DCC-GARCH Approach for Detecting Dynamic Relation among Selected Green Indices of Indian Stock Market

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Abstract

This research analyses the dynamic spillover effects of indices tracking green, energy, carbon, and sustainability sector equities to learn more about the interconnectedness of green finance. The DCC-GARCH model is used to analyze the channels via which shocks are transmitted between these assets using daily data from Feb 2018 to Aug 2023. Based on our research, there is a sizable amount of cross-market volatility. Notably, the Indian stock market benefits from the positive spillover impact of the S&P BSE GREENEX, S&P BSE CARBONEX, S&P BSE ENERGY, and S&P BSE 100ESG indices. The implications of our findings are of great importance for policymakers and investors in developing nations such as India. Furthermore, our research contributes to the growing literature on the interdependence of stock markets. It improves the understanding of stock markets of developing countries like India in the context of interconnection and volatility's influence, enabling informed judgments.

Keywords: dynamic relation; volatility spillover; Indian stock market; GREENEX; energy; DCC-GRACH; sustainability

1. Introduction

There has been a rapid increase in global greenhouse gas emissions, and they remain too high to prevent catastrophic and irreversible climate change repercussions. Carbon pricing and market-based instruments, regulatory action, and targeted assistance for innovation in low-carbon sustainable technologies are all being implemented in more and more countries [1]. The shift to a green and low-carbon economy offers a lucrative opportunity for businesses, governments, and investors worldwide [2]. Therefore, urgent legislative action is needed to promote an unprecedented global infrastructure and technological transition to address climate change [3]. Energy efficiency can also play a crucial role in the sustainable energy revolution [4]. Moreover, many studies highlight the necessity of academic attention to (re)examine the importance of sustainable energy development [5].

Green bonds are one of the most popular means of funding environment-friendly initiatives. Funds raised through the sale of fixed-income securities are then put towards environmentally

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responsible endeavors by global and local environmental groups [6]. In 2019, USD 257.7 billion was issued in green bonds and loans worldwide. The combined issuance of France, China, and the United States in 2019 comprised 44% of the global issue [7]. The total value of green bonds issued between 2008 and 2019 was nearly USD 800 billion [8]. Pressure on businesses to reduce their damaging effects on the environment and boost their impact investment has led to a recent surge of activity in the green bond markets. Green bonds are recognized as effective social and environmental instruments for satisfying the growing demand for green investments worldwide [9]. Various firms related to S&P BSE GREENEX, Energy, CARBONEX, and ESG indices need to grow further and can retain green bonds to meet their funding needs to expand.

Inadequate global investment in energy over the past few years has made the energy system extremely vulnerable to disruptions like those seen in 2022. A substantial increase in clean energy investment flows is necessary to guarantee a safe and effective energy shift. Spending on clean energy and infrastructure must triple by 2030 for the net zero emission scenario to be feasible, and there must be a significant increase in investment in emerging markets and developing nations [10]. While fossil fuel investment is projected to rise by 15%, yearly clean energy investment is expected to see a more significant growth of 24% from 2021 to 2023. This growth will be primarily driven by expanding renewable energy sources and adopting electric cars. However, because China and affluent nations contribute to almost 90% of this increase, there is a significant concern that the transition to clean energy may go slower in other parts of the world, leading to new disparities in energy access [11].

By analyzing the instabilities of green, carbon emission energy, and ESG indices, this study gives essential conclusions concerning the link between the above indices and the characteristics of the green market. In general, asymmetric volatility is present in all index returns, with a greater sensitivity to negative shocks. The existence of unbalanced volatility between the green bond, carbon emission, and energy index is therefore also investigated. We employ the DCC-GARCH model to examine the interplay among markets. Multivariate GARCH models have been used extensively in prior empirical research [12–16].

The rest of the paper is structured as follows. The "Literature Review" section summarizes the relationships between green, energy, carbon, and ESG index as other key points from the literature on green finance. This study's data and econometric models (DCC-GARCH) are described in depth in the "Methodology" section. The "Result and Discussion" section discusses the findings and their significance. The "Conclusion and Policy Implications" portion of the study summarises the report's key conclusions and relevance to various stakeholders in green finance.

2. Literature Review

Research on the veracity of the green premium, or geranium, associated with the issuance of green bonds has been extensive since it makes the issuance of green bonds preferable to the issuance of common bonds. In particular, 121 European Green Bonds allotted from 2013 to 2017 were analyzed, and it was discovered that they have economic advantages over conventional bonds. Companies gain more as a result, and this benefit persists in the ancillary markets [17]. Businesses that want to fund or reorganize ecologically friendly projects at a lower budget might do so with the help of green bonds. Spreads on green state bonds are more comprehensive than on non-green state bonds, whereas spreads on green corporate bonds are narrower. We compare green bonds to their traditionally issued counterparts and find that green bonds perform better in yield, liquidity, and volatility. Institutional green bonds, on the other hand, have a negative premium lest the private issuer is devoted to certifying the "greenness" of bonds, while corporate Green Bonds deliver a positive return. Therefore, green projects may receive subsidized funding, and green bonds may earn a discount [18].

Shah et al. [19] stated that green bonds have a negative premium because their yield is lower than ordinary bonds. Financial and low-rated bonds are particularly susceptible to this. The issue size is a potential determinant of the yield of green bonds. Potential factors that could entice investors to enter the market include the market's size and the existence of influential investors. The academic community is emphasizing green stocks and bonds more, especially in the context of concerns about climate change [20]. Recently, copula-based methods have been used to examine the asset allocation characteristics of green bonds. According to the study's findings, the beneficial effects of green bonds on portfolio management become apparent during periods of increasing returns and decreasing market volatility. Additionally, precious metals and green commodities were considered possible safeguards against climate danger [21]. There was a discernible correlation between the performance of clean energy stocks and that of the broader market. According to past studies' findings, green bonds have been observed to show significant co-movements with other markets, especially during periods of industrial volatility. These findings suggest that green bonds assist investors in lowering their portfolio's exposure to risk [22]. Over the last 10 years, much research has been done on the value of cryptocurrencies as a secure investment and their critical function in risk mitigation, especially during unpredictable times like the present pandemic. In contrast, several studies have shown that the volatility of cryptocurrencies is often higher than that of traditional assets, as per Mohsin et al. [20].

Le et al. [23] examined fintech, green bonds, and cryptocurrencies using daily data from November 2018 to June 2020. In a volatile market, 21st-century technological assets and conventional common equities are highly correlated, increasing the likelihood of simultaneous losses. Second, the US dollar, oil, gold, VIX, and green bonds receive volatility shocks, whereas Bitcoin, MSCIW, MSCI US, and KFTX cause them. Third, short-term volatility signals more than long-term. Long-term asset holdings lower risks, but short-term exchanges increase volatility. Gold, oil, and green bonds hedge Fintech, KFTX, and all assets in the sample due to their low shock transmissions and modest volatility spill-over. This study empirically examined the impact of financial inclusion, green financing, and financial technology on the energy efficiency of economies in the E7. Researchers have found that these financing strategies notably impact energy efficiency. Green financing is the most effective and helpful financing tool for energy efficiency, and it also happens to be the most environmentally friendly [24].

Previous research focuses on the structural features but only analyses price spillovers, ignoring the repercussions in the return distribution's second phase. Instead of focusing on the large gap in understanding how climate bonds and the financial sector interact, asymmetric DCC-GARCH and BEKK models should show or analyze these stylized features. Given the ongoing discussion over the interconnectedness and significance of the COVID-19 pandemic, war, and climate change have been pressing concerns for policymakers since 2021, and stakeholders must tackle this problem.

To summarize, the current body of literature offers valuable insights for investigating how other factors influence the price fluctuations of green bonds. However, the existing research primarily relies on the GARCH model to measure the spillover effect of volatility by examining the significance of correlation coefficients. This methodology does not include the ever-changing and directing features of the spillover impact. It does need to fully represent the entire link between the carbon, coal, and green investment markets in terms of volatility spillover.

This study presents multiple significant contributions. We chose the daily data from India's carbon, energy, environment, sustainable, and green investment markets as the focus of our study. We then analyzed the dynamic association and spillover impact using the DCC-GARCH method. We examined the dynamic features of the spillover across three different time frames: overall (01/02/2018 to 11/08/23), during the COVID-19 pandemic (27/01/20 to 23/02/22), and during times of the Russia-Ukraine war(24/02/22 to 11/08/23).

3. Methodology

This paper uses an empirical research design to investigate the volatility spillover and correlations between the indices. Time-varying correlations and volatility spillover effects are investigated using the Dynamic Conditional Correlation GARCH (DCC GARCH) model. The goals serve as the basis for the formulation of the hypotheses:

H1: There is a consistent degree of volatility spillover between the S&P BSE Greenex and other indices included in the present study.

H2: Time-varying and dynamic asymmetry in volatility spillover effects is present between the S&P BSE Greenex with other indices included in the study.

The aforementioned stock market indices (daily data) are compiled for examination. The S&P BSE GREENEX Index is used as a proxy for the green bond index [25] in this study, making it the dependent variable. S&P BSE Energy, S&P BSE CARBONEX, and S&P BSE 100 ESG are the independent variables in this study. The daily returns are computed to get stationary returns, as:

$$\ln(\text{Return}_t) = \ln\left(\frac{\text{Price}_t}{\text{Price}_{t-1}}\right) \tag{1}$$

ADF and PP tests are applied and checked to check whether series are stationary based on Dickey and Fuller [26] and Mackinnon [27] values. Testing for time-varying variance in a sequence of returns is typically done using the Auto-Regressive Conditional Heteroscedasticity (ARCH) test.

The alternative hypothesis proposes that conditional heteroscedasticity exists, while the null hypothesis rejects this idea. The LM serial correlation test is employed to inspect the null hypothesis of no serial correlation in the time series residuals while applying OLS (Ordinary Least Squares) regression to a time series. Assuming timing effects, specifically, the impact of shocks, or the occurrence of volatility clustering and leverage effects, is observed. The GARCH model that provides the most accurate estimation of conditional variances is employed in this scenario.

The examination of impulsiveness in spillover in various domains has been conducted using a range of models, such as GARCH, BEKK-GARCH, CCC-GARCH,DCC-GARCH and wavelet analysis. The Dynamic Conditional Correlation GARCH model has been subjected to comparative analysis by researchers in order to evaluate its efficacy in capturing volatility spillovers, while also considering the strengths and drawbacks of alternative models.

Bollerslev [28] conducted a study that revealed that the DCC-GARCH model exhibited superior performance compared to the regular GARCH model in accurately capturing the short-term coherence of nominal exchange rates, which was attained through the integration of changing correlations, which are conditional. Engle and Kroner [29] provided empirical evidence to support the efficacy of the Dynamic CC-GARCH model in catching volatility spillovers within a framework that involves more than one variable, hence exceeding the computing requirements of the BEKK-GARCH model.

This paper examines the DCC-GARCH model for analyzing correlations and volatility spillovers between indices. The DCC-GARCH model performs better than the CCC-GARCH model in effectively capturing dynamic correlations and volatility spillovers [30]. The DCC-GARCH model has become a favored option for analyzing volatility spillovers within the range of available models. This model integrates the adaptable nature of the GARCH model in representing individual volatilities with the capability to encompass time-dependent conditional correlations. The DCCGARCH model incorporates bidirectional spillovers and contemporaneous market interactions by estimating the dynamic conditional correlation matrix [31]. The multidimensional character of this approach allows for the concurrent investigation of many variables, which in turn provides a comprehensive perspective on the transmission of precariousness.

Multivariate financial time series data can be estimated as cross-asset correlations and the spillover effect of volatility with the DCC-GARCH model [32]. The model has two parts: the first determines the GARCH parameters, and the second establishes the time-varying correlation.

Two steps make up this model: first, the GARCH parameters are determined, and then the time-varying correlation is specified.

The equation for the time-varying correlation matrix in the DCC-GARCH model is as follows:

$$R'_t = D'_t Q'_t D'_t \tag{2}$$

where R'_t is an important factor in estimating the correlation between variables. D'_t consists of a diagonal matrix where the square roots of the conditional variances are placed on the diagonal. Q'_t The conditional covariance matrix is an important factor to consider.

The diagonal matrix of the conditional variance is:

$$D'_t = \operatorname{diag}\left(\sqrt{\sigma^2_{i,t}}\right) \tag{3}$$

$$\sigma(i,t)^2 = \omega_i + \alpha_i \varepsilon(i,t-1)^2 + \beta_i \sigma(i,t-1)^2 \tag{4}$$

where $\sigma(i,t)$ is the conditional volatility refers to the variability of the return. ω_i, α_i, and β_i are GARCH model parameters.

The GARCH model exhibits stationarity when the total of α_i and β_i is below one, indicating that the volatility of shocks reverts and diminishes with time [33]. Therefore, it must be ensured that each cofficient>/=0 and total< 1. The matrix representing the covariance between variables under certain conditions is as follows:

$$Q'_t = Q^{*-1} Q'_t Q^{*-1} \tag{5}$$

$$Q'_t = \{(1-\alpha-\beta)\bar{Q}\} + \{\alpha\varepsilon_{(t-1)}\varepsilon'_{(t-1)}\} + \beta Q_{(t-1)} \tag{6}$$

where Q'_t is the matrix of conditional covariance. $\bar{Q}$ is the matrix of unconditional covariance. α and β are parameters to determine extent to which the prior covariance matrix and the current squared residuals influence the update of $Q_{(t)}$.

4. Results

The obtained data from several stock indices within the sample were analyzed in order to determine their characteristics. Descriptive statistics pertaining to the daily log returns of the stock indexes taken in the present study are shown in Table 1.

The data's central tendency, dispersion, and normalcy have been evaluated using descriptive statistics, including mean, standard deviation, skewness, kurtosis, and J-B test. The mean denotes the average assessment of a series. On the other hand, the standard deviation quantifies the extent to which individual items in the series deviate from the mean. A higher standard deviation indicates a greater degree of variability within the series. Doane and Seward expounded upon the concept of skewness [34]. In a similar vein, an examination of the notion of kurtosis as a statistical instrument is employed to quantify the degree to which the tail of the distribution diverges from a normal distribution [35]. The author analyses multiple estimating approaches and

Table 1: *Descriptive details of variables included in study*

Stock indices	Mean	Std. dev	Skewness	Kurtosis
Descriptive facts of the overall timeframe				
DCARB	0.000429	0.011758	-1.60584	24.70308
DENERGY	0.000501	0.016183	-0.4816	12.97075
DESG	0.000477	0.011909	-1.45731	22.53486
DGREEN	0.000419	0.011820	-1.29853	18.00183
Descriptive facts of the Covid timeframe				
DGREEN	0.000897	0.014982	-1.66565	17.67111
DCARB	0.000695	0.015567	-1.89178	20.76551
DENERGY	0.000766	0.020331	-0.46574	11.84569
DESG	0.000792	0.015767	-1.70778	18.93907
Descriptive facts of the War timeframe				
DGREEN	0.000329	0.010094	-0.63635	5.264189
DCARB	0.000386	0.00914	-0.53025	5.876375
DENERGY	0.000312	0.01237	-0.48764	5.660627
DESG	0.000325	0.009296	-0.55885	5.768438

offers significant insights into understanding diverse kurtosis values. The distribution exhibits mesokurtosis, characterized by a standard normal curve when the kurtosis coefficient $K = 3$. It displays leptokurtosis, indicating a peaked curve when $K > 3$. Conversely, the distribution demonstrates platykurtosis, signifying a flatter curve when $K < 3$.

The descriptive statistics analysis of all three time periods shows that all variables exhibit a negative skewness. This shows that the indices included in the study possess a longer left tail. Additionally, the kurtosis values suggest that they all are leptokurtic.

Table 2 displays the outcomes of the Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test conducted to assess the volatility of stock exchanges. The results suggest that the logarithmic returns of the stock indices for S&P BSE GREENEX, S&P BSE CARBONEX, S&P BSE 100ESG, and S&P BSE ENERGY exhibit stationarity, as evidenced by p-values, which is below the significance level of 0.05 (highlighted by ***) in both the ADF and PP tests. Once the data has achieved stationarity, we can conduct more analysis. The Autoregressive Conditional Heteroskedasticity (ARCH) model is frequently utilized to analyze volatility in a time series and predict future volatility. This analysis offers valuable perspectives on forthcoming volatility patterns. The current research used the ARCH-LM test statistics to evaluate the null hypothesis that no ARCH effects exist. Engle and Bollerslev, both esteemed sources, examine using the ARCH-LM test in studying volatility and investigating ARCH effects.

Tab. 3 shows that the volatility of all stock indices exhibits significant ARCH effects (p-values below 0.05). So, the GARCH model is used to forecast the direction and variability of stock markets.

The findings from the analysis using symmetric GARCH are displayed in Table 4. When analyzing the GARCH model, it is important to consider and present the values of α, β, and $\alpha + \beta$. The combined values for all stock indices' volatility are positive and below 1. There is a phenomenon of time waning in the perseverance of volatility. Considering the current circumstances, the level of volatility is expected to decrease.

Next, the Dynamic Conditional Correlation (DCC) GARCH method is utilized to measure

Table 2: *PP and ADF test results of variables included in study*

Stock Indices	Dickey-Fuller t-statistics	P-value*	PP t-statistics	P-value*
Unit root of the overall timeframe				
DCARB	-12.693	0.0000***	-38.6584	0.0000***
DENERGY	-38.1674	0.0000***	-38.2053	0.0000***
DESG	-12.8674	0.0000***	-38.6001	0.0000***
DGREEN	-37.7942	0.0000***	-37.9692	0.0000***
Unit root of the Covid timeframe				
DGREEN	-23.4198	0.0000***	-23.3715	0.0000***
DCARB	-23.988	0.0000***	-23.9167	0.0000***
DENERGY	-24.518	0.0000***	-24.4946	0.0000***
DESG	-23.8697	0.0000***	-23.8252	0.0000***
Unit root of the War timeframe				
DGREEN	-18.0375	0.0000***	-18.0371	0.0000***
DCARB	-19.2385	0.0000***	-19.2147	0.0000***
DENERGY	-17.8278	0.0000***	-17.8287	0.0000***
DESG	-19.1691	0.0000***	-19.15	0.0000***

Table 3: *ARCH LM test results*

Stock Exchange	Chi-square	Prob*
ARCH LM value of the whole timeframe		
DGREEN	17.27413	0.0000
DCARB	37.07866	0.0000
DENERGY	103.4930	0.0000
DESG	44.32709	0.0000
ARCH LM value of the Covid timeframe		
DGREEN	4.127091	0.0427
DCARB	10.59753	0.0000
DENERGY	19.69983	0.0000
DESG	12.85892	0.0004
ARCH LM value of the War timeframe		
DGREEN	12.12923	0.0000
DCARB	38.92323	0.0000
DENERGY	22.09912	0.0000
DESG	33.82684	0.0000

Table 4: *GARCH model findings*

Stock Indices	α	β	$\alpha + \beta$
Result of the whole timeframe			
DGREEN	0.115277	0.846417	0.961694
DCARB	0.114549	0.866131	0.980680
DENERGY	0.110547	0.847010	0.957557
DESG	0.106616	0.871256	0.977872
Result of the Covid timeframe			
DGREEN	0.132041	0.810114	0.942155
DCARB	0.122453	0.853890	0.976343
DENERGY	0.122565	0.811664	0.934229
DESG	0.118263	0.859869	0.978132
Result of the War timeframe			
DGREEN	0.118119	0.826004	0.944123
DCARB	0.022965	0.971204	0.994169
DENERGY	0.085596	0.895585	0.981181
DESG	0.019733	0.974506	0.994239

the transmission of effects across two indexes. The findings of DCC-GARCH are displayed in Table 5. The total of estimates shown in Table below demonstrates the correlation of the S&P BSE GREENEX with S&P BSE CARBONEX, S&P BSE 100ESG, and S&P BSE ENERGY. This correlation is indicated by the combined estimates of α_{dcc} and β_{dcc}, which are both smaller than one.

Table 5: *DCC GARCH model results*

Stock exchange	Sum of estimates	α_{dcc}:p-value	β_{dcc}:p-value
Result of the Whole timeframe			
DGREEN and DCARB	0.9575	0.000	0.000
DGREEN and DENERGY	0.953	0.000	0.000
DGREEN and DESG	0.954	0.000	0.000
Result of the Covid timeframe			
DGREEN and DCARB	0.938	0.000	0.000
DGREEN and DENERGY	0.916	0.017	0.017
DGREEN and DESG	0.926	0.000	0.000
Result of the War timeframe			
DGREEN and DCARB	0.988	0.255	0.000
DGREEN and DENERGY	0.922	0.240	0.000
DGREEN and DESG	0.986	0.335	0.000

The above analysis reveals that α_{dcc} values for all pairs of the S&P BSE GREENEX with various other Indian stock indices are positive, but the values are minimal. This indicates a regular volatility spillover between the S&P BSE GREENEX and S&P BSE CARBONEX, S&P BSE ENERGY, and S&P BSE100ESG. Nevertheless, the p-values are near or equivalent to 0 for the complete time frame and for the Covid time frame (implying that these are significant). However, they are greater than .05 for the war timeframe, indicating that these estimates lack statistical significance for this period. This implies that the observed spillover could be attributed to random chance rather than a genuine correlation for the war time period.

The estimates of β_{dcc} for all combinations of S&P BSE GREENEX with other Indian indices are positive and significant in size. The p-values for these estimates are nearly zero, indicating their statistical significance. This suggests a potential for volatile and fluctuating imbalances in the transmission of volatility effects between the two indices, a finding that could have significant implications for the Indian stock market.

Correlation is a standardized measure of the strength and direction of the linear relationship between two variables. A correlation of 1 indicates a perfect positive linear relationship, -1 indicates a perfect negative linear relationship, and 0 indicates no linear relationship. The DCC correlation graph reflects how the relationships between variables change over time.

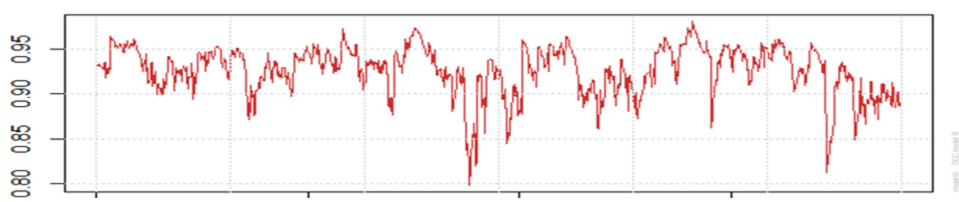

Figure 1: *DCC conditional correlation of DCARB and DGREEN*

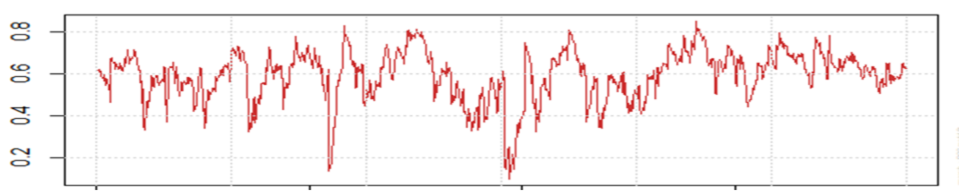

Figure 2: *DCC conditional correlation of DENERGY and DGREEN*

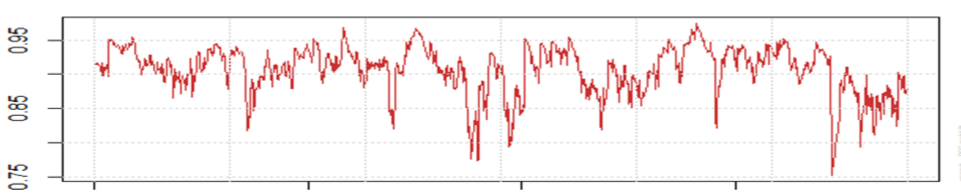

Figure 3: *DCC conditional correlation of DESG and DGREEN*

For the overall timeframe, if we look at the DCC conditional correlation graphs (Fig 1, 2, and 3) of GREEN with other variables, two characteristics can be observed. Firstly, the value is dynamic, and secondly, the relation is strongest with DCARB, less strong with DESG, and even less strong with ENERGY. Volatility clustering can also be observed.

Covariance measures how two variables move together. Positive covariance indicates that the variables tend to move in the same direction, while negative covariance indicates they move in opposite directions. The DCC model takes into account the dynamic nature of these covariances, allowing us to see how they fluctuate over time.

For the overall timeframe, if we look at the DCC conditional covariance graphs (Figs. 4, 5, and 6) of DGREEN with other variables, we can observe that the variables tend to move in the same direction. Sudden shifts in the graphs of the war timeframe suggest changes in the underlying relationships between variables. This could be driven by economic events, policy changes, or other

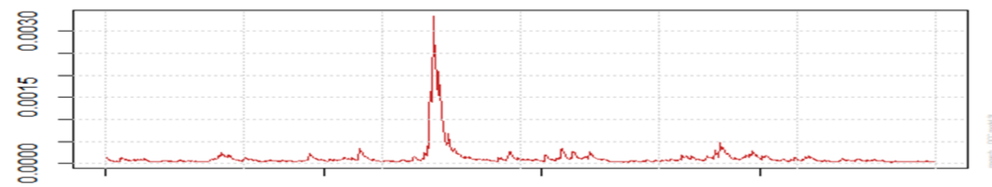

Figure 4: *DCC conditional covariance of DENERGY and DGREEN*

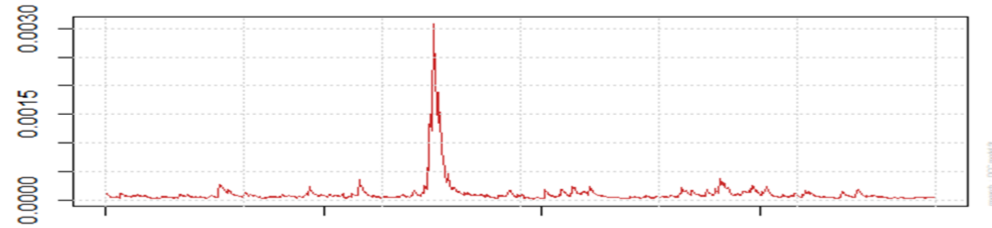

Figure 5: *DCC conditional covariance of DCARB and DGREEN*

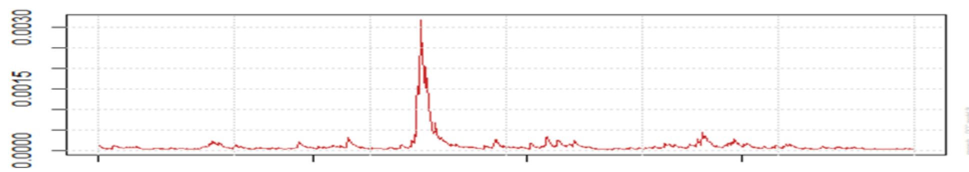

Figure 6: *DCC conditional covariance of DESG and DGREEN*

external factors.

In summary, there is an indication of a steady amount of volatility spillover among the indices described above; the significant p-value for the α_{dcc} estimates and β_{dcc} estimates indicates that this spillover has a significant economic impact. However, the β_{dcc} estimates are more extensive than α_{dcc} estimates, suggesting that there is some asymmetry in the volatility spillover effects, albeit these impacts may be relatively moderate in scale.

5. Conclusion

Central to this paper is the S&P BSE GREENX index, a key proxy for India's green bond stock market. Its analysis provides a crucial lens to understand volatility and the intricate relationships among variables in our study. We delve into the volatility, spillover effects, and linkages of the S&P BSE GREENX index, along with several other national stock indices, using GARCH models.

The DCC GARCH study uncovered several noteworthy insights. They draw attention to the growing interconnectedness of national financial markets and the consequent ease with which volatility can spread from one market to another. Economic and political developments on a worldwide scale, as well as the mood of investors, all have a role in the spread of volatility. Nevertheless, it is crucial to bear in mind that the economic impact of these outcomes may be mitigated by implementing efficient market mechanisms, arbitrage opportunities, and risk management tactics used by institutions and market participants. The significant p-values for DCC see asymmetry in the volatility spillover effects across time. This finding suggests that volatility transmission can fluctuate in size and direction over time. An important factor in determining the degree of asymmetry in spillover effects includes market conditions, investor behavior, and individual occurrences. During increased uncertainty or financial crises, spillover effects might be more pronounced and unevenly distributed.

The exact time frame and subset of stock indices used in this analysis must be recognized as caveats. There is also the possibility that exclusive emphasis on symmetric volatility models understates the complexity of market dynamics. Using more complex models and different econometric methods might yield more information about volatility spillovers.

While both the S&P BSE GREENX and national stock indices demonstrate volatility spillover, their economic impact may be relatively low. Given the asymmetry and volatility transmission's volatility, it becomes imperative to grasp market dynamics and implement effective risk management strategies. The causes of volatility spillovers and their effects on market participants and policymakers should be the focal point of future research, underscoring the urgency and importance of this topic.

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Declaration of interest: None

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