natural experiment demonstrating small-cap resilience, validating policy support effectiveness, and revealing differential sectoral impacts.

The research contributes to bankruptcy prediction literature by extending validated models to Indian small-cap contexts, documenting necessary adaptations, quantifying model concordance, and analyzing temporal dynamics through major economic shocks. Practically, it provides actionable guidance for investors, creditors, corporate managers, and policymakers navigating India's dynamic small-cap landscape. While limitations constrain generalizability, the core contributions advance knowledge in corporate finance while generating actionable insights for stakeholders operating in emerging market environments.

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