Is Nifty ESG Index a Safer Investment Option- An Analysis of Volatility and Volatility Clustering.

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Abstract

Institutional Theory and Resource-based view explain how the external environment may force businesses to adopt specific practices and how ESG can result in value creation, serving as inspiration for the current study. The Institutional Theory & Resource-based view states that legitimacy, ethics, and productivity are crucial pillars for accomplishing business goals and can lead to creation of resources leading to competitive advantages. Based on these claims, the paper postulated that the ESG Index is less risky, which would indicate that the ESG Index is less volatile.

This study is being carried out into two parts. Firstly range-bound volatility estimates viz, 'Parkinson', 'Garman-Klass', 'Roger-Satchell', 'Yang, and Zhang' have been used to determine the realised volatility of the Nifty ESG Index across two distinct time horizons and compared with the Nifty 100 to determine the riskiness. Secondly, the volatility dynamics of the Nifty ESG Index was examined for clustering effect using GARCH.

The findings show that, in comparison to the Nifty 100, the Nifty ESG 100 Index is more volatile in the long-run but less volatile in the short-run. However, the Nifty ESG Index has shown a moderately strong GARCH effect, indicating persistent volatility and volatility clustering. The findings are compatible with all market phenomena and other research, and they complement one another.

Key words- Nifty-ESG, Range-bound volatility estimators, GARCH.

Introduction:

The two primary factors used to evaluate financial investments are return and risk. Return is the anticipated benefit associated with the investment, and risk is the potential losses relative to the anticipated return on any financial asset, The paradigm of risk-return determines the attractiveness of the capital market in addition to sharing investor interests. Risk, in financial terms is measured as deviation from the anticipated returns. Volatility can be used as a stand-in for risk since it gauges how returns deviate from the mean. Hence, scholars worldwide have been examining volatility, its projection, and how it affects asset returns.

The presence of institutional investors, regulatory concerns, liquidity, and governance are among the key elements that contribute to volatility. According to the literature, several other macro and micro variables affect volatility. For instance, Guo and Shi (2024) found evidence of an asymmetric association between the geopolitical risk of China and the United States and investor sentiment and stock market volatility The threat posed by climate change has drawn the interest of scholars and investors worldwide in the last few years.

The literature claims that climate-related risk can cause volatility in both stock market and exchange market along with volatility in energy prices resulting in financial instability. (Wang and Li, 2023; Bonato et al., 2023).

Severe climate change can disrupt business and impact its growth. Thus, regulators encourage firms to establish sustainable business practices to combat climate risk. For the same reason, companies are being forced to adhere to sustainable measures, and ESG (Environmental, Social, and Governance) programs are being regulated. Because they lower business risk, early adherence to ESG norms and integrating green efforts into the company are viewed as value propositions (Chen et al., 2024). There is a growing evidence that investors are considering 'Environment', 'Social' and 'Governance' parameters in the decision making process regarding investments. (Christensen and associates, 2022).

Large Indian equity markets like, the BSE (Bombay Stock Exchange) and the NSE (National Stock Exchange), have lately taken steps to build a "Green Investment" and "Green Finance" index. The Nifty ESG 100 Index, which consists of Nifty 100 equities with a typical Environmental, Social, and Governance (ESG) score, was introduced by the NSE in 2018. The long-term goals of the Sustainable Development Goals and the growth of a sustainable practices are in line with the creation of an ESG index. As a result, having an ESG index serves as a ready portfolio in the form of ETF (Exchange Traded Funds).

This indicates that investing in stocks with good ESG rankings can be less risky and, consequently, less volatile. Leading to formulation of the following research goals.

Objectives of this research:

1. Examining the volatility of Nifty ESG 100 and compare it with the Nifty 100 index to determine its riskiness over a long and a short run.
2. To further investigate the volatility dynamics of ESG Index and examine the Volatility Clustering effect in the ESG Index.

Review of Literature

Ambiguity and information asymmetry are one of the root causes of volatility and impacts market equilibrium Li et al., (2011). The impact of volatility on financial markets has been a subject of numerous research studies. An accurate prediction of volatility is crucial because it influences asset pricing and portfolio allocation. (Azzam,2010; Faugere & Shawky,2005; Bollerslev et al.,2020).

Engle (1982) invented "Autoregressive Conditional Heteroscedasticity" (ARCH), which laid the foundation for one of the earliest time-varying/temporal techniques for evaluating volatility.ARCH was further developed to General Auto Regressive Conditional Heteroscedasticity' (GARCH). These models have demonstrated their reliability in estimating the in-sample volatility parameter and are still used to capture clustering effect, but to determine the riskiness of one Index over another and draw comparisons of two time series on historical volatility is not possible using these models .(Figlewski, 1997; Cumby et al., 1993; Luo et al., 2023). In that case, comparing two time series based on volatility was made easier by realised volatility (RV), which is calculated as the sum of squared intraday returns. RV is used in the framework of HAR,(Corsi,2009) Heterogeneous Autoregressive model of the Realised Volatility, which is an Autoregression (AR) process considering realised volatilities over different interval sizes; usually daily, weekly and monthly. The HAR-RV model was further advanced by adding a few more exogenous variables like cross-market information, implied volatility, leverage effect, realised semi-variance and HAR-RV-X framework was created. (Peng et al., 2019; Zhang et al., 2019) .

Realised volatility can be broken down to produce precision using jump volatility (JV) and continuous volatility (CV).(Barndorff-Nielsen,2008). They further developed upside realised semi-variance (URV) and downside realised semi-variance (DRV) to measure price fluctuations. Backward and inertial movements were added to the HRV model by Luo et al. in 2023. Studies show that the DRV yields more precise volatility and return predictions than the realised volatility (Bollerslev et al., 2020).

Other range-bound volatility estimators commonly used are 'Parkinson', 'Garman and Klass' ,'Yang-Zhang' and 'Rogers-Satchell'. These estimators use Open, High, Low &

Close prices. For this study, 'Parkinson', 'Garman and Klass', 'Yang and Zhang' and 'Rogers and Satchell' serve as better estimators, since there are many stocks common in the chosen Indices for study, thus, HAR-RV-X model may not yield comparable results. Wadhawan and Singh (2019) used these rangebound estimators to predict the long-term volatility of the Nifty 100 Index.

As discussed earlier, ESG stocks ensure that the stocks have a good environmental score, a good social score and desired governance. There is evidence in the literature which suggests investors prefer well-defined regulatory frameworks, markets with little to no information asymmetry, institutional holding and sound governance. (Bennett et al., 2019; Parrino et al., 2003; Boone and White, 2015),These factors ensure the proper flow of information, which is necessary for the market to perform efficiently. In addition, investors always want to know the precise level of risk associated with an investment, and they do not want an environment that is too volatile. (Baltzer and others, 2019). This indicates that investors would prefer stocks with steady growth and sound governance. ESG initiatives and disclosures by business firms provide future clarity and direction regarding business prospects, along with reducing company risk and information opacity (Silva, 2022).Literature also suggests that investors prefer the stock of a well-governed and environmentally responsible firm.(Ilhan et al., 2023; Krueger et al., 2020;). Sharma et al.,2023 conducted a study on specialised ESG Index i.e 'Nifty 100 Enhanced ESG' & 'Nifty 100 sector leaders' and found that both the Indices have performed better.

Research Gaps and Significance.

Sustainable finance and investing in them are relatively new for Indian markets as compared to the developed ones; and given it's vastness and the speed at which it is growing, there's a lot of room to study the same. India attracts significant FIIs(Foreign Institutional Investors) and is expected to grow. There exists immense scope of business expansion given the size of Indian market , which will eventually result in lucrative business outcomes and strong returns. As a result, it is reasonable to assume that

Analytical Framework and Methodology

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investments will continue to enter the Indian market, which makes this research crucial.

Drawing on existing literature, this paper posits that ESG practices and disclosures minimise business risk and reduce information asymmetry between stakeholders and businesses, making investments a secure option. Based on this the first hypothesis of the study is developed as given below.

Ho: The Nifty- ESG 100 index is not less volatile than the Nifty100 Index.

H_1: The Nifty -ESG100 index is less volatile than the Nifty100 Index.

Volatility clustering is very commonly found in financial time series. Clustering effect is formed when volatility shows a positive correlation for a few days (Cont R .,2005). Time series of stock returns may have mean-reverting volatility, persistent volatility or shock driven volatility. Volatility clustering influences investment decisions, thus accurate modelling of the volatility profile is key.

This leads us to our second hypothesis, which is:

Ho: Nifty -ESG 100 Index does not exhibit Volatility Clustering.

H_1: Nifty- ESG 100 Index exhibits Volatility Clustering.

Data Collection and Research Methodology:

The study's objective is to ascertain the Nifty ESG Index's risk-return behaviour and compare it to the Nifty 100. Two sets of information have been gathered. The Nifty ESG 100 Index and Nifty 100 Index prices, which are gathered from NSE India, make up the initial data set. Date period is from 10^{th} January 2022 to 24^{th} December 2025. Each data set contains four data observations: 'Open' price, 'Close' price, 'High price' and 'Low Price'.

A second set of data, the daily returns based on the closing prices of the Nifty ESG Index, is gathered in order to estimate volatility clustering. This was gathered from the NSE's official website from January 10, 2022 to 24th, December 2025. Since the ESG Index data is completely accessible as of January 10th, it will continue to serve as our starting point.

We have used EViews Software to generate the statistical tools and econometric models like the Augmented Dickey Fuller test, ARCH -LM, GARCH models and residual diagnostic tests like autocorrelation correlogram.

Analytical Framework and Methodology

To ascertain the riskiness of the Nifty ESG 100 with respect to Nifty 100 indexes .The following range-bound volatility estimates have been employed.

1. Parkinson estimator- To measure stock volatility Parkinson measure denoted by (1) is used. The estimator uses 'high' and 'low' price points amongst the set of daily prices and assumes absence of price drift.

$$\sigma_P^2 = \frac{1}{4\ln(2)N}\sum_{i=1}^{n} ln\left(\frac{H_i}{L_i}\right)^2 \qquad (1).$$

2. Garman-Klass estimator- Another estimator that accounts for the drift in the price is proposed by the Garman-Klass estimator presented in equation (2). The GK estimator is a weighted average of the Parkinson volatility estimator and the drift (open-to-close squared return). But like Parkinson, this metric is predicated on the idea that the price is a zero-drift mechanism.

$$\sigma_{GK}^2 = \frac{1}{N}\left\{\begin{array}{c} \sum_{i=i}^{n}\frac{1}{2}\left(\ln\left(\frac{h_i}{l_i}\right)^2\right) - \\ (2\ln(2)-1)\left(\ln\left(\frac{C_i}{O_i}\right)\right)^2 \end{array}\right\} \qquad (2).$$

3. Rogers and Satchell formally resolve the drift problem with their estimator σ_{GK}^2, the Rogers and Satchell estimator, as seen in equation (3), provides an extra volatility measure.

$$\sigma_{RS}^2 = \frac{1}{N}\sum_{i=1}^{n}\left\{\begin{array}{c} ln\left(\frac{h_i}{C_i}\right)\ln\left(\frac{h_i}{O_i}\right) \\ +ln\left(\frac{l_i}{C_i}\right)\ln\left(\frac{l_i}{O_i}\right) \end{array}\right\} \qquad (3).$$

Here, 'h_i' is the 'daily high price', '*li*' is the 'daily low price', 'C_i' is the 'daily close price', and 'O_i' is the 'daily Open price' in all the above equations.

4. The efficiency advantage over previous volatility estimators is further enhanced by the Yang and Zhang estimator, which is provided by equation (4). They claim that because their estimate is unbiased and based on a minimum variance, it is unaffected by underlying price movements or jumps.

$$\sigma_{YZ}^2 = = \sigma_{open}^2 + k\sigma_{close}^2 + (1-k)\,\sigma_{RS}^2 \qquad (4).$$

Where, $k = \frac{0.34}{1.34+\frac{N+1}{N-1}}$

$$\sigma_{open}^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(o_i - o^{-}\right))$$

$$\sigma_{Close}^2 = \frac{1}{N-1}\sum_{i=1}^{N}\left(c_i - c^{-}\right)).$$

Where, N= number of observations,
'C_i' is the 'daily close price', and 'O_i' is the 'daily Open price,' σ_{RS}^2 use the Rogers and Satchell estimator calculated using the previous equation.

Close to Close volatility is calculated using the change in logarithmic returns based on the closing price.

Two indices have been compared over two distinct time horizons, "Short term" and "Long term," using rolling windows of 63 days and 252 days, respectively, corresponding to three months and a year. A rolling window reduces structural breaks and shocks and reflects the current market condition. The aforementioned volatility estimates were initially used to compute the daily volatility of the Nifty ESG Index and Nifty 100. The collected daily volatility was transformed into rolling period series over two distinct time horizons in the second stage, resulting in eight series for each index ($For\ e.g\ Nifty\ ESG_{Parkinson}^{63}$, $Nifty\ ESG_{Parkinson}^{252}$) similarly two different set of series for other estimators.

Since the four volatility estimates have different assumptions, pooling of data will lead to measurement error. Thus, the Nifty 100 volatility series obtained using Parkinson for 63-day rolling window must be compared to the Nifty ESG100 volatility series obtained using Parkinson for 63-day rolling window.

Since we are dealing with time series, which often exhibit autocorrelation & heteroscedasticity, which implies that data may not be independent, thus using the standard t test for testing difference in means between Vol Nifty ESG and Vol Nifty 100 may lead to estimation error. Hence, the Newey West t-test has been employed to compare the volatility of two time series. Newey West t-test forms a regression with one time series as the input variable and the other time series as the outcome variable. Thus, for this study, a total of 8 regression equations will be generated in the form given by equation (5)

$$\mathrm{Vol}(Nifty\ 100_{Parkinson}^{63}) = \propto + \beta\mathrm{Vol}(Nifty\ ESG_{Parkinson}^{63}) + \varepsilon \quad (5).$$

Table 1:Interpretation of Newey West t test

β Value	Implication
If $\beta > 1$	One unit change in Nifty 100,implies Nifty ESG changes more than1. Thus, Nifty ESG is more volatile than Nifty 100.
If $\beta < 1$	One unit change in Nifty 100, implies Nifty ESG changes less than1. Thus, Nifty ESG is less volatile than Nifty 100.
If $\beta = 1$	Similar volatility

The second objective is to examine the presence of volatility clustering in the Nifty ESG Index.

The proven and commonly used techniques and to capture volatility clustering are ARCH and GARCH.

ARCH equation models the association of previous term shocks and volatility, it allows volatility to vary with time. GARCH an extended version of ARCH captures the effect of past volatility, thus it is very helpful in determining whether or not the variance error of a specific time series data has serial autocorrelation. Additionally, GARCH enables us to forecast whether or not volatility is mean reverting, that is whether the volatility comes back to the average long-run volatility or the shocks have a lasting effect. Applying GARCH we can also ascertain if persistent volatility is caused by shocks or by its own history using both ARCH and GARCH.

Prior to the estimation of econometric models, daily logarithmic returns were computed using the closing values of the Nifty-ESG 100 Index and distributional characteristics of the return series have been calculated. Table 1 contains the corresponding results.

The diagnostic test for determining unit root called ADF (Augmented Dickey Fuller) was conducted on the daily returns. The ADF result was significant for 'Intercept', 'Trend & Intercept' and for 'None, thus rejecting the possibility of unit root and implying stationarity of the time series.

Equation (6) represents a GARCH(1,1) model.

$$h_t = \varphi + \theta_1 h_{t-1} + \beta_1 u^2_{t-1} \qquad (6)$$

The equation describes that the conditional variance, denoted by (h) at time t is dependent on its previous lagged values, according to the equation, and the shock is captured by the lagged square error term.

Equation (7) represents an extended GARCH (1,1) model, where the lagged terms of conditional variance is denoted by 'p' and the lagged terms of squared errors is being given by 'q'.

$$h_t = \varphi + \sum_{k=1}^{p} \theta_k h_{t-k} + \sum_{i=1}^{q} \beta_i u^2_{t-1} \qquad (7)$$

Where θ_k denotes the GARCH coefficient, β_i is the ARCH coefficient and $\prod$ is the constant.

Before using the GARCH(1,1) model, earlier the ARCH effect was evaluated to determine whether or not the time series needed an ARCH estimation. Obtaining the outcome of the ARCH model given by table 5, GARCH(1,1) model was implemented. Later, by increasing the lags to GARCH(2,2), GARCH(4,4), and GARCH6(,6), other models were investigated. However, it was discovered that the GARCH (1,1) model was more effective because its predictive power dropped with the addition of parameters.

The result is also in line with research by Amudha and Muthukamu (2018) and John et al. (2019), which showed that the GARCH (1,1) model is best suited to forecast volatility clustering.

Findings:

Table 2 summarises the descriptive characteristics of the data sample, Descriptive statistics help in comprehension of the data without making any statistical inferences.

Table2: Descriptive Statistics of returns generated by both the Indices from 10th Jan 2022 to 24th Dec 2025.

Variables	Nifty 100 Returns	Nifty ESG Returns
Mean	0.0369%	0.0556%
Median	0.0810%	0.0905%
Maximum	3.50%	3.85%
Minimum	-6.82%	-5.28%
Standard Deviation	0.009047	0.007794
Skewness	-0.86758	-0.40143

Source: Author's Calculation

As per the summary of the descriptive statistics the Nifty ESG index outperforms Nifty 100 .

Table 3: Result obtained through Newey West (NW) t test.

Volatility Estimate	DV	IV	β *Coefficient*	Std error	P Value	Interpretation
Garman Klass,63 Days.	Nifty 100	Nifty ESG100	0.990024	0.023483	0.000	Since $\beta < 1$, ESG Index is slightly less volatile than Nifty 100.
Garman Klass,252 Days.	Nifty 100	Nifty ESG100	1.04054	0.56780	0.000	Since $\beta > 1$, ESG Index is more volatile than Nifty100
Parkinson,63 Days	Nifty 100	Nifty ESG100	0.990374	0.022846	0.000	Since $\beta < 1$, ESG Index is slightly less volatile than Nifty 100.
Parkinson,252Days	Nifty 100	Nifty ESG100	1.043212	0.055638	0.000	Since $\beta > 1$, ESG Index is more volatile than Nifty100
Roger Satchell,63 Days.	Nifty 100	Nifty ESG100	0.995745	0.018030	0.000	Since $\beta < 1$, ESG Index is slightly less volatile than Nifty 100.
Roger Satchell,252 Days.	Nifty 100	Nifty ESG100	1.052368	0.044699	0.000	Since $\beta > 1$, ESG Index is more volatile than Nifty100
Yang & Zhang,63 Days.	Nifty 100	Nifty ESG100	0.965505	0.015201	0.000	Since $\beta < 1$, ESG Index is less volatile than Nifty 100.
Yang & Zhang,252 Days.	Nifty 100	Nifty ESG100	1.000914	0.031822		Since $\beta > 1$, ESG Index is more volatile than Nifty100

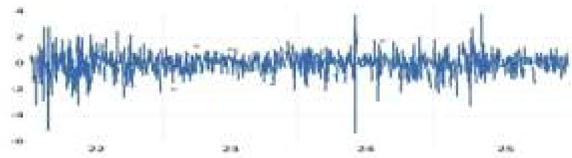
Source: Author's Calculation

Newey West t-test has generated an interesting trend.In the short run, while Nifty ESG is less volatile than Nifty 100 in the near term, Nifty 100 is more volatile over the long term. Indicating a volatility spill-over in the long run, however that cannot be confirmed through this study.

Volatility Clustering:

The visualisation plot obtained from the logarithmic returns of NIFTY ESG 100 Index shows volatility clustering and the histogram plot shows flat tails, indicating that the data distribution is leptokurtic.

Figure1: Line Chart of the logarithmic returns of Nifty ESG 100 over(10/01/2022 to 24/12/25)



Source: NSE.

ARCH heteroscedasticity test data is given by table 4. The result reveals the coefficient of the LM (Lagrange Multiplier) of the ARCH-LM test is 84.74635 with p value is lower than .05 % and is also significant at .01 % level, thus we conclude that the Nifty ESG returns time series exhibits ARCH effect. This implies that the Nifty ESG data series has autoregressive heteroscedasticity, that is its variance is not constant and is dependent on the information from the past data.

Table 4: Heteroscedasticity Test For Nifty ESG -100 Index.

	F-Statistic Value	Probability F-value	LM-Statistic	Probability Chi-Square Value
Nifty ESG-100	92.57927	0.0000	84.74635	0.0000

Source: Author's Calculation

The parameters derived from the GARCH(1,1) model are shown in Table 5.

The variance equation obtained from the model are as follows:

$\hat{h}_t = .039688 + 0.119845\, \hat{h}_{t-1} + 0.83209\, \hat{u}^2_{t-1}$ (8).

At the 1% level, the constant term, ARCH term, and GARCH parameter coefficients are all statistically significant. The ARCH and GARCH term together is less than 1, indicating that volatility is mean-reverting.

Table 5: Estimating Volatility For The Nifty ESG 100 Index Using GARCH(1,1) Model

	ARCH Parameter Value	GARCH Parameter Value	Sum of ARCH and GARCH Value	Akaike Information Criterion	Schwarz Information Criterion	Value of Log Likelihood
Nifty-ESG 100 Index	0.119845*	0.832090 *	0.951935	2.457837	2.477770	-1201.569

Source: Author's Calculation, * significant at 1% level

Residual diagnostic Correlogram Q Statistics test, given in table 6 was performed to check whether there exists any autocorrelation among the residuals of the chosen time series post application of GARCH.

Table 6: Model Adequacy Checking by Using Correlogram Q Statistics For Nifty ESG 100 Index.

No of lags	Autocorrelation	Partial Autocorrelation	Q Stat	Probability
1	-0.003	0.062	3.8417	0.05
2	0.001	-0.002	3.8438	0.146
3	-0.022	0.015	4.0652	0.255
4	0.041	0.006	4.1337	0.388
5	-0.011	-0.047	6.2342	0.284
6	-0.018	-0.028	7.3122	0.293
7	-0.037	-0.045	9.5940	0.213
8	0.003	-0.039	11.624	0.169
9	0.041	0.043	12.877	0.168
10	0.015	0.007	13.020	0.223
11	0.016	0.022	13.576	0.257
12	0.025	0.002	13.673	0.322

Note: The iterations were done till 36 lags and all the calculated values were insignificant.

Since the probability value of the correlogram Q statistic lies above 0.05, we can confirm that there is no autocorrelation between time points that are separated by lags up to 4. Hereby validating our model selection for studying Volatility clustering.

Discussion:

To understand the volatility dynamics of the ESG Index, two different methodologies were used. One was range-bound volatility estimates, and the other conditional volatility estimates like ARCH & GARCH were used to test volatility clustering and persistent volatility.

The GARCH equation obtained revealed the presence of ARCH & GARCH in Nifty ESG series, although ARCH is low at 0.119845 and the GARCH estimates is 0.832090. These findings suggest that the ESG Index reacts to shocks moderately, there is volatility clustering and volatility is persistent in the long run, and the volatility is driven by its own past, not shock-driven.

Arch and GARCH add up to about 0.95, which is less than 1, suggesting that volatility is mean-reverting and that volatility shocks will decay gradually. These results are consistent with those derived from range-bound estimates, which showed that the Nifty ESG Index is less volatile in the short term than the Nifty 100, However in the long-run the Nifty ESG Index is more volatile than the Nifty 100. Since shock-driven volatility is not seen in GARCH, the results further strengthen the argument that the Nifty ESG is a safer index.

Our findings are consistent with recent research on ESG Index. Sharma et al.,2024 discovered that the GARCH term of the Nifty ESG is less than one and that changes in the Nifty 500 have no causal effect on the ESG Index.

Conclusion

This study's objective was to analyse the Nifty ESG Index's potential as a safe investment option.

The hypothesis that Nifty ESG would be less volatile was built on 'Institutional Theory' & 'Resource-Based View'. According to these theories, a competitive advantage might result from the adoption of specific company practices, actions, and resources that are influenced by the external environment. These led to the development of the study's hypothesis that the ESG Index provides a safer investment opportunity than conventional indices.

To compare riskiness, volatility was chosen, and four range-bound volatility measures, 'Parkinson', 'Garman-Klass', 'Roger-Satchell' and 'Yang -Zhang' were used to create daily volatility of both the Nifty ESG & the Nifty 100. Later two different sets of volatility series were calculated using rolling windows of 63 days & 252 days in order to draw a perspective on short-term & long-term volatility dynamics. For all four estimations, it was found that while Nifty ESG showed lower volatility over shorter time horizons, it was more volatile than Nifty 100 over longer time horizons. This suggests that there may be volatility spill over in the ESG Index, which needs to be investigated.

Further to understand volatility clustering in ESG index the study examined volatility clustering by applying GARCH. The result obtained from ARCH & GARCH revealed that there exists significant volatility clustering. We can determine that the volatility is mean-reverting since the ARCH and GARCH coefficients are less than 1 and do not add up to 1. Furthermore, the fact that the ARCH coefficient is lower than the GARCH indicates that the volatility is persistent rather than shock-driven, suggesting that historical volatility is more significant than recent data and that volatility changes gradually.

As sustainable development and finance are transforming the financial and investment sectors and gradually making their way into the mainstream, more work on the ESG Index should be carried out.

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