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ORIGINAL PAPER

Exploring GARCH Family Models for Volatility Prediction of BSE S&P BSE CARBONEX index of Indian stock market

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Abstract:
The research paper delves into an in-depth analysis of the S&P BSE CARBONEX index, which serves as a benchmark for top companies, evaluating and benchmarking their climate change mitigation practices. The study focuses on volatility analysis of BSE CARBONEX, employing various GARCH models such as GARCH, TARCH, EGARCH, IGARCH, PARCH, and APARCH across five distributions. Through meticulous evaluation based on criteria including AIC, SC, and Log Likelihood values, the APARCH (1,1) model is selected, revealing the presence of asymmetry and volatility clustering within the index. This quantitative, applied, exploratory, and explanatory study conducts volatility analysis of S&P BSE CARBONEX over a period of 2485 daily observations from February 28, 2014, to March 15, 2024. To ensure data stationarity, log returns are calculated based on the previous day's price, and the nature of the data is explored using statistical measures such as mean, median, mode, skewness, kurtosis, and standard deviation. Furthermore, the study conducts heteroscedasticity tests through the ARCH LM test, uncovering signs of a leverage effect, albeit with statistically non-significant coefficients. The analysis also scrutinizes periods of dip and volatility, concluding that the year 2020 saw heightened volatility likely attributed to events such as the COVID-19 pandemic and associated variables, followed by a swift recovery. Additionally, the study observes small memory-based volatilities within the index. Through its comprehensive analysis, this research offers valuable insights into the dynamics of volatility within the BSE S&P CARBONEX index, contributing to a deeper understanding of market behaviour and potential implications for investors and policymakers alike.

Keywords: *S&P BSE CARBONEX index, BSE, Sustainability, ESG, Volatility, APARCH, GARCH, Green Investment, Sustainability Index*
JEL Codes: C32, C51, G13, G14, G17, G31, G44, Q56, Q57

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Introduction

The S&P BSE CARBONEX has been a benchmark of top companies measuring and benchmarking them on the basis of their climate change mitigation practices. However, in recent times India has showcased itself as a champion of climate-related issues and it becomes equally important to incorporate similar practices in every way possible so is sustainable investing.

In the case of the Indian Stock market, four indices are representative of sustainability i.e. BSE Carbonex, BSE Greenex, BSE ESG and NIFTY 100 ESG (G. et al., 2024) CARBONEX is affected by Index of Industrial production, M3, Crude oil prices, REER but not WPI(P. Sharma et al., 2021)

There is a need for sustainable investing and study shows there is very little evidence that investment decision is influenced by the green practices of the corporation.(Maji & Mondal, 2015) Healthy CSR positively affects a company's performance not only in the current year but also in the following years.(Garg, 2016)COVID-19 and related events and variables had significant impact on the index and it made the index highly volatile, different from its long memory volatility for a short span of time. Mapping of volatility and reasons and associated variables becomes essential for rational investment and decision making.(Santosh et al., 2023)Post-digital financial inclusion, investment frequency have increased significantly so is digital financial services usage.(Meher et al., 2024)

Literature Review

Volatility of carbonex is similar to that of the market, interesting fact is that during COVID-19, investors of sustainable indices got more returns than non-sustainable investments. Sustainability indices mimics Sensex patterns and GARCH(1,1) analysis concludes there exists a calendar effect (Monday and Tuesday effect).(Kalimuthu & Shaik, 2024) Overall, sustainable indices have more returns than less sustainable corporations.(Debnath & Dinda, 2023a)Both China and India are considering low-carbon policies and practices and carbon neutrality has been in the forefront.(Kedia, 2016) Randomness in the data has little or low impact on the variability of the data.(Lahmiri et al., 2018) Not very significant amount of CSR spending has been spent on environmental activities and there is also discrepancies in the disclosure.(J. Sharma & Verma, 2023) Retail investors' motives to invest in the socially responsible index is motivated by attitude, morality, and subjective financial literacy. (Joshi & Dangi, 2023)Study shows ESG factors have less impact on firm’s performance but individual factors of environment, Social and Govenance have significant impact on performance and individual risk indices have negative impact on operations and finances. (Shobhwani& Lodha, 2023) People are considering green investments especially during the COVID timeline, the study tries to evaluate pre and post-lockdown analysis of investment BSE CARBONEX and inverstor-related variables.(Chowdhury et al., 2023) Number of independent directors, non Chairman-CEO duality has a positive impact on environmental disclosure.(Vig, 2023) Companies of BSE carbonex were comparatively stable in black swan events in comparision to non ESG corporations.(Deshmukh et al., 2022a) A large degree of volatility was seen ain COVID 19 in BSE CARBONEX and rise of 145.8% conditional variance. Analysis was done using GARCH (1,1) model.(Bangur, 2022) COVID-19 brought an opportunity to form awareness about CARBONEX (R., 2021)Oil related corporations in CARBONEX were most affected due to crude oil, volatility.(Ashiq & Shanmugasundaram, 2020) DEA-TOPSIS criteria has been used to rank companies on sustainability.(Mehta et al., 2019)Strong correlation has been witnessed between SENSEX and green indices irrespective of any events such as black swan events.(Deshmukh et al., 2022b)Study finds that GARCH models are better in predicting and modelling volatility in comparison to EWMA model.(Kumar, Kumar Meher, et al., n.d.)There is possibility of presence of asymmetric volatility in crude and allied sectors due to COVID-19.(Kumar Meher et al., 2023) Innovative assets like gold, oil, currency etc were effected by financial spillovers due to outbreak of global pandemic.(Meher et al., 2023) Unpredicted volatility has been witnessed in the crude oil sectors and there are chances for higher fluctuations, henceforth cautious investment decision is suggested.(Meher et al., 2020) More diversified studies of stock indices across the top economies are required for the enhancement in the field of research of volatility fraternity concerning important stocks.(Kumar Meher et al., 2024)To understand GARCH in current context, it becomes very important to focus on G-20 economies.(Kumar, Meher, et al., n.d.) For very precise GARCH estimation, we should also focus on advanced models like DCC-GARCH, M-GARCH and similar models.(Kumar, Anand, et al., n.d.) In case of green indices like CARBONEX and GREENEX there is consistency in returns and post COVID returns are better than pre-COVID returns.(S. Sharma, 2022) Funds like CARBONEX, GREENEX, BSE ESG has caught investors attention and it has been found that they outperformed all the market indices overall irrespective of similar volatility across the market.(Debnath & Dinda, 2023b) There is a need now to think and invest in green.(Chakrabarti & Sen, 2015)

Research Gap

Not many studies have touched on the sustainability index, and even if studies concerning sustainability indices have been done it has not been done on the volatility and associated factors, most studies are exploratory and find linkages with other variables in nature but studies that exclusively study volatility are missing. Not much has been done in the academic field that would be wholesome in the area of sustainability indices. Especially there has been a deficit of studies concerning BSE CARBONEX. In the absence of studies, there is a lack of awareness among investors and the public in general about the index in general and its nature in particular making it not a very much preferred criterion for investment and decision making.

Objectives of the Study

- To study the volatility of BSE CARBONEX from 2014 to 2024
- To formulate an appropriate GARCH model that can capture the asymmetric nature of the index due to significant events in the chosen timeline

Research Methodology

The study conducted is quantitative, applied, exploratory, and explanatory conducting volatility analysis of S&P BSE CARBONEX for 2485 daily observations from 28/02/2014 to 15/03/2024. To make the data stationary Log returns are calculated based on the previous day's price. The nature of data has been explored using mean, median, mode, skewness, kurtosis, and standard deviation. The heteroscedasticity test is done through the ARCH LM test. Various GARCH family models including GARCH, TARCH, EGARCH, IGARCH, PARCH, and APARCH have been tested along Normal

Distribution, Student's t-distribution, Generalized Error distribution, t-distribution (fixed df), Generalized Error Distribution (fixed parameter). Based on AIC, SC, and Log Likelihood appropriate model is chosen for analysis and the coefficients of variance equation is analysed for studying the nature of volatility. The data has been sourced from the BSE historical database and the software used is Eviews10.

Significance of the study

In the times India championing the climate and sustainable causes, it becomes equally important to study the sustainability impact from all and across the sectors. Investors are also now aware of sustainable investing and are actively diversifying their portfolios into green-based investments. It becomes very crucial to do the muti-faceted analysis of the various financial parameters including volatility for informed and rational investment. Not very much study has been done in this regard and no study so far has been performed on individual analysis of BSE CARBONEX in one and half decades. This study is highly significant not only for investors for balanced investment but equally important to companies and corporations to understand the dynamics of the index due to the effect of the internal and external environment.

Limitations of the Study

Although, the analysis is of a time series nature and a significant number of data has been used to analyse with the statistically chosen most appropriate model but the results are not indicative of the entire picture as the indicator was independently analysed without any other regressors. Due lack of knowledge of the minute level of statistics and econometrics, interpretation may be of generalized nature at some instances. Although, APARCH is one of the most advanced yet flexible model of the GARCH family but it fails to map all the regressors and invisible variables that may be affecting the volatility. The intricate nature of volatility is also very difficult to measure in univariable analysis and may require a multivariate analysis. One of the reasons for not being able to go into the desired depth is lack of resources and institutional support, this constrains the deep-level study or maybe a more detailed level study.

Analysis, Results, and Discussion

First of all, it becomes very essential to look at the price graph to visually understand the volatility of the BSE CARBONEX over almost 10 years.

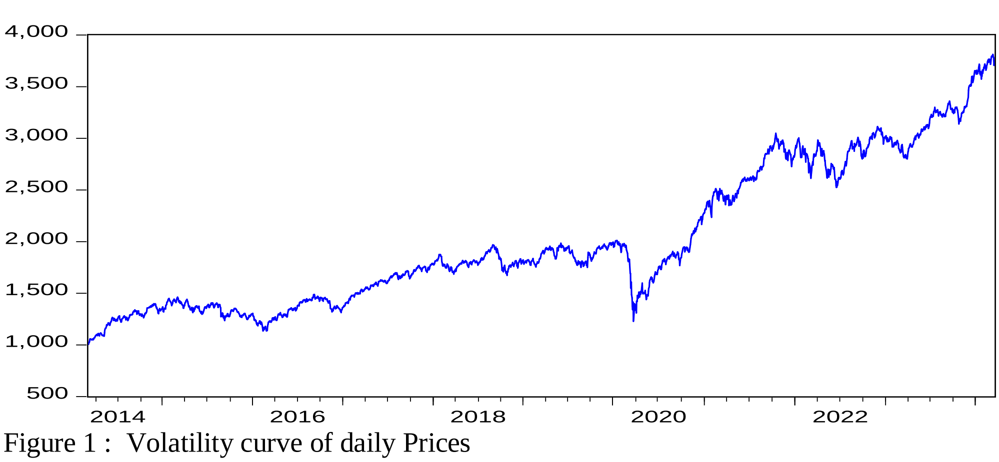


Figure 1 : Volatility curve of daily Prices
Source: Author's Computation using Eviews 10

From the above graph, it is very evident that the index has been very volatile since the start of the period, and a pattern in the volatility is also somewhat evident. To make data stationary and for further analysis, it becomes essential to convert the price into its logarithmic returns. Below is the graphical representation of logarithmic returns.

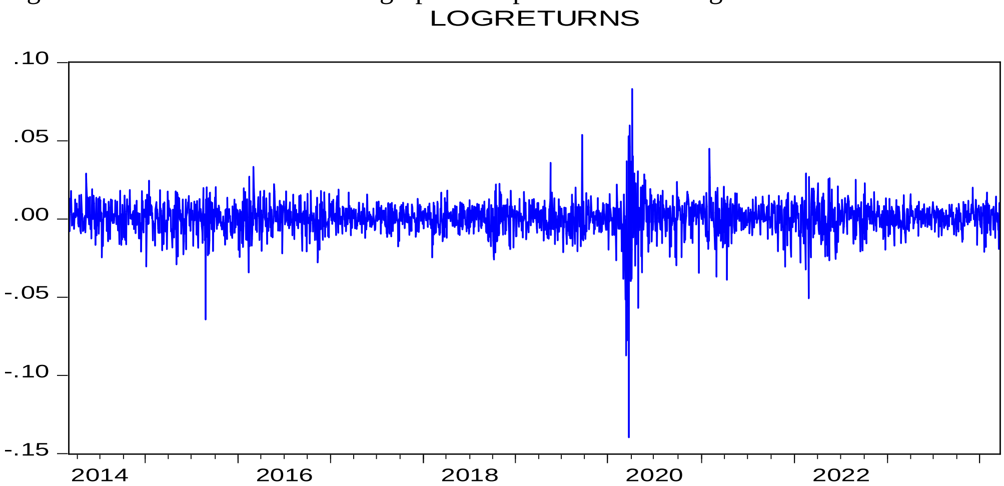


Figure 2: Log returns graph
Source: Author's Computation using Eviews 10

From the logarithmic data clustering of shocks and somewhat patterns in data is evident, to further the analysis, it becomes essential to test the stationarity of the data.

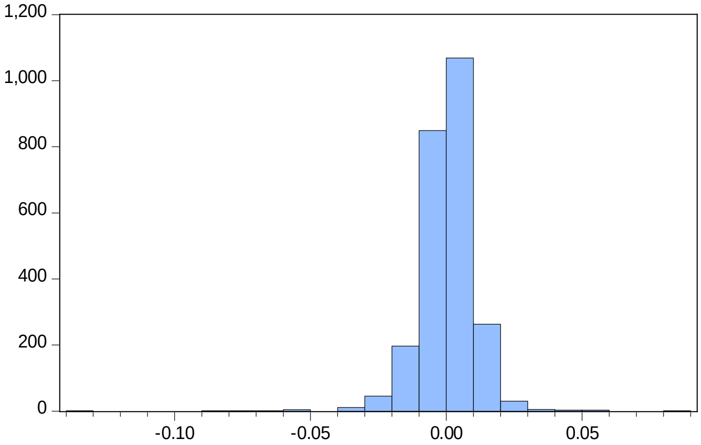
Stationarity Test

Null Hypothesis: LOGRETURNS has a unit root			
Exogenous: Constant			
Lag Length: 6 (Automatic - based on SIC, maxlag=26)			
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-17.82941	0.0000
Test critical values:	1% level	-3.432796	
	5% level	-2.862506	
	10% level	-2.567330	

Table 1: Heteroscedasticity Test
Source: Author's Computation using Eviews 10

Augmented Dickey-Fuller Test was employed to test the stationarity of data and as the P-value is less than 0.05 and t-statistics is less than 5% significant level the data has having unit root and is stationary. To understand the nature of data let’s look at some statistical parameters.

Descriptive Statistics



Series: LOGRETURNS	
Sample 2/28/2014 3/15/2024	
Observations 2484	
Mean	0.000524
Median	0.000945
Maximum	0.083121
Minimum	-0.139610
Std. Dev.	0.010442
Skewness	-1.446288
Kurtosis	23.54969
Jarque-Bera	44572.98
Probability	0.000000

Figure 3: Test Statistics
Source: Author’s Computation using Eviews 10

The mean and median are not very similar, the data is slightly negatively skewed meaning longer tails at the negative side and the data is also leptokurtic signifying a very high peak, meaning sharper peak and fatter tails and the standard deviation signifies a moderate level of volatility. The presence of a fatter tail resembles t t-type distribution.

To proceed with the volatility analysis, it becomes essential to test the heteroscedasticity of the data, which is done to ARCH LM test of the residuals.

Heteroscedasticity Test

Heteroskedasticity Test: ARCH			
F-statistic	67.75694	Prob. F(1,2480)	0.0000
Obs*R-squared	66.00816	Prob. Chi-Square(1)	0.0000

Table 2 :ARCH LM Test
Source: Author’s Computation using Eviews 10

From the analysis, it is very evident that the ARCH effect is present and we should follow with autocorrelation tests. GARCH is chosen over ARCH due to its limitations in considering weights and it has been established by many studies that GARCH is fit to estimate conditional variance of parsimonious models. Now to find the appropriate GARCH model, GARCH, EGARCH, TARCH, IGARCH, PARCH, and APARCH were estimated across five distributions.

Distribution	Criteria	GARCH	IGARCH	TARCH	EGARCH	PARCH	APARCH
Normal Distribution	*Akaike info criterion*	-6.6111	-6.3469	-6.6499	-6.6494	-6.6107	-6.6553
	Schwarz criterion	-6.5994	-6.3399	-6.6358	-6.6354	-6.5967	-6.6389
	Log Likelihood	8212.6440	7882.7310	8261.8000	8261.2790	8213.2040	8269.5610
	ARCH significant	yes	yes	yes	yes	yes	yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	yes	yes	yes	yes	yes	yes
	significant coefficient	yes	yes	yes	yes	yes	yes
Student's T	*Akaike info criterion*	-6.6643	-6.6465	-6.6923	-6.6942	-6.6636	-6.6973
	Schwarz criterion	-6.6503	-6.6371	-6.6759	-6.6778	-6.6472	-6.6786
	Log Likelihood	8279.774	8255.6000	8315.5510	8317.8460	8279.8990	8322.7100
	ARCH significant	yes	yes	yes	yes	yes	yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	yes	yes	yes	yes	yes	yes
	significant coefficient	yes	yes	yes	yes	yes	yes
Generalized Error	*Akaike info criterion*	-6.6570	-6.6411	-6.6848	-6.6851	-6.6564	-6.6888
	Schwarz criterion	-6.6430	-6.6318	-6.6684	-6.6687	-6.6400	-6.6701
	Log Likelihood	8270.7030	8248.9810	8306.1830	8306.5830	8270.9160	8312.1540
	ARCH significant	yes	yes	yes	yes	yes	yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No

	GARCH significant	yes	yes	yes	yes	yes	yes
	significant coefficient	yes	yes	yes	yes	yes	yes
T distribution (Parameter)	*Akaike info criterion*	-6.6610	-6.5017	-6.6910	-6.6926	-6.6603	-6.6962
	Schwarz criterion	-6.6493	-6.4946	-6.6769	-6.6786	-6.6463	-6.6798
	Log likelihood	8274.594	8074.8030	8312.8590	8314.9020	8274.8090	8320.2730
	ARCH significant	yes	yes	yes	yes	yes	yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	yes	yes	yes	yes	yes	yes
	significant coefficient	yes	yes	yes	yes	yes	yes
Generalised Error (Parameter)	*Akaike info criterion*	-6.6547	-6.6386	-6.6846	-6.6848	-6.6542	-6.6888
	Schwarz criterion	-6.6430	-6.6316	-6.6705	-6.6708	-6.6401	-6.6724
	Log Likelihood	8266.8640	8244.8780	8304.9160	8305.1920	8267.1460	8311.1510
	ARCH significant	yes	yes	yes	yes	yes	yes
	Autocorrelation	No	No	No	No	No	No
	ARCH LM-Test	No	No	No	No	No	No
	GARCH significant	yes	yes	yes	yes	yes	yes
	significant coefficient	yes	yes	yes	yes	yes	yes

Table 3: Decision table for GARCH Selection
Source: Author's formulation using MS Office

From the table above it could be concluded that APARCH (1,1) at student's t-distribution has the lowest AIC value, comparatively lowest SC value and highest Log Likelihood value, making it a suitable model for the analysis. Let's proceed with APARCH test.

APARCH (1,1)

Dependent Variable: LOGRETURNS
Method: ML ARCH - Student's t distribution
Sample (adjusted): 3/04/2014 3/15/2024
Included observations: 2483 after adjustments
Convergence achieved after 22 iterations
WARNING: Singular covariance - coefficients are not unique
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(7) = C(3) + C(4)*(ABS(RESID(-1)) - C(5)*RESID(
-1))^C(7) + C(6)*@SQRT(GARCH(-1))^C(7)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000630	0.000156	4.039760	0.0001
LOGRETURNS(-1)	0.105472	0.020547	5.133175	0.0000
	Variance Equation			
C(3)	0.000187	0.000151	1.237197	0.2160
C(4)	0.075412	0.169146	0.445837	0.6557
C(5)	1.000000	3.721383	0.268717	0.7881
C(6)	0.886855	0.015611	56.81026	0.0000
C(7)	1.167592	0.172457	6.770342	0.0000
T-DIST. DOF	7.253487	0.902071	8.040929	0.0000

R-squared	-0.011304	Mean dependent var	0.000527
Adjusted R-squared	-0.011711	S.D. dependent var	0.010442
S.E. of regression	0.010503	Akaike info criterion	-6.697310
Sum squared resid	0.273704	Schwarz criterion	-6.678567
Log-likelihood	8322.710	Hannan-Quinn criter.	-6.690503
Durbin-Watson stat	2.208005		

Table 4: APARCH (1,1)
Source: Author’s formulation using MS Office

The variance equation is as follows:

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{q} \alpha_j \left(|\varepsilon_{t-j}| - \gamma_j \varepsilon_{t-j}\right)^{\delta} + \sum_{i=1}^{p} \beta_i (\sigma_{t-i})^{\delta}$$

Notation	Meaning
ω C (3)	A constant term representing the baseline of volatility
α C (4)	Persistence of Volatility/Absolute Past Residual
γ C (5)	Scaling Factor
β C (6)	Persistence of Volatility/Lagged Conditional Standard Deviation
δ C (7)	Decay Rate/Power Term/Asymmetry Term

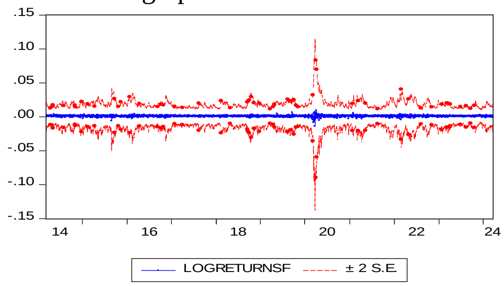
Table 5: Notation Table
Source: Author's formulation using MS office

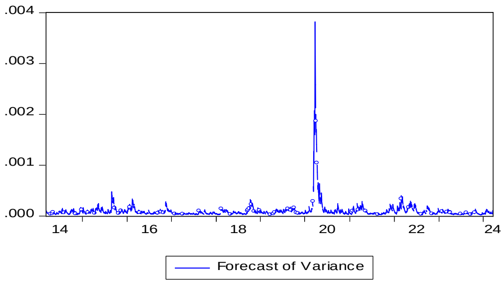
From the above APARCH(1,1) analysis it is very clear that there is very little impact of baseline and positive shock persistence due to their very low coefficient value along with the fact they are statistically non-significant as their P-value is far more than 0.05. However, it is also evident that the scaling factor becomes very important to be noticed as its value is absolutely 1 which signifies high persistence of past volatility and its effect is in absolute terms. (although P-value >1)

However, when we move to the persistence of volatility due to negative events we see the value is close to .9, which means continued persistence of either high or low volatility, and along with that, we see there is a possibility (highly) of asymmetric effect as the coefficient is greater than 1 i.e. volatility acting opposite to the nature of the overall shock.

The analysis also suggests the presence of volatility clustering as the persistence value of C (4) is non-significant we cannot exactly conclude presence of leverage effect. Some of the reason of the volatility might be due to COVID-19 pandemic and associated macro-economic variable events.

To understand the volatility better and check the fitness of model, let's look at the forecast graph





Forecast: LOGRETURNSF	
Actual: LOGRETURNS	
Forecast sample: 2/28/2014 3/15/2024	
Adjusted sample: 3/04/2014 3/15/2024	
Included observations: 2483	
Root Mean Squared Error	0.010499
Mean Absolute Error	0.007050
Mean Abs. Percent Error	NA
Theil Inequality Coefficient	0.893506
Bias Proportion	0.000226
Variance Proportion	0.791227
Covariance Proportion	0.208546
Theil U2 Coefficient	NA
Symmetric MAPE	162.3447

Figure 4: Forecast Graph
Source: Author's Computation using Eviews 10

From the forecast graph it is very clear that there was huge volatility in 2020 may be due to COVID-19 pandemic and its effect on variable such as interest rate, inflation, crude oil volatility, geopolitical shocks etc. but what is very important to understand is overall there is low volatility and pattern is seen usually in the form of small shocks persistent throughout which makes 2020 dip a temporary dip. However, it was also observed that sustainable investments paid more in comparison to less sustainable investments. We can see that the forecast matches our analysis, which makes us conclude that APARCH (1,1) is a fit model to estimate the volatility of S&P BSE CARBONEX.

Conclusion and Recommendations

Through APARCH analysis we have been able to know the reasons and associated variables that are responsible for the unique volatility of the BSE CARBONEX Index. There is presence of asymmetry to a larger extent and evidence are also there of volatility clustering and long memory volatility. However, there was volatility in 2020 that was different from the usual nature maybe due to COVID-19 and associated variables such as inflation, lack of disclosure, money supply imbalance, crude oil, demand-supply asymmetry and macroeconomic variables. However, soon the volatility was replaced by small shocks that are typical to the nature of CARBONEX.

But what is very crucial to be noted that that the analysis is not all inclusive of factors of volatility due to limitations of APARCH model and univariate analysis. It is highly suggested to have a more deep analysis with company/ sector wise volatility mapping in order to avoid generalization which has been a case in this analysis to a certain extent. It is also suggested to incorporate more complex models and software and AI and ML for a larger picture of the volatility and access to more minute information in the larger interest of investors and society and industry at large.

Authors' Contributions:
The authors contributed equally to this work.

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