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Volatility Dynamics of Sustainability Indices in India: Evidence from BSE 100 ESG, GREENEX and CARBONEX

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Abstract

The intention of the research is to examine the volatility dynamics of sustainability indices in India, namely the BSE 100 ESG Index, BSE GREENEX and BSE CARBONEX. Taking day-to-day closing price data from January 2018 to August 2024, the study analysed volatility patterns using econometric models from the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) family. The study focused on finding volatility clustering, persistence and asymmetric volatility effects using GARCH (1, 1), EGARCH (1, 1) and EGARCH (1, 1) models. The results of the GARCH (1,1) model confirm the existence of significant volatility clustering and high volatility persistence in all three sustainability indices. The EGARCH (1,1) model's negative and significant leverage parameter (γ) shows that negative market news has a greater effect on volatility than good news of the same size. The existence of asymmetric volatility and leverage effects in the sustainability indices is further supported by the TGARCH (1,1) model implying that negative information or adverse market events generate higher volatility compared to positive news. It is concluded that ESG index outperformed better than other two indices revealing substantial volatility clustering, high persistence of shock and leverage effects during the sample period.

Keywords: *GARCH Family Models, Leverage Effect, Market Return, Volatility Clustering.*

Introduction

The actions of investors in financial markets have changed significantly in the last few years. Usually, investment decisions were predominantly conducted by financial metrics like profitability, liquidity and risk-return trade-offs. Investors today understand that non-financial issues, particularly those pertaining to Environmental, Social and Governance (ESG) aspects, are inextricably tied to long-term financial success. These days, investors are pickier than ever before about the companies they back, considering not just their financial success but also their ethics, sustainability and the effect they will have on society in the long run.

Investors worldwide are increasingly incorporating ESG aspects into their investment decisions because of the growing concern about climate change, environmental degradation, corporate failures etc. Short-term profits are no longer sufficient for investors, rather they look into businesses that use resources responsibly, have lower carbon footprints, use fair employment standards and have open governance for investment. The old objective of maximizing the profit is slowly replaced by a modern and broader approach of emphasizing long-term value creation. This paves the way for sustainable investing, which is now a crucial part of contemporary investment strategy. This change has led to the development of 'sustainable finance' in which choices about capital allocation include both financial and ethical goals. As a result of this paradigm change, major economies have developed sustainability-focused stock indexes that are used as benchmarks for ethical investment and performance assessment. Firms that implement sustainable business practices are seen to be more vigorous during times of economic uncertainty and market instability, i e COVID 19 epidemic has considerably increased investor interest in ESG-focused investing.

Since trading activity has expanded due to the growing interest in ESG and sustainable investments, it is vital to research their price fluctuations. Furthermore, the return and risk behaviour of the sustainable indices will differ from that of the standard stock market indexes due to their strong effect on climate change, carbon control, and social responsibility. Hence it is very important to understand the volatility dynamics of sustainability indices from both theoretical and practical perspectives. Theoretically, in ESG focused financial markets, volatility behaviour talks more about information transmission, investor sentiment, and market efficiency. But practically, analysing volatility dynamics is critical for investors, portfolio managers, policymakers, and financial institutions. Hence, investors who prioritize sustainability investment must need to know whether ESG indices exhibit stable return patterns or sensitive to market conditions.

In India, sustainable investment has gained significant hold in recent years as a result of rising environmental awareness, and increased engagement by responsible investors. The Bombay Stock Exchange (BSE) in India has established specialised indices, such as the BSE 100 ESG Index, BSE GREENEX and BSE CARBONEX, have become important benchmarks to monitor and assess the performance of businesses exhibiting better energy efficiency, reduced carbon emissions intensity and superior ESG practices. Even while sustainability indices are reflecting the ethical businesses, there are still concerns about their financial practices, especially market risk and volatility. Therefore, studying volatility characteristics of sustainability indices becomes essential for evaluating long-term investment potential of sustainable financial markets.

Numerous researches have attempted to analyse and explore the performance of sustainability index viz., Chikatla and Krishna Chaitanya (2023), Sharma and Jasuja (2020), Deshmukh et al. (2022), Sharma (2024). For instance, Nair et al. (2024) examined the BSE 100 ESG index's volatility and financial viability, emphasising the existence of asymmetric impacts and volatility persistence and pointed out that the negative shocks frequently have a bigger effect on volatility than positive one, which is in line with the leverage effect that is frequently seen in financial markets. Similarly, several studies have also found that sustainability indexes exhibit volatility clustering, time-varying conditional variance and asymmetric reactions to market information, making volatility modelling an essential element of sustainable finance study. In this regard, the current work combines symmetric and asymmetric GARCH family models to investigate the volatility dynamics of Indian sustainability indices.

Literature Review and Research Gap

Since the Bombay Stock Exchange introduced sustainability focused benchmarks, the academic researchers focus also switched toward understanding their volatility persistence, risk-return dynamics and reaction to market shocks. The theoretical and empirical research on sustainability index performance and volatility is reviewed in this section. Several investigators have made an effort to explore the volatility behaviour of sustainability indices across nation (Derwall et al. 2011; Aouadi and Marsat 2018; Nogueira and Madaleno 2022; Banumathy 2023).

The research conducted by Gupta and Chaudhary (2023) examined ESG indices in emerging economies including China, Brazil and India and found out that ESG indices outperform the overall market indices in all countries. According to research on the BRICS nations (Sahoo and Kumar 2022) ESG indexes shows notable volatility features like persistence and market-wide spillover effect suggesting that shocks in one market might affect volatility in other emerging economies. A recent study of HadjMohamed (2025) also proved the evidence of asymmetric volatility spillovers, particularly during periods of heightened uncertainty, where negative shocks had a stronger effect on volatility than positive shocks. Similarly, the literature on Indian sustainability indices has also appeared largely in the recent decade with researchers adapting worldwide findings. For instance Malik and Yadav (2020), Sharma (2024), Gupta and Tamta (2025) focused on identifying the volatility dynamics of sustainability indexes in India and found that the sustainability specialized indices have good return predictability in long run. It was proved by the recent study of Gupta and Chaudhary (2026), where they pointed out that sustainable investments offer competitive returns with better downside protection, especially for long term investors. The ARCH/GARCH-type models developed by Bollerslev (1986) has been used in their research in order to describe the volatility dynamics of sustainability indexes since GARCH family models are very particularly useful for financial return series because they can simulate volatility clustering.

Sharma (2024) examined the volatility patterns of BSE GREENEX, BSE CARBONEX and BSE 100 ESG and found that the performance of ESG index is found to be relatively stable. Similarly, Nazareth and Reddy (2024) analysed the performance of India's sustainability index, the S&P BSE GREENEX by applying Long Short-Term Memory (LSTM) deep learning model and found that machine-learning models may reliably forecast sustainability index fluctuations, giving important insights for green investors. Sudha (2015) used the GARCH model to compare the performance of India's ESG index to the Nifty and S&P CNX 500, revealing that the ESG index outperformed both. Sharma and Jasuja (2020) examined the performance of three sustainable indices of India and pointed out that CARBONEX outperformed GREENEX by a wide margin. Deshmukh et al. (2022) applied GARCH models to study the performance of GREENEX and CARBONEX over significant financial crises and discovered that ESG indices behave pretty consistently during market shocks. On the other hand, there are also many studies which incorporated the extended GARCH models, viz. EGARCH and TGARCH will helps in figuring out the asymmetric volatility and the presence of leverage effect (Goudarzi and Ramanarayanan 2011; Banumathy and Azhagaiah 2015; Aliyev et al. 2020; Gupta 2025). Using the EGARCH model, Passah et al. (2020) examined the asymmetric volatility impacts of five Asian nations' sustainability indexes and shown that negative market news had a greater influence on volatility than good ones. Shukla and Gupta (2025) used the TGARCH model to find asymmetry in sustainable index returns. The model revealed fat-tail features and considerable asymmetry, particularly during tumultuous periods, showing that volatility responses might worsen during market stress. Makkar et al. (2023) looked at how well sustainability indices performed in India before and during the COVID-19 epidemic. The NIFTY 100 Enhanced ESG index's volatility was estimated using the EGARCH model and result revealed that there was no leverage impact in the ESG index during either of the two time periods. With a particular focus on Energy, Greenex, Utility and Healthcare indices, including the TGARCH and EGARCH models, Kumar and Sharma (2024) analyzed the volatility features of a few indexes from BSE. Asymmetric volatility spillovers across sectoral indices were found in the study, suggesting that shocks in one index might spread differently across markets.

The current study is motivated by a number of significant gaps that are shown by a thorough review of the literature.

First, majority of empirical research has focused on identifying whether sustainability indices perform better or worse than standard market indexes in terms of average returns, risk-adjusted returns or portfolio performance metrics. However, these evaluations can only help in figuring out the profitability and they give a limited picture of how investors behave (Derwall et al. 2011; Aouadi and Marsat 2018; Sharma and Jasuja 2020; Malik and Yadav 2020; Nogueira and Madaleno 2022).

Secondly, most research has looked at examining individual index's return performance and analysing the behaviour only during specific period like financial crises or economic downturns (Singh et al. 2021; Beloskar and Rao 2023; Sharma et al. 2024). This limits the generalizability of results and does not offer a complete image of how sustainability indexes respond under normal and volatile market condition.

Third, there is no much study which simultaneously examines multiple sustainability indices such as BSE ESG, GREENEX, and CARBONEX within a single framework. Hence, a comprehensive analysis is essential to understand relative risk and return profile of sustainability indices. Furthermore, the problem of asymmetric volatility (leverage effects) is still not well understood and hence understanding its behaviour is critical for investors.

Although previous research has mostly concentrated on contrasting the return performance of sustainability indices with traditional indices or examining their behaviour during particular times of crisis, it only offers a limited knowledge of the risk characteristics of these indexes. The current study is motivated by the need to provide investigation on volatility dynamics over a long period of time of three sustainability indices simultaneously, which provides a deeper knowledge of the risk characteristics and a meaningful comparative evaluation of their behaviour in terms of volatility, persistence and responsiveness to market shocks. In addition, with the use of advanced econometric models from the GARCH family (symmetric and asymmetric specifications) the study tries to captures volatility clustering, persistence and also asymmetric effects (leverage effects).

As a result, the current study fills in the gaps in the literature and gives a comprehensive, methodologically sound and comparable analysis that sheds light on the dynamic risk-return behaviour of sustainability indices in India. In accordance with the research problem and gaps, the current study focused in:

1. Examining the volatility dynamics of sustainability indices in India, namely the 'BSE 100 ESG Index, BSE GREENEX and BSE CARBONEX'.
2. Analysing volatility clustering and persistence in the return series of these indices using GARCH family models.
3. Investigating the existence of asymmetric volatility effects (leverage effects), i.e., whether volatility is more affected by negative shocks than by positive ones.

The research paper is structured in such a way that it gives an overview of sustainable indices and the significance of investing in them in the first section. Reviews of previous empirical research on volatility modelling and sustainability indices are included in the second section and followed by research methodology in the third section which includes data sources, sample duration, diagnostic tests and econometric methods used in the study. The study presents the findings from the descriptive statistics, diagnostic tests and GARCH model and interprets it in detail. The fifth part summarizes the main conclusion and also emphasizes the consequences for policymakers and investors; makes recommendations for future research.

Research Methodology

Source of Data: For the research purpose, the secondary data comprising daily closing price of three indices namely BSE 100 ESG Index, BSE Greenex and BSE Carbonex were collected for a common sample period between January 2018 and August 2024 and the same is employed for the analysis.

Diagnostic Tests for Return Series: It is essential to examine the statistical characteristics of the return series of the three indices over the sample period before estimating volatility models. Accordingly, the study tests for normality, stationarity, and heteroscedasticity.

1. **Test of Normality:** Initially, to determine if the returns for the study period are normally distributed, the descriptive statistics showing mean, standard deviation, skewness, kurtosis, and the Jarque–Bera statistic were computed.

   H_0 – 'Returns are normally distributed'

   H_1 – 'Returns are not normally distributed'

2. Test of Stationarity: To observe the existence of unit root, the Augmented Dickey-Fuller Test (ADF) developed by Dickey and Fuller (1979) has been employed.

   H_0 – 'Returns are not stationary (contains a unit root)'

   H_1 – 'Returns are stationary (does not contain a unit root)'

3. Test for Heteroscedasticity: The study applied the Autoregressive Conditional Heteroscedasticity - Lagrange Multiplier (ARCH-LM) for identifying the existence of heteroscedasticity in the residual of the returns.

   H_0 –'There is no ARCH effect'

   H_1 – 'There is an ARCH effect'

Volatility Modelling using GARCH Family Models

The study used univariate symmetric and asymmetric GARCH specifications models viz., GARCH, EGARCH and TGARCH, which focuses on volatility clustering and leverage effects in each index separately.

The study employed GARCH (1, 1) model because it effectively captures volatility clustering and persistence in financial return series and also estimate time-varying volatility (heteroskedasticity), developed by Bollerslev (1986). The specification is as under:

Mean equation: $rt = \mu + \varepsilon\, t$

Variance equation: $\sigma^2 t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$

where

μ – average return,

s2*t* - conditional variance (volatility)

ω – constant term

α – ARCH effect (impact of past shocks)

β – GARCH effect (impact of past volatility)

Additionally, the study employed Exponential GARCH (EGARCH) and Threshold GARCH (TGARCH) model because they account asymmetric volatility and leverage effect. That is, these models help the investors to identify how negative news about sustainable investment creates strong impact than the positive news.

The specification of EGARCH developed by Nelson (1991) is as follows:

Mean equation: $Y_t = \mu + \varepsilon\, t$

Variance equation:

where

$\sigma^2 t$ - conditional variance

ω – constant term

β – persistence parameter

α – measures asymmetric (sign) effect

γ - magnitude (size) effect

- standardized residual

$$Ln(\sigma_t^2) = \omega + \beta_1 Ln(\sigma_{t-1}^2) + \alpha_1\left\{\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right\} - \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

The specification of TGARCH model developed by Zakoian (1994) is as follows:

Mean equation: $Yt = \mu + \varepsilon\, t$

Variance equation: $\sigma^2 t = \omega + \alpha 1\varepsilon^2 t\text{-}1 + \gamma dt\text{-}1$ e2 t-1 + b1s2t-1

where

$\sigma^2 t$ - conditional variance

ω – constant term

β – GARCH effect (volatility persistence)

α – ARCH effect (impact of past shocks)

γ - Asymmetric (threshold) parameter

where, $dt\text{-}1$ =1, < 0, indicates negative shocks (bad news) and $dt\text{-}1$ = 0, ≥ 0, indicates positive shocks (good news)

Empirical Results

For the purpose of the study, the daily price for all three sustainability indices of BSE were collected during the period from 2nd January 2018 to 30th August 2024 and the return is calculated on it. Table 1 displays the result of descriptive statistics of the daily returns of all three sustainability indices of BSE namely ESG Index, Greenex, and Carbonex.

TABLE 1: Descriptive Statistics and Augmented Dickey Fuller test

ITEMS	ESG INDEX	GREENEX	CARBONEX
Descriptive Statistics			
Mean	0.0015	0.0301	0.0155
Median	0.0028	0.0494	0.2810
S.D.	0.0250	0.4231	0.2548
Skewness	-0.7687	-0.8234	-0.9734
Kurtosis	10.4904	11.8698	14.0810
JB Statistics	4017.38*	5591.89*	8697.11*
Augmented Dickey Fuller Test			
ADF Statistics	-41.7981*	-41.6062*	-42.3133*
MacKinnon one side *critical values*		1%	-3.4341
5%		-2.8630	
10%		-2.5676	

Source: Computed results based on secondary data of 1649 daily observations of three indices.

*Notes: S.D. =Standard Deviation; JB= Jarque-Bera; *Significant at 1%.*

It is observed that all the mean returns exhibit a positive average return, with Greenex recording highest of it indicating relatively better performance during the period. The standard deviation, which quantifies volatility, indicates that Greenex is the most volatile index, suggesting it offers greater average returns associated with increased risk. All indices exhibit high kurtosis values (exceeding 3) signifying the existence of fat tails and indicating a leptokurtic distribution rather than a normal distribution. The value of negative skewness also proves that the return series are asymmetry and deviated from the characteristics of a normal distribution. Furthermore, Jarque-Bera statistics are statistically significant at 1% level leading to the rejection of the null hypothesis of normality. Overall, the returns of all the indices are not normally distributed.

The result of Augmented Dickey Fuller test is also displayed in table 1, which examines the stationarity properties of the returns of indices. The test statistics for all the indices are lower than the Mackinnon critical values at 1%, 5% and also at 10% significance levels, which indicates that all the variables are stationary at levels and exhibits the existence of unit root. Hence the null hypothesis 'returns are not stationary' is rejected at 1% level for all three indices.

TABLE 2: ARCH – LM test

	ESG INDEX	GREENEX	CARBONEX
ARCH LM test statistics	241.11*	305.28*	300.66*
P value	0.0000	0.0000	0.0000

*Source: Computed results based on secondary data of 1649 daily observations of three indices.*Significant at 1%.*

The presence of conditional heteroscedasticity in the return series is examined using ARCH Lagrange Multiplier (ARCH LM) test and the result were presented in the table 2. The result which is reported in the table indicates that the ARCH LM test statistics for all the indices are highly significant at 1% level and hence the null hypothesis of 'no ARCH effect' is rejected for all which confirms the presence of time varying volatility and volatility clustering in the return series. Since the ARCH LM test confirms strong evidence of conditional heteroscedasticity in all three return series, the GARCH family models are employed to capture the dynamic behaviour of volatility of ESG Index, Greenex and Carbonex returns.

TABLE 3: Results of GARCH (1, 1) estimation

COEFFICIENTS	ESG INDEX	GREENEX	CARBONEX
(α) μ (constant)	0.0017*	0.0234*	0.0175*
(β) ω (Constant)	0.0001*	0.0027*	0.0011*
α (ARCH effect)	0.1073*	0.1090*	0.1180*
β (GARCH effect)	0.8831*	0.8823*	0.8722*
α+β	0.9904	0.9913	0.9902
Log likelihood	3962.22	-689.73	156.94
Akaike Info. Criterion (AIC)	-4.80	0.84	-0.18
Schwarz Info. Criterion (SIC)	-4.78	0.85	-0.18

Source: Computed results based on secondary data of 1649 daily observations of three indices

*Notes: (a) mean equation (b) variance equation; *Significant at 1% level.*

Table 3 reports the result of the GARCH (1, 1) model estimated for three indices capturing volatility dynamics. The constant term (μ) in the mean equation, (captures the average return behaviour) is positive for all three indices, indicating positive average returns during the study period; out of which GREENEX (μ = 0.0234) records the highest mean return indicating stronger return potential for environmentally focused firms. The variance equation in a GARCH model, on the other hand, uses the parameters ω (Constant), α (ARCH effect) and β (GARCH effect) to describe time-varying volatility (called risk). The ARCH coefficient (α) measures the influence of recent shocks and all indices have a positive and statistically significant ARCH coefficient, where CARBONEX exhibits the highest ARCH effect, suggesting the existence of short-term volatility clustering. The GARCH coefficient (β) is substantial for all indices, suggesting that previous volatility strongly impacts future volatility and the total α + β is near to unity, indicating extremely persistent volatility. All three indices are satisfactorily fitted by the GARCH (1,1) specification, according to model adequacy diagnostics based on log-likelihood, AIC and SIC values. The ESG Index demonstrates the highest model adequacy with higher log-likelihood and lower information criteria values.

TABLE 4: Results of EGARCH (1, 1) estimation

COEFFICIENTS	ESG INDEX	GREENEX	CARBONEX
(α) μ (constant)	0.0012*	0.0168**	0.0117*
(β) ω (Constant)	-0.4538*	-0.2441*	-0.3216*
α (ARCH effect)	0.2405*	0.2475*	0.2726*
β (GARCH effect)	0.9642*	0.9698*	0.9611*
γ (Leverage effect)	-0.0656*	-0.0506*	-0.0575*
α+β	1.2047	1.2173	1.2337
Log likelihood	3967.06	-689.55	161.51
Akaike Info. Criterion (AIC)	-4.80	0.84	-0.18
Schwarz Info. Criterion (SIC)	-4.79	0.85	-0.17

Source: Computed results based on secondary data of 1649 daily observations of three indices

*Notes: (a) mean equation (b) variance equation; *Significant at 1% level, **Significant at 5% level.*

Drawing from 1,649 daily observations, Table 4 presents the estimated parameters of the EGARCH (1, 1) model for the all three indices. It is evident from the table that all three indices have a positive and statistically significant constant term (μ) in the mean equation (at the 1% and 5% levels) suggesting that the indices provide a positive average daily return throughout the course of the sample period; which means the mean returns deviate from zero in a regular manner. The constant coefficient of variance equation (ω) are negatively significant indicating that the indices has a stable underlying volatility structure, where GREENEX showing relatively higher mean returns compared to the other indices. The coefficients of ARCH and GARCH confirm the existence of short run volatility clustering and persistence of volatility respectively. Since the total of these coefficients (α+β) are greater than unity, it may be inferred that the volatility shocks have a significant memory and tend to remain for a prolonged period. GREENEX shows the highest persistence among the three (0.9698). The parameter γ for all indices are negative and highly significant confirming the presence of an asymmetric (leverage) effect. It indicates bad news (negative shocks) raise volatility more than good ones (positive shocks) of the same level. Among the indices, ESG shows the strongest leverage effect (-0.0656), followed by CARBONEX and GREENEX. This implies ESG is more sensitive to adverse market information.

Overall the indices show asymmetric and persistent volatility dynamics, with conditional variance being more strongly impacted by negative shocks. Moreover, log-likelihood values indicate satisfactory model estimation. Further, a strong model fit is suggested by the low values of the SIC and AIC for ESG suggesting EGARCH (1,1) model offers superior in sample fit in capturing its volatility dynamics compared to other two indices.

TABLE 5: Results of TGARCH (1, 1) estimation

COEFFICIENTS	ESG INDEX	GREENEX	CARBONEX
(a) μ (constant)	0.0013*	0.0188**	0.0137*
(b) ω (Constant)	0.0001*	0.0032*	0.0013*
α (ARCH effect)	0.0670*	0.0868*	0.0796*
β (GARCH effect)	0.8729*	0.8732*	0.8615*
γ (Leverage effect)	0.0852*	0.0554*	0.0840*
α+β	0.9399	0.9600	0.9411
Log likelihood	3968.81	-686.83	163.08
Akaike Info. Criterion (AIC)	-4.80	0.83	-0.19
Schwarz Info. Criterion (SIC)	-4.79	0.85	-0.17

Source: Computed results based on secondary data of 1649 daily observations of three indices

*Notes: (a) mean equation (b) variance equation; *Significant at 1% level, **Significant at 5% level.*

Alternative model to further test the leverage effect is TGARCH (1, 1) and the result of it is presented in Table 5. The model aims to capture the asymmetric volatility effects, specifically to investigate whether negative shocks have a greater impact on volatility than positive shocks. The constant term (μ,ω) in mean and variance equation are highly significant ensuring the presence of long run volatility in each index. The coefficients α and β are positively significant, indicating that the volatility is persistence in nature. Since, leverage parameter (γ) is greater than zero and significant, it confirms the presence of asymmetric effects (i.e volatility is increased more by bad news than by good news). ESG (0.0852) has the highest leverage effect, meaning it is most sensitive to negative news. Further, the log-likelihood values suggest satisfactory estimation as AIC and SIC values are lowest for ESG index.

Concluding Remarks

The present study examined the volatility dynamics of the sustainability indices viz., ESG INDEX, GREENEX and CARBONEX using daily returns from 2nd January 2018 to 30th August 2024. The symmetric and asymmetric GARCH family model viz., GARCH (1, 1), EGARCH (1, 1) and TGARCH (1, 1) were employed and its results clearly illustrates that all three sustainable investment indexes exhibit time varying and clustered volatility. The result of standard symmetric model GARCH (1, 1) used in the study confirmed the presence of significant ARCH and GARCH effects, indicating volatility clustering and high persistence in returns. The result supported the findings of Sudha (2015), Banumathy and Azhagaiah (2015), Malik and Yadav (2020). The results of both asymmetric models (EGARCH and TGARCH) found the presence of leverage effects (asymmetric effects) in three indices. It is proved from EGARCH model that ESG index has largest leverage impact (-0.0656), followed by GREENEX and CARBONEX suggesting that negative market information has a greater impact on ESG.

Similarly, the positive and substantial threshold parameter from the TGARCH model proposes that ESG (0.0852) has the highest leverage effect, proving that it is most sensitive to the negative news, which is consistent with the data supporting the existence of leverage effects. Hence, the 'leverage effects' is confirmed from EGARCH and TGARCH models and the current conclusion is consistent with earlier studies by Passah et al. (2020) and Shukla and Gupta (2025). The study concludes that ESG index outperformed the other two indices exhibiting substantial volatility clustering, high persistence of shock and leverage effects during the sample period. Further, the results from the study have an important implication for the investors and portfolio managers to think about dynamic risk management techniques rather than depending on static models. In order to provide investors with precise and trustworthy information that can assist lower market uncertainty, it is critical that policymakers enhance their reporting systems. Additionally, the stock exchanges and regulators may promote and help the market grow by offering more ESG-related investment options and encouraging investors to participate.

The study is limited only on three sustainability indices, whereas a more thorough investigation using other indices or a comparison with traditional indices might yield more comprehensive findings. Though widely used GARCH model were used in the study, which may not adequately capture severe market situations and structural breakdowns. Hence further studies could be explored on applying multivariate GARCH models. The study only looks at data from 2018 to 2024 and leaves out significant macroeconomic variables such as inflation, interest rates and world events, have great impact on the volatility of sustainability indexes. To further understand how macroeconomic factors affect the volatility of sustainability indexes, future studies might use a longer time frame.

References

Aliyev, F., Ajayi, R. A. & Gasim, N. (2020). Modelling Asymmetric Market Volatility with Univariate GARCH Models: Evidence from NASDAQ-100. The Journal of Economic Asymmetries 22.

Aouadi, A., & Marsat, S. (2018). Do ESG Controversies Matter for Firm Value? Evidence from International Data. Journal of Business Ethics 151 (4), 1027-1047.

Banumathy, K., & Azhagaiah, R. (2015). Modelling Stock Market Volatility: Evidence from India. *Managing Global Transitions* 13(1), 27–42.

Banumathy, K. (2023). Modelling Stock Market Volatility during the COVID-19 Pandemic: Evidence from BRICS Countries. Managing Global Transitions 21 (3), 253–268.

Beloskar, V. D., & Rao, S. V. D. N. (2023). Did ESG Save the Day? Evidence from India during the COVID-19 Crisis. Asia-Pacific Financial Markets 30, 73-107.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics 31 (3), 307–327.

Chikatla, P., & KrishnaChaitanya, K. (2023). A Comparative Analysis of BSE Sustainability Indices: Implications for Climate Finance and Sustainability Outcomes. Journal of Emerging Technologies and Innovative Research 10 (11), 429-445.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autogressive Time Series with a Unit Root. Journal of American Statistical Association 74 (366), 427–431.

Derwall, J., Koedijk, K., & Horst, J. (2011). A Tale of Values-driven and Profit-seeking Social Investors. Journal of Banking & Finance 35(8), 2137-2147.

Deshmukh, P., Sharma, D & Sharma, P. (2022). Do Socially Responsible Indices Outperform the Market during Black Swan Events: Evidence from Indian Markets during Global Financial and COVID-19 Crises. Australasian Accounting, Business and Finance Journal 16 (5), 19-37.

Goudarzi, H., & Ramanarayanan, C. S. (2011). Modeling Asymmetric Volatility in the Indian Stock Market. International Journal of Business and Management 6 (3), 221-231.

Gupta, H. (2025). Analysing volatility patterns in emerging markets: Symmetric or asymmetric models? Journal of Economic and Administrative Sciences 41 (5), 1928–1946.

Gupta, A., & Tamta, N. (2025). Sustainability and Stability: The Impact of ESG Ratings on Stock Price Volatility in India. International Journal of Environmental Sciences 11 (22), 5178–5185.

Gupta, H., & Chaudhary, R. (2023). An Analysis of Volatility and Risk-Adjusted Returns of ESG Indices in Developed and Emerging Economies. *Risks* 11 (10), 182.

Gupta, H., & Chaudhary, R. (2026). Assessing the Risk-adjusted Performance and Volatility of Sustainability-focused Indices of the Emerging Indian Market. Global Business Review.

HadjMohamed, W. (2025). ESG Uncertainty and Volatility Spillovers among BRICS Markets. International Journal of Research and Innovation in Social Science 9 (11), 2104-2129.

Kumar, K., & Sharma, D. (2024). Exploring Asymmetric Volatility Spillovers among Major Bombay Stock Exchange Indices. PRAGATI: Journal of Indian Economy 11 (2), 107-132.

Makkar, M. K., Ghayas, A. & Gupta, N. (2023). Performance of Conventional and Sustainable Index in Pre and During the COVID-19 Pandemic: A Comparative Analysis. Indian Journal of Finance 17 (5), 39-52.

Malik, C., and S. Yadav. 2020. 'Forecasting and Asymmetric Volatility Modeling of Sustainability Indexes in India.' *Corporate Governance and Sustainability Review* 4 (1): 56-64.

Nair, A., K. Goel, & Rallan. P. (2024). 'The Financial Feasibility of Investing in a Sustainability Index in India. Economic Sciences 20 (1), 115–126.

Nazareth, N., and Y. V. Reddy. 2024. 'Predictive analysis of S&P BSE Greenex Index: Unlocking insights for sustainable investments.' *Australasian Accounting, Business and Finance Journal* 18 (3): 223-247.

Nelson, D. B. (1991). Conditional Heteroscedasticity in Asset Returns: A New Approach. Econometrica 59 (2), 347–70.

Nogueira, M. C., & Madaleno, M. (2022). Are Sustainability Indices Infected by the Volatility of Stock Indices? Analysis before and after the COVID-19 Pandemic. Sustainability 14 (22), 15434.

Passah, H., G. G. Ninan, & Anuradha, P. S. (2020). Asymmetric Effects of Sustainability Indices in Emerging Asian Countries. Indian Journal of Research in Capital Market 7 (4), 8-18.

Sahoo, S., & Kumar, S. (2022). Integration and Volatility Spillover among Environmental, Social and Governance Indices: Evidence from BRICS Countries. Global Business Review 23 (6), 1280-1298.

Sharma, S. (2024). Performance Analysis of Sustainable Responsible Companies: An Empirical Study of Indian Sustainability Indices. GRENZE International Journal of Engineering and Technology 10 (2), 2426-2434.

Sharma, P., & Jasuja, D. (2020). Socially Responsible Investing and Stock Performance: A Study on Comparison of Sustainability Indices in India (ARCH & GARCH Approach). Delhi Business Review 22 (1), 85-97.

Sharma, P., Arora, G. Kalyani, S. Olasiuk, H. & Jindal, P. (2024). Sectoral Performance of ESG Enabled Stocks during COVID-19 Pandemic in the Indian Stock Market. International Journal of Economics and Financial Issues 14 (6), 232-238.

Shukla, U. N., & Gupta. H. (2025). Tail Behaviour of BSE Indices and their Impact on ESG risk-return: A Quantile Regression and GARCH-M Approach. Journal of Global Responsibility.

Singh, N. P., P. Makhija, & Chacko, E. (2021). Sustainable Investment and the COVID-19 effect - Volatility analysis of ESG index. International Journal of Sustainable Economy 13(4), 357-368.

Sudha, S. (2015). Risk-return and Volatility analysis of Sustainability Index in India. Environment, Development and Sustainability 17, 1329-1342.

Zakoian, J. M. (1994). Threshold Heteroscedasticity Models. Journal of Economic Dynamics and Control 18 (5), 931–955.