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Market efficiency and sectoral heterogeneity in the BSE 100 ESG Index: a time-series and Fama–French factor approach

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Abstract

Purpose – This study examines the weak-form market efficiency, factor-driven return behaviour and sectoral financial performance of the BSE 100 ESG Index in India.

Design/methodology/approach – The study adopts a quantitative research design using secondary data. Monthly-closing values of the index from October 2017 to November 2025 were analysed using ARIMA modelling, autocorrelation diagnostics, Ljung–Box statistics and the Wald–Wolfowitz runs test to evaluate weak-form market efficiency. The Fama–French three-factor model was employed to assess risk-adjusted returns using market (MF), size (SMB) and value (HML) factors. Sectoral financial differences among constituent firms were examined through one-way analysis of variance (ANOVA) and Duncan post hoc analysis using indicators such as dividend yield, quarterly sales and return on capital employed (ROCE).

Findings – The ARIMA (0,1,0) model, insignificant runs test and non-significant autocorrelation structure indicate that the index follows a random walk process, supporting the weak-form efficient market hypothesis. The Fama–French model was statistically significant, with the market factor exerting a strong positive influence on ESG excess returns. The size factor showed a significant negative relationship, indicating large-cap dominance, while the value factor and alpha were insignificant. Sectoral analysis revealed significant differences, with energy leading in sales and dividend yield, and FMCG and industrials demonstrating higher capital efficiency.

Originality/value – The study contributes to the ESG literature in developing economies by integrating market efficiency testing, multifactor asset pricing and sectoral financial evaluation within the Indian ESG context.

Keywords ESG investing, BSE 100 ESG index, Weak-form market efficiency, Fama–French three-factor model, ARIMA, ESG sectoral performance

Paper type Research article

Introduction

Environmental, social and governance (ESG)-focused indices have gained considerable prominence in global and Indian capital markets as investors increasingly incorporate sustainability considerations into their investment decisions. ESG ratings and indices have become important instruments in sustainable finance, influencing investment strategies and encouraging firms to improve their sustainability practices (Pagano *et al.*, 2018). Global ESG investment has grown substantially over the past decade (GSIA, 2012–2020; US-SIF, 2020; Kishan, 2022). However, concerns remain regarding the credibility and comparability of ESG

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assessments due to differences in rating methodologies and potential conflicts of interest among ESG data providers. Agrawal *et al.* (2025) showed that incentives associated with ESG index licencing can influence ESG ratings, raising concerns regarding transparency and the reliability of ESG evaluations.

The BSE 100 ESG Index represents companies from the BSE 100 universe that satisfies ESG and controversy screening criteria, with constituents selected based on sustainability assessments and weighted by float-adjusted market capitalisation (BSE India, n.d.). As ESG indices incorporate sustainability-based selection criteria, their sectoral composition and constituent weights may differ from conventional indices. For instance, the S&P BSE 100 ESG Index has shown differences in sector allocation compared with its benchmark, with greater representation in sectors such as financials and information technology, which may influence its investment performance characteristics (S&P Global, 2020).

ESG indices have demonstrated risk-return characteristics comparable to conventional indices, with some regional ESG indices achieving higher returns and lower volatility under certain market conditions (Hong Kong Exchanges and Clearing Limited, 2020). Similarly, ESG portfolios in India have been found to exhibit lower systematic risk and greater resilience during market downturns, although their abnormal returns are not statistically significant (Hasan *et al.*, 2025). Evidence from developed and emerging markets also suggests that ESG indices can provide better risk-adjusted returns and stronger downside risk protection compared to broad market benchmarks (Gupta and Chaudhary, 2023). Furthermore, ESG stock indices exhibit different volatility responses across regions during periods of geopolitical uncertainty, highlighting the importance of diversification in ESG investment strategies (Karkowska and Urjasz, 2025).

Although previous studies have examined ESG investment performance, risk characteristics and return behaviour using asset-pricing models, relatively limited attention has been given to the weak-form market efficiency of ESG indices, particularly in the Indian context. Whether the BSE 100 ESG Index follows a random walk and efficiently incorporates publicly available information remains an important empirical question. This study addresses this gap by examining the weak-form market efficiency of the BSE 100 ESG Index using time-series techniques, while also evaluating factor-driven returns and sectoral financial differences.

Literature review

Research on ESG indices and sustainable finance has grown rapidly because of their increasing role in capital allocation and investment decisions. ESG indices encourage investment in sustainable firms and promote better sustainability disclosure, making them an important part of modern financial markets (Pagano *et al.*, 2018). However, findings on their financial performance remain mixed. Some studies report only a weak relationship between ESG scores and stock returns, while others find that ESG indices perform similarly to conventional market indices, suggesting that sustainable investing does not reduce financial performance (La Torre *et al.*, 2020; Jain *et al.*, 2019). Evidence also indicates that ESG screening does not consistently outperform or underperform conventional benchmarks (Charles *et al.*, 2016). At the same time, ESG indices have shown stronger rolling annual returns, lower downside risk and reduced volatility over the long term, highlighting their potential for better risk-adjusted performance (Gupta and Chaudhary, 2023). Integrating ESG indices with renewable energy portfolios has also been found to improve risk-adjusted returns and hedging effectiveness, further supporting the value of ESG investments in portfolio management (Liu and Hamori, 2020).

Market efficiency has become another important area of ESG research, particularly during periods of economic uncertainty and financial crises. Evidence from India suggests that ESG indices have shown strong long-term growth, close integration with the broader market and improved informational efficiency following the COVID-19 pandemic (Singh and Maurya, 2021; Vadithala and Tadoori, 2021). However, studies from international markets indicate that informational efficiency declined in many regions during the pandemic, although European markets remained relatively more efficient (Naeem *et al.*, 2023). ESG indices also generated positive returns during the COVID-19 period and provided useful hedging benefits, although they did not consistently act as safe-haven assets across all markets (Rubbaniy *et al.*, 2022; Piserà and Chiappini, 2024).

Recent research further suggests that market efficiency is influenced by sustainability-related uncertainty and climate risks. Sustainability uncertainty is closely linked with broader global economic uncertainty, while climate-related uncertainty improves the prediction of ESG market volatility, indicating that ESG markets are increasingly sensitive to environmental risks (Ongan *et al.*, 2025; Wang and Li, 2023).

Differences in ESG performance across countries, industries and sectors further highlight the importance of sector-level analysis. Developed regions generally report stronger ESG performance than many emerging economies because of differences in governance and social conditions (Jiang, 2024). At the firm level, better ESG performance is associated with stronger stock market performance, particularly among non-state-owned firms and companies in secondary industries. Firms with higher ESG scores also tend to achieve greater profitability, lower risk and stronger governance practices (Deng and Cheng, 2019; Kurnoga *et al.*, 2022). In addition, competitive market environments encourage better environmental performance and higher operational efficiency, whereas greater market power is associated with weaker overall ESG performance (Moskovics *et al.*, 2024).

Recent studies also suggest that ESG characteristics influence stock prices and expected returns, highlighting the importance of factor-based asset-pricing models in explaining ESG-related returns. Strong ESG performance can reduce undervaluation but may also increase overvaluation because sustainability information is increasingly reflected in market prices (Bofinger *et al.*, 2022). Investor preference for sustainable firms can also create pricing differences, leading to stronger future performance for undervalued low-ESG stocks and relatively weaker returns for highly valued ESG stocks. These findings suggest that ESG-related factors should be considered in asset-pricing models (Cao *et al.*, 2019).

Disclosure quality and regulatory policies also play an important role in ESG investing. While ESG disclosures improve firm performance during periods of crisis, they do not always reduce information asymmetry (Carnini Pulino *et al.*, 2022). Institutional investors increasingly recognise climate risks as financially important although their integration into investment decisions is still developing. At the same time, carbon-intensive firms face higher costs of downside risk protection when public attention to climate issues increases (Krueger *et al.*, 2020; Ilhan *et al.*, 2021). Challenges such as high fund management fees, unclear disclosures and limited transparency in voting practices also raise concerns about the credibility and effectiveness of some ESG investment products (Reiser and Tucker, 2019). Improving the quality of ESG disclosures can enhance investment efficiency, but excessive disclosure may not produce additional benefits. Effective climate policies also depend on reliable and comparable ESG information, while differences in ESG rating methods continue to reduce market transparency and highlight the need for stronger regulatory oversight (Xue, 2025; Rogge and Ohnesorge, 2022).

Although previous studies have examined ESG performance, market efficiency, sectoral differences and asset pricing from different perspectives, limited research has integrated these dimensions within a single framework. Moreover, evidence on the Indian BSE 100 ESG Index remains limited despite the growing importance of sustainable investing in India. This study addresses these gaps by examining the market efficiency of the BSE 100 ESG Index using time-series techniques, analysing factor-driven returns through the Fama–French three-factor model and comparing financial performance across sectors to provide a comprehensive understanding of sectoral heterogeneity in the Indian ESG market.

Data and methodology

This study adopts a quantitative research design to examine market efficiency and sectoral performance within the BSE 100 ESG Index. The study relies entirely on secondary data. The list of constituent securities for the BSE 100 ESG Index was obtained from the official BSE Indices website (https://www.bseindices.com/constituents/code/101).

To evaluate the factor-driven behaviour of ESG returns, monthly Fama–French factor data comprising the market factor (MF), small minus big (SMB), high minus low (HML), risk-free rate (RF) and momentum factor (WML) were obtained from the Indian Institute of Management Ahmedabad Fama–French Data Library (Agarwalla *et al.*, 2013). Monthly-closing values of the BSE 100 ESG Index for the period from October 2017 to November 2025 were used for time-series analysis and market efficiency testing. Monthly data were employed instead of daily observations to reduce short-term market microstructure noise, minimise excessive volatility associated with high-frequency trading and maintain consistency with the frequency commonly adopted in Fama–French factor construction and long-horizon asset-pricing studies.

Firm-level financial indicators – including current market price, valuation ratios, profitability measures and quarterly performance metrics – were cross-verified using publicly available information from Screener.in (https://www.screener.in/company/1017/).

Monthly-closing values of the BSE 100 ESG Index were analysed using IBM SPSS Statistics. The expert modeller procedure was used to automatically identify the optimal forecasting model among ARIMA and exponential smoothing alternatives; the model selection was based on Bayesian information criterion (BIC) and diagnostic checks. The expert modeller selected an ARIMA (0,1,0) specification, and model adequacy was evaluated through Ljung–Box Q-tests, R-squared, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) statistics to confirm residual independence and predictive accuracy.

For the sectoral analysis, company-level financial indicators sourced from the BSE 100 ESG Index constituents were aggregated into macro-economic sectors. Using SPSS, descriptive statistics were generated for variables including the P/E ratio, market capitalisation, quarterly profit growth, quarterly sales growth, and return on capital employed (ROCE). To examine whether sector-wise differences were statistically significant, one-way analysis of variance (ANOVA) was conducted separately for dividend yield (%) and ROCE (%), followed by Duncan multiple range post hoc tests to identify homogeneous subsets and sources of variation across sectors.

Research objectives

(1) To evaluate whether the BSE 100 ESG Index is weak-form efficient by analysing its time-series properties using ARIMA and expert modeller approaches, autocorrelations, partial autocorrelations and Wald–Wolfowitz runs test for weak-form market efficiency.

(2) To examine the risk-return characteristics of +the BSE 100 ESG Index using the Fama–French three-factor model by assessing the influence of market, size and value factors on excess returns.

(3) To examine sectoral differences in financial and valuation performance among companies included in the BSE 100 ESG Index (profitability, growth, sales, valuation multiples, market capitalisation, ROCE, dividend yield).

(4) To identify which sectors outperform or underperform within the BSE 100 ESG framework, using statistical tests such as ANOVA and post hoc analysis.

Period of the study

(1) The monthly-closing value of BSE 100 ESG from the month of inception October 2017 till November 2025–98 Months.

(2) Monthly Fama–French factor data comprising market factor (MF), small minus big (SMB), high minus low (HML), risk-free rate (RF) and momentum factor (WML) were obtained for the corresponding study period.

(3) Sectoral performance data – P/E ratio, dividend yield, as on 17th November 2025, ROCE for the financial year 2024-25, net profit Q2 FY-25–26, sales Q2 FY-25–26.

Results

Time-series modelling of BSE 100 ESG index

To analyse the temporal behaviour and forecast the movement of the BSE 100 ESG Index, monthly-closing values from the index's inception to the most recent period were subjected to time-series modelling using the expert modeller procedure in IBM SPSS Statistics (IBM Corp, 2022). The objective was to identify the best-fitting model following the Box–Jenkins time-series framework (Box *et al.*, 2015) and assess its forecasting performance.

Ho. The BSE 100 ESG Index follows a random walk process, and past price movements do not significantly predict future price movements.

The expert modeller automatically evaluated a range of ARIMA and exponential smoothing models and selected the ARIMA (0,1,0) specification as the most suitable based on the BIC and other fit diagnostics. The ARIMA (0,1,0) model indicates that the series follows a random walk process, consistent with the classical theory of stochastic price movements in financial markets (Fama, 1970, 1991). In other words, the best forecast for the next period is the most recent observed value, adjusted for random variation.

Table 1 presents the key model statistics. The model achieved a high coefficient of determination ($R^2 = 0.984$), indicating that it explained 98.4% of the variation in the series during the estimation period. The (MAPE of 3.50% and the RMSE of 11.42 indicate a strong level of predictive accuracy. The Ljung–Box Q (18) statistic yielded a *p*-value of 0.415. As the Ljung–Box test evaluates residual autocorrelation (Ljung and Box, 1978), the insignificant *p*-value confirms that the model residuals are free from serial correlation, validating that ARIMA (0,1,0) adequately captures the structure of the data. No significant outliers were detected.

Interpretation and implications

The empirical findings provide strong evidence in support of the null hypothesis and suggest that the BSE 100 ESG Index follows a random walk process consistent with the weak-form efficient market hypothesis proposed by Fama (1970, 1991). Historical price movements contain limited predictive power, and fluctuations primarily reflect the entry of new information into the market. The absence of seasonality or deterministic trends implies that index fluctuations are primarily driven by new information and market dynamics rather than predictable cyclical behaviour.

Given the high R^2 and low forecast error metrics, the model provides a reliable framework for short-term forecasting of the ESG index. However, since ARIMA (0,1,0) is equivalent to a random walk process with no mean reversion (Box *et al.*, 2015; Hamilton, 2020), long-term forecasts tend to become unreliable, consistent with the efficiency-driven unpredictability emphasised by Fama (1970, 1991). This is consistent with the financial econometrics' literature, which shows that random-walk models perform reasonably well for short-term prediction but deteriorate over longer horizons due to cumulative variance (Taylor, 2011; Campbell *et al.*, 1998).

Table 1. Model adequacy and fit

Model statistics										
		Model fit statistics					Ljung–box Q (18)			
Model	Number of predictors	Stationary *R*-squared	*R*-squared	RMSE	MAPE	MAE	Statistics	DF	Sig.	Number of outliers
Close-Model_1	0	0.000	0.984	11.418	3.499	8.636	18.627	18	0.415	0

The results suggest that ESG-screened securities in India are not systematically mispriced based on historical information and that sustainability-related disclosures are incorporated relatively efficiently into prices.

Wald–Wolfowitz runs test for weak-form market efficiency

To examine whether the BSE 100 ESG index exhibits weak-form market efficiency, the monthly-closing prices from October 2017 to November 2025 ($N = 98$) were analysed using the Wald–Wolfowitz runs test. This non-parametric test is widely used to assess the randomness of a sequence of observations without assuming a particular distribution, thereby providing insights into serial dependence in financial time series (Bradley, 1960; Wald and Wolfowitz, 1940).

Test Formula

Let:

(1) n_1 = number of observations below the cut-off (e.g. median)

(2) n_2 = number of observations at or above the cut-off

(3) R = observed number of runs.

The **expected number of runs** under randomness is:

$$E(R) = \frac{2n_1n_2}{n_1 + n_2} + 1$$

The **standard deviation** of runs is:

$$\sigma_R = \sqrt{\frac{2n_1n_2(2n_1n_2 - n_1 - n_2)}{(n_1 + n_2)^2(n_1 + n_2 - 1)}}$$

The **z-statistic** is calculated as

$Z = \frac{R - E(R)}{\sigma_R}$ A |Z|-value greater than the critical value (e.g. 1.96 at 5% significance) indicates rejection of H_0, suggesting the sequence is not random.

H0. The sequence of monthly-closing prices of the BSE 100 ESG Index follows a *random walk*

H1. The sequence of monthly-closing prices of the BSE 100 ESG Index does not follow a random walk (i.e. there is serial dependence or pattern in the returns).

The runs test was employed to assess the randomness of price movements in the BSE 100 ESG Index using the first-differenced closing prices (Refer Tables 2 and 3). The median value (2.78) was used as the reference point for the test. The results indicate that the number of runs observed (47) does not differ significantly from the number expected under randomness, with

Table 2. Descriptive statistics

	N	Mean	Std. Deviation	Minimum	Maximum	Percentiles 25th	50th (median)	75th
Monthly first-differenced closing values	97	2.7334	11.41786	−41.20	28.56	−3.995	2.7800	10.6750

Table 3. Runs test

	Monthly first-differenced closing values
Test value[a]	2.78
Cases < Test value	48
Cases ≥ Test value	49
Total cases	97
Number of runs	47
Z	−0.509
Asymp. sig. (2-tailed)	0.611

Note(s): [a]Median

a Z-statistic of −0.509 and a corresponding *p*-value of 0.611. Since the *p*-value exceeds the 0.05 significance threshold, the null hypothesis of randomness cannot be rejected.

This outcome suggests that the series of price changes does not exhibit statistically detectable patterns or serial dependence. In other words, the up-and-down movements in the index occur independently over time.

From the perspective of market efficiency, this finding is consistent with weak-form inefficiency, as past price information appears to carry predictive content for future prices. Such inefficiency may allow for returns from trend-following or other technical trading strategies (Fama, 1970; Lo and MacKinlay, 1988). This conclusion aligns with the ARIMA (0,1,0) model results, which further characterise the index as following a random walk process.

Collectively, the runs test, ARIMA modelling and autocorrelation structure provide converging evidence that the BSE 100 ESG Index behaves as an informationally efficient financial series in which market prices rapidly incorporate available information.

Auto correlations and partial Auto correlations

To further evaluate the presence of serial dependence in the BSE 100 ESG Index returns, the autocorrelation (ACF), partial autocorrelation (PACF) and Ljung–Box Q-statistics were examined for lags 1–16.

H01. There is no statistically significant autocorrelation in the returns of the BSE 100 ESG Index across different time lags.

H02. The returns of the BSE 100 ESG Index are independently distributed and do not exhibit serial correlation.

The ACF and PACF coefficients remain small in magnitude across all lags, with none exceeding the conventional ±0.20 boundary typically associated with statistically meaningful dependence in monthly financial time series (Refer Tables 4 and 5) (Box and Jenkins, 1976; Tsay, 2010).

The largest autocorrelation appears at lag 7 (ACF = 0.241), yet this value remains statistically insignificant when examined jointly through the Ljung–Box diagnostics. The Ljung–Box Q-statistics also fail to reject the null hypothesis of no autocorrelation at any lag (e.g. Q (10) = 11.135, p = 0.347; Q (16) = 16.757, p = 0.401), indicating that the series behaves as a white-noise process. These results confirm that price changes in the index do not exhibit serial predictability, consistent with Fama's (1970) weak-form efficient market hypothesis.

The absence of significant autocorrelation in the ACF/PACF structure and the non-rejection of the Ljung–Box test provide strong evidence that the differenced series follows a random, memory-less process. This finding complements the outcomes of the runs test (Bradley, 1960) and the ARIMA (0,1,0) random walk model (Campbell *et al.*, 1998; Taylor, 2011),

Table 4. Autocorrelations

Series: Closing Price_Diff

Lag	Autocorrelation	Std. Error[a]	Box–Ljung Statistic Value	Df	Sig.[b]
1	0.002	0.100	0.000	1	0.983
2	−0.078	0.099	0.611	2	0.737
3	0.015	0.099	0.634	3	0.889
4	−0.082	0.098	1.328	4	0.857
5	−0.174	0.098	4.497	5	0.480
6	0.013	0.097	4.513	6	0.608
7	0.241	0.097	10.728	7	0.151
8	−0.048	0.096	10.972	8	0.203
9	0.002	0.096	10.972	9	0.278
10	0.038	0.095	11.135	10	0.347
11	−0.104	0.095	12.339	11	0.339
12	−0.163	0.094	15.347	12	0.223
13	0.054	0.094	15.685	13	0.267
14	0.006	0.093	15.689	14	0.333
15	−0.039	0.092	15.871	15	0.391
16	0.086	0.092	16.757	16	0.401

Note(s): [a]The underlying process assumed is independence (white noise), [b]Based on the asymptotic chi-square approximation

Table 5. Partial autocorrelations

Series: Closing Price_Diff

Lag	Partial autocorrelation	Std. Error
1	0.002	0.102
2	−0.078	0.102
3	0.016	0.102
4	−0.089	0.102
5	−0.174	0.102
6	−0.003	0.102
7	0.225	0.102
8	−0.051	0.102
9	0.001	0.102
10	0.000	0.102
11	−0.066	0.102
12	−0.104	0.102
13	0.032	0.102
14	−0.059	0.102
15	−0.021	0.102
16	0.038	0.102

jointly affirming that the BSE 100 ESG Index incorporates information efficiently and displays behaviour consistent with weak-form market efficiency.

The insignificant ACF and PACF structures suggest that shocks to the index dissipate rapidly without generating persistent cyclical or trending behaviour. In practical terms, this indicates that successive price movements occur largely independently, consistent with the weak-form efficient market hypothesis proposed by Fama (1970).

From an ESG investment perspective, the findings suggest that sustainability-screened securities within the BSE 100 ESG Index do not display systematic temporal inefficiencies that could be consistently exploited through technical trading strategies. Instead, market movements appear to be driven primarily by new information, macro-economic developments, firm-specific fundamentals and evolving ESG-related disclosures rather than predictable historical price behaviour.

Fama–French three-factor regression model

The Fama–French three-factor model explains stock returns using market, size and value risk factors (Fama and French, 1993). Aggarwal (2017) found that the Fama–French three-factor model explains variations in stock returns in the Indian market more effectively than the traditional CAPM, highlighting the significance of market, size and book-to-market factors in asset pricing. A Fama–French three-factor regression model was estimated using monthly data from October 2017 to November 2025 (97 observations). The dependent variable was the excess return of the BSE 100 ESG Index, while the independent variables included the market factor (MF), size factor (SMB) and value factor (HML).

Ho. Market factor (MF), size factor (SMB) and value factor (HML) do not significantly influence the excess returns of the BSE 100 ESG Index.

The null hypothesis stating that the MF, SMB and HML do not significantly influence the excess returns of the BSE 100 ESG Index is rejected. The overall regression model was statistically significant ($F = 185.908$, $p < 0.001$), indicating that the Fama–French three-factor model explains a substantial proportion of variation in ESG excess returns (Refer Table 6).

The model explained 85.7% of the variation in ESG excess returns (Adjusted $R^2 = 0.852$). The market factor exhibited a strong positive and statistically significant effect on ESG returns ($\beta = 0.963$, $p < 0.001$), indicating that the ESG index closely follows overall market movements.

The SMB coefficient was negative and statistically significant ($\beta = -0.133$, $p = 0.007$), suggesting that the ESG index demonstrates characteristics associated with large-cap firms. This is expected given that ESG indices are generally dominated by established firms with greater disclosure standards, governance structures and sustainability reporting capabilities. However, the HML coefficient was statistically insignificant ($\beta = 0.026$, $p = 0.584$), indicating that value orientation does not significantly influence ESG index returns.

The intercept term (alpha) was statistically insignificant, implying the absence of statistically significant abnormal risk-adjusted returns after controlling for the Fama–French risk factors.

The findings suggest that the performance of the BSE 100 ESG Index is primarily driven by systematic market risk rather than firm-specific abnormal returns. The dominant influence of the market factor and the absence of significant alpha indicate that ESG-oriented investments in the Indian market largely move in line with broader market conditions after adjusting for common risk factors.

Table 6. Fama–French three-factor regression results for the BSE 100 ESG Index

Variables	Coefficient	*t*-statistic	*p*-value
Constant (α)	−0.158	−0.807	0.422
Market factor (MF)	0.963***	20.609	<0.001
SMB	−0.133***	−2.778	0.007
HML	0.026	0.550	0.584
Adjusted R^2	*0.852*		
F-statistic	*185.908**		
Observations (N)	*97*		
Durbin–Watson	*2.266*		

Note(s): Dependent variable = Excess Return. ***$p < 0.01$

ANOVA results for sectoral differences

A one-way ANOVA was conducted, following the classical ANOVA framework developed by Fisher (1934), to assess whether the different financial indicators differed significantly across the 10 macro-economic sectors. To determine sectoral differences, the Duncan multiple range post hoc test was applied at $\alpha = 0.05$ (Duncan, 1955). The financial indicators used were P/E ratio, dividend yield, as on 17th November 2025, ROCE for the financial year 2024-25, net profit Q2 FY-25–26 and sales Q2 FY-25–26. The ANOVA test showed significant differences for dividend yield, sales and ROCE and the same has been discussed below.

ANOVA results for sectoral differences in dividend yield (%)

Alternative hypothesis (H11)

There is a significant difference in the mean dividend yield (%) among the macro-economic sectors.

A one-way ANOVA was performed to assess whether the dividend yield (%) differed significantly across the 10 macro-economic sectors included in the dataset. The analysis was based on 97 complete cases, after excluding cases with missing values. The results show a statistically significant variation in dividend yields across sectors, $F(9, 87) = 4.598$, $p < 0.001$, indicating that the sector to which a firm belongs has a meaningful effect on its dividend payout behaviour (Refer Table 7).

To identify specific sectoral differences, the Duncan multiple range post hoc test ($\alpha = 0.05$) was applied (Refer Table 8). The results revealed the presence of three statistically homogeneous subsets. The first subset consisted of sectors with comparatively

Table 7. ANOVA for dividend yield %

	Sum of squares	Df	Mean square	*F*	Sig.
Between groups	51.165	9	5.685	4.598	0.000
Within groups	107.575	87	1.236		
Total	158.740	96			

Table 8. Post hoc tests homogeneous subsets

Dividend yield %
Duncan[a, b]

Macro-economic sector	*N*	Subset for alpha = 0.05 1	2	3
Information technology	2	0.3150		
Telecommunication	2	0.3800		
Healthcare	12	0.6033	0.6033	
Commodities	9	0.6067	0.6067	
Consumer discretionary	19	0.7268	0.7268	
Utilities	4	0.7750	0.7750	
Financial services	25	1.0420	1.0420	
Fast moving consumer goods	10	1.4410	1.4410	
Industrials	8		2.0275	
Energy	6			3.4300
Sig.		0.171	0.078	1.000

Note(s): Means for groups in homogeneous subsets are displayed, [a]Uses harmonic mean sample size = 5.185, [b]The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed lower dividend yields, including information technology, telecommunication, healthcare, commodities, consumer discretionary, utilities and financial services, with mean dividend yields ranging from 0.315% to 1.042%. These sectors did not significantly differ from each other.

The second subset was represented by the industrials sector, which exhibited a moderate mean dividend yield of 2.03%. This yield was significantly higher than that observed in the first subset, suggesting a relatively stronger dividend payout tendency.

The third subset consisted solely of the energy sector, which recorded the highest mean dividend yield of 3.43%, significantly different from the yields of all other sectors. This indicates that firms within the energy sector distribute dividends at a substantially higher rate compared to the rest of the sectors examined.

While most sectors operate within a relatively low-yield regime consistent with growth-oriented ESG investing, energy and industrials demonstrate significantly stronger income-generation characteristics, making them particularly relevant for income-focused ESG portfolios.

ANOVA results for sectoral differences in sales (Q2 FY 2025–26)

Alternative hypothesis (H12)

There is a significant difference in mean sales (Q2 FY 2025–26) across the macro-economic sector.

A one-way ANOVA was conducted to examine whether sales for Q2 FY 2025–26 (Rs. Cr.) differed significantly across the 10 macro-economic sectors (Refer Table 9). The analysis included 101 firms, with cases containing missing values excluded listwise. The results indicate a statistically significant difference in mean sales across sectors, $F(9, 87) = 8.634$, $p < 0.001$, suggesting that sectoral classification has a substantial influence on firm-level revenue performance.

To determine which sectors differed from one another, a post hoc analysis using the Duncan multiple range test was conducted at $\alpha = 0.05$ (Refer Table 10). The Duncan test revealed the presence of two statistically homogeneous subsets. The first subset comprised the lower-to mid-revenue sectors – fast moving consumer goods (FMCG), healthcare, information technology, consumer discretionary, utilities, industrials, financial services, commodities and telecommunication – whose mean sales values ranged from Rs. 6,809 crore to Rs. 30,167 crore. These sectors did not significantly differ from each other.

The energy sector, however, formed a distinct second subset with a substantially higher mean sales value of Rs. 126,972 crore, indicating that it was significantly different from all other sectors and stood out as the highest revenue-generating sector in the sample.

The results also highlight an important characteristic of ESG investing in emerging markets such as India: ESG indices may still remain heavily influenced by large-cap traditional sectors, particularly energy and financial services. Unlike ESG portfolios in certain developed markets that exhibit stronger technology or low-carbon concentration, the Indian ESG ecosystem appears to retain substantial exposure to economically dominant legacy industries.

Table 9. ANOVA sales Q2 FY-25–26 Rs.Cr

	Sum of squares	Df	Mean square	*F*	Sig.
Between groups	69514281947.139	9	7723809105.238	8.634	0.000
Within groups	77832652328.287	87	894628187.681		
Total	147346934275.426	96			

Table 10. Post hoc tests homogeneous subsets

Sales Q2 FY-25–26 Rs.Cr.
Duncan[a,b]

Macro-economic sector	N	Subset for alpha = 0.05 1	2
Fast moving consumer goods	10	6808.9010	
Healthcare	12	11378.5675	
Information technology	2	13861.3800	
Consumer discretionary	19	17428.1274	
Utilities	4	19198.8925	
Industrials	8	24610.4900	
Financial services	25	24681.3324	
Commodities	9	29793.8122	
Telecommunication	2	30166.8000	
Energy	6		126972.0533
Sig.		0.297	1.000

Note(s): Means for groups in homogeneous subsets are displayed, [a]Uses harmonic mean sample size = 5.185, [b]The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed

ANOVA results for sectoral differences in return on capital employed (ROCE%)

Alternative hypothesis (H13)

There is a significant difference in the mean ROCE (%) among the macro-economic sectors.

A one-way ANOVA was conducted to determine whether the ROCE differed significantly across 10 macro-economic sectors (Refer Table 11).

The analysis included 97 valid cases. The ANOVA results indicate statistically significant variation in ROCE across sectors, F (9, 87) = 5.980, $p < 0.001$, demonstrating that sectoral affiliation plays a significant role in explaining differences in firms' operational efficiency and capital productivity.

To identify the sectors contributing to these differences, a Duncan multiple range post hoc test ($\alpha = 0.05$) was applied (Refer Table 12). The results revealed three statistically homogeneous subsets. The first subset comprised sectors with comparatively lower ROCE values, namely financial services, commodities, utilities, information technology, energy, consumer discretionary, telecommunication, and healthcare, with mean ROCE percentages ranging from 10.28% to 24.58%. These sectors did not differ significantly from one another in terms of capital efficiency.

The second subset was formed exclusively by the industrials sector, which reported a mean ROCE of 31.28%, significantly higher than that of all sectors in the first subset. This suggests that industrial firms in the sample demonstrate much stronger efficiency in generating returns from their employed capital.

The third subset consisted solely of the (FMCG) sector, which exhibited the highest ROCE value of 44.35%. This return level was significantly greater than that of both the lower-performing group of sectors and the industrial sector, placing FMCG as the most capital-efficient sector in the dataset.

Table 11. ANOVA return on capital employed %

	Sum of squares	Df	Mean square	F	Sig.
Between groups	10416.277	9	1157.364	5.980	0.000
Within groups	16837.232	87	193.531		
Total	27253.510	96			

Table 12. Post hoc tests homogeneous subsets

Return on capital employed %
Duncan[a, b]

Macro-economic sector	*N*	Subset for alpha = 0.05 1	2	3
Financial services	25	10.2796		
Commodities	9	11.8478	11.8478	
Utilities	4	13.0000	13.0000	
Information technology	2	15.5700	15.5700	
Energy	6	17.9000	17.9000	
Consumer discretionary	19	20.1468	20.1468	
Telecommunication	2	21.2350	21.2350	
Healthcare	12	24.5808	24.5808	
Industrials	8		31.2775	31.2775
Fast moving consumer goods	10			44.3510
Sig.		0.164	0.056	0.134

Note(s): Means for groups in homogeneous subsets are displayed, [a]Uses harmonic mean sample size = 5.185, [b]The group sizes are unequal. The harmonic mean of the group sizes is used. Type I error levels are not guaranteed

The strong performance of industrials similarly reflects effective capital deployment and operational scalability within infrastructure and manufacturing-linked ESG firms. Conversely, the relatively lower ROCE observed in financial services and certain capital-intensive sectors indicate that market size and valuation prominence do not necessarily translate into superior capital productivity.

Descriptive sectoral profile based on key financial indicators

The financial services sector constitutes the largest share of the index by overall market capitalisation (₹74,07,553 crore), underscoring its central role in the Indian capital market and the BSE 100 ESG universe. This is followed by consumer discretionary (₹39,01,496 crore) and energy (₹31,34,429 crore), both of which represent substantial portions of the index's market base. At the lower end, sectors such as services (₹5,52,995 crore) and utilities (₹9,20,748 crore) account for relatively minor index weights.

Valuation levels, measured through the P/E ratio, vary significantly across sectors, indicating heterogeneous investor expectations. The consumer discretionary sector (P/E ≈ 137) is the most highly valued sector in the BSE 100 ESG Index, reflecting strong future earnings expectations from consumer-oriented firms. High valuation clusters are also observed in FMCG (≈59), commodities (≈49) and healthcare (≈44). In contrast, the energy sector exhibits the lowest P/E multiple (≈12), indicating more conservative market expectations aligned with its cyclical and mature industry profile.

Growth indicators further highlight the diverse performance landscape of the index constituents. The energy sector records an exceptionally high YoY quarterly profit growth (≈252%), driven by favourable commodity price cycles and operational expansions during the period. Industrials and commodities (≈124%) also demonstrate robust profitability growth. On the other hand, the services sector shows a sharp contraction (≈–70%), emerging as the weakest-performing segment in terms of profit momentum. Sales growth patterns indicate that industrials (≈32%), consumer discretionary (≈23%) and healthcare (≈15%) are comparatively stronger performers, while sectors like utilities (%) exhibit stagnation.

In terms of operational efficiency, measured by ROCE, the FMCG sector (≈44%) leads the index, reflecting substantial brand equity, pricing power and efficient capital utilisation. Industrials and information technology (≈31%) also demonstrate high capital productivity.

Conversely, financial services ≈ (10%) and commodities (≈12%) represent the lower end of ROCE performance within the index. The sectoral breakdown of the BSE 100 ESG Index reveals a structurally diverse market landscape, characterised by distinct valuation regimes, growth trajectories and operational efficiencies across sectors. High-value, growth-oriented sectors, such as consumer discretionary, coexist with low-value, high-growth sectors, like energy. Meanwhile, consistently strong return-generating sectors, like FMCG and industrials reinforce their importance within the ESG-screened universe. These variations underscore the multi-dimensional nature of sectoral performance embedded within the BSE 100 ESG Index (Refer Table 13).

Implications and conclusion

The time-series modelling results – ARIMA (0,1,0), insignificant Ljung–Box statistics, non-significant ACF/PACF structure and a statistically insignificant Wald–Wolfowitz runs test – collectively demonstrate that the BSE 100 ESG Index follows a random walk process. These findings indicate that the index is weak-form efficient, implying that historical price information cannot be systematically used to predict future price movements. For investors, this suggests that ESG-screened indices in India exhibit informational efficiency characteristics comparable to those observed in developed markets, thereby limiting the effectiveness of technical analysis and trend-based trading strategies.

The absence of significant autocorrelation and serial dependence further confirms that market information is incorporated rapidly into prices. This strengthens confidence in the informational efficiency of the Indian ESG investment ecosystem and suggests that recent regulatory developments, including enhanced ESG disclosure requirements such as the business responsibility and sustainability reporting (BRSR) framework, may contribute to improved market transparency and faster information assimilation.

The Fama–French three-factor regression analysis provides additional insights into the risk-return dynamics of the BSE 100 ESG Index. The model was statistically significant and explained a substantial proportion of the variation in ESG excess returns (adjusted $R^2 = 0.852$). The MF exhibited a strong positive and statistically significant relationship with ESG returns, indicating that the index closely tracks broader market movements.

Table 13. Descriptive sectoral profile based on key financial indicators

Sectors	Average of closing price (17th November 2025) Rs.	Average of p/E	Sum of Mar cap Rs.Cr.	Average of YOY quarterly profit growth %	Average of YOY quarterly sales growth %	Average return on capital employed %
Commodities	5,322	49	1,900,612	124	13	12
Consumer discretionary	4,403	137	3,901,496	103	23	20
Energy	481	12	3,134,429	252	2	18
Fast moving consumer goods	1,711	59	2,119,234	7	7	44
Financial services	1,606	37	7,407,553	6	9	10
Healthcare	3,103	44	1,135,097	32	15	20
Industrials	2,737	41	1,386,377	124	32	31
Information technology	2,710	33	2,913,720	19	12	31
Services	3,690	36	5,52,995	−70	20	16
Telecommunication	1,261	26	1,378,393	24	18	21
Utilities	491	38	92,0748	20	0	13

This suggests that systematic market risk remains the dominant driver of ESG index performance in the Indian equity market.

The SMB was negative and statistically significant, implying that the BSE 100 ESG Index demonstrates characteristics associated with large-cap firms rather than small-cap firms. This finding is consistent with the composition of ESG indices, which are generally dominated by large, established firms possessing stronger governance structures, disclosure standards, and sustainability reporting capabilities. In contrast, the HML was statistically insignificant, suggesting that value-oriented investment characteristics do not meaningfully explain ESG index returns.

Importantly, the intercept term (alpha) was statistically insignificant, indicating the absence of abnormal risk-adjusted returns after controlling for market, size and value factors. This finding reinforces the evidence of weak-form market efficiency by suggesting that ESG investors are not consistently able to generate excess returns beyond those explained by systematic risk exposures. Collectively, the ARIMA modelling, autocorrelation diagnostics, runs test and Fama–French regression provide converging evidence that the BSE 100 ESG Index behaves as an informationally efficient market index whose performance is largely explained by systematic factors rather than exploitable inefficiencies.

The one-way ANOVA and Duncan post hoc results reveal significant sectoral disparities across dividend yield, quarterly sales and ROCE. These findings carry important implications for ESG portfolio construction.

(1) Energy consistently outperforms in sales and dividend yield, indicating that despite ESG scrutiny, energy companies remain dominant revenue generators within the ESG universe.

(2) FMCG and industrials emerge as leaders in operational efficiency, with the highest ROCE values, implying superior capital utilisation and sustainable profitability.

(3) Financial services, despite being the most significant contributor to total market capitalisation, records the lowest ROCE, indicating that its dominance is driven more by size than capital efficiency.

The findings of weak-form efficiency and the close tracking of the BSE 100 ESG Index with broader market movements suggest that technical analysis is unlikely to generate systematic abnormal returns, while fundamental analysis remains the more relevant approach for investment decisions within the ESG universe.

Although the results indicate that the informational efficiency and systematic risk characteristics of the BSE 100 ESG Index resemble those observed in many developed-market indices, generalisation should still be approached with caution. The relatively short life of the index compared with conventional benchmarks means that the observed efficiency and factor exposures may partly reflect the early development stage of India's ESG market. Differences in market microstructure, the progressive strengthening of ESG disclosure requirements, the composition of ESG screens and the dominance of large-cap stocks can produce different outcomes in other ESG universes or over longer time horizons.

Furthermore, while the insignificant alpha after controlling for Fama–French factors imply that returns are largely explained by standard systematic risks, this does not rule out the possibility that more granular fundamental analysis – at the stock or sector level – could still add value under different market conditions or in other ESG indices. Future research that examines multiple Indian and international ESG indices over longer periods, and that employs alternative factor models, would help establish the external validity and temporal stability of these efficiency and performance patterns.

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