

A Two-Stage Discriminant Analysis and Entropy-Weighting Approach to Combining Financial and Market Performance: Evidence from Listed SMEs on India's Dedicated Exchanges

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Abstract

This study constructs a Financial and Stock Market Performance Index (FSMPI) for 142 Indian SMEs listed on BSE SME and NSE Emerge across six fiscal years. Stepwise Discriminant Analysis, applied separately to financial and market variable pools using an external Profitable/Loss-Making classification, produces two sub-indices combined through entropy weighting to avoid circularity. Financial variables discriminate performance considerably more strongly than market variables ($R^2 = 0.460$ versus 0.063), and the two dimensions are related only weakly and non-linearly, pointing to genuine pricing inefficiency in this market segment and offering a transferable methodology for other emerging SME exchanges.

Keywords: SME exchanges, discriminant analysis, entropy weighting, composite index, India

1. Introduction

Dedicated SME stock exchanges have become a common policy instrument for channelling equity capital to growth-stage small and medium enterprises that fall short of main-board listing requirements. India established two such platforms in 2012 — BSE SME, launched in March, and NSE Emerge, launched in September — following a 2010 Prime Minister's Task Force recommendation, under a dedicated, deliberately lighter regulatory chapter of the SEBI (Issue of



Capital and Disclosure Requirements) Regulations. Over a decade later, several thousand companies have listed across the two platforms, yet the empirical literature on how these companies actually perform post-listing remains fragmented along a familiar disciplinary line: accounting-based studies examine financial ratios, and finance-based studies examine stock returns and risk, with very few attempts to integrate the two dimensions into a single, validated measurement instrument.

This fragmentation is not merely an academic inconvenience. A retail investor evaluating an SME-exchange listing, a market maker pricing inventory risk, or a regulator assessing whether a listing platform is functioning as intended each needs a combined view of company performance — not two separate, unreconciled pictures. The present study addresses this directly by constructing a Financial and Stock Market Performance Index (FSMPI) for a sample of 142 companies listed on BSE SME and NSE Emerge, observed across six fiscal years spanning a complete pre-pandemic, pandemic-shock, and recovery cycle (FY 2019-20 to FY 2024-25).

The methodological approach follows Altman's (1968) discriminant-analysis logic for corporate distress prediction, adapted here to a two-stage design: rather than building a single combined model across both financial and market variables, we construct two independent sub-indices — a Financial Performance Index (FPI) and a Stock Market Performance Index (SMPI) — using stepwise Discriminant Analysis applied separately to each variable domain, and combine them through an entropy-weighting procedure that does not depend on the classification variable either sub-index was built to predict. This design choice, detailed in the next section, is itself a contribution: it avoids a circularity that a single combined discriminant model, or a combination weighted by discriminatory power, would introduce.

The remainder of this paper proceeds as follows. The next section situates the study within the SME-exchange performance literature and details the data and five-stage FSMPI methodology. This is followed by the empirical results, a discussion of the central finding — a pronounced gap between the discriminatory power of the financial and market sub-indices — against theory and prior evidence, and a concluding section.

2. Literature Review

The Altman (1968) Z-score remains the methodological template for composite financial performance measurement: a broad ratio pool, reduced via discriminant analysis to a small set of empirically-weighted predictors of a binary outcome, building on the single-ratio precedent Beaver (1966) had established two years earlier. Applications of this logic to SME populations specifically remain comparatively rare and geographically scattered. A financial competitiveness index for Gujarat-based listed SMEs, built by Mehta and Brahmhatt (2019) using Principal Component



Analysis, identified profitability as the dominant driver of firm performance — a finding this study's own results independently corroborate through an entirely different technique. Leverage determinants tell a similar story elsewhere: across a large panel of European listed SMEs, Kenourgios, Karali and colleagues (2019) found profitability, asset structure, and firm size dominating capital structure outcomes regardless of country or size grouping, a result that lines up closely with the deleveraging pattern documented here for the Indian sample.

On the market side, the SME-exchange literature consistently points to structural features distinct from main-board markets: thin trading, weak analyst coverage, and correspondingly elevated noise in price discovery. In Korea's KOSDAQ SME segment, noise trading has been shown to dominate pricing altogether, magnifying idiosyncratic volatility well beyond what the main board experiences (Kim & Park, 2019). A parallel pattern shows up in transmission dynamics rather than volatility alone — Nguyen, Chaiechi, Eagle and Low (2020) traced significant bidirectional volatility transmission between SME-segment and main-market indices, conditioned throughout by thin trading effects — and in outright price shocks, with Saudi SME-exchange stocks found disproportionately exposed to illiquidity-driven swings (Bensoltane, 2023). The Indian evidence fits this broader pattern closely. Dhamija and Arora (2017) documented systematic post-listing performance differences between BSE SME and NSE Emerge, while Thukral, Kushwah and Bhatti (2025), working more recently and specifically on the NIFTY SME EMERGE index, confirmed statistically significant bidirectional volatility spillover with India's main board.

What this literature has not produced, to the authors' knowledge, is a validated composite index integrating both financial and market performance dimensions for a substantial cross-section of Indian listed SMEs. Existing Indian composite-index work addresses one dimension or the other, and existing dual-dimension observations — such as Ajith and Priya's (2023) GARCH-based volatility analysis of NIFTY SME EMERGE stocks during the COVID-19 period — do not extend to constructing a validated combined index across a full economic cycle. This is the specific gap the present study addresses, and its relevance extends beyond India to any emerging-market SME exchange where financial and market performance data are separately available but have not been integrated into a single instrument.

3. Data and Methodology

3.1. Sample and Study Period

The study population comprises 748 companies listed and actively trading on BSE SME or NSE Emerge as of 31 March 2020. Applying data-completeness and data-quality criteria — continuous listing status, availability of standalone audited financial statements for all six study years, and a minimum trading-days threshold per year to exclude the most severely thin-traded observations —



narrowed this population to a final sample of 142 companies, yielding 852 firm-year observations across FY 2019-20 to FY 2024-25. This six-year window was selected for two reasons: it is the earliest point at which sufficient post-2012 platform history existed to support a sample of this size with complete data, and it happens to span a full economic cycle — pre-pandemic conditions, the COVID-19 shock, and subsequent recovery — functioning as a natural robustness check on the constructed index.

3.2. Variable Pool and Multicollinearity Screening

Forty-eight candidate variables were computed from standalone audited financial statements and daily BSE/NSE price data: thirty-three financial ratios spanning profitability, liquidity, solvency, and efficiency, and fifteen stock market variables spanning return, risk, and risk-adjusted performance measures. Beta was estimated via ordinary least squares regression of each company's daily returns against its own listing platform's benchmark index — the NIFTY SME EMERGE index for NSE Emerge companies and the S&P BSE SME IPO index for BSE SME companies — rather than a single broad market index, on the reasoning that a platform-specific benchmark better reflects the trading dynamics each company actually participates in. The full candidate pool was screened for multicollinearity using the Variance Inflation Factor; four variables identified as structural or near-perfect duplicates of a retained counterpart were dropped prior to the discriminant procedure.

3.3. Sample Classification

Each firm-year observation was classified as Profitable or Loss-Making based on the sign of Net Profit Margin, an externally verifiable criterion requiring no algorithmic estimation. Of the 852 observations, 660 (77.5 per cent) were classified Profitable and 191 (22.4 per cent) Loss-Making, with one observation unclassified due to a data gap. This binary classification serves as the external grouping variable for the discriminant procedure described below, in the same structural role bankruptcy status served in Altman's (1968) original application.

Table 1: Sample Composition and Classification

Item	Value
Population (BSE SME + NSE Emerge, as of 31 Mar 2020)	748 companies
Final sample	142 companies

Item	Value
Panel size	852 firm-year observations (142 × 6 years)
BSE SME observations	492 firm-years (57.7%)
NSE Emerge observations	318 firm-years (37.3%)
Profitable classification	660 firm-years (77.5%)
Loss-Making classification	191 firm-years (22.4%)
Unclassified (data gap)	1 firm-year (0.1%)
Study period	FY 2019-20 to FY 2024-25 (6 years)

3.4. Two-Stage Discriminant Analysis

Stepwise Discriminant Analysis was applied independently to the financial and stock market variable pools, each using the Profitable/Loss-Making classification as the grouping variable. This departs deliberately from a single combined-pool model: pilot analysis indicated the two variable domains carry markedly different discriminatory power, and a single combined stepwise procedure would let the financial variables dominate variable selection by virtue of their considerably stronger group separation, silently suppressing the weaker but still informative market-side signal. Running the two domains independently keeps both visible.

The financial procedure reduced twenty-seven candidate ratios to six retained predictors — Return on Assets, EBIT Margin, Gross Profit Margin, Net Working Capital to Sales, Working Capital Turnover, and Debt-Equity Ratio — producing the Financial Performance Index:

$$FPI = 0.810 + 2.143 \cdot ROA + 0.358 \cdot EBIT \text{ Margin} - 0.239 \cdot Gross \text{ Profit Margin} + 0.030 \cdot NWC/Sales + 0.0002 \cdot WC \text{ Turnover} + 0.009 \cdot Debt-Equity \text{ Ratio}$$

The stock market procedure reduced nine candidate variables to three — Price-Earnings Ratio, Beta, and Average Daily Return — producing the Stock Market Performance Index:

$$SMPI = 0.708 + 0.0003 \cdot P/E + 0.173 \cdot Beta + 14.91 \cdot Average \text{ Daily Return}$$

Table 2: Retained Variables and Discriminant Coefficients

Sub-index	Retained Variable	Discriminant Coefficient
FPI	Return on Assets (ROA)	+2.143
FPI	EBIT Margin	+0.358
FPI	Gross Profit Margin	−0.239
FPI	Net Working Capital / Sales	+0.030
FPI	Working Capital Turnover	+0.0002
FPI	Debt-Equity Ratio	+0.009
SMPI	Price-Earnings Ratio	+0.0003
SMPI	Beta	+0.173
SMPI	Average Daily Return	+14.91

Note: FPI constant = 0.810; SMPI constant = 0.708. FPI reduced from 27 candidate ratios ($R^2 = 0.460$); SMPI reduced from 9 candidate variables ($R^2 = 0.063$).

3.5. Entropy-Weighted Combination

FPI and SMPI were combined into the overall FSMPI through an entropy-weighting procedure rather than a further discriminant step. A discriminant-based combination would have been circular: both sub-indices were already constructed to maximise separation on the same Profitable/Loss-Making classification, so weighting their combination by that same discriminatory criterion would double-count the same information. Entropy weighting instead assigns weight based purely on each sub-index's cross-sectional variation — an information-theoretic criterion entirely independent of the classification — following the same rationale Saini, Deora and Gadiya (2024) applied to a financial competitiveness index for listed Indian real estate companies. This produced weights of 30.7 per cent for FPI and 69.3 per cent for SMPI:

$$FSMPI = 0.307 \cdot FPI(\text{normalised}) + 0.693 \cdot SMPI(\text{normalised})$$

Both sub-indices were validated through discriminant classification accuracy and Wilks' Lambda: FPI achieved 81.3 per cent classification accuracy ($\Lambda = 0.858$) and SMPI achieved 77.9 per cent ($\Lambda = 0.933$), both significantly better than chance.

3.6. Hypothesis Testing

Thirteen hypotheses, tested at the 5 per cent significance level, examine year-wise and platform-wise differences in financial and market performance, the relationship between FPI and SMPI, the impact of the COVID-19 shock and subsequent recovery on FSMPI, and whether sector of listing moderates the FPI-SMPI relationship. One-way ANOVA tests year-wise differences; Welch's independent-samples t-test, robust to unequal variances, tests platform differences; paired-samples t-tests compare matched companies across the COVID-19 shock and recovery periods; Pearson and Spearman correlation jointly test the FPI-SMPI relationship; and a nested F-test on a moderated regression specification tests sector moderation.

4. Results

Financial Performance

Of seventeen financial ratios tested for year-wise differences, only Return on Equity ($F = 2.231$, $p = 0.049$) and Debt-Equity Ratio ($F = 3.228$, $p = 0.007$) showed statistically significant movement across the six study years; the remaining fifteen, spanning profitability, liquidity, and efficiency, showed none. Return on Equity rose from 3.9 per cent in FY 2019-20 to 10.5 per cent in FY 2024-25, dipping to near zero in the pandemic year. Debt-Equity Ratio fell steadily from 0.77 to 0.34, a sustained deleveraging trend. Financial performance, measured through FPI, did not differ significantly between BSE SME and NSE Emerge companies ($t = 1.670$, $p = 0.096$).

Stock Market Performance

Annual stock return differed significantly across the six study years ($F = 13.136$, $p < 0.0001$), moving from -16.2 per cent in FY 2019-20 to a peak of 82.1 per cent in FY 2022-23 before falling to 29.4 per cent in FY 2024-25. Beta differed significantly by platform ($t = -8.589$, $p < 0.0001$): NSE Emerge companies (mean 0.350) showed substantially higher systematic risk than BSE SME companies (mean 0.114). SMPI likewise differed significantly by platform ($t = -3.888$, $p = 0.0001$), NSE Emerge scoring higher (0.798) than BSE SME (0.768).

The FSMPI and Its Central Result

Table 3: Summary of Key Empirical Results

Result	Statistic
Financial Performance Index (FPI)	6 ratios retained; $R^2 = 0.460$; 81.3% classification accuracy; Wilks' $\Lambda = 0.858$

Result	Statistic
Stock Market Performance Index (SMPI)	3 variables retained; $R^2 = 0.063$; 77.9% classification accuracy; Wilks' $\Lambda = 0.933$
Entropy weights	FPI = 0.307; SMPI = 0.693
FPI-SMPI relationship	Pearson $r = 0.052$ (n.s.); Spearman $\rho = 0.240$ ($p < 0.0001$)
Platform comparison (BSE SME vs NSE Emerge)	No significant FPI difference; significant differences in Beta, SMPI, FSMPI (NSE Emerge higher throughout)
COVID-19 impact on FSMPI (FY19-20 vs FY20-21)	$t = -0.580$, $p = 0.563$ (not significant)
Post-pandemic recovery (FY20-21 vs FY24-25)	$t = -2.179$, $p = 0.032$ (significant)
Sector moderation of FPI-SMPI relationship	$F = 1.133$, $p = 0.342$ (not significant)

The gap between FPI's R^2 (0.460) and SMPI's R^2 (0.063) is the study's central empirical result. Financial ratios discriminate Profitable from Loss-Making companies substantially more strongly than market variables do — a sevenfold difference in explained variance between two sub-indices constructed on identical methodological footing.

Temporal Trend and Cross-Sectional Distribution

FSMPI rose from a panel mean of 0.363 in FY 2019-20 to a peak of 0.473 in FY 2023-24, before easing to 0.437 in the final study year — a trajectory broadly consistent with the annual-return cycle documented above, though considerably more muted, reflecting the composite's substantial financial-side weighting of company fundamentals that moved far less over the same period. The cross-sectional spread of average FSMPI across the 136 sample companies with sufficient panel coverage (a minimum of three study years) ranged from 0.789 for the highest-ranked company to 0.255 for the lowest, confirming the index produces genuine cross-company discrimination rather than clustering scores near a common mean. Sector-wise averages likewise varied meaningfully,

with renewable energy companies recording the highest mean FSMPI and financial services and healthcare sectors recording among the lowest, though sector was not found to significantly moderate the underlying FPI-SMPI relationship.

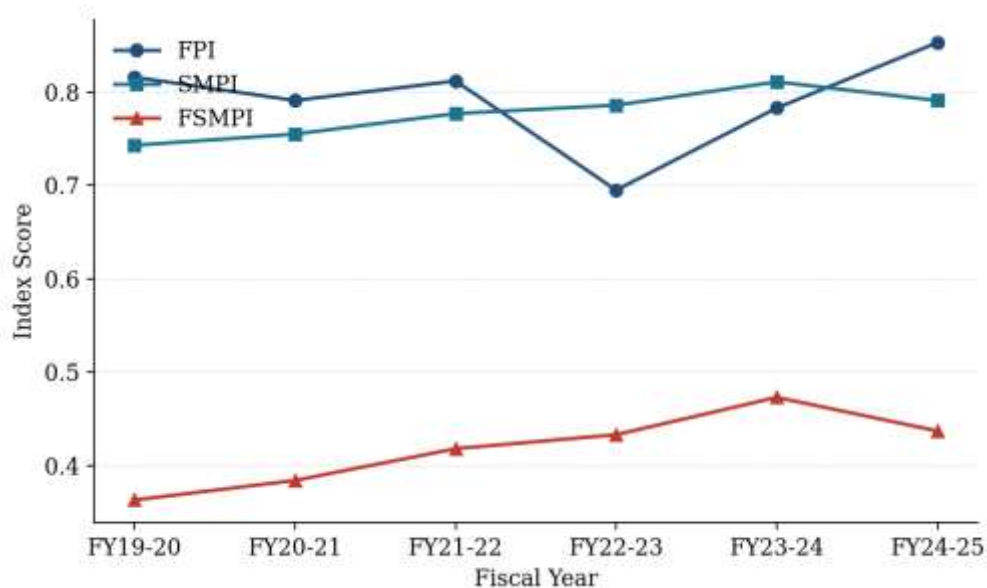


Figure 1: Year-wise Trend in FPI, SMPI, and FSMPI (FY 2019-20 to FY 2024-25)

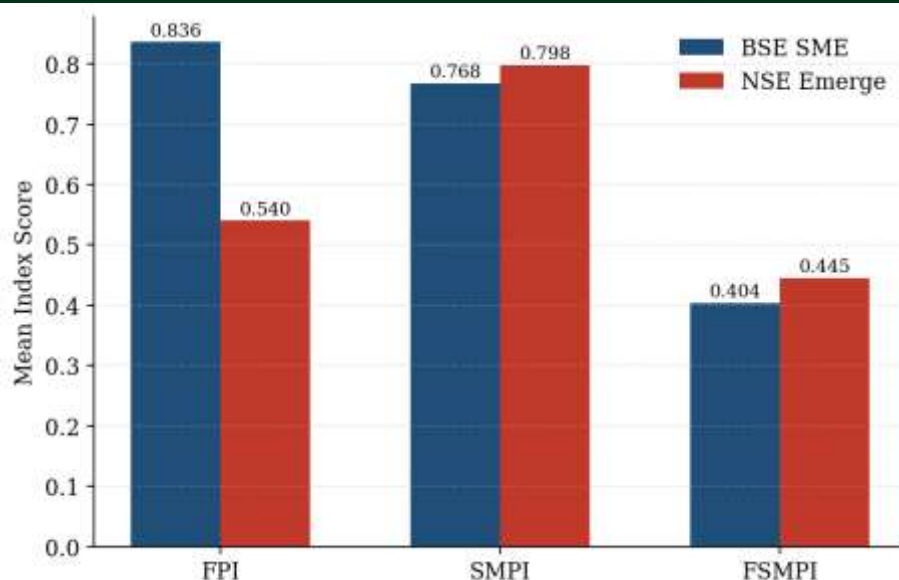


Figure 2: Mean FPI, SMPI, and FSMPI by Listing Platform

Table 4: Complete Hypothesis Testing Summary

Hypothesis	Tests	Statistic	Decision
H01–H04	Financial ratio groups across 6 years	F = 0.14–3.23	Rejected (ROE, Debt-Equity Ratio only)
H05	FPI by platform	t = 1.670, p = 0.096	Not rejected
H06	Annual return across 6 years	F = 13.136, p < 0.0001	Rejected
H07	Beta by platform	t = −8.589, p < 0.0001	Rejected (NSE Emerge higher)
H08	FPI-SMPI relationship	r = 0.052 (n.s.); p = 0.240 (p < 0.0001)	Rejected (monotonic only)

Hypothesis	Tests	Statistic	Decision
H09	SMPI by platform	$t = -3.888, p = 0.0001$	Rejected (NSE Emerge higher)
H010	COVID-19 impact on FSMPI	$t = -0.580, p = 0.563$	Not rejected
H011	FSMPI by platform	$t = -3.692, p = 0.0002$	Rejected (NSE Emerge higher)
H012	Post-pandemic recovery	$t = -2.179, p = 0.032$	Rejected
H013	Sector moderation of FPI-SMPI	$F = 1.133, p = 0.342$	Not rejected

5. Discussion

The pronounced R^2 gap between FPI and SMPI admits two non-exclusive interpretations. The first is genuine market inefficiency: consistent with Kim and Park's (2019) finding that noise trading dominates SME-segment pricing in Korea and Nguyen et al.'s (2020) evidence of thin-trading-conditioned volatility transmission, Indian SME-exchange stocks may simply be priced with only weak reference to current-period accounting profitability, reflecting thin trading and minimal analyst coverage rather than a flaw in variable selection. The second is that the market prices a different information set entirely — growth expectations, promoter reputation, or other forward-looking signals this study's variable pool does not capture. Both mechanisms are plausible and likely co-exist; what the data rule out with reasonable confidence is that SME-exchange market pricing tracks current profitability tightly, since an R^2 of 0.063 is inconsistent with a close relationship under either explanation.

This interpretation is reinforced by the weak, non-linear FPI-SMPI relationship documented directly: a non-significant linear correlation (Pearson $r = 0.052$) alongside a modest but highly significant monotonic one (Spearman $\rho = 0.240$) indicates the two performance dimensions are related, but not through a simple linear mechanism — a pattern consistent with Ajith and Priya's (2023) direct observation, for individual NSE Emerge companies during the COVID-19 period, that financial and market performance frequently diverge rather than move in lockstep.

The consolidated platform comparison — no significant financial-side gap between BSE SME and NSE Emerge, but a significant and consistent market-side gap across Beta, SMPI, and FSMPI —



is a single finding confirmed four times through independent measures, not four unrelated results. Read alongside Dhamija and Arora's (2017) documentation of a listing-quality differential between the two platforms, and Thukral, Kushwah and Bhatti's (2025) evidence of bidirectional volatility spillover specifically between NIFTY 50 and the NIFTY SME EMERGE index, the most defensible explanation is that whatever quality differential exists between the platforms expresses itself in market pricing and trading behaviour rather than in the accounting fundamentals of the companies each platform lists.

The absence of a significant FSMPI decline during the COVID-19 shock itself, alongside a statistically significant recovery by the end of the study period, should be read together rather than as an isolated null result: a significant recovery implies a trough existed to recover from, even where the initial shock-period test — likely constrained by its matched-pair sample size — could not confirm that trough was statistically distinguishable from the pre-pandemic baseline.

Two further results merit brief theoretical placement. First, the entropy-weighted combination assigns greater weight to SMPI (69.3 per cent) than to FPI (30.7 per cent) despite FPI's considerably stronger discriminatory power — an outcome that can appear counterintuitive until the two criteria are distinguished explicitly. Entropy weighting rewards cross-sectional variation, not classification accuracy; SMPI simply displays more genuine dispersion across companies once both sub-indices are normalised onto a common scale. Second, the steady deleveraging trend documented above, occurring alongside rising Return on Equity, is consistent with pecking-order behaviour under capital structure theory — internally generated funds substituting for debt as profitability improves — though the present design tests the pattern rather than the underlying mechanism directly.

6. Conclusion

This study constructs and validates the first composite index, to the authors' knowledge, integrating financial and stock market performance for a substantial cross-section of Indian listed SMEs. Its central contribution is twofold. Substantively, it establishes that financial and stock market performance are only weakly and non-linearly related for this population, with market pricing tracking current profitability considerably less closely than financial-ratio-based classification alone would suggest — a finding with direct relevance for retail investors, market makers, and exchange regulators currently relying on informal heuristics or single-dimension measures. Methodologically, it demonstrates a two-stage discriminant-analysis-and-entropy-weighting design as a workable alternative to a single combined model whenever two variable domains display markedly different discriminatory power, a design choice transferable to other emerging-market SME-exchange contexts facing the same underlying problem.

The study's limitations bear directly on the scope of these conclusions. The sample is confined to the 142 of 748 population companies meeting strict data-completeness criteria, and the excluded majority may differ systematically in ways this study cannot characterise. Return on Assets, the dominant FPI predictor, remains conceptually adjacent to the Net Profit Margin classification basis, introducing a residual circularity risk explicitly acknowledged rather than resolved. The design is descriptive-analytical, establishing association rather than causal mechanism. Future research extending this panel forward in time, incorporating governance and cash-flow-based variables as disclosure quality improves, and pursuing a causal identification strategy for the financial-market relationship documented here would each extend the present findings meaningfully.

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