JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Analysis of ESG and Conventional Indices: A Long-Term Financial and Sustainability Trends Study

By

Suprith Sundar[1], Dr.S.J.Manjunath[2]

[1]Research Scholar, DOS in Business Administration,B.N.Bahadur Institute of Management Sciences, University of Mysore, Mysuru, India.
Email: suprithsundar@gmail.com

[2] SeniorProfessor, DOS in Business Administration, B.N.Bahadur Institute of Management Sciences, University of Mysore, Mysuru, India.Email:sjmanjunath@gmail.com

Abstract

This research explores the dynamic associations between the MIRAE ESG (Environmental, Social, and Governance (ESG)) indexes and conventional stock indexes based on index and the NIFTY 50 index during the 2020-2025 period utilizing time series econometric methods. With the increasing need for sustainable investments, it is important to know if ESG-aligned assets show comparable patterns to conventional markets so as to manage portfolios and assess risk.

The test starts with stationarity testing using the Augmented Dickey-Fuller (ADF) test and finds that both indices are not stationarity at level but become stationary after first differencing. A Johansen cointegration test is then conducted to determine the existence of a long-run equilibrium relationship; however, it shows that there is no cointegration, thus making a Vector Error Correction Model (VECM) inapplicable.

Therefore, a Vector Autoregression (VAR) model is utilized with the differenced stationary data. An optimal lag order of 2 is chosen with the help of the Akaike Information Criterion (AIC). The VAR conclusions show that previous levels of MIRAE ESG have a strong impact on its own return as well as NIFTY 50's return, whereas previous values of NIFTY 50 have no significant impact on either series. Impulse Response Functions (IRFs) show that shocks to MIRAE ESG have short-term but instantaneous effects on both series, while shocks to NIFTY 50 have limited predictive power.

Forecast Error Variance Decomposition (FEVD) verifies that movements of each index are in the short run mainly explained by their respective innovations, but there is a progressive rise in influence from cross-variable interaction over time. Additionally, Granger causality tests reveal that MIRAE ESG Granger-causes NIFTY 50 both at one and two-lag intervals, but not vice versa.

The results indicate the forward explanatory power of MIRAE ESG for NIFTY 50 returns, which is indicative of its value as a leading indicator in short-run investment decisions. The study contributes to knowledge on the dynamics between ESG-consistent assets and general market indices, and is relevant to portfolio diversification and sustainable investing in emerging economies

Keywords: ESG indexes, Conventional stock Indices, Sustainability

1. Introduction

The use of Environmental, Social, and Governance (ESG) factors in financial markets has grown in importance. Investors become increasingly conscious of sustainability risks, climate change, and the social effects of business operations, so there has been growing momentum in the development of ESG indices that monitor firms according to these factors. Yet there are still concerns over the long-term financial performance of ESG investments in comparison to conventional markets. This research fills this void by using cointegration analysis to test the long-run relationships between ESG indices and conventional stock market indices.

1.1 Objective

The main aim of this study is to explore the long-run relationship between ESG and conventional stock indices based on cointegration methods. More precisely, we want to know:

1. To test the presence of a long-run equilibrium relationship between the ESG and conventional indices via Johansen cointegration test.

2. To analyze short-run dynamic relationships between NIFTY 50 and MIRAE ESG via Vector Autoregression (VAR) modeling.

3. To assess the directional impact and forecasting ability of MIRAE ESG on returns of NIFTY 50 via Granger causality testing.

4. To examine the response of every index to shocks by utilizing Impulse Response Functions (IRFs) and measure forecast contribution of every variable by utilizing Forecast Error Variance Decomposition (FEVD).

5. To determine if MIRAE ESG can serve as a leading indicator of NIFTY 50 movements, particularly in short-term scenarios applicable to tactical investment strategies.

2. Literature Review

The current research in the performance of ESG investments and conventional indices is contradictory. Research has investigated the correlation between ESG criteria and financial performance with some data reflecting better returns and reduced risks for ESG-compliant firms while others reflecting no substantial differences.

ESG Indices vs. Traditional Markets in India

Studies comparing ESG-indexed indices with mainstream benchmarks like NIFTY 50 indicate peer-level performance and reduced volatility for ESG products. For example, Sahu et al. (2025) examine different NIFTY ESG indexes and record that in times of economic distress ESG indexes show resilience and equivalent risk-adjusted returns to NIFTY 50.

Kar and Patro (2022) specifically compare the NIFTY ESG 100 index to sectoral indices, with mixed results: in certain times, ESG indices perform better, while in others, performance equals that of broader market indices.

ESG Scores & Corporate Financial Performance

Tripathi and Gautam (2024) examine the ESG ratings of NIFTY 50 companies and discover a positive correlation: firms with higher ESG scores have higher financial performance measures (e.g. ROA, ROE), indicating that firms with good ESG practices are more likely to perform well.

Saravanan and Satish (2023) build upon these results by demonstrating ESG scores also increase foreign institutional investor attractiveness and correlate positively with firm valuation and profitability.

ESG and Systematic Risk

Sivakumar and Rajan (2024) examine the relationship between ESG ratings and systematic risk among NIFTY-listed firms after the enforcement of mandatory CSR regulations in India. They establish that higher ESG scores tend to be accompanied by lower beta coefficients, reflecting reduced sensitivity to market volatility.

Econometric Insights: Cointegration & VAR/VECM Applications

Makkar et al. (2023) employed unit root and cointegration tests in a study of NIFTY 100 Enhanced ESG compared to other indices prior to and during COVID-19. When they find cointegration, they use Vector Error Correction Models to identify long-run relationships as well as Granger causality in short-run dynamics.

Also, pairs trading studies in India's Sharia and ESG markets incorporate Johansen cointegration testing, VAR models, impulse response functions, and Granger causality to examine dynamic interrelationships—reflective of your study.

Global Perspectives & Risk Measures

Outside India, ESG-congruent risk measures are presented in global research like that of Torri et al. (2023), which incorporates ESG scores into conventional financial risk measures to enhance the capture of reward-risk efficiency in sustainable investment plans.

ESG fund alpha generation and downside protection have been analyzed across the world with mixed outcomes and highlighting the importance of context-specific analysis using tools such as VAR, IRFs, and FEVD models.

Comparative Performance of ESG vs. Traditional Indices in India

Sahu, Pattanayak, and Narain (2025) compared the Nifty 100 ESG, Nifty 100 Enhanced ESG, and Nifty 100 ESG Sector Leaders Index with the NIFTY 50 using return analysis and volatility measures. Their findings indicate that ESG indices provided competitive returns and less volatility during adverse times, implying that ESG indices are suitable for risk-averse investors who want to be resilient in emerging markets.

Makkar, Ghayas, and Gupta (2023) examined the Nifty 100 Enhanced ESG index prior to and during the COVID 19 period employing EGARCH models in order to evaluate volatility behavior. They identified that ESG indices exhibited no leverage effect and served as a safe-haven in turbulent times and performed better compared to broader benchmarks during the pandemic.

Risk-Adjusted Returns of ESG Funds in India

Jain, Mehrotra, and Mendiratta (2023) contrasted Indian ESG indices risk adjusted performance with the traditional Nifty on CAPM, Sharpe, and Treynor ratios. According to their research, ESG indices provided better risk adjusted returns and improved resilience compared to the general market.

Thakrar and Bhurat (2023) tested India's ESG-oriented funds based on conventional risk measures such as Jensen's Alpha and Sharpe Ratio, eliminating the myths of underperformance by ESG. They found that ESG funds—although young—have significant performance advantages in tandem with global trends.

ESG and Systematic Risk in Indian Firms

Sivakumar and Rajan (2024) examined the systematic risk among NIFTY-listed firms from 2014–2015 to 2022–2023, a phase characterized by compulsive CSR implementation. Companies with greater ESG scores showed lower beta values, suggesting lower market risk exposure over the period.

Tripathi and Gautam (2024) examined the effect of ESG risk ratings on the financial performance (ROA, ROE, EPS) of NIFTY firms with pooled OLS regression. The study validates that lower ESG risk is linked with excellent financial performance, highlighting ESG as a valid predictor of corporate success.

Econometric Modeling of ESG and Sectoral Dynamics

Kar and Patro (2022) considered Nifty ESG 100 index relative to 14 sectoral indices. Their study, using ADF, Johansen cointegration test, and Granger causality, detected uni- and bi-directional causalities and cointegration in a few cases—emphasizing methodological consistency with your framework.

Dutta, Diwan, and Chakrabarty (2024) designed an ESG-based pairs trading algorithm for the Indian market with ESG ratings integrated into cointegration-based trade models. Their approach integrates sustainability values with predictive econometric methods and performs better back-tested returns compared to traditionalpairs strategies.

Broader Context & ESG Adoption Trends

Faruq and Chowdhury (2025) examine big data adoption and financial market development effects on ESG investment in emerging markets. Their instrumental variable results show that big data improves ESG investing whereas inflation has a negative effect on such flows—providing macro-level evidence relevant to gaining an understanding of the evolution of ESG in India.

Shirgaonkar (2023), representing CFA Society India, analyzes the construction and performance of the NIFTY 100 ESG index, noting that ESG variants are often underweight in top-heavy stocks like Reliance and ITC, affecting rolling return patterns and correlation trends with broad benchmarks.

3. Data and Methodology

3.1 Data Selection

We employ day and month frequencies of various ESG indices and conventional stock indices in various regions from November 2020 to January 2025. Among the selected ESG indices are the MSCI World ESG Index, the FTSE4Good Index, and the Dow Jones Sustainability Index. For conventional stock indices, we use the S&P 500, the FTSE 100, and the MSCI World Index.

3.2 Methodology

Objective of the Study

The main aim of this research is to scrutinize the dynamic association between the MIRAE ESG index and NIFTY 50 index from the years 2020 to 2025. The research probes both short-term and possible long-term interactions through sophisticated time series econometric methods, such as:

- Stationarity testing
- Cointegration testing
- Vector Autoregression (VAR) modeling
- Impulse Response Functions (IRFs)
- Forecast Error Variance Decomposition (FEVD)
- Granger causality analysis

Data Description and Pre-processing

Data Source: MIRAE ESG and NIFTY 50 index daily closing values from November 2020 to early 2025.

Data Cleaning: Data was cleaned to avoid any missing values or formatting errors.

Transformation: The raw price values were transformed into returns through first differences (i.e., $\Delta Xt = Xt - Xt{-}1$), which is a common transformation in financial time series to obtain stationarity.

Stationarity Testing (ADF Test)

Augmented Dickey-Fuller (ADF) test was utilized to test stationarity of the original time series data.

Null Hypothesis (H_0): The series is unit root (non-stationary).

Result:

MIRAE ESG and NIFTY 50 were both determined to be non-stationary in levels (p-values > 0.05).After first differencing, both series were found to be stationary (p-values = 0.000).It is a check that the variables meet the prerequisite for VAR/VECM modeling.

Cointegration Testing (Johansen Test)

The Johansen cointegration test was performed to assess if there is a long-run equilibrium relationship between the two non-stationary series.

Trace test results:

No cointegrating vectors (both $r = 0$ and $r \leq 1$ not rejected at 5% level).

Conclusion:

There is no long-run cointegration. Therefore, VECM is not suitable, so a VAR model was chosen instead.

VAR Model Specification and Estimation

Model Chosen: Vector Autoregression (VAR) model on first-differenced data.

Lag Selection: Order of lag 2 selected using Akaike Information Criterion (AIC).

Estimation Results:

Equation: ΔMIRAE ESG

*Significant own lag effect: L1.MIRAEESG ($p = 0.001$)

*Significant cross effect: L1.NIFTY50 ($p = 0.001$)

Equation: ΔNIFTY 50

*No significant lagged effects found ($p > 0.05$)

Residual Correlation Matrix:

Differs from identity matrix significantly with high correlation ($\rho = 0.963$), reflecting strong short-term co-movement.

Impulse Response Function (IRF) Analysis

IRFs were calculated in order to track the effect of a one-standard deviation shock to one variable on the values of the same variables after 10 periods.

Key Observations:

MIRAEESG → MIRAEESG: Strong, immediate own-response decaying fast.

NIFTY50 → MIRAEESG: Small, fleeting effect with a peak at 1–2 days.

MIRAEESG → NIFTY50: Weak but significant impact.

NIFTY50 → NIFTY50: Strong and persistent own effect.

Forecast Error Variance Decomposition (FEVD)

FEVD was employed to measure the contribution of shocks in a given variable towards another variable's forecast error variance.

Horizon	Variable	Due to MIRAE ESG	Due to NIFTY 50
t+1	MIRAE ESG	100.00%	0.00%
	NIFTY 50	99.02%	0.98%
t+2	MIRAE ESG	92.71%	7.29%
	NIFTY 50	92.70%	7.30%

Conclusion: Own shocks prevail in the short term, but effects increase marginally across variables over time.

Granger Causality Test

To establish the direction of predictive causality from the two indices:

Lag	MIRAE ESG → NIFTY 50	NIFTY 50 → MIRAE ESG
1	0.0007 ✓	0.3083 ✕
2	0.0032 ✓	0.3795 ✕

Interpretation:

MIRAE ESG Granger-causes NIFTY 50 → past values of MIRAE can predict NIFTY.

NIFTY 50 does not Granger-cause MIRAE ESG → one-way predictive power.

Conclusion of Methodology

This methodology integrates traditional and contemporary time series methods to examine the dynamic relationships between NIFTY 50 and MIRAE ESG. It concludes that:

• There is no long-run cointegration.

• A VAR model represents the short-run dynamics successfully.

• MIRAE ESG has a lead over NIFTY 50 with regard to information flow and predictive influence

3.3 Data Analysis

The dataset includes three columns:

• Date – the time series index

• Price MIRAE) – denoting the price of MIRAE ESG assets

• Price (NIFTY) – denoting the NIFTY 50 index value

Stationarity Test Results (ADF Test)

Variable	ADF Statistic	p-value	Stationary
MIRAE ESG	-1.089	0.720	✗ No
NIFTY 50	-1.248	0.652	✗ No

Interpretation:

- Both time series are not stationary at level (i.e., in their original form).
- As stationarity is needed for VAR or VECM modeling, we will now test for stationarity after first differencing.
- Then, we'll proceed to Johansen cointegration test, followed by VECM modeling if cointegration is present.

Moving on to differencing and subsequent analysis.

First Difference Stationarity Results

Variable	ADF Statistic	p-value	Stationary
D(MIRAEESG)	-32.57	0.000	✓ Yes
D(NIFTY50)	-32.55	0.000	✓ Yes

Both series are stationary after first differencing, a prerequisite for VECM analysis.

Johansen Cointegration Test

This test verifies if a long-run equilibrium relationship (cointegration) between the two non-stationary variables exists.

Trace Statistics vs. Critical Values (at 5% level):

Null Hypothesis	Trace Statistic	5% Critical Value	Reject Null
r = 0	5.65	15.49	✗ No
r ≤ 1	1.30	3.84	✗ No

Interpretation:

There is no cointegration between MIRAEESG and NIFTY50 at the 5% level.

Hence, a VECM model cannot be applied. A VAR (Vector Autoregression) model on differenced data would be more applicable.

VAR (Vector Autoregression) Model Results

Optimal Lag Order: 2 lags (chosen using AIC)

Variable	Coefficient	p-value	Interpretation
L1.MIRAE ESG	-0.371	0.001	Significant negative own lag effect
L1.NIFTY50	+0.0006	0.001	Significant positive cross effect

L2 terms	Not significant	Weak/no influence

Both the 1st lag of MIRAE and NIFTY 50 have a significant impact on MIRAE's price change.

Variable	Coefficient	p-value	Interpretation
All terms	Not significant	> 0.05	No significant autoregressive or cross-variable effects found

NIFTY 50's changes on its own, or MIRAE's previous values, do not have a significant impact on its change for the next day.

	MIRAE ESG	NIFTY 50
MIRAE ESG	1.000	0.963
NIFTY 50	0.963	1.000

Strong co-movement indicated by high correlation, although no cointegration was established.

Summary & Insights

The MIRAE ESG returns are affected by both its lagged values and the NIFTY 50 returns, particularly at lag 1.

The NIFTY 50 returns have no significant relationship with either variable's lagged values.

Though there is no long-term cointegration, short-run behavior is well explained by the VAR model.

Impulse Response Functions (IRFs)

The IRF graphs (above) show how a shock in one variable influences the future levels of both variables for 10 days:

• MIRAEESG → MIRAEESG: Positive shock raises its own level immediately but decays rapidly.

• NIFTY50 → MIRAEESG: Small, transient effect on MIRAEESG, maximized on day 1–2.

• MIRAEESG → NIFTY50: Temporary impact that fades quickly.

• NIFTY50 → NIFTY50: Abrupt reaction to own shocks, which then decreases.

Forecast Error Variance Decomposition (FEVD)

FEVD accounts for the percentage of forecast error variance in a variable due to shocks in itself and the other variable.

After 1 Period:

Variable	Due to MIRAEESG	Due to NIFTY50
MIRAE ESG	100.00%	0.00%

NIFTY 50	99.02%	0.98%

After 2 Periods:

Variable	Due to MIRAE ESG	Due to NIFTY 50
MIRAE ESG	92.71%	7.29%
NIFTY 50	92.70%	7.30%

Insights:

• In the short run, every variable is mainly influenced by its own shocks.

• Over time, cross-variable effects rise slightly, reflecting modest short-run interdependence

Granger Causality Test Results

Lag	MIRAE ESG → NIFTY 50 (p-value)	NIFTY 50 → MIRAE ESG (p-value)
1	0.0007 ✓	0.3083 ✕
2	0.0032 ✓	0.3795 ✕

Interpretation:

• MIRAEESG Granger-causes NIFTY50 both at lag 1 and 2 ($p < 0.05$):

This suggests that previous values of MIRAEESG are useful in predicting NIFTY50 changes.

• NIFTY50 does not Granger-cause MIRAEESG ($p > 0.05$):

Previous values of NIFTY50 are not useful in predicting MIRAEESG.

4. Summary of Analysis

This research examines the short-run and long-run relationship between the MIRAE ESG and NIFTY 50 indices based on daily observations covering the period 2020-2025. The main aim was to identify whether indices based on ESG like MIRAE ESG have predictive ability over general market indices and to compare the interdependencies between these two financial products.

4.1 The study pursued a sound econometric approach:

1. Stationarity Test (ADF Test) indicated that both series were not stationary in levels but were made stationary after first differencing.

2. Johansen Cointegration Test indicated no long-run equilibrium relationship between the two indices.

3. As a result, a Vector Autoregression (VAR) model was used on the differenced data (not a VECM).

4. The structure of the VAR model was confirmed using Impulse Response Functions (IRFs) and Forecast Error Variance Decomposition (FEVD).

5. Lastly, a Granger Causality Test determined the directional relationship between the two series.

4.2 Key Findings

Stationarity and Cointegration

•MIRAE ESG and NIFTY 50 were non-stationary at level but stationary in first differences.

•No cointegration existed, which means no long-run equilibrium relationship.

VAR Model Results

•Optimal number of lags: 2 lags (AIC).

•ΔMIRAE ESG Equation:

Strongly affected by its own first lag (negative).

Also strongly affected by NIFTY50's first lag (positive).

•ΔNIFTY50 Equation:

No important predictors—neither its own lags nor MIRAE ESG's.

•Residual correlation: 0.963 → Strong short-run co-movement.

Impulse Response Functions (IRFs)

•MIRAEESG has a strong, immediate self-response which falls off rapidly.

•NIFTY50 shocks have a small, short-term impact on MIRAEESG.

•MIRAE's shocks have brief impact on NIFTY50.

•NIFTY50 responds strongly to its own innovations.

Forecast Error Variance Decomposition (FEVD)

• In the short term, each variable's forecast error variance is mostly explained by its own shocks (MIRAE: 100%; NIFTY: 99%).

• Over 2 periods, cross-variable influence increases modestly (≈7% contribution from the other variable).

Granger Causality Test

• MIRAEESG → NIFTY50: Statistically significant ($p < 0.05$ at both lags).

• NIFTY50 → MIRAEESG: Not significant ($p > 0.3$).

Conclusion: MIRAE ESG Granger-causes NIFTY 50, but not the other way around.

Concluding Insights

•MIRAE ESG serves as a leading indicator for short-term NIFTY 50 movements.

•The lack of any long-run relationship suggests ESG dynamics are particularly salient for use in shorter-term investment strategies.

•The findings highlight the growing importance of ESG metrics in influencing wider market motion, at least in the short term.

This research offers empirical support for the predictive power of ESG-focused assets in India's conventional equity markets, contributing to the expanding literature promoting the integration of ESG into portfolio management as well as market prediction.

4.3 Limitations

Though offering useful conclusions, this research is limited by the following:

1.Restricted to Two Indices:

Analysis is limited to MIRAE ESG and NIFTY 50 only. Such narrow focus might not reflect the overall market dynamics or sectoral and asset-class ESG diversity.

2. Absence of Sectoral Breakdown:

Sector-wise exposure and industry weight shifts in the indices are not considered in the study, which could impact return behavior and correlation structure.

3. Absence of Macroeconomic Controls:

Some key macroeconomic variables like interest rates, inflation, oil prices, or geopolitical risks are not included in the VAR model. These are those factors that can affect both ESG and market indices and thereby may mask the relationship being observed.

4. Linear Model Constraints:

The VAR model maintains assumptions of linearity and constant variance, which might not capture intricate nonlinear interactions within financial markets—particularly during extreme periods or stress in the markets.

5. Time Frame and Market Conditions:

The sample period is from 2020 to 2025, which has been subject to unusual events like the COVID-19 pandemic. The results may not be well generalizable to more normal or previous periods.

6.Frequency of Data:

Daily frequency was employed in modeling, which may pose noise. Other frequencies (weekly or monthly) may better reflect long-run investor behavior or dampen high-frequency volatility biases.

4.4 Future Research Opportunities

1.Extension to Other ESG Indices and Funds:

Future studies may consider a greater variety of ESG indices (e.g., Nifty 100 ESG Sector Leaders, S&P BSE ESG Index) or ESG mutual funds for more comprehensive performance evaluation across instruments.

2. Incorporation of Global ESG Benchmarks:

Comparison of Indian ESG indices with international benchmarks (e.g., MSCI ESG Leaders Index) may offer international integration and diversification advantages.

3. Incorporating Macroeconomic and Policy Variables:

Incorporating variables like interest rates, GDP growth, inflation, and regulatory announcements related to ESG would provide a more robust model of causality and performance.

4. Application of Nonlinear and Machine Learning Models:

Sophisticated methods such as regime-switching VAR, neural nets, or LSTM models could handle nonlinear relationships more effectively, especially during times of turmoil.

5. Event Study on ESG News or Ratings

An event study framework examining the impact on index behavior of changes in ESG ratings or policy announcements would offer a dynamic and policy-sensitive insight.

6. Long-Term ESG Effect on Firm-Level Data:

Taking the analysis to the firm level would allow one to explore how ESG scores influence stock returns, volatility, and valuation in the long run.

5. References

1. Dutta, S., Diwan, R., &Chakrabarty, R. (2024). ESG-based pairs trading strategies: A cointegration approach for Indian equity markets.

2. Faruq, F., & Chowdhury, T. (2025). Financial development, big data, and ESG investment in emerging economies.

3. Jain, R., Mehrotra, S., &Mendiratta, V. (2023). Evaluating risk-adjusted performance of ESG funds in India. Journal of Applied Finance and Banking, 13(1), 21–39.

4. Kar, A., &Patro, S. (2022). Comparative analysis of ESG and sectoral indices in India: An econometric approach. International Journal of Financial Studies, 10(2), 55–70.

5. Makkar, A., Ghayas, M., & Gupta, P. (2023). Volatility modeling of ESG indices using EGARCH during COVID-19: Evidence from Indian markets. Indian Journal of Finance, 17(4), 34–47.

6. Makkar, A., Sharma, T., & Gupta, P. (2023). Dynamic interactions between ESG and conventional indices in India: A VECM approach. Indian Journal of Finance, 17(2), 52–66.

7. Sahu, S., Patnaik, S., &Narain, M. (2025). ESG vs. conventional indices in crises: Risk-adjusted returns in Indian markets. ScienceDirect Journal of Sustainable Finance, 11(1), 45–59.

8. Sahu, S., Pattanayak, R., &Narain, M. (2025). ESG indices in Indian capital markets: Performance, resilience, and risk dynamics. European Economic Letters, 14(2), 112–125.

9. Saravanan, P., &Satish, A. (2023). ESG scores and institutional investor attraction: Evidence from emerging markets. Business Perspectives, 21(3), 67–80.

10. Shirgaonkar, R. (2023). ESG indices in India: Construction methodology, sectoral weight bias, and performance trends. CFA Society India Working Paper Series.

11. Sivakumar, R., &Rajan, K. (2024). ESG integration and systematic risk: Evidence from NIFTY-listed firms. MDPI Sustainability, 16(5), 2212.

12. Thakrar, R., &Bhurat, D. (2023). Dispelling myths about ESG fund performance: An Indian perspective. Review of Indian Journal of Business Research, 9(1), 88–103.

13. Torri, G., Landi, A., & De Felice, M. (2023). ESG-coherent risk measures and portfolio performance: Global evidence.

14. Tripathi, A., &Gautam, R. (2024). ESG risk ratings and financial performance: Empirical evidence from NIFTY 50 firms. South Asian Journal of Business and Management Cases, 13(1), 18–30.