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Dynamics of Volatility Spillovers: Evidence from Implied Volatility Indexes to Conventional and Green Equities in the Indian Context

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Abstract

Green investments are considered crucial for achieving inclusive and sustainable economic growth, necessitating profitability for companies offering eco-friendly products. However, commodity price fluctuations can impact their profitability. This research investigates volatility transmission between the implied volatility indexes with traditional and green investments in the Indian market. Employing the dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model, we analyze daily data from Nov 2012 to Oct 2023. Results suggest that there has been a strong and persistent spillover effect among these financial assets, as the joint values for all pairs are very high and statistically significant. This implies a strong positive correlation between the volatility of the implied volatility indexes with traditional and green investment indexes and suggests that when the implied volatility index rises, the volatility of green investments also tends to rise, and vice versa. The study's findings have implications for both investment strategies and policy decisions.

Keywords: green stock, traditional stocks, implied volatility indexes, BEKK-DCC-GARCH.

1. Introduction

Research on socially conscious investing has gained momentum, particularly in the rapidly growing field of green investing, with a surge in research examining the stock performance of environmentally friendly firms. This surge in interest reflects the growing belief that investment decisions aligned with ethical principles can not only contribute to positive social and environmental outcomes but also potentially lead to higher financial returns (Sadrosky, 2014). Al-Najjar and Anfimiadou (2012) reveal that the impact of green investing on stock market performance remains a subject of debate among researchers. While some studies have found that sustainable stocks tend to generate higher returns than their conventional stock counterparts, others have concluded that corporate social responsibility (CSR) practices do not exert a measurable influence on a company's financial standing (Managi et al., 2012; Santis et al., 2016). Gangi and Varrone's (2018) study delves into the intricacies of the investment selection process employed by socially responsible funds, providing valuable insights into the factors that guide their decisions. A recent study by Gangi et al. (2020) highlights that embracing environmental responsibility and developing innovative green products can significantly enhance a company's reputation. In addition to stock returns, accurate assessments of fluctuating volatility and correlation are crucial for comprehending the risk profile of portfolio investments, which is essential for comprehending the risk associated with portfolio investments. Notably, understanding how volatility spreads between different financial assets is crucial for both investors and policymakers. The existing body of literature on green investments needs a comprehensive analysis incorporating volatility. Additionally, several studies, including those by Hoti et al. (2007), Schaeffer et al. (2012), Sariannidis et al. (2013), Sadorsky (2014), and Mensi et al. (2017), have investigated the link between SRI and financial performance. These studies exclusively examined developed markets.

Companies that adopt green technology outperform their more polluting competitors regarding financial health (Ameer & Othman, 2017; Banerjee & Chakrabarti, 2013; Porter & van der Linde, 1995). The involvement of financial markets and investments is crucial for achieving the objectives stated during the Paris climate summit. The difference between the supply and demand of green funds can be closed using environmentally responsible investing techniques (Polzin & Sanders, 2020). These studies on the success of carbon-neutral investments often concentrate on developed markets. However, developing economies are vulnerable to structural concerns, including institutional vacuum and sustainability issues (Sousa et al., 2020). Green investment, a financial endeavor primarily focused on environmental preservation and governance, plays a crucial role in fostering sustainable economic growth. Both carbon emissions reduction and green investment are potent tools in combating environmental pollution, but their effectiveness in mitigating emissions varies across different emissions levels, with lower, middle, and higher emissions quantiles exhibiting distinct patterns. Therefore, a positive correlation exists between economic growth and CO2 emissions, a relationship that holds statistical significance in both short-term and long-term analyses. This implies that as economic activity expands, CO2 emissions tend to increase as well (Puzon, 2012; Cabanero, 2023).

Due to government plans to use green projects and eco-friendly infrastructure to reduce CO2 emissions by 50% by 2050 and reach net zero by 2070, green investing has gained popularity in India (Bhatnagar et al., 2023). India is chosen as the research focus due to its emerging green investment market, limited research on Indian green stocks, and unique environmental and economic context. As green investment is still rather recent in India, Indian green enterprises' stock prices are very erratic and susceptible to outside influences. To comprehend the underlying risk of these green stocks, it is imperative to calculate their volatility precisely. The ideas of modern portfolio theory (Zhang & Umair, 2023) align with the investigation of volatility spillover effects and risk assessment of Indian green stocks in the context of this study. Investors can design and allocate assets in their portfolios with knowledge of the risk and volatility characteristics specific to the green investment space.

Our study explores the crucial role played by strategic implied volatility indexes like OVX, GVZ, and VIX in shaping the risk profile of traditional and green investment stocks, consistent with previous research findings (Sadorsky, 2014). Mensi et al. (2017) further substantiate this concept by demonstrating the seamless transfer of volatility from oil, gold, and silver markets to green stock indexes. Their work additionally suggests the possibility of forecasting socially responsible portfolio risk by utilizing information embedded within commodity prices. However, our study distinguishes itself from existing research by examining the impact of implied volatility indexes, rather than conventional oil and metal commodity prices, on the stock returns of traditional and green indexes. Moreover, we conduct our analysis in India, a large emerging economy that needs to be studied more in this context. Our contribution lies in strengthening the growing body of evidence that commodity VIX indexes hold greater informational value compared to traditional commodity prices due to their forward-looking nature (Haugom et al., 2014; Maghyereh et al., 2016; Raza et al., 2016; Dutta et al., 2017; Ahmad et al., 2018; Xiao et al., 2018; Dutta et al., 2020).

2. Literature Review

According to Degiannakis et al. (2014), supply and demand shocks specific to oil do not affect stock market volatility, but changes in oil prices brought about by overall demand shocks do. Volatility in the stock market is unaffected by the shock to the oil supply. Conversely, demand shocks have a major effect on the volatility of the G7 stock markets. This implies that the development of financial regulation and economic policies aimed at mitigating the adverse effects of unanticipated fluctuations in oil prices has to account for the factors that give rise to oil price fluctuations (Bastian et al., 2016). The two markets' volatilities follow each other closely. However, this co-movement fluctuates with time and depends on the time scale. It is robust at yearly horizons but noticeably weaker at vistas of a few days.

The stock market's sensitivity to unexpected oil price shocks varies depending on the prevailing market conditions. Specifically, during periods of high volatility, the stock market exhibits positive and statistically significant responses to these shocks, with the exception of China. This observation suggests that the rise in oil prices in these countries may be attributed to demand-side factors. Conversely, during times of market turbulence, such as the COVID-19 pandemic and the Russia-Ukraine conflict, crude oil volatility's spillover effect on the stock market was not statistically significant. Despite these crises, asymmetric volatility remained prevalent, emphasizing the importance for investors to consider both dynamic volatility and crude oil-stock price correlations when diversifying their portfolios to maximize returns and minimize risk (Kantaphayao & Sukcharoensin, 2021; Vu, 2019; Koh, 2015; Gupta & Chaudhary 2022; Sun et al., 2022; Seth & Sidhu, 2020).

Additionally, there is a correlation between implied and realized volatilities for the stock market, but there is none between implied and realized volatilities for the oil market (Bašta & Molnár, 2018). Liu et al. (2020) found a substantial positive time-varying relationship between implied volatility returns of stocks and oil. Amid the global financial crisis, the correlation between the price of oil and stock markets became even more significant. The implied volatility of the oil and stock markets also significantly overlaps. Compared to industrialized countries, emerging economies' stock markets are more volatile, and this volatility is more susceptible to external factors like the price of oil and the Global Economic Policy Uncertainty (GEPU) Index. This indicates that changes in these global determinants have a larger potential to impact developing market stock markets, potentially resulting in increased market volatility (Syed & Bouri, 2022). Rahman (2022) found that when the price of oil increases, stock returns tend to decrease more than when the price of oil drops. This is because oil price volatility hurts stock returns. When oil prices are volatile, it is more difficult for businesses to plan for the future, leading to lower investment and economic growth. This, in turn, can lead to lower stock prices.

Stock markets are the backbone of any country's economy, reflecting its overall health (Mo et al., 2023). Green stock investing is an investment niche with the fastest growth rates (Yousaf et al., 2022; Sadiq et al., 2022; Zhang et al., 2022). Gaining more insight into the disparities in returns and dangers among investing in green assets and other kinds of assets is imperative as the popularity of green stocks rises. Most other studies mainly focus on the oil, gold, and silver markets (Dutta et al., 2021; Zhou et al., 2020)**.** In developing countries like India, where capital inflow to green sectors is estimated to reach US$ 686 billion by 2033, the risk transmission link between green equities and other financial assets is still poorly understood (Desalegn & Tangl, 2022). As per Bello (2005), investing in socially responsible stocks yields greater returns than investing in traditional stocks. Several other studies (Becchetti & Ciciretti, 2009; Cortez et al., 2012; Kolk, 2016; Kumar et al., 2012) showed that social responsibility does not affect the stock market performance. Exploring the effects of volatility spillovers between financial assets is essential for investors and policymakers.

Our analysis sheds light on how strategic commodities impact green investments, providing crucial insights for policymakers dedicated to fostering sustainable businesses. When the oil market undergoes a downturn, it reduces the appeal for environmentally conscious investors, potentially resulting in a decline in the value of green assets. Conversely, rising oil prices often drive investment, leading to an increase in the stock prices of green companies. This corresponds with the discoveries of Dutta et al. (2020), emphasizing a positive relationship between changes in oil prices and the value of green stocks. Furthermore, considering the inverse relationship between WTI price and OVX (Dutta, 2019), a rise in OVX might negatively impact green stocks. This implies that increased volatility in the crude oil market could heighten the volatility levels of green assets. Gold, a long-revered precious metal, has been widely advocated as a shield against inflation's erosive effects. As Ahmad et al. (2018) aptly point out, inflation diminishes the real value of investments, and inflationary periods present a prime opportunity for savvy investors to employ gold as an effective hedging instrument. In other words, gold is often viewed as an alternative asset for preserving value. Moreover, gold plays a significant role in the Indian economy due to its substantial demand in the jewelry export market, one of the country's fastest-growing sectors and a major source of foreign exchange earnings. In India, gold stands as a highly cherished adornment and a coveted investment option. Embodying affluence, silver is often regarded as a practical substitute for gold. Sharing inherent similarities and partial interchangeability, both exhibit arbitrage and low-risk spread trading characteristics (Pradhan et al., 2020), rendering them extensively utilized in eco-conscious enterprises. As an illustration, silver consumption within the clean energy sector has experienced a significant surge, given its pivotal role in the photovoltaic process for generating solar energy. Dutta (2019) expresses apprehension that an escalation in silver market volatility could potentially disrupt the stability of the solar energy industry.

The objective of this study is to examine the time-varying correlations and volatility dynamics between the assets used in this study. This analysis could provide valuable insights into the interdependencies between them and their responses to market shocks and can assess the volatility spillover effects on green stocks by employing the dynamic conditional correlation-generalized autoregressive conditional heteroskedasticity (DCC-GARCH) model. Overall, the application of DCC-GARCH to OVX, GVZ, and VIX with traditional and green stocks could inform investment decisions, risk management strategies, and policymaking initiatives aimed at promoting sustainable investing.

3. Data and Methodology

The study utilizes sustainability indices (S&P BSE CARBONEX and S&P BSE GREENEX) based on daily closing prices obtained from the Bombay Stock Exchange (BSE). Moreover, this study also considered S&P BSE 500 as a traditional stock index with implied volatility indexes, namely VIX (S&P 500 index), OVX (crude oil), and GVZ (gold) to test the transmission effect of information through volatility spillover. The empirical analysis encompasses the indices above and covers daily closing prices from Nov 2012 to Oct 2023, and each index consists of 2721 observations. The daily log returns are calculated by using the formula :

$$R_{it} = ln\left(\frac{P_{it}}{P_{i,t-1}}\right) \tag{1}$$

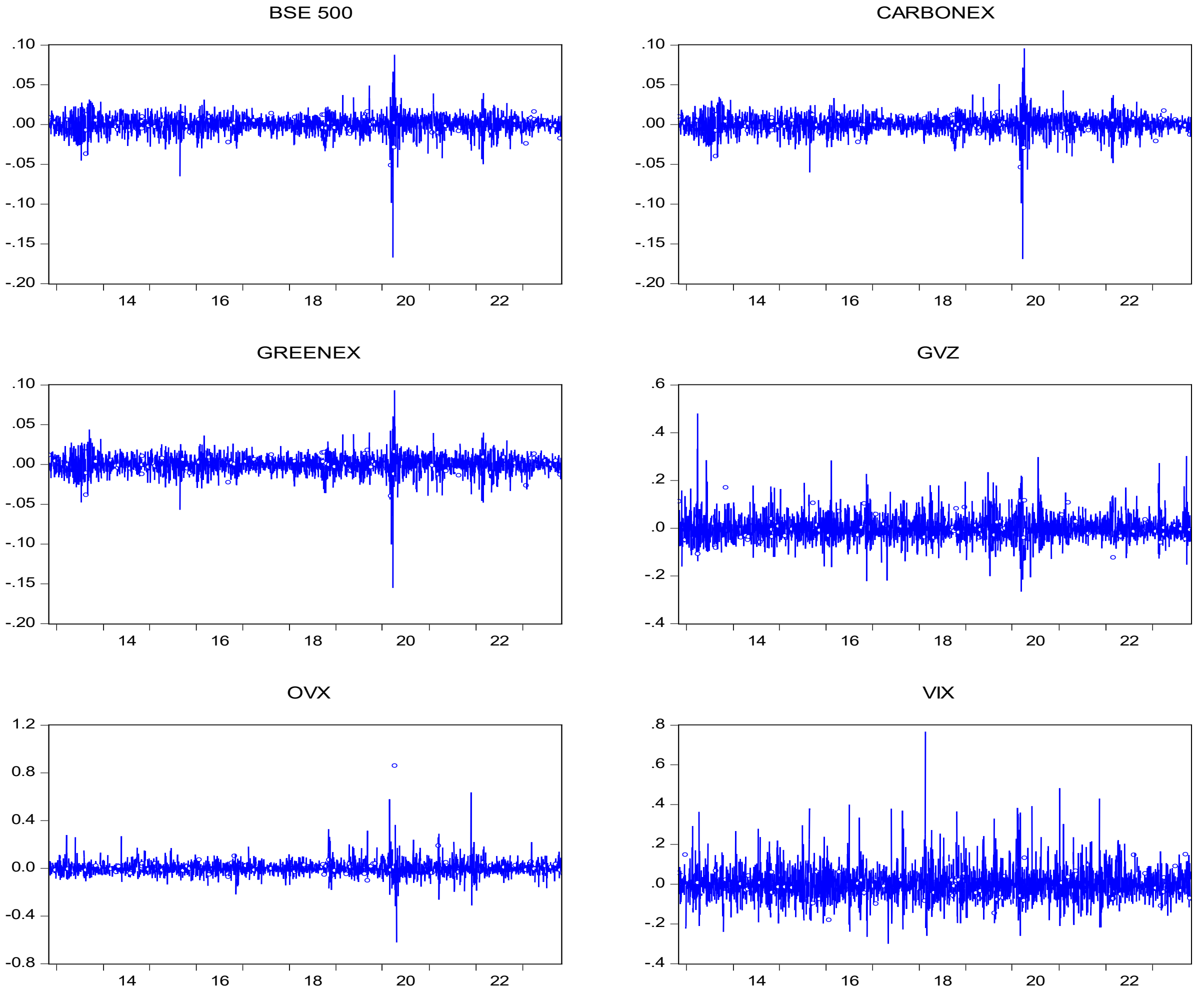
where R_{it} is the daily *log* return of asset at day t, P_{it} is the closing price of asset at day t, and $P_{i,t-1}$ is the closing price of asset at day $t-1$.

Table 1 contains descriptive statistics for six variables: BSE 500, CARBONEX, GREENEX, VIX, OVX, and GVZ. Daily returns for stocks and commodity indexes were slightly positive by an average of 0.0002, but standard deviations, indicating risk or volatility, were much larger. The VIX index, a measure of stock market volatility, had the highest standard deviation (0.0790), followed by OVX (0.0603), CARBONEX (0.0115), GREENEX (0.0116), BSE500 (0.0114), and GVZ (0.0531). Markets with higher standard deviations experience more dramatic price swings, making them riskier than markets with lower standard deviations. All daily returns within our sample fluctuate around a zero average (Figure 1), suggesting a tendency for volatility over time. The presence of the ARCH effect in the all-time series further evidences this.

Table 1. Descriptive statistics of returns in the full period

	BSE 500	CARBONEX	GREENEX	VIX	OVX	GVZ
Mean	0.0003	0.0002	0.0002	0.0001	0.0001	0.0001
Std.Dev.	0.0114	0.0115	0.0116	0.0790	0.0603	0.0531
Skewness	-1.561***	-1.405***	-1.117***	1.176***	1.800***	0.977***
Kurtosis	25.445***	25.414***	16.333***	6.611***	29.123***	5.928***
JB	58219.661***	57851.423***	30809.020***	5583.285***	97626.724***	4417.074***
ADF	-21.202	-21.436	-21.932	-25.843	-24.815	-25.172

Figure 1. Daily log returns of BSE 500, CARBONEX, GREENEX, VIX, OVX, and GVZ



3.1 Unit root test

For accurate analysis and forecasting of a time series, the data must exhibit stationarity. Non-stationary data, characterized by a fluctuating distribution over time, presents challenges in identifying patterns and making reliable predictions. In contrast, stationary data possesses consistent properties, maintaining a stable mean, variance, and covariance across periods. This stability allows for meaningful analysis and forecasting. So, to evaluate whether the data contains a unit root with a single structural break test, the values mentioned in Table 1 were utilized. The ADF test assumes the absence of stationarity in the data as its null hypothesis.

$$\Delta y_t = \propto_0 + \theta y_{t-1} + \sum_{i=1}^{n} \propto \Delta y_t + e_t \quad (2)$$

The given equation represents the value of the data point (y_t) at a specific time (t). The optimal number of lags (n) is also indicated. The constant term is denoted by δ, and the error term is represented by e. Table 2 shows the number of structural breaks identified for each variable, along with the estimated break dates, by using the Zivot-Andrews test (2002). All six variables (BSE500, CARBONEX, GREENEX, OVX, GVZ, and IVX) exhibit one structural break, which occurred in April 2020. The presence of a structural break for all six variables in April 2020 coincides with the beginning of the COVID-19 pandemic and subsequent global lockdowns.

Figure 2. Zivot-Andrews break points dates from Nov 2012 to Oct 2022

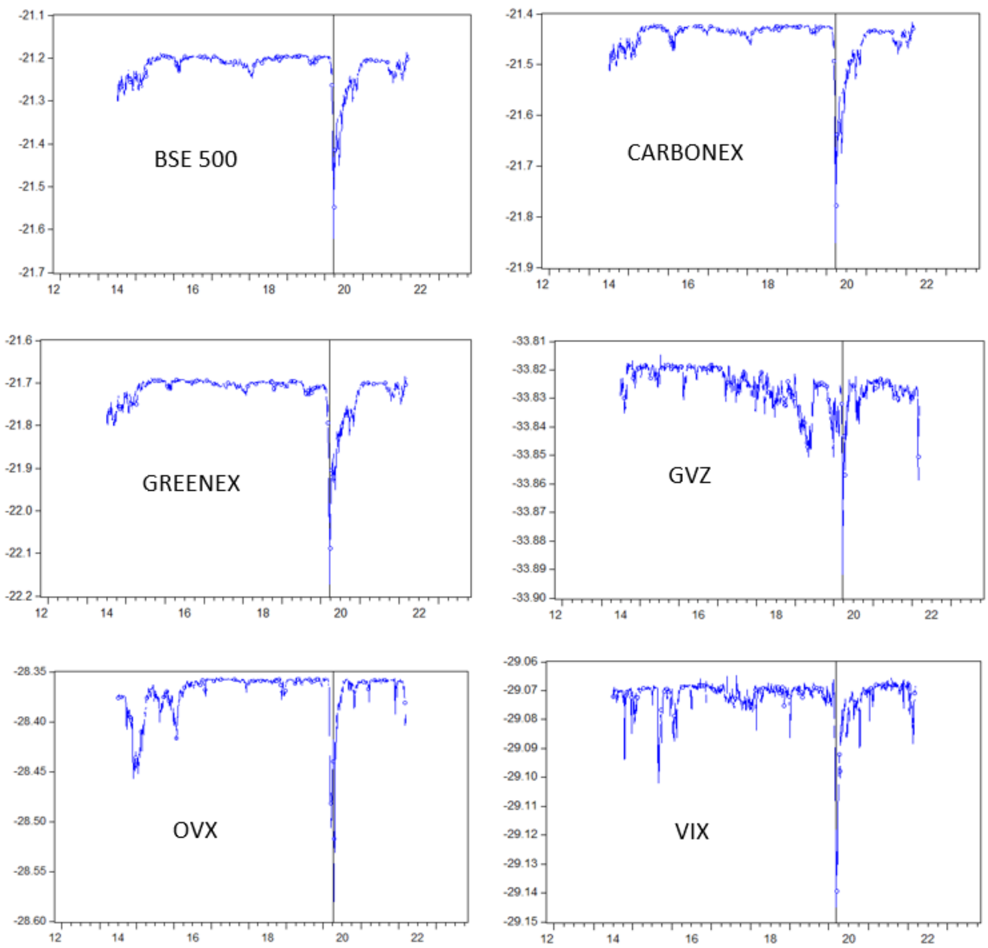


Table 2. Structural breaks details

Variables	**No. of Breaks**	**Estimated break dates**
BSE500	1	2020M4
CARBONEX	1	2020M4
GREENEX	1	2020M4
OVX	1	2020M4
GVZ	1	2020M4
IVX	1	2020M4

3.2 ARCH effect

Applying GARCH models requires ensuring the data meets two key assumptions: stationarity (no unit root) and homoskedasticity (constant variance). The presence of heteroskedasticity (non-constant variance) motivates the use of GARCH to model conditional volatility, capturing the dynamic changes in volatility over time. To assess the presence of heteroskedasticity in the residuals of a time series model, the ARCH-LM test, also known as the autoregressive conditional heteroskedasticity–Lagrange multiplier test, is employed.

$$u_t^2 = \gamma_0 + \gamma_1 u_{t-1}^2 + \gamma_2 u_{t-2}^2 + \cdots + \gamma_p u_{t-p}^2 + v_t \quad (3)$$

In the context of time series analysis, u denotes the squared residuals of a mean regression model, where the residuals represent the differences between the observed values of a time series and the fitted values obtained from the mean regression model. The symbol p represents the lag length in the residual regression model, which describes the number of previous time steps considered when modeling the current residual. Table 3 clearly indicates the presence of an ARCH effect in all six time series. This implies that the variance of the residuals in these time series is different over time. In simpler terms, the magnitude of changes in these time series could be more consistent, with larger changes tending to be followed by larger changes and smaller changes tending to be followed by smaller changes. The ARCH effect has significant implications for financial forecasting and risk management. For instance, if the ARCH effect is present in a stock price series, it indicates that the volatility of the stock price is not constant. Therefore, the use of the GARCH model is necessary to assess the influence of conditional volatility accurately.

Table 3. ARCH effect

	BSE500	CARBONEX	GREENEX	VIX	OVX	GVZ
F-static	38.75	22.32	23.65	55.40	80.43	66.28
Prob	0.000	0.000	0.000	0.000	0.000	0.000

We employed the ARIMA (1,1) model, known as the autoregressive moving average model, to estimate the mean equation for asset returns. This model was chosen due to its superior performance in capturing the influence of both past returns and residuals on future returns.

Conditional Mean Equation and Conditional variance equation :

$$y_t = c + b_1 y_{t-1} + b_2 e_{t-1} + e_t \tag{4}$$

$$h_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 \tag{5}$$

y_t is conditional mean, c is the intercept, b_1 is the coefficient of AR(1), b_2 is the coefficient of MA(1), and e_t indicates error term at time t. Table 4 demonstrates that the historical returns and residual errors play a significant role in determining the current returns of BSE500, CARBONEX, and GREENEX.

Table 4. ARIMA (1,1) model.

	BSE500		CARBONEX		GREENEX		OVX		GVZ		VIX	
	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob	Coeff.	Prob
C	0.0002	0.216	0.0001	0.235	0.0002	0.251	0.0001	0.8907	-0.0001	0.876	0.0002	0.682
Ar(1)	-0.8545	0.000	-0.8691	0.000	-0.8242	0.000	0.7869	0.000	0.8573	0.000	0.9280	0.000
MA(1)	0.8864	0.000	0.8969	0.000	0.8458	0.000	-0.8340	0.000	-0.9165	0.000	-0.9783	0.000

Equation (5) highlights two essential parameters, α1 and β1, associated with the ARCH and GARCH terms, respectively. α1 captures the ARCH effect, measuring the sensitivity of current volatility to recent news or shocks in the market. On the other hand, β1, associated with the GARCH effect, assesses the persistency of volatility, indicating how long it takes for volatility to dissipate. A high value of α1 signifies a stronger influence of recent news on volatility, while a large β1 implies that volatility is more persistent and takes longer to fade away (Chaudhary et al., 2020; Rastogi, 2014).

3.3 Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH)

We have opted for the Engle (2002) Dynamic Conditional Correlation (DCC) model, built upon the foundation laid by the Bollerslev (1990) Constant Conditional Correlation (CCC) model, taking the concept of modeling time-varying conditional covariance matrices to a more nuanced level, unlike the CCC model's assumption of constant conditional correlations. This model is particularly notable for its ability to anticipate future shifts in variance flexibility (Yan et al., 2022). Its effectiveness stems from its utilization of historical data and squared residuals, offering a more profound understanding of the constantly changing volatility dynamics. From two-time series datasets,

$r_{i,t}$ and $r_{j,t}$, modeled using AR(1) models, we derive two sets of residual time series variables, $a_{i,t}$ and $a_{j,t}$. The matrix *Ht* represents the dynamic conditional covariance matrix calculated for these paired time series, $r_{i,t}$ and $r_{j,t}$.

The matrices H_t, R_t, D_t, and D_t^{-1} are interconnected in the analysis of dynamic conditional correlations and variances within time series data. H_t serves as the covariance matrix, R_t represents the dynamic conditional correlation matrix, and D_t is derived from H_t and is a diagonal matrix, while D_t^{-1} stands as the inverse of the diagonal matrix D_t. These matrices collectively offer insights into the relationships and fluctuations among variables in the time series context.

The connections among the matrices H_t, R_t, D_t, and D_t^{-1} can be summarized as follows:

$$H_t = D_t R_t D_t \tag{6}$$

$$R_t = D_t^{-1} H_t D_t^{-1} \tag{7}$$

By implementing two GARCH (1,1) models, we derived two normalized residual variables, $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$. The subsequent relationship is established by defining the following variables, where Q_t stands as the Covariance Matrix, G_t represents the Diagonal Matrix extracted from the Covariance Matrix Q_t, $Q_t - 1$ denotes the inverse of Q_t, and C_t indicates the Correlation Matrix in this context.

The relationships between the matrices of Q_t, C_t, G_t, and D_t^{-1} are :

$$Q_t = G_t C_t G_t \tag{8}$$

$$C_t = G_t^{-1} Q_t G_t^{-1} \tag{9}$$

Considering matrices of second order, namely R_t, H_t, and Q_t, let us assume:

$$R_t = \begin{pmatrix} p_{i,t} & p_{ij,t} \\ p_{ji,t} & p_{j,t} \end{pmatrix} \; H_t = \begin{pmatrix} \sigma_{i,t} & \sigma_{ij,t} \\ \sigma_{ji,t} & \sigma_{j,t} \end{pmatrix} \; Q_t = \begin{pmatrix} q_{i,t} & q_{ij,t} \\ q_{ji,t} & q_{j,t} \end{pmatrix} \tag{10}$$

$$\sigma_{ij,t} = \sigma_{i,t} P_{ij,t} \sigma_{j,t}, \qquad \sigma_{ji,t} = \sigma_{i,t} P_{ji,t} \sigma_{j,t} \tag{11}$$

The evolving correlations under conditional dynamics between these two series can be expressed as:

$$P_{ij,t} = \frac{q_{ij,t}}{q_{i,t} q_{j,t}}, P_{ji,t} = \frac{q_{ji,t}}{q_{j,t} q_{i,t}} \quad Where\ P_{ij,t} = P_{ji,t} \tag{12}$$

Due to the consideration of the time variable t, the correlation variables $P_{ij,t}$ and P_{ji} depict fluctuating correlations.

The DCC-GARCH model incorporates two parameters, (α) and (β), to capture the dynamic nature of correlations in assets market volatility. Both parameters are time-varying and reflect the evolving relationships between asset prices over time. The coefficient (α) specifically quantifies the short-term persistence of volatility shocks, indicating how much yesterday's unexpected price movements influenced today's volatility. The coefficient β within the DCC-GARCH model quantifies the lingering impact of past volatility shocks on the conditional correlations between asset prices. This parameter reflects the persistence of shocks in the correlation dynamics, indicating how long the effects of past events continue to influence current correlations. The constraint that the sum of (α) and (β) is less than one ensures the stability of the model and prevents correlations from becoming permanently fixed at past values, allowing for dynamic adjustments over time.

Tables 5a, 5b, and 5c suggest a strong interrelationship in volatility among the different assets. This is evidenced by the spillover effect observed across all variables and pairs of variables in the long run. The individual values of alpha and beta are positive and significant, endorsing the persistence of volatility, and the sum of alpha and beta for all the series is less than 1, which shows decay over time in volatility persistence. The Joint β coefficient exceeding 0.9 for all pairs in the DCC model indicates a very strong lingering effect of shock impact on the conditional correlations. This implies that shocks to one variable have a significant and persistent impact on the correlations with another variable. The study also highlights the persistence of volatility over time, which is consistent with Abakah et al.'s (2020) findings. Moreover, it suggests that incorporating structural breaks can help reduce this persistent behavior. A consistent pattern of dynamic correlations emerges across all variables, evident in the DCC graphs (Figure 3) during the COVID-19 pandemic. This points toward a robust and enduring interconnectedness among all the variables.

Table 5a. DCC results

		OVX/CARBONEX		OVX/GREENEX		OVX/BSE500	
		Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
1	[A] $\alpha 1$	0.1732	0.0053	0.1732	0.0053	0.1732	0.0053
2	[A] $\beta 1$	0.7371	0.0000	0.7371	0.0000	0.7371	0.0000
3	[B] $\alpha 1$	0.0794	0.0000	0.0846	0.0000	0.0863	0.0000
4	[B] $\beta 1$	0.9007	0.0000	0.8869	0.0000	0.8863	0.0000
5	[Joint] dcc$\alpha 1$	0.0000	0.9998	0.0000	0.9971	0.0000	0.9999
6	[Joint] dcc$\beta 1$	0.9027	0.0000	0.9096	0.0000	0.9010	0.0000

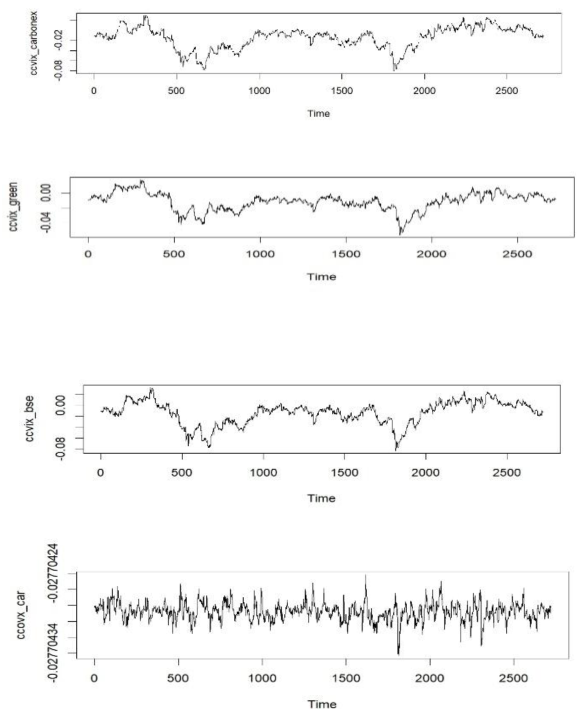
Table 5b. DCC results

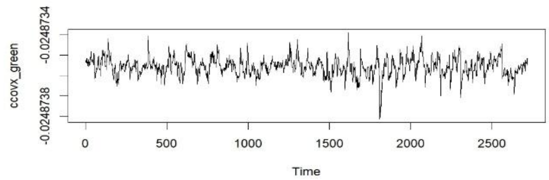
		GVZ/CARBONEX		GVZ/GREENEX		GVZ/BSE500	
		Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
1	[A] $\alpha 1$	0.1461	0.0000	0.1461	0.0000	0.1461	0.0000
2	[A] $\beta 1$	0.7801	0.0000	0.7801	0.0000	0.7801	0.0000
3	[B] $\alpha 1$	0.0794	0.0000	0.0846	0.0000	0.0863	0.0000
4	[B] $\beta 1$	0.9007	0.0000	0.8869	0.0000	0.8863	0.0000
5	[Joint] dcc$\alpha 1$	0.0080	0.4684	0.0096	0.3901	0.0078	0.4565
6	[Joint] dcc$\beta 1$	0.8036	0.0006	0.9278	0.0000	0.8282	0.0000

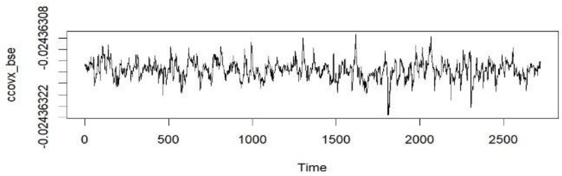
Table 5c. DCC results

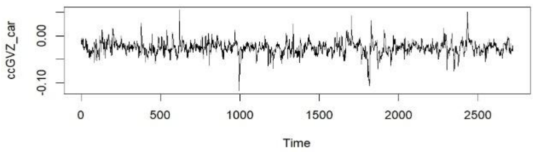
		VIX/CARBONEX		VIX/GREENEX		VIX/BSE500	
		Estimate	Pr(>|t|)	Estimate	Pr(>|t|)	Estimate	Pr(>|t|)
1	[A] $\alpha 1$	0.1856	0.0000	0.1856	0.0000	0.1856	0.0000
2	[A] $\beta 1$	0.5845	0.0000	0.5845	0.0000	0.5845	0.0000
3	[B] $\alpha 1$	0.0794	0.0000	0.0846	0.0000	0.0863	0.0000
4	[B] $\beta 1$	0.9007	0.0000	0.8869	0.0000	0.8863	0.0000
5	[Joint] dcc$\alpha 1$	0.0024	0.2578	0.0015	0.4944	0.0025	0.2595
6	[Joint] dcc$\beta 1$	0.9908	0.0000	0.9908	0.0000	0.9202	0.0000

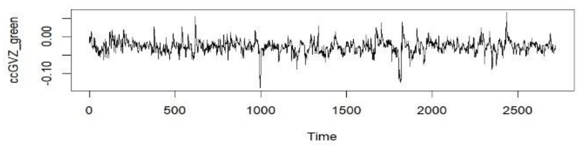
Figure 3. Dynamic Conditional Correlation

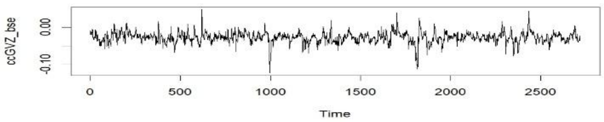












3.4 BEKK GARCH

The findings from the BEKK-GARCH estimation are presented in Tables 6a and 6b. The existence of the ARCH effect in the daily data for all variables has permitted the application of GARCH models for analyzing and studying volatility shocks between implied volatility indexes and their influence on both conventional and environmentally conscious (green) stocks. Various pairs have been studied, as illustrated in Table 6, to uncover connections and relationships between them and highlight two key coefficients, A11 and A22. These coefficients tell us that past positive news has a positive impact on the current change in the variable and vice versa. This means good news in the past tends to lead to further good news in the present, and bad news in the past tends to lead to further bad news. Interestingly, this pattern holds true for all the variables studied, suggesting a strong connection between past news and present volatility. This connection shows how shocks from the past values of each variable can influence their own volatility in the present. This pattern holds true for all variables studied, highlighting what is called the "volatility spillover effect." This effect essentially means that past volatility tends to "spill over" and influence the present level of volatility within the same variable. Just like positive news, past volatility also plays a major role in shaping current volatility. Table 6 shows this through the coefficients B11 and B22, which reveal that previous ups and downs have a significant impact on the current volatility of each variable.

The coefficients A12, A21, B12, and B21, representing both short-term and long-term persistence in the variables, have been examined from Tables 6a and 6b to uncover shock transmission and volatility spillover effects between the Implied Volatility Index and traditional as well as green stocks. The analysis reveals that coefficients A12 and A21 do not demonstrate a significant relationship between the variables, suggesting that past news did not exert any discernible influence on the current changes in these variables. Similarly, coefficients B12 and B21 also do not show any notable relationship between the variables, indicating that past volatility did not affect the current conditional volatility in these variables. Consequently, during the study period, there seems to be an absence of short-term interconnectedness between the variables. Ensuring the reliability of empirical findings is crucial, and conducting robustness checks serves this purpose. In this study, a multi-method approach has been utilized to validate the results. Both the BEKK-GARCH and DCC-GARCH models were employed on the identical set of variables. This strategy bolsters the credibility of the conclusions by confirming consistent outcomes through diverse methodologies, thus strengthening the robustness of the findings.

Table 6a. BEKK-GARCH estimates

	OVX/BSE500	**OVX/CARBONEX**	**OVX/GREENEX**	**GVZ/BSE500**	**GVZ/CARBONEX**	**GVZ/GREENEX**
C_{11}	0.0192***	0.0202***	0.0193***	0.0190***	0.0192***	0.0193***
C_{21}	0.0001	-0.0002	-0.0002	0.0001	0.0001	-0.0002
C_{22}	0.0011***	0.0016***	0.0012***	0.0013***	0.0011***	0.0012***
A_{11}	0.4001***	0.3415***	0.4061***	0.4981***	0.4001***	0.4061***
A_{12}	0.0072	0.0050	0.0057	0.0072	0.0072	0.0057
A_{21}	-0.2427	-0.5715***	-0.1937	-0.2318	-0.2427	-0.1937
A_{22}	0.2326***	0.2643***	0.2316***	0.2374***	0.2326***	0.2316***
B_{11}	0.8422***	0.8637***	0.8395***	0.8446***	0.8422***	0.8395***
B_{12}	-0.0087***	−0.0095***	-0.0081***	-0.0093***	-0.0087***	-0.0081***
B_{21}	0.1347***	0.3551***	0.1512***	0.1528***	0.1347***	0.1512***
B_{22}	0.9654***	0.9501***	0.9649***	0.9616***	0.9614***	0.9649***
Log Likelihood	12962.937	12744.006	12866.878	12982.298	12962.937	12866.878

Note: AIC refers to Akaike Information Criterion. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Table 6b. BEKK-GARCH estimates

	VIX/BSE500	**VIX/CARBONEX**	**VIX/GREENEX**
C_{11}	0.0410***	0.04151***	0.0412***
C_{21}	0.0000	0.0000	0.0000
C_{22}	0.0016***	0.0012***	0.0015***

A_{11}	0.4146***	0.4204***	0.4236***
A_{12}	−0.0011	−0.0001	0.0002
A_{21}	-0.1896	-0.2074	-0.3232
A_{22}	0.2504***	0.2355***	0.2434***
B_{11}	0.7465***	0.7396***	0.7411***
B_{12}	-0.0029	-0.0049	-0.0051
B_{21}	0.1327	0.1368	0.2365***
B_{22}	0.9552***	0.9632***	0.9582***
Log Likelihood	11852.533	11835.558	11738.673

4. Conclusion

Green investments are increasingly recognized as crucial for achieving inclusive and sustainable economic growth. However, ensuring the profitability of companies offering eco-friendly products is essential for attracting private capital and fueling this growth. This research investigated the dynamic and interconnected nature of volatilities between implied volatility indexes, traditional investments, and green investments in the Indian market. Utilizing the robust DCC-GARCH and BEKK-GARCH models and analyzing daily data from November 2012 to October 2023, we unveiled compelling evidence of a strong and persistent spillover effect among these financial assets. The results demonstrate a remarkable positive correlation between the implied volatility index and both traditional and green investments. This indicates that increases in the overall market volatility, as measured by the implied volatility index, lead to corresponding increases in the volatility of both green and traditional investment options. This finding highlights the inherent interconnectedness of these assets and emphasizes the need for investors to consider the broader market context when making investment decisions.

Furthermore, the analysis revealed a long-run interrelationship in the volatilities of all variables and pairs of variables. This indicates that the observed spillover effect extends beyond short-term fluctuations and persists over longer timeframes. This finding underscores the importance of incorporating volatility dynamics into long-term investment strategies and risk management frameworks, as the research has the potential to impact both portfolio construction and risk management practices significantly. Investors and portfolio managers should carefully analyze their exposure to green stock indexes to optimize asset allocation and implement effective risk mitigation measures. Additionally, industry participants and regulatory bodies can enhance market volume management and introduce various countermeasures specifically tailored to the green market. Such measures have the potential to effectively mitigate the adverse impacts of extreme economic events on global green stock markets. This study opens doors for further investigation into the complexities of volatility dynamics in financial markets. Future research could investigate the impact of additional factors, such as economic news announcements, policy changes, and geopolitical events, on the volatilities and correlations of these assets.

In light of the findings from our investigation into the volatility transmission between implied volatility indexes with traditional and green investment indexes in the Indian market, it is imperative to consider the broader implications for Southeast Asian economies. The region, known for its dynamic economic landscape and commitment to sustainable development, stands at a critical juncture where green investments are not just beneficial but essential for ensuring long-term economic resilience and inclusivity. The strong and persistent spillover effects observed in the Indian market highlight the interconnectedness of traditional and green financial assets, a phenomenon likely mirrored across Southeast Asia due to similar economic structures and investment behaviors. The implications of our research for Southeast Asian economies are twofold. Firstly, the observed volatility transmission suggests that policymakers and investors in the region need to adopt a holistic view of the market, recognizing the interplay between traditional and green investments. This understanding is crucial for developing robust financial strategies that can withstand the pressures of commodity price fluctuations, thereby ensuring the profitability and sustainability of green investments. Secondly, the evidence underscores the importance of creating supportive policy environments that can mitigate the adverse effects of market volatility on green investments. For Southeast Asia, this could mean enhanced regulatory frameworks, incentives for eco-friendly business practices, and investment in green technologies, all of which can contribute to making green investments more attractive and less susceptible to market whims.

By integrating these considerations into economic planning and policy-making, Southeast Asian countries can leverage green investments as a vehicle for achieving sustainable growth. This approach not only aligns with the global agenda for sustainability but also offers a pathway to economic resilience by fostering industries that are less reliant on finite resources and more adaptable to the demands of a changing world. Therefore, our study's findings, while based on the Indian market, offer valuable insights for enhancing the economic strategies of Southeast Asian nations in their pursuit of a green and inclusive economic future.

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Author contribution

Ubaid Ahmad Peer: writing original draft, data curation, conceptualization, and methodology. Dr. Rupinder Katoch: visualization, investigation, reviewing, and editing. Dr. Arpit Sidhu: supervision, software, validation, interpretation, reviewing, and editing.

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