An Empirical Risk and Return Analysis of BSE Broad Market Indices: Evidence From 2015–2024

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ABSTRACT

This study examines the risk-return characteristics of the BSE Broad Market Indices—BSE 100, BSE MidCap, and BSE SmallCap—using monthly data from January 2015 to December 2024 within the Indian equity market context. Employing log return analysis, CAPM regression, principal component analysis, and efficient frontier simulation, the paper evaluates performance, volatility, and diversification potential across these indices. The findings reveal that the MidCap and SmallCap indices deliver higher average returns alongside higher volatility, while the BSE 100 offers greater stability, appealing to risk-averse investors. CAPM analysis confirms significant betas, indicating strong co-movement with market movements, while PCA highlights the dominance of a market-wide factor influencing returns. Efficient frontier analysis demonstrates opportunities for investors to achieve enhanced risk-adjusted returns through diversified allocation across size segments. The results contribute to the literature on emerging market indices and provide practical guidance for investors seeking to align return objectives with risk tolerance in portfolio construction within the Indian equity market.

Key Words-BSE Indices; Risk-Return Analysis; CAPM; Principal Component Analysis; Indian Equity Market; Portfolio Diversification.

JEL Classification

G11; G12; G15; C32; C58

INTRODUCTION

The Indian equity market has experienced significant growth and diversification over the last decade. The Bombay Stock Exchange (BSE) offers a wide array of indices that represent various market capitalizations and sectors, giving investors tools for diversified investment strategies. While flagship indices like the SENSEX have been studied extensively, there is growing interest in evaluating the broader set of indices to understand how they perform across market cycles.

This paper initiates the empirical investigation into the Indian equity market by focusing on the BSE Broad Market Indices, which represent various segments of the market in terms of market capitalization and overall composition. These indices include the BSE 100, BSE MidCap and BSE SmallCap. Using monthly closing prices from December 2014 to December 2024, this paper evaluates the risk-return characteristics of these indices from January 2015 to December 2024.

Accordingly, this study aims to achieve the following objectives:

To analyze the risk-return characteristics of the BSE 100, BSE MidCap, and BSE SmallCap indices using monthly data over the period 2015–2024.

To evaluate the normality, autocorrelation, stationarity, and heteroskedasticity of the indices' returns to ensure the validity of subsequent econometric analysis.

To apply the Capital Asset Pricing Model (CAPM) and Principal Component Analysis (PCA) to assess the co-movement and underlying factor structure of the indices.

To construct an efficient frontier to identify optimal portfolio allocations that maximize risk-adjusted returns or minimize volatility across the indices.

To provide practical insights for investors regarding the diversification potential and risk-return dynamics of the BSE Broad Market Indices within the Indian equity market context.

LITERATURE REVIEW

Jayashree and Vijay (2025) examine four firms—Bajaj Finance, Shriram Finance, Chola Fin, and Bajaj Holdings—within the BSE Finance Index using monthly data. They find Bajaj Holdings exhibits lowest volatility and strongest correlation with the index, while Chola Fin shows the opposite. The study underscores sector-level variations in risk-return trade-offs. Their correlation and volatility analyses closely mirror our methods and provide empirical justification for segment-level index evaluation.

Lobo and Bhat (2021) analyze risk-return dynamics across Indian financial services stocks and find significant beta-driven differences, particularly highlighting IIFL Finance's higher returns relative to sector benchmarks. Their use of beta and comparative portfolio analysis offers a strong econometric complement to the CAPM and Jensen's Alpha frameworks in this study.

Komara et al. (2023) test CAPM on Indonesian infrastructure stocks and conclude that only 20 of 50 companies significantly explain returns via CAPM regression. Their findings on market inefficiencies help contextualize CAPM validation in emerging economies and reinforce our approach within the Indian context.

Sharma, Bhargava, and Sunail (2024) study Sensex stocks' risk-return and portfolio diversification, concluding that portfolio construction can outperform the Sensex in both return and risk metrics. This supports our findings on diversification benefits identified through PCA and optimized portfolios.

Xiao (2022) compares CAPM and Fama–French across international datasets, finding CAPM alone underperforms in emerging markets. This justifies our inclusive use of advanced statistical tools beyond CAPM—such as PCA and factor regression—in the Indian equity context.

Despite the valuable insights offered by previous research, a comprehensive and comparative analysis of BSE Broad Market Indices over a decade-long period remains limited. Most prior studies either focus on short-term horizons, select index or individual firms.

This study addresses this research gap by conducting a holistic, time-spanning risk-return analysis of BSE Broad Market Indices by applying modern quantitative tools to evaluate their investment potential and diversification benefits.

METHODOLOGY

Selection of indices and period of the study

This study conducts a comprehensive statistical analysis of the BSE 100, BSE MidCap, and BSE SmallCap indices using monthly closing price data from December 2014 to December 2024, with corresponding log returns calculated from January 2015 to December 2024. These three indices were chosen to ensure there is no overlap of constituent companies among them.

Data source

Monthly closing price data were retrieved from the official BSE India website (www.bseindia.com). To download the data, navigate to 'Historical Data' → 'Indices' → 'Indices Historical Prices', select the desired index and period (Daily/Monthly/Yearly), specify the date range, and download the dataset.

Data Preprocessing

All downloaded datasets were checked for completeness and consistency, and no missing monthly closing prices or data gaps were found during the period under study. The monthly closing prices for each index were organized in a single Excel sheet, with the first column indicating the period (December 2014 to December 2024) and the subsequent columns labeled as LargeCap, MidCap, and SmallCap. Log returns were calculated and were available from the second period onward, resulting in 120 monthly return observations for each index for the period January 2015 to December 2024.

Tests employed

The analyses include log return calculation, normality tests, autocorrelation tests, stationarity tests, ARCH effect tests, CAPM regression, and residual diagnostics.

Why log returns

Logarithmic returns are preferred over simple returns in financial modelling because they are time-additive, more statistically tractable, and often approximate a normal distribution better. This makes them particularly suitable for econometric models like CAPM. The log return is calculated using the formula:

$R_t = \ln(P_t / P_{t-1})$

Where P_t is the price at time t and P_{t-1} is the price at the previous time step, and ln denotes the natural logarithm.

ANALYSIS AND DISCUSSION

Descriptive Summary of Risk and Returns

Table 1: Average return and annualized volatility of indices

Index	Average Annual Return (%)	Annualized Volatility (%)
BSE 100 (LargeCap)	11.11%	16.56%
MidCap	16.17%	19.49%
SmallCap	17.41%	22.63%

Source: Calculated and Compiled by the authors using data from BSE India

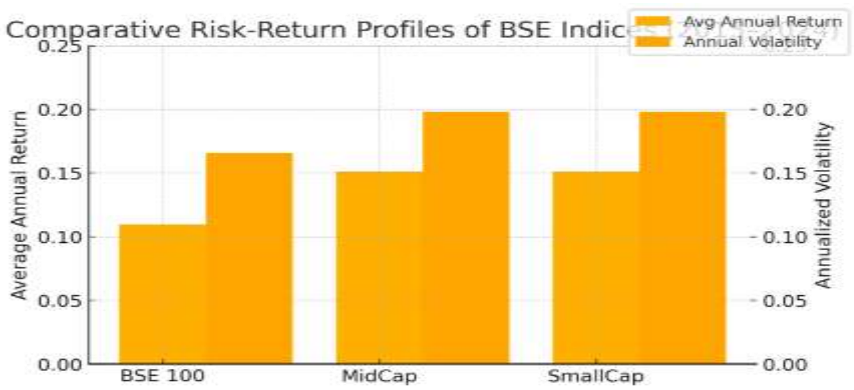

Figure 1: Comparative average annual return and annualized volatility for BSE 100, BSE MidCap, and BSE SmallCap indices (2015–2024).

Source: Computed by the authors using indices' returns data

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The descriptive analysis reveals that the BSE SmallCap index exhibits the highest average annual return of approximately 17.41% with an annualized volatility of 22.63%, followed by the MidCap index with an average return of 16.17% and volatility of 19.49%. The BSE 100 (LargeCap) index provides a comparatively lower return of 11.11% but with lower volatility of 16.56%, making it appealing to risk-averse investors. These observations align with the broader understanding that higher potential returns are typically accompanied by higher volatility, a finding consistent with subsequent CAPM and efficient frontier analyses presented in this study.

Normality Tests

Normality tests are essential to check if return distributions follow a bell curve, which underpins many statistical models. Three main tests were conducted:

Shapiro-Wilk Test (small-sample normality)

Jarque-Bera Test (based on skewness and kurtosis)

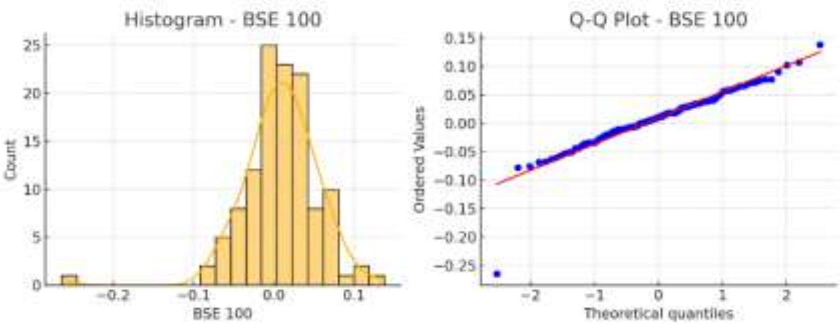
Kolmogorov-Smirnov Test (distribution shape comparison)

Additionally, histograms and Q-Q plots were used for visual inspection.

Table 2: Normality test results

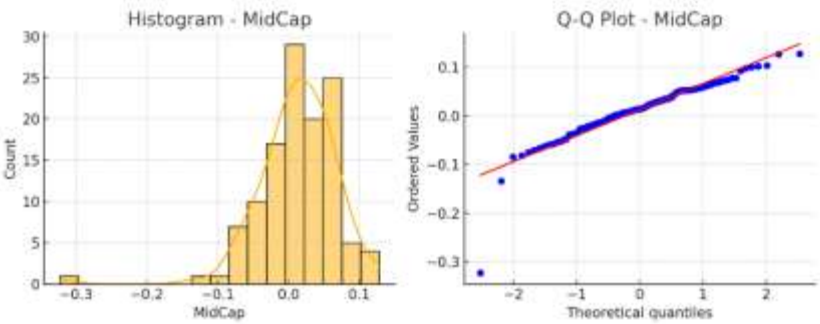
Index	Shapiro-Wilk p	Jarque-Bera p	K-S p	Skewness	Kurtosis
BSE 100	0.0000	7.88e-74	0.3817	-1.37	7.74
MidCap	0.0000	4.47e-108	0.4454	-1.82	9.25
SmallCap	0.0000	3.87e-74	0.2162	-1.73	7.46

Source: Calculated and Compiled by the authors using data from BSE India



Figures 2 and 3: Histogram and Q-Q Plot of BSE 100

Source: Computed by the authors using indices’ returns data



Figures 4 and 5: Histogram and Q-Q Plot of BSE MidCap

Source: Computed by the authors using indices’ returns data

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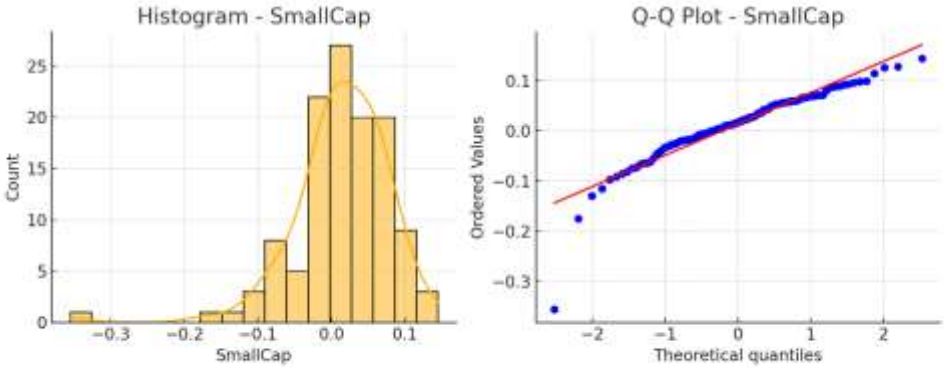

Figures 6 and 7: Histogram and Q-Q Plot of BSE SmallCap

Source: Computed by the authors using indices' returns data

The tests confirmed that none of the indices follow a normal distribution. This is evident from the skewed histograms, fat-tailed Q-Q plots, and very small p-values for Shapiro-Wilk and Jarque-Bera tests.

Autocorrelation Test

Autocorrelation measures the correlation between current and past returns. If returns are autocorrelated, they can be predicted from past values, violating weak-form market efficiency. We used the Autocorrelation Function (ACF) and the Ljung-Box Q-test (lag 12) to test for autocorrelation in monthly log returns.

Table 3: Autocorrelation test results

Index	Ljung-Box Stat	p-value
BSE 100	15.99	0.1917
MidCap	15.00	0.2416
SmallCap	14.43	0.2744

Source: Calculated and Compiled by the authors using data from BSE India

ACF Plots for Autocorrelation

Autocorrelation across 12 lags for each index.

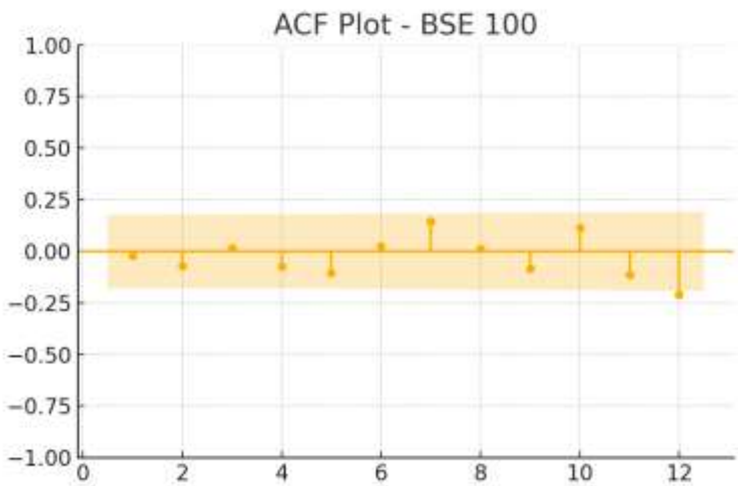

Figure 8: ACF Plot of BSE 100 index returns

Source: Computed by the authors using indices' returns data

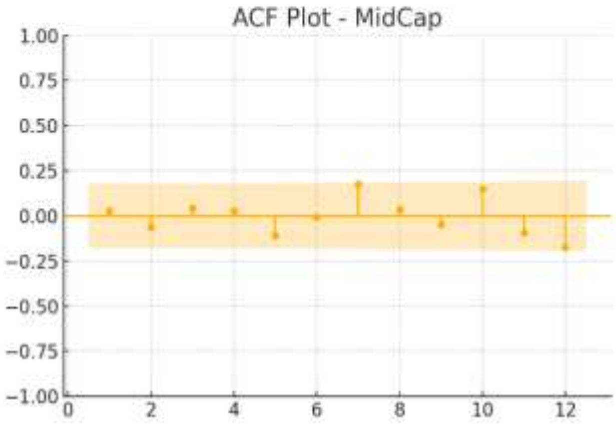

Figure 9: ACF Plot of BSE MidCap index returns

Source: Computed by the authors using indices' returns data

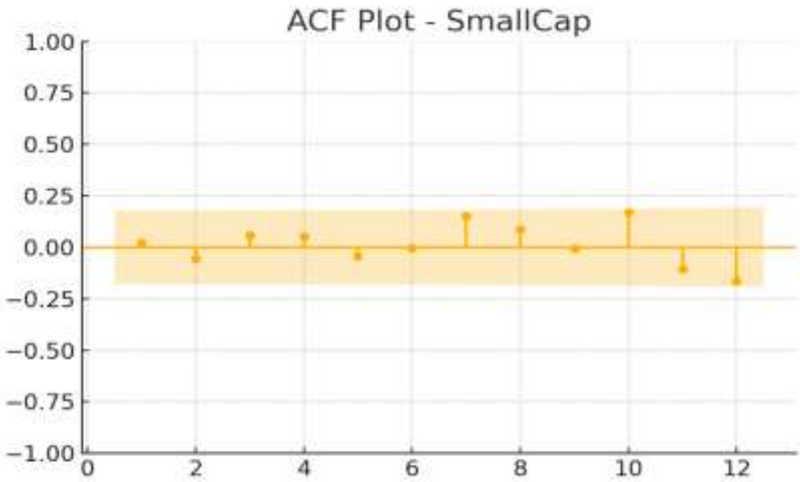

Figure 10: ACF Plot of BSE SmallCap index returns

Source: Computed by the authors using indices' returns data

The Ljung-Box test p-values were all above 0.05, and the ACF plots showed no significant autocorrelation, indicating that returns are serially independent.

Stationarity Test

Stationarity means the statistical properties (mean, variance) of a time series remain constant over time. Most time series models, including CAPM, require stationarity. We used the Augmented Dickey-Fuller (ADF) test to check for stationarity in the log return series.

Table 4: Stationarity test results

Index	ADF Statistic	p-value
BSE 100	-11.09	4.08e-20
MidCap	-10.52	9.86e-19
SmallCap	-10.58	7.13e-19

Source: Calculated and Compiled by the authors using data from BSE India

All three series are stationary with very low p-values, allowing further econometric modelling.

Heteroskedasticity and ARCH Effects

Heteroskedasticity occurs when volatility varies over time. ARCH (Autoregressive Conditional Heteroskedasticity) effects indicate volatility clustering, common in financial data. We visually inspected squared returns and ran the ARCH LM test (lag=12) to check for these effects.

Table 5: ARCH LM Stat results

Index	ARCH LM Stat	p-value
BSE 100	11.10	0.5200
MidCap	5.24	0.9493
SmallCap	5.22	0.9501

Source: Calculated and Compiled by the authors using data from BSE India

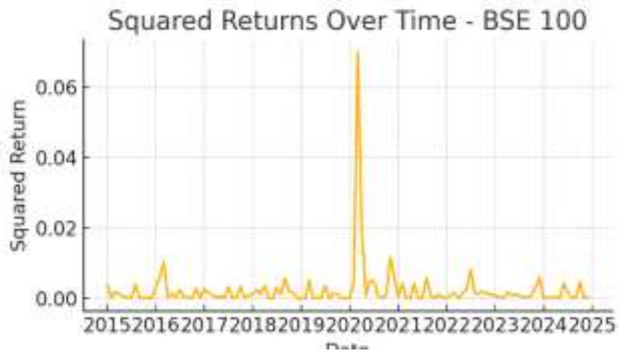

Figure 11: Squared returns over time – BSE 100

Source: Computed by the authors using indices' returns data

Figure 12: Squared returns over time – BSE MidCap

Source: Computed by the authors using indices' returns data

Figure 13: Squared returns over time – BSE SmallCap

Source: Computed by the authors using indices' returns data

None of the indices showed significant ARCH effects (all p-values > 0.5), suggesting volatility is not clustered

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monthly.

CAPM Regression and R-Squared Analysis

The Capital Asset Pricing Model (CAPM) estimates the relationship between excess returns of an asset and excess returns of the market. The model is given by:

$$R_i - R_f = \alpha + \beta (R_m - R_f) + \varepsilon$$

Where R_i is the return on the asset, R_f is the risk-free rate, R_m is the market return, α is Jensen's Alpha, and β is market sensitivity (Beta).

Monthly excess returns (over the 7% annual risk-free rate) for each index were calculated and the benchmark used is SENSEX.

Table 6: CAPM Analysis results

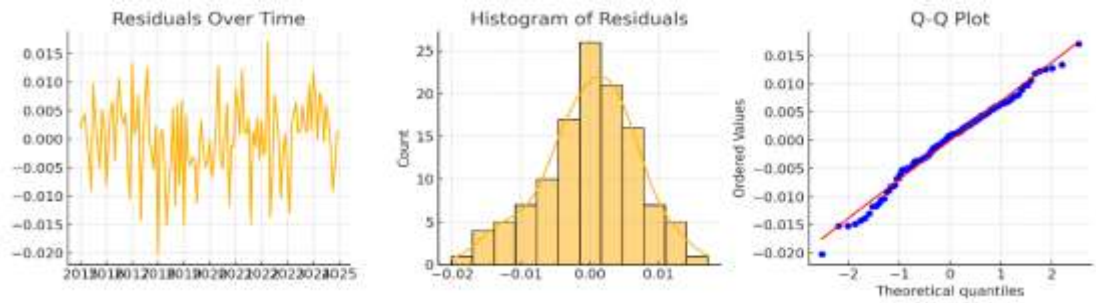
Index	Alpha	Beta	R^2	p(Alpha)	p(Beta)
BSE 100	0.0004	0.998	0.979	0.484	2.72e-101
MidCap	0.0037	1.034	0.760	0.148	2.54e-38
SmallCap	0.0043	1.110	0.649	0.225	1.39e-28

Source: Calculated and Compiled by the authors using data from BSE India

All three indices had statistically significant betas, showing strong co-movement with the market. However, none had significant alpha, indicating no consistent excess return after accounting for market risk.

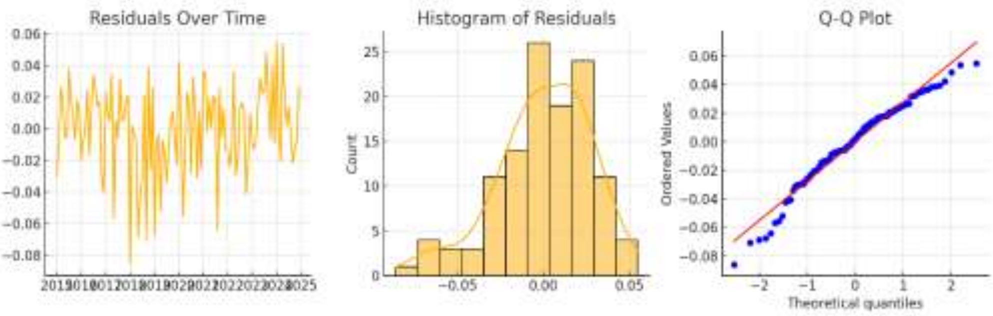
Residual Diagnostics

To validate the CAPM regressions, residuals were tested for independence, normality, and randomness using plots: time series, histogram, and Q-Q plot.



Figures 14, 15 and 16: Residual Diagnostic Plots for BSE 100

Source: Computed by the authors using indices' returns data



Figures 17, 18 and 19: Residual Diagnostic Plots for MidCap

Source: Computed by the authors using indices' returns data

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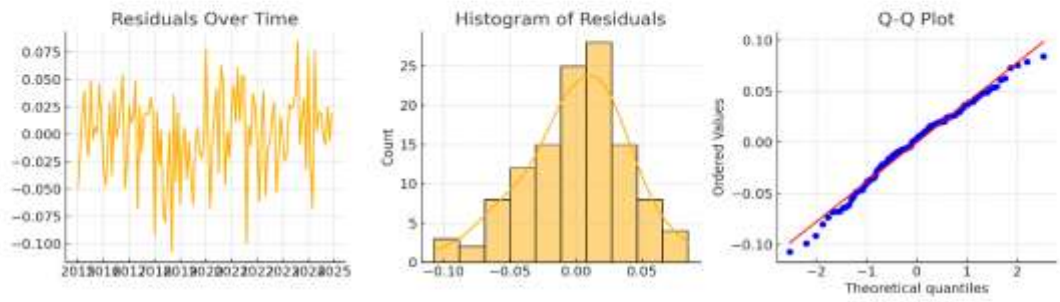


Figures 20, 21 and 22: Residual Diagnostic Plots for SmallCap

Source: Computed by the authors using indices' returns data

BSE 100 residuals appear nearly normal and randomly distributed. MidCap and SmallCap residuals show mild non-normality, mostly in tails. No autocorrelation or structure is evident, validating the regression assumptions.

Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is a dimensionality reduction technique used to identify the most important directions (components) in which data varies. Applied to the standardized monthly log returns of BSE 100, MidCap, and SmallCap, PCA helps identify shared factors and reduce noise or redundancy.

Table 7: PCA results

Principal Component	Explained Variance Ratio
PC1	0.9407
PC2	0.0498
PC3	0.0096

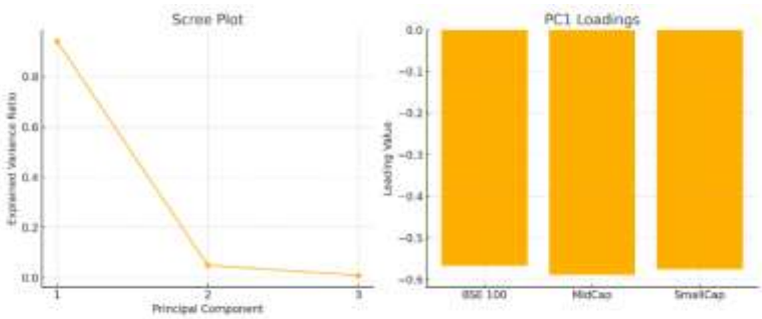
Source: Calculated and Compiled by the authors using data from BSE India

The following table shows the component loadings for each principal component:

Table 8: Principal Component Loadings

Component	BSE 100	MidCap	SmallCap
PC1	-0.5673	-0.5889	-0.5757
PC2	0.7751	-0.1457	-0.6148
PC3	-0.2781	0.7950	-0.5391

Source: Calculated and Compiled by the authors using data from BSE India



Figures 23 and 24: Scree Plot and PC1 Loadings for BSE 100, MidCap and SmallCap

Source: Computed by the authors using indices' returns data

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Principal Component Analysis (PCA) was conducted on the standardized monthly log returns of BSE 100, BSE MidCap, and BSE SmallCap indices to identify latent factors driving their movements. The analysis revealed that the first principal component (PC1) explained approximately 94.07% of the total variance, indicating the presence of a dominant underlying factor common to all three indices—likely overall market behavior. The second and third components explained only 4.98% and 0.96% of the variance, respectively, suggesting that the incremental informational value of additional components is minimal. The loadings on PC1 were high and similar across all indices, further confirming the presence of strong comovement. This implies that despite differing market capitalization focuses, the BSE 100, MidCap, and SmallCap indices are largely driven by a shared market dynamic. Such findings justify the use of a single-factor model like CAPM and also signal potential redundancy in using all three indices simultaneously in portfolio construction or risk modeling.

Efficient Frontier Analysis

The efficient frontier represents a set of portfolios that offer the highest expected return for a given level of risk. Based on the historical log returns of BSE 100, MidCap, and SmallCap indices from January 2015 to December 2024, we constructed an efficient frontier using a simulation of 10,000 random portfolio weight combinations. Each portfolio's expected annual return, risk (volatility), and Sharpe ratio (assuming a 7% annual risk-free rate) were calculated.

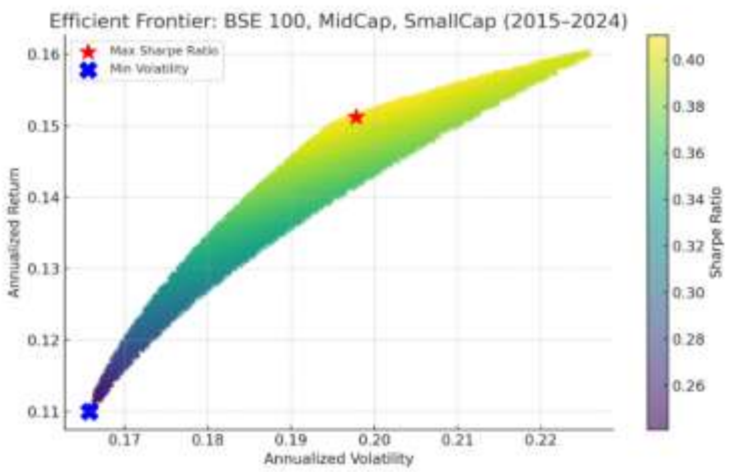

Figure 25: Efficient frontier - BSE 100, MidCap and SmallCap

Source: Computed by the authors using indices' returns data

Efficient Frontier with Max Sharpe Ratio and Min Volatility Portfolios

The following table summarizes the composition and performance of the optimal portfolios:

Table 9: Efficient frontier analysis results

Portfolio Type	BSE 100 Weight	MidCap Weight	SmallCap Weight	Expected Return	Volatility	Sharpe Ratio
Max Sharpe Ratio	0.0003	0.8730	0.1266	0.1512	0.1978	0.4107
Min Volatility	0.9934	0.0036	0.0030	0.1100	0.1658	0.2411

Source: Calculated and Compiled by the authors using data from BSE India

The efficient frontier analysis reveals that the maximum Sharpe ratio portfolio is dominated by the MidCap index (approximately 87%), indicating its strong return potential relative to risk. Meanwhile, the minimum volatility portfolio is overwhelmingly weighted towards BSE 100 (approximately 99%), confirming its role as

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the most stable index among the three. This analysis demonstrates the usefulness of diversification and highlights the risk-return characteristics of each index.

Supplementary Statistical Tests on BSE Index Log Returns

This section presents additional statistical tests conducted on the monthly log returns of BSE 100, MidCap, and SmallCap indices over the period January 2015 to December 2024. The purpose is to assess market efficiency, average return significance, and variance comparability.

Variance Ratio Test (Lag = 2)

The Variance Ratio test evaluates whether the return series follows a random walk. A ratio close to 1 indicates random walk behavior. Values significantly above or below 1 suggest serial correlation.

Table 10: Variance ratio test results

Index	Variance Ratio
BSE 100	1.1637
MidCap	1.1800
SmallCap	1.1578

Source: Calculated and Compiled by the authors using data from BSE India

All three indices exhibit mild deviations from 1, indicating weak short-term autocorrelation. This does not strongly violate the assumption of market efficiency.

T-Test for Mean Return Significance:

A one-sample t-test was performed to check if the average monthly log return is significantly different from zero.

Table 11: T-test results

Index	t-statistic	p-value
BSE 100	2.0939	0.0384
MidCap	2.4329	0.0165
SmallCap	2.2424	0.0268

Source: Calculated and Compiled by the authors using data from BSE India

All indices show statistically significant positive mean returns at the 5% level, suggesting the average returns are not zero.

Variance Equality Tests

Levene’s and Bartlett’s tests were used to check if the return variances across the indices are statistically equal. Bartlett’s test is sensitive to deviations from normality but is more powerful when that assumption holds.

Table 12: Variance equality tests’ results

Test	Statistic	p-value
Levene’s Test	2.8372	0.0599
Bartlett’s Test	11.4138	0.0033

Source: Calculated and Compiled by the authors using data from BSE India

Bartlett's test indicates strong evidence of unequal variances across the indices, confirming that volatility characteristics differ significantly, especially between large-cap and small-cap segments.

CONCLUSION

This study provides an empirical analysis of the BSE 100, BSE MidCap, and BSE SmallCap indices over 2015–2024 using advanced statistical methods. The results confirm that MidCap and SmallCap indices offer higher average returns with higher volatility, while the BSE 100 provides lower volatility and greater stability. CAPM analysis indicates significant market co-movement across all indices, and PCA confirms a dominant market-wide factor influencing returns. Efficient frontier analysis highlights that MidCap-heavy portfolios can enhance risk-adjusted returns, while BSE 100-heavy portfolios minimize volatility.

Overall, the findings demonstrate that these indices present differentiated yet complementary risk-return profiles, enabling investors to construct diversified portfolios aligned with their risk tolerance and return objectives within the Indian equity market.

When compared with similar studies in other emerging markets such as Indonesia (Komara et al., 2023) and China (Xiao, 2022), the risk-return dynamics of the BSE indices align with typical emerging market characteristics, exhibiting higher returns accompanied by higher volatility and strong market co-movement. These similarities emphasize the relevance of robust diversification strategies and the applicability of CAPM within emerging economies.

Limitations and Future Scope

This study is based solely on historical price data and does not incorporate macroeconomic or behavioral factors that may influence index performance.

Additionally, the analysis is limited to BSE Broad Market Indices and does not include comparisons with NSE or global indices, which may affect the generalizability of the findings.

Future research could incorporate multi-factor models using macroeconomic variables such as interest rates, inflation, and GDP growth to assess index sensitivities.

Comparative studies with global and sectoral indices may further enhance understanding of diversification opportunities.

Incorporating market sentiment or machine learning approaches could also provide deeper insights into dynamic risk-return relationships in the Indian equity market.

Author Contributions

All authors contributed equally to the conception, analysis, writing, and revision of this manuscript.

Conflict of Interest

The authors declare no conflict of interest related to this work.

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