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MODELLING ASYMMETRIC AND LONG MEMORY VOLATILITY IN GREEN INNOVATION STOCKS: FIEGARCH ANALYSIS OF S&P BSE GREENEX

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Abstract. *Purpose* – This research examines the long-memory volatility within the S&P BSE Greenex, considering increasing investor focus on sustainability and the impact of green innovation on corporate environmental outcomes.

Research methodology – The study analyses volatility using the Fractionally Integrated Exponential Generalized Autoregressive Conditional Heteroskedasticity (FIEGARCH) model.

Findings – The empirical results reveal that higher volatility is negatively associated with expected returns, consistent with the presence of persistent volatility clustering and a leverage effect in green stock returns.

Research limitations – This study does not address the influence of exogenous factors or sector-specific effects, highlighting potential scope for further research.

Practical implications – The study findings highlight the substance of volatility modelling in sustainable investing. The presence of long-memory effects suggests that historical volatility data can aid in forecasting future trends in green stocks. Policymakers are suggested to consider measures to stabilize market conditions while promoting environmental sustainability, as reduced volatility can enhance investor confidence and encourage long-term sustainable investments.

Originality/Value – To the best of the author's knowledge, no prior research has examined the long-memory volatility of the sustainability index using the FIEGARCH model, highlighting the originality and contribution of this study.

Keywords: volatility, long memory effects, sustainability, S&P BSE Greenex.

JEL Classification: C58, G17, Q01, Q56.

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1. Introduction

Environmental challenges represent major global threats to ecosystems and human well-being. A central issue is climate change, primarily driven by historical greenhouse gas emissions from industrialized nations characterized by high levels of production and consumption. According to the IPCC Sixth Assessment Report (Working Group I), global temperatures have risen by 1.07 °C since the pre-industrial era, highlighting the urgency of managing the remaining carbon budget. As of 2019, 83% of the budget for limiting warming to 1.5 °C had already been used, leaving approximately 500 gigatonnes of CO_2 before this threshold is likely exceeded. For a 2 °C increase, 65% of the budget is already consumed (Press Information Bureau, 2022). These figures emphasize the lasting impact of past emissions and the pressing need to reduce ongoing emissions from energy, industry, transport, and agriculture. Industrial activities continue to be a key driver of environmental degradation. Air pollution from fossil fuels, water contamination from industrial waste, and land degradation due to deforestation and mining contribute significantly to biodiversity loss and waste accumulation. These interlinked pressures exacerbate the climate crisis and demand integrated mitigation strategies.

Thus, industrial activities significantly affect the global environment. While they are essential catalysts of economic growth, they also generate significant waste and pollution. Nevertheless, industries hold substantial potential to contribute to environmental sustainability. Increasingly, firms are recognizing the importance of addressing ecological challenges through sustainable practices. These efforts span regulatory compliance, emission reductions, resource efficiency, and long-term environmental stewardship. A key component is environmental innovation, which involves adopting advanced technologies and strategies such as renewable energy use, material optimization, waste recycling, sustainable design, and lifecycle management (Han et al., 2021; Rani, 2019). Such initiatives not only mitigate environmental impacts during production (Ammer et al., 2020), but also reflect a growing corporate commitment to ethical responsibility and proactive sustainability engagement (Ullah, 2024).

To implement effectively sustainability, firms are integrating these principles into their core products, policies, and operations. This integration is crucial for demonstrating a commitment to sustainable development and contributing to economic prosperity, societal well-being, and environmental conservation (Masocha, 2018). The adoption of sustainability practices by firms is influenced by factors such as institutional frameworks, top management commitment, and the involvement of key stakeholders. As firms increasingly embrace sustainable development, they not only enhance their value and performance but also address crucial environmental concerns (Siregar et al., 2024; Chong et al., 2018). Moreover, adopting sustainable development practices is increasingly linked to improved financial performance, reinforcing the imperative for holistic growth that advance economic resilience, environmental stewardship, and social equity (Phan et al., 2020).

In the current discussion addressing environmental issues and promoting sustainable practices across various sectors, the performance of green stock indices is highly relevant. This is crucial for investors, firms, and the global economy, because of its multifaceted benefits. The green stock index evaluates firms that show exceptional performance in ESG criteria and provides ethical investment opportunities for investors (Huang, 2023; Tian et al., 2023). Currently, the increase in green stock issuance and green bonds demonstrates a firm's dedication to sustainability and attracting investors' attention (Ahmed et al., 2023; Bužinskė & Stankevičienė, 2023). This movement, backed by the UN SDGs and the Paris Agreement, has led to new governance models and business-society collaborations (Ahmed et al., 2023). Investors prefer green investments for their sustainability and potential for higher returns, while companies enjoy improved reputations and access to ESG-focused capital (Mukhopadhyay & Sarkar, 2021; Sailendra, 2023). Moreover, from an economic standpoint, green stock indices boost sustainable development, market effectiveness, innovation, global collaboration, and their impact on global policies.

2. Literature review

Recent years have seen a surge in global environmental awareness, prompting a deeper focus on how financial mechanisms influence environmental outcomes within environmental economics (Wang & Wang, 2022). Green finance has emerged as a significant force in this context, driven by the rise of eco-friendly companies and the shift towards sustainable practices in established sectors. Unlike traditional finance, green finance emphasizes environmental conservation and resource management, aiming to improve environmental stability and support sustainable development through effective resource allocation. It seeks to reduce pollution and mitigate the negative impacts of clean technology by directing investments away from inefficient, high-pollution businesses and fostering innovation in these areas. Additionally, green finance addresses funding challenges for environmentally beneficial projects, lowers barriers to technological innovation, and supports the green transformation of industries with considerable environmental impacts (Zhang et al., 2023). Thus, it is a significant positive drivers of sustainable practices (Yang et al., 2022). In this regard, studying the volatility of green stocks is critically significant. The integration of ESG criteria into finance has led to significant shifts in investment patterns, influencing the performance and behaviour of green stocks. Such studies are crucial for evaluating how green stocks react to market dynamics, policy changes, and advancements in green technology. By analysing the volatility, investors and policymakers can gain insights into the risk profiles of green investments, allowing for better management of potential fluctuations and uncertainties.

Gurung and Sarkar (2023) discovered that stock prices within BSE Green Index, which adhere to ESG criteria, do not exhibit the market efficiency according to the EMH. Similarly, Khan et al. (2021) found that neither the US Dow Jones Environmental SRI nor the Shariah Compliance indices uphold the weak form of the EMH. This indicates that stocks within these indices do not fully incorporate past market information into their performance, which calls into question the validity of the EMH in the context of sustainability-driven investments. From these, it becomes evident that sustainability indices may not adhere to the market efficiency principles outlined by the EMH. This advocates that there could exist prospects for investors to identify and potentially exploit pricing inefficiencies within these markets.

Karim and Naeem (2022) identified sustainability indices as significant transmitters of spillovers across green, Islamic, and conventional financial markets. This underscores their role not only in reflecting investor sentiment towards sustainable practices but also in influencing broader market dynamics. By shaping perceptions and guiding capital allocation, sustainability indices play a pivotal role in financial markets, highlighting the increasing importance of integrating sustainability metrics into investment strategies amidst economic uncertainty and global market volatility. Understanding these indices is crucial for stakeholders navigating evolving market trends and preferences. On the other hand, Almansour et al. (2023) concluded that S&P500, S&P Euro 50 and DJWI primarily originate market shocks, with S&P and DJ sustainability indices more often absorbing these impacts passively. This suggests that sustainability indices react to broader market movements driven by conventional counterparts rather than instigating significant market changes themselves. Despite this, they noted a convergence of sustainability indices towards conventional norms in their market responses, indicating a growing alignment with mainstream market dynamics and investor assessments of risk and performance. From these findings, it is evident that sustainability indices play a dual role: they act as both transmitters of market spillovers and responders to broader market dynamics, illustrating their increasing integration into global financial markets.

Chatziantoniou et al. (2022) found that clean energy and green bond indices are net shock recipients, while sustainability indices are net transmitters. Zhao and Luo (2024) studied how climate uncertainty affects the price fluctuations of green indices in China by employing indicators such as US climate policy uncertainty index (UCPU), Chinese Climate Policy Uncertainty (CPU), and Chinese Climate Uncertainty (CU). Their results indicate that CPU and CU are strong predictors of green index volatility, whereas UCPU lacks predictive effectiveness for these indices. Singh et al. (2021) examined how the COVID-19 pandemic affected the volatility of the BSE ESG index using the EGARCH (1, 1, 1) model and concluded that the outbreak of the pandemic had no substantial effect on the index's return and volatility. Cagli et al. (2023) identified a significant two-way information flow involving crude oil volatility and sustainability indices, as well as within the interaction of cryptocurrency uncertainty and sustainability indices, particularly during extreme market conditions.

Sehrawat et al. (2022) investigated the effect of macroeconomic variables on sustainability indices in India. Their analysis, using the ARDL approach, revealed significant long-term relationships and detected volatility clustering in Greenex and Carbonex through a GARCH (1,1) model. Similarly, Kaur and Chaudhary (2022) examined the S&P BSE Carbonex index, uncovering a long-term equilibrium with factors like CPI, exchange rates, forex reserves, and interest rates, though only interest rates had a notable short-term impact. Both studies offer valuable insights for policymakers and investors regarding market dynamics and investment strategies.

Sharma (2022) analysed the BSE Greenex, showing consistent returns and improved performance post-COVID-19 compared to pre-pandemic periods, indicating stability and profitability in sustainable finance. Nazareth and Reddy (2024) used LSTM deep learning to study the BSE Greenex, noting its stable performance and increased returns in the post-pandemic era. Neenu and Nishad (2021) examined factors affecting carbon intensity in India, identifying the S&P BSE Greenex as a reliable investment with lower volatility than broader market indices, emphasizing its responsiveness to news events as a measure of sustainability. Sood et al. (2022) found improved returns for sustainability indices like Greenex during COVID-19, while Jonwall et al. (2024) concluded that socially responsible indices do not significantly differ in returns from conventional indices, suggesting ESG factors may not lead to superior financial performance. Debnath and Dinda (2023) explored performance trends of BSE Greenex, BSE Carbonex, and BSE ESG 100 indices, noting investor wealth growth caused by increasing interest in sustainable investments during and after the pandemic. Bhuvaneskumar et al. (2022) demonstrated that Sustainable Responsible Companies (SRCs) within the BSE Greenex exhibit stable performance and resilience against bankruptcy risks, supporting sustainability's role in financial stability. In contrast, Bakshi (2024) highlighted that non-green portfolios, particularly in automotive and BFSI sectors, outperformed green portfolios, suggesting higher market returns despite lower risk indicated by lower beta values in both portfolio types.

Sudha (2014) compared the S&P ESG India Index's performance against Nifty and S&P CNX 500 through daily data and GARCH models, revealing that while its daily returns paralleled the others, its annual returns surpassed them with less volatility, indicating that a focus on sustainability enhances benefits for companies, investors, and society, underscoring the rising allure of socially responsible investments in India. Malik and Yadav (2020) assessed the forecasting of returns and volatility for sustainability indices. They used the ARIMA method to model the autoregressive nature of the indices and applied GARCH modelling to address volatility clustering.

Among the sustainable indices in India, BSE Greenex is the oldest, having been launched in February 2012 by Bombay Stock Exchange. The index monitors how companies listed on the BSE perform, particularly those that lead in green innovation and environmental sustainability. It reflects the performance of green stocks that are committed to reducing their carbon footprint and adopting eco-friendly business practices. The empirical findings of the BSE Greenex reveal several key insights into its performance and role within sustainable finance. Studies indicate that the index has demonstrated consistent returns and improved performance after the COVID-19 pandemic, suggesting stability and profitability in sustainable investments. It has also shown stable performance and increased returns during the post-pandemic period, indicating resilience and positive market response. Furthermore, the index is noted for its lower volatility compared to broader market indices, making it a reliable investment option. The observed improved returns during periods of economic uncertainty, such pandemic, underscore its attractiveness and resilience in sustainability-focused investments. Thus, investing on the stock of BSE Greenex may be a financially stable choice for the investors for the sustainable investment.

Although the index is less volatile, as observed by Neenu and Nishad (2021), studying its long memory effects in volatility is crucial because green stocks are inherently tied to long-term sustainability goals, which may lead to persistent or prolonged dependencies over time. Analysing these long memory effects can yield significant understanding regarding the persistence of volatility patterns, which is essential for developing robust forecasting models, particularly for long-term investors focused on green portfolios. However, no previous studies have explored the long-memory effects on the index's volatility during the study period. Therefore, the present research work aims to achieve the objective as follows:

To measure conditional volatility and asymmetric effects in the BSE Greenex with a focus on both short-term and long-term volatility behaviour.

3. Methodology

The study uses daily closing data of the BSE Greenex, sourced from the BSE website (https://www.bseindia.com) for the period spanning 22nd February 2012 to 18th July 2024. The daily log return is calculated using the equation, Log Return (r_t) = $n\frac{P_t}{P_{t-1}}$, where, In denotes the natural logarithm, P_t and P_{t-1} represent the stock prices on the present day (t) and the previous day ($t-1$), respectively.

Volatility within financial time series represents a dynamic metric that signifies the level of uncertainty and risk inherent in asset returns. It is distinguished by phenomena such as clustering, persistence, and asymmetry (Lawrance, 2013; Wang et al., 2015; Abdullah et al., 2019; Aliyev et al., 2020). Furthermore, volatility can be categorized into components that are both predictable and unpredictable, with a substantial focus on the predictable aspect. This aspect of volatility is referred to as the conditional variance (Pagan & Schwert, 1990).

Engle's (1982) Autoregressive Conditional Heteroskedasticity (ARCH) model, the first volatility model, captures the phenomenon of volatility clustering by allowing volatility to fluctuate temporally, contingent upon past errors or shocks. Bollerslev (1986) further developed this model by integrating lagged conditional variance and residuals, resulting in the formulation of the Generalized ARCH (GARCH) model. This model has gained widespread application owing to its proficiency in accurately representing the occurrence of volatility clustering, wherein high volatility phases are often succeeded by additional high volatility, while phases of low volatility tend to precede further low volatility (Karmakar, 2007).

Fractionally Integrated Exponential GARCH (FIEGARCH) model of Bollerslev and Mikkelsen (1996) is used in the study. This model captures long-term volatility trends and asymmetric responses. This is an extension of the standard Exponential GARCH (EGARCH) model of Nelson (1991) that incorporates fractional integration to capture long-term persistence in volatility dynamics. The model allows for fractional orders of integration, denoted by d. The parameter d can take any value between 0 and 1, allowing the model to account for persistence in volatility. When $d = 0$, the model simplifies to the standard EGARCH model, while setting $d = 1$, transforms it into the Integrated EGARCH (IEGARCH) model. This model does not require the parameters to satisfy nonnegativity constraints for the model to be well-defined, and assumes that shocks to the conditional variance dissipate at a slow hyperbolic rate. This means that the influence of a shock decreases gradually over time, a key feature of long-memory behaviour. Again, the FIEGARCH-M model is an extension of the FIEGARCH model, incorporating a volatility-in-mean effect. This model allows for a relationship between volatility and returns, capturing the effect of changing behaviour of conditional volatility. Following Christensen et al. (2010), Jeribi et al. (2015) and Goudarzi (2010), the study adopts ARIMA (1,0,0)-FIEGARCH-M (1, d, 1) model. Under the study, the FIEGARCH-M model with ARCH-M variance showed insignificance, but using standard deviation yielded significant results. Therefore, FIEGARCH-M model with conditional standard deviation is specified as follows:

Mean Equation:

$$r_t = \mu_0 + \mu_1 r_{t-1} + \lambda\sigma_t + \varepsilon_t. \tag{1}$$

Variance Equation:

$$\ln\left(\sigma_t^2\right) = \omega + \frac{\alpha(L)}{\beta(L)}\pi(L)g\left(z_{t-1}\right); \tag{2}$$

$$\alpha(L) = 1 - \sum_{i=1}^{p}\alpha_i L^i; \tag{2.1}$$

$$\beta(L) = 1 - \sum_{i=1}^{q}\beta_i L^i; \tag{2.2}$$

$$\pi(L) = (1 - L)^{-d}; \tag{2.3}$$

$$g(z_t) = \gamma_1 z_t + \gamma_2 \left(|z_t| - \mathbb{E}|z_t|\right); \tag{2.4}$$

$$\varepsilon_t = \sigma_t z_t, \tag{2.5}$$

where: r_t – Return series at time t; μ_0 – Constant term in the mean equation; μ_1 – First-order autoregressive coefficient of returns; λ – ARCH-M coefficient measuring the effect of conditional standard deviation on returns; σ_t – Conditional standard deviation at time t; σ_t^2 – Conditional variance at time t; ε_t – Error term (innovation) at time t; z_t – Standardised residual, $z_t \sim i.i.d.(0,1)$; ω – Constant term in the variance equation; $\alpha(L)$ – Lag polynomial capturing short-run shock dynamics; $\beta(L)$ – Lag polynomial governing volatility persistence; d – Fractional integration (long-memory) parameter, $0 < d < 0.5$, ensuring hyperbolic decay and finite unconditional variance; $g(z_t)$ – News impact function capturing asymmetric volatility; γ_1 – Coefficient of magnitude effect; γ_2 – Coefficient of sign (leverage) effect.

The analysis commenced with the Augmented Dickey-Fuller (ADF) test for checking stationarity, which confirmed that the series was stationary. Model estimation was then conducted under normal, Student's t, and generalized error distributions. As results under the normal distribution were insignificant, they are not reported. Finally, four models were estimated: $FIEGARCH_{STD}$ (assuming Student's t distribution), $FIEGARCH_{GED}$ (assuming generalized error distribution), FIEGARCH-M_{STD} (incorporating the ARCH-M effect in the mean equation assuming STD), and FIEGARCH-M_{GED} (incorporating the ARCH-M effect in the mean equation assuming GED).

The feasibility of these models was tested using the Ljung-Box Q test, ARCH-LM test, and Engle's sign test to assess autocorrelation, heteroskedasticity, and leverage effect, respectively. The final model selection for drawing inference was based on the lowest AIC, SIC, and HQC values and the highest log-likelihood, ensuring the best fit for the data.

4. Results and discussion

As shown in Table 1, the stationarity test result shows that the ADF test statistic is –27.76321, with $p < 0.01$. Therefore, the test result confirms stationarity in the BSE Greenex return series.

Table 1. ADF Test to the daily return of BSE Greenex (source: author's analysis)

	t-statistic	p value	Level of significance			Null hypothesis	Decision
			1%	5%	10%		
ADF Test	–27.76321***	0.0000	–2.565717	–1.940927	–1.616630	Unit root	Reject

Note: *** indicates significance at 0.01.

Table 2 provides key insights into performance of BSE Greenex daily returns over the study period. The mean daily return is 5.29×10^{-4}, with a median of 9.28×10^{-4}. The returns show significant volatility, with a standard deviation of 0.037674, ranging from a maximum of 1.446785 to a minimum of –1.387892. The positive skewness of 2.102756 indicates a tendency for higher positive returns, while the high kurtosis of 1309.295 points to the presence of extreme values. The total sum of daily returns is 1.624315, and the sum of the squared deviations is 4.355814 based on 3070 observations.

Table 2. Descriptive statistics of the daily return of BSE Greenex (source: author's analysis)

Mean	5.29×10^{-4}
Median	9.28×10^{-4}
Maximum	1.446785
Minimum	–1.387892
Std. Dev	0.037674
Skewness	2.102756
Kurtosis	1309.295
Sum	1.624315
Sum Sq. Dev	4.355814
Observations	3070

The Jarque-Bera test result, summarized in Table 3, shows a statistic value of 2.18×10^8 with $p < 0.01$, confirming that the returns are not normally distribution. Further, the high kurtosis value (1309.295) classifies the data as "leptokurtic," indicating it exceeds the threshold of 3. Leptokurtic distributions suggest a higher likelihood of extreme returns, which significantly impacts volatility modelling. As such, the study used student's t and generalised error distribution for the volatility estimation.

Table 3. Jarque-Bera test of the daily return of BSE Greenex (source: author's analysis)

Test statistic value	p value	Null hypothesis	Decision
$2.18 \times 10^{8***}$	0.0000	Normal distribution	Reject

Note: *** indicates significance at 0.01

With regard to the diagnostic results of the FIEGARCH models, Table 4 depicts that the Ljung-Box test reveals notable differences in autocorrelation behaviour across different error distributions. The $FIEGARCH_{STD}$ model shows no significant autocorrelation, with Q_{10} and Q_{100} values of 3.5136 and 42.648, respectively, and Q^2_{10} and Q^2_{100} values of 0.0053 and 0.0609, all of which are insignificant. This implies that the residuals and squared residuals are consistent with white noise, indicating a well-fitting model. Similarly, the $FIEGARCH_{GED}$ model also demonstrates no significant autocorrelation, with Q_{10} and Q_{100} values of 2.7527 and 47.581, and Q^2_{10} and Q^2_{100} values of 0.0067 and 0.0713, all of which are insignificant. This suggests that this model also effectively captures the dynamics of the data without significant autocorrelation. The ARCH LM test of the FIEGARCH model with Student's t and generalized error distributions show test statistic values of 4.01×10^{-5} and 0.000353, respectively, both of which are insignificant. These results suggest that these models adequately capture volatility clustering, as indicated by the lack of significant ARCH effects in their residuals. The sign test results for the FIEGARCH models reveal distinct biases in the models with different error distributions. For the $FIEGARCH_{STD}$ model, the test shows Sign-Bias of –0.898874, Negative-Bias of 0.011206, Positive-Bias of 0.294820, and Joint-Bias of 1.023137, all of which are insignificant. Similarly, the $FIEGARCH_{GED}$ model exhibits Sign-Bias of –0.939083, Negative-Bias of 0.019182, Positive-Bias of 0.271938, and Joint-Bias of 1.086784, all also insignificant. These results indicate that both the models do not exhibit significant biases, suggesting that these models may provide a more balanced representation of the data.

With regard to the FIEGARCH-M models, as provided in Table 4, the Ljung-Box test of the model with the student's t error distribution shows Q_{10} and Q_{100} values of 3.6528 and 40.006, respectively, with both Q^2_{10} and Q^2_{100} values at 0.0050 and 0.0575, respectively, all insignificant. For the generalized error distribution, the Q_{10} and Q_{100} values are 2.1095 and 46.202, respectively, and the Q^2_{10} and Q^2_{100} values are 0.0066 and 0.0799, respectively, with all values remaining insignificant. These results indicate that both the models do not show significant autocorrelation. The ARCH LM test also indicate that all models exhibit insignificant values. Specifically, the test statistic for the FIEGARCH-M_{STD} is 0.000189, and for the FIEGARCH-M_{GED} is 0.000125. These insignificant test statistic values suggest that none of the models exhibit significant ARCH effects in their residuals. The sign test results for the FIEGARCH-M_{STD} model shows Sign-Bias of –0.902220, Negative-Bias of 0.009595, Positive-Bias of 0.322594, and Joint-Bias of 1.055429, all of which are insignificant. The FIEGARCH-M_{GED} model exhibits Sign-Bias of –0.929516, Negative-Bias of 0.015670, Positive-Bias of 0.321929, and Joint-Bias of 1.113128, with all biases also proving to be insignificant. These findings suggest that both the models do not exhibit significant bias in their estimations across different error distributions.

Based on the diagnostic test results, the analysis indicates that the $FIEGARCH_{STD}$ model is the most suitable among the FIEGARCH models. This preference extends to the FIEGARCH-M model when incorporating the ARCH-M effect in the mean equation. Therefore, the study selects the FIEGARCH-M_{STD} model for final inference, as it performs best across key information criteria metrics, including the lowest AIC (–6.511857), SIC (–6.492212), HQC (–6.504799), and the highest Log-Likelihood Ratio (10002.44). It is important to note that although the SIC and HQC of FIEGARCH-M_{STD} are slightly higher than those of $FIEGARCH_{STD}$, these differences are not significant because differences of less than 2 do not provide strong evidence against a model (Fabozzi et al., 2014). This outcome is consistent with those of Christensen et al. (2010) and Goudarzi (2010).

Therefore, based on the estimates of the selected model, it can be inferred from the λ = –0.038271 with $p < 0.05$, that there is a negative and significant connection between volatility and the expected returns of the BSE Greenex. This implies that higher market volatility is associated with lower expected return on the index. Moreover, the value of μ_0 at 0.000910 and significant at $p < 0.01$, reflects a robust baseline level of returns for the index. The μ_1 coefficient of 0.072697, significant at $p < 0.01$, highlights the persistence of return dynamics, with past returns having a significant influence on current returns.

In the variance equation, the estimated ω value (–0.097754) is statistically insignificant, suggesting that constant term does not significantly affect the long-term volatility of the index. Thus, the fluctuations in volatility are better explained by other factors such as past shocks and long memory effects. Both the values of α (–1.000810) and β (1.000095) are statistically significant at $p < 0.01$, which reflect the high persistence and structural features of the green equity return series of the index.

Regarding the shock effects, γ_1 (0.297713) being positive and significant ($p < 0.01$), indicates that the magnitude of past shocks, regardless of sign, symmetrically affects current volatility, with larger shocks leading to higher volatility. This robust statistical association supports the presence of volatility clustering in the index, indicating that pronounced market shocks are often succeeded by persistent volatility. On the other hand, γ_2 capturing asymmetric effect

(–0.211555) shows that downward movements increase current volatility more than upward movements of the same magnitude. This significantly negative coefficient suggests the existence of a leverage effect, where bad news results in higher volatility compared to good news. This finding can be illustrated with the News Impact Curve (NIC) as depicted in Figure 1.

The NIC indicates that adverse shocks lead to a considerably greater rise in volatility than favourable shocks, indicating a sharp rise on the negative side of the x-axis. In contrast, conditional variance responds weakly to positive shocks, as seen from the flat part of the curve for $\epsilon_{t-1} > 0$. This suggests that BSE Greenex exhibits high volatility in response to adverse

Table 4. Estimation results of FIEGARCH models of daily return for the BSE Greenex (source: author's analysis)

	$FIEGARCH_{STD}$	$FIEGARCH_{GED}$	$FIEGARCH\text{-}M_{STD}$	$FIEGARCH\text{-}M_{GED}$
λ	–	–	–0.038271** (0.017783)	–0.044198** (0.037329)
μ_0	0.000304** (0.000146)	0.000649*** (0.000121)	0.000910*** (0.000241)	0.001172*** (0.000323)
μ_1	0.087422*** (0.020232)	0.073959*** (0.015937)	0.072697*** (0.019923)	0.062933*** (0.062933)
ω	–0.109423 (0.244707)	–0.026071 (8.847297)	–0.097754 (14.79244)	–0.606626 (599.6954)
α	–1.002298*** (2.67×10^{-5})	–1.001671*** (0.001896)	–1.000810*** (0.001328)	–0.598484*** (0.156545)
β	1.000226*** (8.66×10^{-7})	1.000148*** (5.66×10^{-6})	1.000095*** (0.000101)	1.000079*** (0.006335)
γ_1	0.294490*** (0.027169)	0.418835*** (0.052842)	0.297713*** (0.028646)	0.344244*** (0.039594)
γ_2	–0.206462*** (0.025790)	–0.298437*** (0.038312)	–0.211555*** (0.027177)	–0.242959*** (0.035551)
d	0.479159*** (0.136993)	0.613064*** (0.187130)	0.286666** (0.133758)	–7.207684 (179.8187)
AIC	–6.511749	–6.414056	–6.511857	–6.400530
SIC	–6.494068	–6.396375	–6.492212	–6.380785
HQC	–6.505397	–6.407703	–6.504799	–6.393372
Log likelihood	10001.28	9851.369	10002.44	9831.460
Q_{10}	3.5136	2.7527	3.6528	2.1095
Q_{100}	42.648	47.581	40.006	46.202
Q^2_{10}	0.0053	0.0067	0.0050	0.0066
Q^2_{100}	0.0609	0.0713	0.0575	0.0799
ARCH LM test	4.01×10^{-5}	0.000353	0.000189	0.000125
Sign-Bias	–0.898874	–0.939083	–0.902220	–0.929516
Negative-Bias	0.011206	0.019182	0.009595	0.015670
Positive-Bias	0.294820	0.271938	0.322594	0.321929
Joint-Bias	1.023137	1.086784	1.055429	1.113128

Note: *** and ** indicate significance at 0.01 and 0.05.

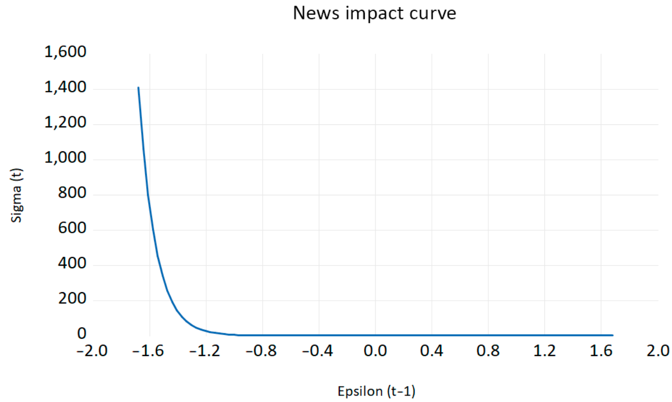

Figure 1. News impact curve (source: author's analysis)

events or negative information, likely due to the relatively nascent and potentially less stable nature of green stocks in the Indian market. Therefore, investors holding stocks within the sustainable index should recognise that negative news will disproportionately increase volatility during periods of market stress or negative economic developments.

The fractional integration *d* parameter, with a value of 0.286666 ($p < 0.05$), shows that the autocorrelations of the volatility process decay at a hyperbolic rate, indicating a gradual decline in the influence of past shocks over time. Since $0 < d < 0.5$, the volatility process is mean-reverting, implying that despite periods of high volatility due to market shocks or policy changes, the index will eventually return to its long-term average level. Furthermore, with $d < 0.5$ the existence of population variance is assured, which in turn confirms the model's dependability for practical applications (Bollerslev & Mikkelsen, 1996). This guarantees that the model is reliable and predictable without leading to uncontrolled volatility growth.

The above findings make significant empirical and theoretical contributions to the understanding of the Indian green equity market. The negative and significant risk-return relationship implies that investors in the Indian green equity market exhibit risk-averse behaviour during turbulent periods. This contradicts the classical risk-return trade-off predicted by Modern Portfolio Theory (Markowitz, 1952; Sharpe, 1964) but is consistent with recent studies on ESG and green financial markets, which report a negative or weak risk premium under heightened uncertainty (Sabbaghi, 2022; Gupta & Chaudhary, 2023). The strong persistence and long-memory behaviour in volatility extend evidence from previous studies (Wu & Qin, 2024; Pham et al., 2025) and augment long-memory and fractal market theories by demonstrating that shocks to the Indian green stocks exert prolonged effect that decay hyperbolically rather than exponentially. The significant leverage effect aligns with the asymmetric volatility hypothesis commonly found in financial markets (Raza et al., 2024), confirming that the Indian green market reacts more adversely to bad news than to favourable developments. The findings differ from some earlier studies reporting a positive risk-return trade-off in sustainable indices, primarily because the Indian green market is still at a nascent stage of development, has relatively low liquidity, and is more susceptible to sentiment, policy uncertainty, and information asymmetry (Negi et al., 2025). These contextual differences help explain the divergence from classical theory and highlight the importance of market-specific behavioural and structural factors in shaping green investment outcomes.

5. Conclusions

The growing global emphasis on ESG concerns has elevated sustainable business practices from a niche priority to a strategic imperative. Companies now recognize that embedding sustainability into core operations is no longer optional; rather, it is critical for maintaining long-term competitiveness, driven by international standards and growing stakeholder expectations for transparency. Empirical studies indicate that firms embracing sustainability not only enhance their reputations but also achieve superior financial performance, as evidenced by the participation of over 13,000 companies in the UN Global Compact, highlighting a significant commitment to sustainable development (Qi et al., 2020; Davis et al., 2020; Lozano, 2019; Kundu, 2023). This trend has motivated the present study to focus on BSE Greenex as a benchmark for sustainability-focused investors.

Particularly, in the above underlined context of sustainable finance and investment strategies, the study mainly focuses on assessing of long memory volatility, i.e., prolonged impact of past shock on future volatility, in this sustainability index. Inclusion of this phenomenon in the volatility model will benefit the investors in their sustainable investment decisions making. Concisely, the study demonstrates that the FIEGARCH-M model with a student's t error distribution provides the most robust framework for analysing the volatility and returns of the BSE Greenex. The results reveal strong statistical proof of inverse relationship between expected returns and volatility, significant impact of historical volatility on current volatility, existence of leverage effect and presence of a strong long memory effect.

These findings offer implications across three key areas. First, investors in green stocks should integrate volatility as a critical factor in their decision-making processes. The study highlights that periods of elevated volatility are associated with lower expected returns, emphasizing the importance of strategic risk management in green investments. Second, the observed long memory effect and persistent volatility indicate that past volatility trends are useful for forecasting future market behaviour. This insight allows analysts and portfolio managers to develop more accurate volatility forecasts and enhance their risk management strategies. Finally, for policymakers, understanding the interplay between volatility and returns in the green stock market plays a vital role in shaping the effective environmental sustainability policies. Stabilizing market conditions through policy measures could make green investments more attractive by reducing excessive volatility.

The present study analyses the volatility of one sustainable index only using the FIEGARCH-M model without considering exogenous variables. Future research could extend this analysis by incorporating exogenous factors like environmental regulations and government policies to examine their influence on green stock performance and sustainability index volatility. Additionally, there is potential for sector-specific analysis within the sustainable index to explore whether the volatility-return relationship varies across different sectors of green investments.

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