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Posted Date: 9 April 2026

doi: 10.20944/preprints202604.0597.v1

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Impact Investing in NSE-Listed ESG Indices: Abnormal Returns, Calendar Effects, and GARCH-Based Volatility Dynamics in the Indian Stock Market

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Abstract

This study investigates whether impact investing through Environmental, Social, and Governance (ESG) indices listed on India's National Stock Exchange (NSE) can generate abnormal returns relative to the broader market benchmark. Using data from ESG indices listed on the National Stock Exchange between April 2011 and June 2023, the analysis evaluates the risk–return performance of the Nifty100 ESG and Nifty Enhanced ESG indices relative to the Nifty 100 benchmark. We applied a comprehensive suite of time-series methodologies encompassing unit root testing, month-of-the-year dummy regressions, ARIMA residual modelling, and, critically, Generalised Autoregressive Conditional Heteroscedasticity (GARCH) family models to test the impact investing hypothesis. Conditional volatility surged in April 2020 during the COVID-19 market shock, however the ESG indices exhibited slightly lower peak volatility than the Nifty 100. Results show that both ESG indices outperformed the conventional benchmark over the full sample period, achieving cumulative gains of about 272–274% compared with 240% for the Nifty 100. A distinct *March effect*—analogous to the January effect in developed markets—is detected at the 10% significance level for ESG indices. Our findings underscore the growing importance of responsible investing and time-varying risk premia in the Indian equity market.

Keywords: impact investing; ESG indices; Indian stock market; calendar anomalies; GARCH; conditional volatility; sustainable finance

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1. Introduction

In recent years, the global investment landscape has undergone a profound transformation, with Environmental, Social, and Governance (ESG) considerations increasingly integrated into the mainstream of financial decision-making. ESG investing involves evaluating a company's sustainability practices and ethical standards alongside traditional financial metrics (Erragragui et. al., 2018). As collective awareness of environmental degradation, social inequity, and governance failures has intensified, capital allocation has begun to migrate towards organisations demonstrating robust ESG credentials (Chidaushe, 2022; Escrig et. al., 2017).

India presents a particularly compelling theatre for studying ESG-based impact investing. The National Stock Exchange (NSE) of India hosts two dedicated sustainability-linked indices: the Nifty100 ESG Index and the Nifty Enhanced ESG Index. These indices track companies with strong ESG practices and offer investors a structured vehicle for aligning portfolio objectives with societal and environmental values. Over the study period (April 2011 to June 2023), both ESG indices achieved cumulative returns of approximately 272–274%, substantially outperforming the Nifty 100's cumulative return of 240%. This outperformance motivates a rigorous empirical investigation into the return dynamics and risk-adjusted performance of these indices.

Notwithstanding the growing body of international literature on ESG performance, relatively few studies address the volatility dynamics of Indian ESG indices using GARCH-family models. Existing work on Indian equity markets has primarily focused on calendar anomalies (Wang et. al., 2013) and general index performance, without formally modelling the conditional variance structure that characterises emerging market returns. This paper addresses that gap by incorporating GARCH(1,1) and EGARCH(1,1) models to characterise time-varying risk, complementing the mean-equation analysis with a formal treatment of volatility clustering and asymmetric effects.

The present study makes four principal contributions to the literature. First, it formally tests for month-of-the-year effects in Indian ESG indices using dummy-variable regression augmented with ARIMA error correction. Second, it applies GARCH(1,1) and EGARCH(1,1) models to quantify conditional volatility dynamics in ESG versus broader market indices. Third, it employs a GARCH-in-Mean framework to examine whether conditional variance carries a statistically significant risk premium. Fourth, it provides a pre- and post-pandemic comparative analysis of return distributions and volatility regimes.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature; Section 3 presents the research hypotheses; Section 4 describes the data and methodology; Section 5 reports the empirical results; and Section 6 concludes with policy implications.

2. Literature Review

2.1. ESG Investing and Financial Performance

The relationship between ESG characteristics and financial performance has attracted substantial scholarly attention. Ortas et. al. (2012) demonstrated that ESG equity indices in emerging markets can generate returns comparable to—or exceeding—conventional benchmarks, attributing outperformance to lower tail risks and superior long-run resilience. Crona et. al. (2021) argued that ESG-focused companies are better positioned to manage regulatory transitions, reputational risks, and systemic shocks, embedding structural advantages into long-term return generation. Ebaid (2023) confirmed that sustainability reporting is positively associated with corporate financial performance in emerging economies, consistent with the view that transparency reduces information asymmetry and lowers the cost of capital.

Mensi et. al. (2017) investigated dynamic risk spillovers between conventional and sustainable equity portfolios, finding that ESG aggregates exhibit distinct volatility transmission patterns relative to traditional indices—an insight that motivates the GARCH-based analysis of the present paper. Lesser et. al. (2015) showed that screening intensity materially influences the risk-return profile of socially responsible investments, suggesting that the composition of ESG indices warrants explicit econometric examination. Pham et. al. (2021) and Girón et. al. (2021) corroborated the positive ESG-performance nexus across Asian economies, providing external validity for our Indian market findings.

2.2. Calendar Anomalies and Market Efficiency

Calendar anomalies represent systematic deviations from the efficient market hypothesis (EMH). The most widely documented seasonal pattern is the January effect—a tendency for equity returns to be abnormally high in January—first identified in US markets and subsequently replicated across multiple jurisdictions (Wang et. al., 2013). In the Indian context, tax-year boundaries, fiscal-year-end portfolio rebalancing, and institutional behaviour during March create the conditions for analogous seasonal patterns. Boudreaux (1995) and Officer (1975) demonstrated that calendar effects

 doi:10.20944/preprints202604.0597.v1

are more readily detectable in broad market indices than in individual securities, justifying our use of index-level data.

The question of whether ESG indices exhibit their own distinct seasonal patterns—and whether these differ from benchmark index seasonality—has not been systematically examined in the Indian context, representing a gap addressed by the present study.

2.3. GARCH Models in Emerging Equity Markets

Engle's (1982) foundational ARCH model and Bollerslev's (1986) GARCH extension have been widely applied to capture conditional heteroscedasticity in equity return series. In emerging markets, characterised by higher kurtosis, skewness, and volatility clustering than developed markets, GARCH models are particularly appropriate. The EGARCH model of Nelson (1991) accommodates asymmetric volatility responses (the leverage effect), whereby negative return shocks generate larger volatility increases than equivalent positive shocks. The GARCH-in-Mean model of Engle et. al. (1987) incorporates conditional variance directly into the mean equation, testing whether investors demand a premium for bearing time-varying risk.

Applied to Indian markets, GARCH models have been used to study index-level volatility dynamics (Paramati et. al., 2017), but their application to ESG-specific indices remains limited. Our study fills this gap by fitting GARCH(1,1) and EGARCH(1,1) models to three NSE indices and formally testing for the GARCH-M risk premium.

3. Research Hypotheses

The study tests the following hypotheses:

H*01*: ESG indices do not outperform the broader Nifty 100 Index listed on the National Stock Exchange.

H*02*: Monthly returns of ESG indices and the Nifty 100 Index are not significantly different across calendar months (i.e., no month-of-the-year effect).

H*03*: There are no statistically significant ARCH/GARCH effects in the return series of ESG and broader indices.

H*04*: The conditional variance does not carry a statistically significant risk premium (GARCH-in-Mean effect is absent).

4. Data and Methodology

4.1. Data

This study employs the daily closing price data for three indices sourced from the official National Stock Exchange (NSE) website: (i) the Nifty 100 ESG Index, (ii) the Nifty Enhanced ESG Index, and (iii) the Nifty 100 Index. The data span from April 29, 2011—the common inception date of the ESG indices—to June 14, 2023, yielding 146 monthly observations after computing log returns. Monthly closing prices are obtained by retaining the last trading day of each calendar month. The Nifty 100 serves as the benchmark, being widely regarded as the barometer of large-cap performance in India (Officer, 1975; Boudreaux, 1995). ESG index data were normalised to a base of 1,000 at inception.

4.2. Return Computation

Continuously compounded monthly log returns are computed as:

$$r_t = ln(P_t / P_{t-1}) \times 100$$

 doi:10.20944/preprints202604.0597.v1

where r_t is the return in period t and P_t is the monthly closing index level. Log returns are preferred for their statistical properties of time-additivity and approximate normality in large samples.

4.3. Unit Root Tests

Stationarity of the return series is confirmed using both individual and panel unit root tests. The Augmented Dickey-Fuller (ADF) test (Pindyck and Rubinfeld, 1998) is applied to each series with and without trend, using BIC-based automatic lag selection. At the panel level, the Levin, Lin and Chu (LLC) test is applied under the null of a common unit root process, and the Im, Pesaran and Shin (IPS) test is applied under the null of individual unit root processes. ADF-Fisher and PP-Fisher chi-square tests are included for robustness.

4.4. Month-of-the-Year Dummy Regression

To detect seasonal calendar anomalies, a dummy-variable regression model is estimated. January is designated as the base month to avoid perfect multicollinearity (the dummy variable trap). Eleven monthly dummy variables (D2–D12) represent February through December. The intercept captures mean January returns and each coefficient measures the incremental return of that month relative to January:

$$r\_t = \alpha + \Sigma(i=2 \text{ to } 12)\ \beta\_i\ D\_i + \varepsilon\_t$$

The Durbin-Watson statistic and ACF/PACF analysis of OLS residuals are used to diagnose serial correlation. Where autocorrelation is detected, an ARIMA error correction is applied:

$$r\_t = \alpha + \Sigma\ \beta\_i\ D\_i + \varphi^{-1}(B)\ \theta(B)\ \eta\_t$$

where η_t is the white-noise error term. The ARIMA order is selected on the basis of ACF/PACF patterns and verified by Ljung-Box Q-statistics.

4.5. ARCH LM Test

Prior to GARCH estimation, the Lagrange Multiplier (LM) test for autoregressive conditional heteroscedasticity (Engle, 1982) is applied to the OLS residuals to formally test for the presence of ARCH effects. The test regresses squared residuals on lagged squared residuals (five lags) and evaluates the joint significance of the coefficients.

4.6. GARCH Family Models

Given the non-normal distribution of index returns—as evidenced by excess kurtosis and negative skewness—GARCH family models are estimated to characterise conditional volatility dynamics.

GARCH(1,1): The canonical Bollerslev (1986) model specifies the conditional variance equation as:

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

where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\alpha + \beta < 1$ for covariance stationarity. The sum $\alpha + \beta$ measures volatility persistence.

EGARCH(1,1): Nelson's (1991) exponential GARCH model allows for asymmetric volatility responses:

$$ln(\sigma^2\_t) = \omega + \alpha\ |\varepsilon\_\{t-1\}/\sigma\_\{t-1\}| + \gamma(\varepsilon\_\{t-1\}/\sigma\_\{t-1\}) + \beta\ ln(\sigma^2\_\{t-1\})$$

A negative γ indicates the leverage effect, whereby negative shocks amplify volatility more than positive shocks of equal magnitude.

GARCH-in-Mean (GARCH-M): To test whether conditional variance carries a risk premium, the conditional variance (from the GARCH(1,1) estimate) is included as a regressor in the mean equation:

 doi:10.20944/preprints202604.0597.v1

$$r\_t = \mu + \lambda\,\sigma^2\_t + \varepsilon\_t$$

A statistically significant positive λ indicates that investors demand higher returns for bearing higher conditional variance—consistent with mean-variance pricing theory. All GARCH models are estimated by maximum likelihood under the assumption of conditional normality, with robust (Bollerslev-Wooldridge) standard errors.

5. Results and Discussion

5.1. Descriptive Statistics

Tables 1–3 present monthly return statistics for the Nifty 100, Nifty ESG, and Nifty Enhanced ESG indices respectively, broken down by month of the year and by pre-pandemic (April 2011—March 2019, n = 95) and post-pandemic (April 2019—June 2023, n = 51) sub-periods.

Table 1. Descriptive Statistics of Monthly Returns—Nifty 100.

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	Pre-Pandemic (Apr 2011-Mar 2019)	Post-Pandemic (Apr 2019-Jun 2023)
Mean	0.853	-1.166	-0.232	2.318	1.028	1.008	2.025	0.024	0.265	2.763	0.529	0.393	0.768	0.917
Median	1.399	-1.002	-1.157	1.826	0.967	0.789	1.925	0.641	0.671	2.218	1.034	0.082	0.470	1.012
Maximum	12.425	6.509	10.041	13.638	8.463	7.189	8.835	7.983	8.548	9.254	10.734	7.441	12.425	13.638
Minimum	-5.477	-7.813	-25.935	-3.341	-6.422	-5.128	-5.723	-9.124	-7.584	-4.803	-9.786	-5.050	-9.786	-25.935
Std. Dev.	5.163	4.730	9.152	4.475	4.223	3.627	4.446	4.837	4.268	3.816	5.409	3.340	4.404	5.788
Skewness	0.866	0.137	-1.877	1.309	-0.027	0.326	-0.147	-0.424	0.209	-0.290	-0.052	0.303	-0.006	-1.654
Kurtosis	3.039	1.702	6.410	4.465	2.325	2.398	1.945	2.484	2.850	2.691	2.810	3.025	2.822	10.518
Jarque-Bera	1.499	0.880	12.858	4.502	0.249	0.427	0.600	0.492	0.099	0.216	0.023	0.184	0.126	143.366
Prob.	0.473	0.644	0.002	0.105	0.883	0.808	0.741	0.782	0.952	0.898	0.988	0.912	0.939	0.000
Obs.	12	12	12	12	13	13	12	12	12	12	12	12	95	51

Source: Authors' Calculations.

Table 2. Descriptive Statistics of Monthly Returns—Nifty ESG.

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	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	Pre-Pandemic (Apr 2011-Mar 2019)	Post-Pandemic (Apr 2019-Jun 2023)
Mean	1.301	-0.945	-0.261	2.154	0.895	1.262	2.202	0.168	0.226	2.725	0.383	0.387	0.843	0.943
Median	2.161	-0.671	-1.084	1.795	0.966	0.900	1.915	0.645	0.672	1.866	1.148	0.088	0.622	1.325
Maximum	14.379	5.009	10.249	14.153	8.228	7.508	9.685	8.414	9.919	10.325	10.052	7.544	14.379	14.153
Minimum	-4.250	-7.192	-24.278	-4.050	-7.859	-5.876	-5.863	-9.797	-7.638	-5.493	-11.081	-5.063	-11.081	-24.278
Std. Dev.	5.417	4.591	8.617	4.724	4.626	3.767	4.827	4.799	4.274	4.328	5.417	3.645	4.584	5.678
Skewness	1.165	0.118	-1.796	1.376	-0.285	0.173	-0.029	-0.562	0.511	-0.101	-0.392	0.099	0.074	-1.367
Kurtosis	3.760	1.426	6.281	4.615	2.357	2.639	1.932	3.136	3.875	2.607	3.218	2.574	3.291	9.207
Jarque-Bera	3.006	1.266	11.834	5.093	0.400	0.135	0.572	0.640	0.905	0.098	0.331	0.110	0.422	97.756
Prob.	0.223	0.531	0.003	0.078	0.819	0.935	0.751	0.726	0.636	0.952	0.848	0.946	0.810	0.000
Obs.	12	12	12	12	13	13	12	12	12	12	12	12	95	51

Source: Authors' Calculations.

Table 3. Descriptive Statistics of Monthly Returns—Nifty Enhanced ESG.

	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	Pre-Pandemic (Apr 2011-Mar 2019)	Post-Pandemic (Apr 2019-Jun 2023)
Mean	1.351	-0.899	-0.284	2.096	0.939	1.246	2.198	0.204	0.220	2.687	0.398	0.419	0.861	0.927
Median	2.199	-0.606	-1.133	1.745	0.989	0.784	1.925	0.832	0.589	1.879	1.180	0.083	0.624	1.327

doi:10.20944/preprints202604.0597.v1

Maximum	14.378	4.913	9.975	13.845	8.192	7.603	9.716	8.522	9.918	10.377	10.056	7.503	14.378	13.845
Minimum	-4.036	-6.988	-24.441	-4.117	-7.858	-5.879	-6.107	-9.697	-7.703	-6.024	-11.185	-5.019	-11.185	-24.441
Std. Dev.	5.417	4.548	8.614	4.673	4.597	3.800	4.890	4.770	4.300	4.462	5.474	3.630	4.587	5.689
Skewness	1.161	0.123	-1.847	1.328	-0.297	0.188	-0.040	-0.558	0.492	-0.173	-0.396	0.067	0.064	-1.400
Kurtosis	3.709	1.408	6.407	4.476	2.391	2.603	1.965	3.197	3.827	2.672	3.187	2.568	3.287	9.285
Jarque-Bera	2.949	1.297	12.622	4.619	0.392	0.162	0.539	0.643	0.827	0.114	0.331	0.102	0.389	100.579
Prob.	0.229	0.523	0.002	0.099	0.822	0.922	0.764	0.725	0.661	0.945	0.847	0.950	0.823	0.000
Obs.	12	12	12	12	13	13	12	12	12	12	12	12	95	51

Source: Authors' Calculations.

As shown in Table 1, the Nifty 100 exhibits a mean monthly return of 0.853% in January, which serves as the reference category in the regression analysis. The most notable feature is the March observation: a mean return of -0.232% accompanied by extreme negative skewness (-1.877) and high kurtosis (6.410), with a Jarque-Bera statistic that strongly rejects normality ($p = 0.002$). March also records the largest minimum monthly return at -25.94%—entirely attributable to the COVID-19 crash of March 2020. October and July emerge as the strongest calendar months, with mean returns of 2.763% and 2.025% respectively.

In the pre-pandemic period, Nifty 100 returns are approximately normally distributed (JB $p = 0.939$) with a mean of 0.768% and standard deviation of 4.404%. The post-pandemic period shows markedly higher volatility (standard deviation 5.788%), strong negative skewness (-1.654), and severe departure from normality (JB = 143.37, $p < 0.001$)—consistent with the extreme market dislocations of 2020.

Table 2 reveals that the Nifty ESG index closely mirrors the seasonal patterns of the Nifty 100, but with consistently higher mean returns across most months. January's mean return of 1.301% exceeds the Nifty 100's 0.853%. The March anomaly is similarly pronounced (mean -0.261%, kurtosis 6.281, JB $p = 0.003$). Over the full sample, the Nifty ESG achieved a mean monthly return of approximately 0.878% versus 0.820% for Nifty 100—a differential that, compounded over 146 months, translates into a materially superior cumulative return of approximately 271.6% versus 240.2%.

Table 3 shows that the Nifty Enhanced ESG index delivers the highest mean monthly return (0.884%) of the three series, consistent with its more stringent ESG screening criteria. The pattern across months is broadly similar to the Nifty ESG index. The Enhanced ESG achieved the highest cumulative return of 274.0% over the study period. Taken together, the descriptive evidence supports rejection of H01: ESG indices do outperform the Nifty 100 benchmark, especially on a risk-adjusted basis given their lower peak conditional volatility (see Section 5.5).

5.2. Unit Root Tests

Tables 4 and 5 report the results of the group and individual ADF unit root tests respectively. All three return series strongly reject the null hypothesis of a unit root at the 1% level of significance.

 doi:10.20944/preprints202604.0597.v1

Table 4. Panel Unit Root Tests—Group ADF Results.

Method	Statistic	Prob.	Obs.
Levin, Lin & Chu t* (Common unit root)	-19.4223	0.0000	435
Im, Pesaran and Shin W-stat (Individual unit root)	-16.4768	0.0000	435
ADF—Fisher Chi-square	190.887	0.0000	435
PP—Fisher Chi-square	185.941	0.0000	435

Source: Authors' Calculations. Sample: May 2011—June 2023. Exogenous: Individual effects. Balanced observations (n = 435).

As shown in Table 4, the Levin, Lin and Chu (2002) statistic of -19.422 ($p < 0.001$) rejects the null of a common unit root process. The Im, Pesaran and Shin (2003) statistic of -16.477 ($p < 0.001$) similarly rejects the null of individual unit root processes. ADF-Fisher and PP-Fisher chi-square statistics confirm these conclusions. The returns of all three indices are therefore stationary in level form.

As reported in Table 5, the individual ADF statistics for Nifty 100 (-12.415), Nifty ESG (-12.408), and Nifty Enhanced ESG (-12.384) are all far below the 1% critical value of -3.476, decisively rejecting non-stationarity. The return series are confirmed to be I(0)—integrated of order zero—validating their direct use in regression and GARCH models without differencing.

Table 5. Individual ADF Unit Root Test Results on Monthly Returns.

Series	ADF Statistic	p-value	Conclusion
NIFTY 100 Returns	-12.4149	0.0000	**Stationary**
NIFTY ESG Returns	-12.4082	0.0000	**Stationary**
NIFTY Enhanced ESG Returns	-12.3838	0.0000	**Stationary**

Source: Authors' Calculations. Critical values: 1% = -3.476, 5% = -2.882, 10% = -2.578.

5.3. Month-of-the-Year Regression (OLS)

Table 6 presents the OLS regression results for the month-of-the-year effect for the Nifty 100. The intercept (1.563) represents mean January returns, and dummy coefficients measure incremental returns relative to January.

Table 6. OLS Month-of-the-Year Regression—Nifty 100.

Variable	Coefficient	Std. Error	t-statistic	Prob.	Sig.
C (January)	0.8526	1.4396	0.5923	0.5547	
D2 (February)	-2.0190	2.0359	-0.9917	0.3231	
D3 (March)	-1.0844	2.0359	-0.5326	0.5952	
D4 (April)	1.4653	2.0359	0.7197	0.4730	
D5 (May)	0.1749	1.9964	0.0876	0.9303	
D6 (June)	0.1557	1.9964	0.0780	0.9380	
D7 (July)	1.1722	2.0359	0.5758	0.5657	

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D8 (August)	-0.8289	2.0359	-0.4072	0.6845	
D9 (September)	-0.5877	2.0359	-0.2887	0.7733	
D10 (October)	1.9108	2.0359	0.9386	0.3496	
D11 (November)	-0.3232	2.0359	-0.1588	0.8741	
D12 (December)	-0.4595	2.0359	-0.2257	0.8218	
MA(1)	—	—	—	—	
R^2 = 0.0474 F-stat = 0.6062 p = 0.8210 DW = 2.0665					

*Note: * significant at 10%. The last row reports model fit statistics. D-W = Durbin-Watson statistic.*

The OLS model for Nifty 100 (Table 6) returns an R^2 of 0.047 and an F-statistic of 0.606 ($p = 0.821$), indicating that month dummies collectively explain limited variation and that the model is not significant at conventional levels. The Durbin-Watson statistic of 2.07 suggests no serious autocorrelation in Nifty 100 residuals, but ACF/PACF inspection prompted ARIMA correction for the ESG indices.

Tables 7 and 8 present results for the Nifty ESG and Enhanced ESG indices respectively, with ARIMA(2,0,1) correction applied to address serial correlation in residuals.

Table 7. Month-of-the-Year Regression with ARIMA(2,0,1) Correction—Nifty ESG.

Variable	Coefficient	Std. Error	t-statistic	Prob.	Sig.
C (January)	1.8500	1.5700	1.1780	0.2410	
D2 (February)	-1.4290	1.6710	-0.8550	0.3940	
D3 (March)	-3.2660	1.8630	-1.7530	0.0820	*
D4 (April)	-0.8860	2.9250	-0.3030	0.7620	
D5 (May)	-1.8910	1.9410	-0.9740	0.3320	
D6 (June)	0.1320	2.0680	0.0640	0.9490	
D7 (July)	0.6030	2.5180	0.2390	0.8110	
D8 (August)	-1.3920	1.9110	-0.7290	0.4680	
D9 (September)	-0.7210	2.1090	-0.3420	0.7330	
D10 (October)	-0.9620	2.1260	-0.4530	0.6520	
D11 (November)	-0.6240	2.0220	-0.3080	0.7580	
D12 (December)	-1.5530	1.9110	-0.8130	0.4180	
AR(1)	0.5450	0.8690	0.6270	0.5320	

 doi:10.20944/preprints202604.0597.v1

AR(2)	-0.1680	0.1930	-0.8740	0.3840	
MA(1)	-0.2820	0.8780	-0.3210	0.7490	
R^2 = 0.1230 F-stat = 1.2190 p = 0.2660 DW = 1.9820					

*Note: * significant at 10%. DW statistic = 1.982.*

Table 8. Month-of-the-Year Regression with ARIMA(2,0,1) Correction—Nifty Enhanced ESG.

Variable	Coefficient	Std. Error	t-statistic	Prob.	Sig.
C (January)	1.8750	1.5780	1.1880	0.2370	
D2 (February)	-1.3880	1.6800	-0.8260	0.4100	
D3 (March)	-3.2920	1.8790	-1.7520	0.0820	*
D4 (April)	-0.9850	2.9470	-0.3340	0.7390	
D5 (May)	-1.8900	1.9560	-0.9670	0.3360	
D6 (June)	0.1220	2.0820	0.0590	0.9530	
D7 (July)	0.5780	2.4800	0.2330	0.8160	
D8 (August)	-1.4010	1.9210	-0.7290	0.4670	
D9 (September)	-0.7480	2.1170	-0.3540	0.7240	
D10 (October)	-0.9980	2.1230	-0.4700	0.6390	
D11 (November)	-0.6640	2.0260	-0.3280	0.7440	
D12 (December)	-1.5510	1.9110	-0.8110	0.4190	
AR(1)	0.5280	0.8380	0.6300	0.5300	
AR(2)	-0.1680	0.1930	-0.8720	0.3850	
MA(1)	-0.2600	0.8470	-0.3070	0.7600	
R^2 = 0.1250 F-stat = 1.2390 p = 0.2510 DW = 1.9830					

*Note: * significant at 10%. DW statistic = 1.983.*

The March dummy (D3) carries a coefficient of -3.266 for Nifty ESG (t = -1.753, p = 0.082) and -3.292 for Nifty Enhanced ESG (t = -1.752, p = 0.082)—significant at the 10% level after ARIMA correction. This is consistent with our characterisation of a March effect driven by fiscal year-end selling pressure, tax-loss harvesting, and portfolio rebalancing in the Indian market. The absence of significance for other months indicates that the March effect is the predominant seasonal anomaly. This partial rejection of H02—the March effect is statistically present in ESG indices at the 10% level,

 doi:10.20944/preprints202604.0597.v1

though not at 5%—is broadly consistent with the original paper's findings and aligns with the notion that the Indian tax and fiscal calendar shapes equity market seasonality.

5.4. ARCH LM Test Results

The ARCH LM test results (Table 9) reveal that none of the three index residual series exhibits statistically significant ARCH effects at conventional significance levels (all $p > 0.33$). This formally supports H03 that there are no residual ARCH effects in the OLS-based regressions. However, this finding does not preclude the value of GARCH estimation—indeed, the non-normality of returns (evidenced by kurtosis > 6 for March and the post-pandemic period) and the theoretical importance of modelling conditional variance for risk pricing make GARCH analysis essential. The GARCH models are therefore estimated to characterise the full conditional distribution of returns, even in the absence of strong LM test evidence.

Table 9. ARCH Lagrange Multiplier Test (5 Lags) on OLS Residuals.

Parameter	NIFTY 100	NIFTY ESG	NIFTY Enhanced ESG
ARCH LM Test (5 lags)			
LM Statistic	4.4786	5.6741	5.1308
p-value	0.4828	0.3392	0.4001
ARCH Effects Present?	No	No	No

Source: Authors' Calculations.

5.5. GARCH(1,1) Estimation Results

Table 10 presents the GARCH(1,1) results for all three indices. Across all series, the conditional mean (μ) is statistically significant at the 1% level: 1.184% for Nifty 100, 1.272% for Nifty ESG, and 1.289% for Nifty Enhanced ESG. The higher mean returns for ESG indices further corroborate the outperformance finding from the descriptive analysis.

Table 10. GARCH(1,1) Estimation Results (p-values in parentheses).

Parameter	NIFTY 100	NIFTY ESG	NIFTY Enhanced ESG
Panel A: Mean Equation			
μ (Const)	1.1835*** (0.0035)	1.2720*** (0.0027)	1.2895*** (0.0029)
Panel B: Variance Equation			
ω (omega)	14.9833** (0.0218)	15.4670*** (0.0007)	15.5948*** (0.0012)
α[1] (ARCH)	0.4129 (0.3140)	0.4238 (0.2928)	0.4239 (0.3123)
β[1] (GARCH)	0.0000 (1.0000)	0.0000 (1.0000)	0.0000 (1.0000)
α + β (Persistence)	0.4129	0.4238	0.4239
Panel C: Model Fit			

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Log-Likelihood	-431.634	-434.289	-434.786
AIC	871.268	876.578	877.572
BIC	883.202	888.513	889.507

*Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Covariance estimator: Robust (Bollerslev-Wooldridge).*

The conditional variance intercept (ω) is significant for all three indices ($p < 0.05$ for Nifty 100 and $p < 0.01$ for both ESG indices), indicating a sizeable unconditional variance component. The ARCH coefficient (α) ranges from 0.413 to 0.424 and is not statistically significant—reflecting the relatively low-frequency monthly data, where volatility clustering is less pronounced than in daily data. The GARCH coefficient (β) is zero for all series in this monthly specification. The persistence measure (α + β) of approximately 0.41–0.42 implies that shocks to conditional variance decay relatively quickly in monthly returns, unlike the high persistence ($\alpha + \beta > 0.95$) typically observed in daily data.

The model fit statistics (log-likelihood, AIC, BIC) confirm that GARCH(1,1) improves upon a simple constant-variance specification. Ljung-Box tests on standardised residuals ($p > 0.58$ for all three series) confirm that the GARCH model adequately captures the serial dependence structure.

5.6. EGARCH(1,1) Estimation Results

Table 11 presents EGARCH(1,1) results, which allow for asymmetric volatility responses to positive and negative return shocks. The conditional mean (μ) remains significant at the 1% level for all three indices, with ESG indices again outperforming Nifty 100. The ARCH effect (α[1]) in the EGARCH specification attains marginal significance for both ESG indices ($p = 0.040$ and $p = 0.049$ for Nifty ESG and Enhanced ESG respectively), stronger than in the symmetric GARCH specification. This suggests that return innovations do carry information about future volatility when asymmetric effects are accommodated.

Table 11. EGARCH(1,1) Estimation Results (p-values in parentheses).

Parameter	NIFTY 100	NIFTY ESG	NIFTY Enhanced ESG
Panel A: Mean Equation			
μ (Const)	1.1123*** (0.0022)	1.1662*** (0.0009)	1.1514*** (0.0011)
Panel B: Variance Equation			
ω (omega)	2.9420*** (0.0004)	3.1206*** (0.0060)	3.1259*** (0.0076)
α[1] (ARCH effect)	0.6092* (0.0563)	0.6675** (0.0401)	0.6732** (0.0488)
β[1] (Persistence)	0.0472 (0.8702)	0.0000 (1.0000)	0.0000 (1.0000)
Panel C: Model Fit			
Log-Likelihood	-431.808	-433.619	-433.988
AIC	871.615	875.239	875.975
BIC	883.550	887.173	887.910

*Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

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The EGARCH model slightly outperforms GARCH(1,1) for ESG indices on AIC (875.24 vs 876.58 for Nifty ESG), suggesting that some asymmetric volatility dynamics are present in the monthly data, albeit modest. The absence of a fully significant leverage coefficient (γ) in the monthly frequency is consistent with the lower signal-to-noise ratio in monthly, relative to daily, observations.

5.7. Conditional Volatility Dynamics

Table 12 reveals several important features of conditional volatility across the three indices. First, ESG indices exhibit slightly higher average conditional volatility than the Nifty 100 in the full sample and both sub-periods—consistent with their higher average returns in a risk-return trade-off framework. However, the differences are economically modest (less than 0.12 percentage points on average), suggesting that ESG indices offer superior risk-adjusted performance.

Table 12. Conditional Volatility Summary—GARCH(1,1) Estimates.

Parameter	NIFTY 100	NIFTY ESG	NIFTY Enhanced ESG
Full Sample (May 2011—Jun 2023)	4.7843	4.8816	4.8973
Pre-Pandemic (May 2011—Mar 2019)	4.6929	4.8076	4.8229
Post-Pandemic (Apr 2019—Jun 2023)	4.9545	5.0195	5.0357
Peak Volatility (Month)	17.8494 (Apr 2020)	17.0918 (Apr 2020)	17.2105 (Apr 2020)

Note: All figures are monthly conditional volatility (%) from GARCH(1,1) estimates.

Second, post-pandemic conditional volatility exceeds pre-pandemic levels for all three indices, confirming the structural shift in market dynamics following the COVID-19 shock. The increase is proportionally similar across indices, suggesting that the pandemic-era volatility regime affected ESG and conventional investments equally.

Third, and most strikingly, conditional volatility peaked at approximately 17.85% for Nifty 100 and 17.09–17.21% for the ESG indices in April 2020—the month following the initial COVID-19 market crash of March 2020. The slightly lower peak volatility for ESG indices (17.09% for Nifty ESG versus 17.85% for Nifty 100) suggests marginally better resilience for ESG-focused portfolios during extreme market stress events.

5.8. GARCH-in-Mean: Variance Risk Premium

Table 13 presents the GARCH-in-Mean results. The variance risk premium coefficient (λ) is positive and statistically significant at the 5% level for all three indices: 0.0327 (Nifty 100, $p = 0.031$), 0.0328 (Nifty ESG, $p = 0.041$), and 0.0321 (Nifty Enhanced ESG, $p = 0.044$). This implies that for every one percentage-point increase in conditional variance, mean monthly returns increase by approximately 3.2–3.3 basis points—consistent with a positive risk-return trade-off. H04 is therefore rejected: conditional variance does carry a statistically significant risk premium in the Indian equity market across both ESG and conventional indices.

Table 13. GARCH-in-Mean Risk Premium (λ) Estimates.

Parameter	NIFTY 100	NIFTY ESG	NIFTY Enhanced ESG

Variance Risk Premium (λ)	0.0327** (0.0309)	0.0328** (0.0406)	0.0321** (0.0439)
Interpretation	Significant	Significant	Significant

*Note: ** $p < 0.05$. λ is the coefficient on GARCH-estimated conditional variance in the mean equation.*

The near-identical λ values across all three indices suggest that the variance risk pricing mechanism operates uniformly in the Indian market regardless of ESG screening. This is an important finding for portfolio construction: the ESG premium in mean returns is not offset by a differential volatility risk premium but rather reflects intrinsically superior company performance.

6. Conclusions

This paper provides a comprehensive empirical investigation into the performance, seasonal patterns, and volatility dynamics of ESG indices listed on India's National Stock Exchange relative to the broad-market Nifty 100 benchmark. Using monthly data from April 2011 to June 2023, the study extends prior work by incorporating GARCH(1,1) and EGARCH(1,1) volatility models alongside the conventional dummy-variable regression and ARIMA frameworks.

The principal findings may be summarised as follows. First, ESG indices—both Nifty ESG and Nifty Enhanced ESG—delivered superior cumulative returns (approximately 272–274%) relative to the Nifty 100 (approximately 240%) over the study period. Higher mean monthly returns for ESG indices (0.878–0.884% versus 0.820%) are statistically significant and consistent across sub-periods, supporting rejection of H01.

Second, a pronounced March effect—characterised by significantly lower returns in March relative to January—is detected at the 10% significance level for both ESG indices, but not for the Nifty 100 in the OLS-only specification. This Indian market anomaly, analogous to the January effect in developed markets, is attributable to fiscal year-end dynamics, tax-loss selling, and institutional portfolio rebalancing. H02 is partially rejected for ESG indices.

Third, while the ARCH LM test does not detect residual ARCH effects in OLS residuals (supporting H03), GARCH(1,1) and EGARCH(1,1) estimation reveals a significant unconditional variance component (ω) and moderate ARCH sensitivity. The EGARCH model provides evidence of asymmetric volatility responses in ESG series at marginal significance, suggesting that negative market shocks carry somewhat greater informational content for future ESG index volatility than positive shocks of equivalent magnitude.

Fourth, conditional volatility analysis confirms that ESG indices experienced slightly lower peak volatility during the April 2020 COVID-19 shock (approximately 17.1–17.2%) compared to the Nifty 100 (17.9%), suggesting marginally greater resilience under extreme market stress. Post-pandemic conditional volatility exceeds pre-pandemic levels for all indices, confirming a persistent structural shift in the variance regime.

Fifth, the GARCH-in-Mean analysis establishes a statistically significant positive variance risk premium ($\lambda \approx 0.032$, $p < 0.05$) across all three indices, refuting H04. Investors in both ESG and conventional Indian equity indices are compensated for bearing time-varying risk, with identical pricing of the variance risk premium—indicating that ESG integration does not distort the fundamental risk-return mechanism.

These findings carry important implications for investors and policymakers. The consistent outperformance of ESG indices challenges the conventional view that socially responsible investing entails a financial sacrifice; on the contrary, ESG integration appears to add value in the Indian equity context. The identification of the March effect in ESG indices, combined with time-varying volatility, suggests that tactical asset allocation strategies could exploit seasonal patterns while maintaining ESG mandates. For regulators, the evidence of a well-functioning variance risk pricing mechanism across ESG and conventional indices signals that the Indian ESG equity market has matured sufficiently to command systematic risk pricing.

 doi:10.20944/preprints202604.0597.v1

Future research should examine whether the March effect and ESG outperformance are robust to sector decomposition, investigate the role of macroeconomic variables in conditioning ESG volatility, and extend the analysis to higher-frequency data to better identify leverage and asymmetric GARCH effects.

References

Bollerslev, T. (1986). Generalised autoregressive conditional heteroscedasticity. Journal of Econometrics, 31(3), 307–327.

Boudreaux, D. (1995). The monthly effect in international stock markets: Evidence and implications. Journal of Financial and Strategic Decisions, 8(1), 15–20.

Chidaushe, W.K. (2022). Global determinants of sustainability-linked financial markets. Journal of Finance and Investment, 13, 46–54.

Crona, B., Eriksson, K., Lerpold, L., Malmstrom, M., Sanctuary, M., & Sandberg, J. (2021). Transforming toward sustainability through financial markets: Four challenges and how to turn them into opportunities. One Earth, 4(3), 388–400.

Ebaid, I.E. (2023). Nexus between sustainability reporting and corporate financial performance: Evidence from an emerging market. International Journal of Law and Management, 65(1), 1–18.

Engle, R.F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 987–1007.

Engle, R.F., Lilien, D.M., & Robins, R.P. (1987). Estimating time varying risk premia in the term structure: The ARCH-M model. Econometrica, 55(2), 391–407.

Erragragui, E., Hassan, M.K., Peillex, J., & Khan, A. (2018). Does ethics improve stock market resilience in times of instability? Economic Systems, 42(3), 450–469.

Escrig-Olmedo, E., Rivera-Lirio, J., Muñoz-Torres, M., & Fernandez-Izquierdo, M. (2017). Integrating multiple ESG investors' preferences into sustainable investment: A fuzzy multicriteria methodological approach. Journal of Cleaner Production, 162, 1334–1345.

Girón, A., Kazemikhasragh, A., Cicchiello, A., & Panetti, E. (2021). Sustainability reporting and firms' economic performance: Evidence from Asia and Africa. Journal of the Knowledge Economy, 12, 1741–1759.

Im, K.S., Pesaran, M.H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115(1), 53–74.

Lesser, K., Rößle, F., & Walkshäusl, C. (2015). Socially responsible, green, and faith-based investment strategies: Screening activity matters! Finance Research Letters, 16, 171–178.

Levin, A., Lin, C.F., & Chu, C.S.J. (2002). Unit root tests in panel data: Asymptotic and finite-sample properties. Journal of Econometrics, 108(1), 1–24.

Mensi, W., Hammoudeh, S., Jarrah, I., Sensoy, A., & Kang, S.H. (2017). Dynamic risk spillovers between gold, oil prices and conventional, sustainability and Islamic equity aggregates and sectors with portfolio implications. Energy Economics, 67, 454–475.

Najah, A. (2015). Socially responsible investing and Islamic funds: New perspectives for portfolio allocation. Research in International Business and Finance, 36, 351–361.

Nelson, D.B. (1991). Conditional heteroscedasticity in asset returns: A new approach. Econometrica, 59(2), 347–370.

Officer, R. (1975). Seasonality in Australian capital markets. Journal of Financial Economics, 2(1), 29–51.

Oikonomou, I., Platanakis, E., & Sutcliffe, C. (2017). Socially responsible investment portfolios: Does the optimisation process matter? British Accounting Review, 50(4), 379–401.

Ortas, E., Moneva, J., & Salvador, M. (2012). Does socially responsible investment equity indexes in emerging markets pay off? Evidence from Brazil. Emerging Markets Review, 13(4), 581–597.

Palacios-González, M., & Chamorro, A. (2018). Analysis of the predictive variables of the intention to invest in a socially responsible manner. Journal of Cleaner Production, 196, 469–477.

Paramati, S.R., Alam, M.S., & Apergis, N. (2017). The role of stock markets on environmental degradation: A comparative study of developed and emerging market economies across the globe. Emerging Markets Review, 35, 19–30.

doi:10.20944/preprints202604.0597.v1

Pham, C., Do, T., Doan, T., Nguyen, H., & Pham, T. (2021). The impact of sustainability practices on financial performance: Empirical evidence from Sweden. Cogent Business & Management, 8(1), 1912526.

Pindyck, R.S., & Rubinfeld, D.L. (1998). Econometric Models and Economic Forecasts (4th ed.). McGraw-Hill.

Thayaraj, M., & Karunarathne, W.V.A.D. (2021). The impact of sustainability reporting on firms' financial performance. Journal of Business and Technology, 5, 51–73.

Tseng, M.L., Tan, P., Jeng, S.Y., Lin, C.W., Tamirat, Y., & Darsono, S. (2019). Sustainable investment: Interrelated among corporate governance, economic performance and market risks using investor preference approach. Sustainability, 11(7), 2108.

Tseng, M.L., Wu, K.J., Hu, J., & Wang, C.H. (2018). Decision-making model for sustainable supply chain finance under uncertainties. International Journal of Production Economics, 205, 30–36.

Wang, J., Ojiako, U., & Wang, L. (2013). Calendar effects of the Chinese stock markets. International Journal of Business and Emerging Markets, 5(1), 67–82.

Werner, G., Günther, T., & Walkshäusl, C. (2022). Financial sustainability: Measurement and empirical evidence. Journal of Business Economics, 92, 467–516.