Commodity market risks and green investments: Evidence from India

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Commodity Market Risks and Green Investments: Evidence from India

Abstract

Green investing has recently received considerable attention in India in light of the local government plans to significantly reduce the level of CO_2 emissions through conducting and funding various types of eco-friendly infrastructures and green projects on a national scale. Given that investment in environmentally friendly projects is still relatively new in India, the stock prices of Indian green companies could be highly volatile and very prone to risk transmission from other assets, which requires a precise estimation of the time-varying volatility of these green stocks to understand their underlying risk. In this paper, we examine if the stock volatility of Indian green companies can be predicted based on the information contents of commodity market implied volatility indexes (VIX) by employing a GARCH-based quantile regression model on daily data. The results show that risk significantly transmits from crude oil, gold, and silver markets to various Indian green stock indexes. The impact of the transmission from commodity market VIXs is stronger during the bearish stock market periods compared to bullish stock market periods, suggesting that green stock indexes are more likely to receive volatility from energy and precious metal markets during the periods of high uncertainty. Our findings are useful to socially responsible investors who focus not only on the environmental performance of a firm but also consider its financial performance.

Keywords: India; Green investments; Commodity market VIX; Risk spillover; Sustainability; GARCH-quantile regression

1. Introduction

Research on the stock market behavior of socially responsible (henceforth, SR) firms has grown rapidly over the past two decades concurring with a rising interest in socially responsible investing, including green investing, which constitutes one of the fastest growing sectors of endowment (Sadrosky, 2014). Some studies (e.g., Al-Najjar and Anfimiadou, 2012) reveal that investing in SR stocks leads to higher returns relative to conventional stocks, while other studies demonstrate that the adoption of CSR does not impact the stock market performance (Becchetti and Ciciretti, 2009; Cortez et al., 2012; Managi et al., 2012; Santis et al., 2016). Furthermore, Gangi and Trotta (2015) examine the risk/return relationship of SR funds and provide reasonable evidence to imply that SR funds behave as a sort of "refuge funds" for the investor. Xiao et al. (2017) study the financial performance of socially responsible investments and argue that investors "will not be disadvantaged financially by investing in socially responsible funds or corporations". Gangi and Varrone (2018) offer important insights into the selection activity of SR funds. Allevi et al. (2019) evaluate the performance of green investments and indicate evidence of a positive association between the level of "greenity" and the efficiency score. Recently, Gangi et al. (2020) indicate that corporate environmental responsibility and green product innovation can enhance corporate reputation. Besides stock returns, precise estimates of time-varying volatility and correlation are of paramount importance to understanding the risk of portfolio investments. Specifically, studying the volatility spillover effects among financial assets has significant implications to investors and policymakers. Surprisingly, the current literature on green investments lacks an in-depth analysis involving volatility. Furthermore, few studies investigate the volatility of SR stocks (Hoti et al., 2007; Schaeffer et al., 2012; Sariannidis et al., 2013; Sadorsky, 2014; Mensi et al., 2017), and their focus is on developed markets only.

The risk transmission relationship between green stocks and other financial assets remains unclear in large emerging markets such as India where capital flow to green sectors is expected to reach US$ 686 billion cumulatively by 2033[1]. Since the inauguration of the 'United Nations Framework Convention on Climate Change (UNFCCC) Paris Agreement' in 2016, green

[1]https://shaktifoundation.in/wp-content/uploads/2019/08/CatalysingPrivateCapitalforGreenInvestmentsinIndia.pdf. Several factors have contributed to the tremendous growth of investments in the Indian renewable energy sector, including "the removal of tariff caps, consistent regulatory policies, and rising renewable energy targets". (https://www.financialexpress.com/industry/indias-green-energy-sector-may-get-bag-full-of-investments-in-next-3-years-renewables-foreign-investors/2105409/).

investing has received considerable attention in India. The local government has set an ambitious target to increase the share of renewable fuel sources to 40% of installed power capacity by 2030 and decrease CO_2 emissions by 35% comparative to 2005 levels by the same period[2]. Accordingly, the Indian government has planned to fund additional types of eco-friendly infrastructures and green projects[3]. However, despite the tremendous growth, investment in environmentally friendly projects is still relatively new in India. This can render the stock prices of Indian green companies highly volatile and prone to risk transmission from other assets and market uncertainty, leading to important implications to investors and portfolio managers regarding asset pricing and volatility predictability. In fact, recent evidence (Cornell, 2021) suggests that the positive preference among investors for companies with ESG (environmental, social and governance) ratings, that include green companies, would lead to risk-adjusted expected returns on green stocks that are lower than in the equilibrium. Cornell (2021) argues that due to the adjustment process during the so-called transition period (because green investments represent relatively a new notion in the investment world compared to conventional stock investments) in which preferences for ESG and green stocks are changing, investors tend to engage in the so-called "washing machine" strategy. Specifically, investors first establish a significant position in "bad" green companies and later on move to "good" green companies. This leads to a drop in the discount rate used in the stock valuation and thereby to large price variations in ESG and green stock investments during the transition period[4]. Accordingly, the high risk of green stock investments in India during the transition period can adversely affect their attractiveness to investors through a reduction in their risk-adjusted returns, which can endanger portfolio allocation and risk management inferences. It is, therefore, crucial to precisely estimate the time-varying volatility of Indian green stock indexes to realize their underlying risk. Moreover, since green investments in India have recently received attention from local policymakers and eco-friendly investors, proper knowledge on how this new asset class behaves under diverse market conditions is still lacking. For instance, major events such as stock market downturns, oil price decline or natural disasters may cause a substantial impact on green assets and hence, the risk transmission linkage with other asset classes tends to have a different pattern during the periods of high uncertainty. Besides, under various states of markets, green assets might receive heterogeneous shocks from

[2] See https://www.investindia.gov.in/sector/renewable-energy

[3] The government has already invested roughly US$ 42 billion in this sector since 2014. See https://www.ibef.org/industry/renewable-energy.aspx. Such development works are mainly sponsored by banks and non-banking financial companies (NBFCs), accounting for 62% and 36% respectively.

[4] More details are given in Cornell (2021).

various macroeconomic variables such as oil prices, gold prices, etc. indicating that the volatility transmission relationship may vary and that spillover effects appear to be different. Tiwari et al. (2018), for example, show that in a bear market, Indian green indexes are sensitive to asymmetric oil price shocks, which is, however, not the case in a bull market. This justifies the significance of studying the effect of commodity prices on green stocks in India during the periods of low and high uncertainty. Given that the volatilities of oil and gold markets often experience phases of upside and downside trends, significant reactions of green assets to the changes in the levels of commodity market volatilities make these stock indexes more vulnerable to bad news/events that further contribute towards volatile and uncertain economic environment. Thus, analyzing the impact of commodity market volatility on this new asset class could provide a better understanding of possible investment risks which might help the market participants to forecast the risk linked to green stocks more precisely. Such analyses are also important for determining the timing of investment.

Against this backdrop, this paper examines the predictability of the volatility of Indian green stock index based on the information contents of three commodity market implied volatility indexes (commodity VIXs)[5] covering crude oil, gold, and silver. To this end, we apply a GARCH-based quantile regression model, which allows for differentiating across low, middle, and high quantiles of the volatility of the Indian green stock index.

Our current paper is related to a field of research highlighting the importance of strategic commodities such as crude oil and gold to the risk of SR stocks (e.g., Sadorsky, 2014). Furthermore, Mensi et al. (2017) show that volatility significantly transmits from oil and gold markets to sustainability indexes and provide evidence on the possibility to predict the risk of SR portfolios by utilizing the information contents of commodity prices[6]. However, our current paper is different from the above cited articles given that we do not consider the effect of

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[5] It is noteworthy that India is one of the leading commodity importers in the world. In 2018, India ranks the 3rd, 4th and 2nd as an importer of oil, gold and silver respectively. Given that the Indian economy is booming, the government continues importing these important commodities on a large scale and consequently, energy and metal sectors exert significant impacts on its national economy.

[6] During the post 2008 financial crisis periods, some studies show that gold is a key portfolio component for diversifying the underlying risk of stock markets (Beckmann et al., 2015). In addition, oil and silver have also been included in the portfolio as hedging tools (Sadorsky, 2012; Bouri, 2015; Mensi et al., 2015; Tiwari et al., 2018; Noor and Dutta, 2017). As a result, the correlations between commodity and stock markets have increased substantially (Mensi et al., 2017; Junttila et al., 2018).

conventional prices of oil and metal commodities but rather focus on the effect of commodity VIX indexes on stock returns of green firms. Furthermore, we examine this in an understudied large emerging economy such as India. In that sense, our current paper adds to a growing body of literature arguing that commodity VIX indexes contain more valuable information than traditional commodity prices because VIX indexes are forward looking measures of risk (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, Bouri et al., 2020).

Our main results indicate that risk significantly transmits from crude oil, gold and silver markets to Indian green equity indexes and its transmission is stronger during bearish periods than during bullish periods. Hence, Indian green stock indexes are more likely to receive volatility from crude oil and precious metal markets during periods of high uncertainty.

The next section reviews related studies. Section 3 outlines the materials and methods. Section 4 presents and discusses the empirical results. Section 5 concludes.

2. Related literature and hypothesis development

In this section, we review the academic literature dealing with the volatility dynamics of SR investing, especially green investing, and develop the research hypotheses.

As mentioned earlier, the related academic literature on the volatility of SR investments is scarce. We begin with Hoti et al. (2005) who employ symmetric and asymmetric GARCH processes for modeling the time-varying volatility of Dow Jones Sustainability Indexes (DJSI). They document the presence of volatility clustering in these markets and report that the asymmetric parameter is positive, revealing the existence of leverage effects in these sustainability indexes. Another study by Hoti et al. (2007) provides robust evidence of volatility clustering and leverage effect in Dow Jones Sustainability Indexes and the Ethibel Sustainability Index using asymmetric GARCH models. Schaeffer et al. (2012) examine the market value of selected energy firms that participate in the Dow Jones Sustainability Index. They show a time-varying volatility pattern for the stock returns of such firms and argue that the adhesion of these companies to the DJSI does not make any change in the volatility behavior. Using a GARCH framework, Sariannidis et al. (2013) find that the financial performance of SR companies declines with the increase in the global CO_2 emission index.

Another strand of literature explores the volatility transmission relationship between commodity markets and Dow Jones Sustainability Indexes. Sadorsky (2014) employs a DCC-GARCH model to estimate the volatility spillover effects between oil/gold and the DJSI and shows that, like the conventional firms, the risk of SR firms can be hedged by holding assets in oil, gold and DJSI markets. Mensi et al. (2017) consider the application of the multivariate DECO-FIAPARCH model to measure the time-varying correlations among oil, gold and Dow Jones sustainability world indexes. They document that these indexes are intercorrelated and highlight that the 2008 global financial crisis has intensified the correlation. Recently, Dutta, Jana et al. (2020) examine if socially responsible investments react to energy market shocks, while using two recently introduced sustainability indexes: MSCI global environment index and MSCI global green building index within a two-state Markov regime switching approach. They find that those indexes do not react to the variations in global oil prices but are sensitive to oil volatility shocks.

In this paper, we build on those previous studies and extend the above-mentioned second strand of literature by examining the risk spillover from strategic commodity markets to Indian green stock indexes. We do this using a GARCH-based quantile regression model capable of uncovering the impact of the commodity implied volatility indexes on the lower, middle, and upper quantiles of the volatility of Indian green stock indexes.

Our analysis is important for policymakers to comprehend the impact of strategic commodities on green investments and develop appropriate strategies for promoting sustainable businesses. For example, when the oil market experiences a downturn, the incentives for environmentally friendly investors will decrease, and hence, there could be a drop in the prices of green assets. In contrast, when oil prices go up, incentives will be growing, which leads the equity prices of green firms to increase. Dutta, Jana et al. (2020) find a similar positive linkage between oil price changes and stock prices of green stocks. Moreover, since WTI price and OVX are inversely linked (Dutta, 2019), an increase in the level of OVX could exert a negative impact on green stocks. This suggests that increased crude oil volatility can lead to an upsurge in the volatility levels of green assets[7].

Regarding gold, this popular precious metal has long been advocated as a tool to hedge inflation risk. Ahmad et al. (2018), for example, argue that inflation erodes the real value of investments and that inflationary environments produce an extraordinary opportunity for the rational

[7] Another strand of literature associates food prices to energy prices (Bahel et al., 2013).

investor to use gold as an effective hedging instrument. In other words, gold is often viewed as an alternative asset to store value. Besides, gold has significant effects on the Indian economy because of its heavy demand in the jewelry export market, which is one of the fastest growing industries in the country and a leading foreign exchange earner.

In parallel, silver represents another precious metal which is also popular among the mass people in India as a jewelry product or an investment option. In India, silver is seen as a symbol of virtues of fortune and considered as a close substitute to gold. Due to silver's miniature substitutability and high similarities with gold, both precious metals pursue arbitrage and low risk spread trading properties (Pradhan et al., 2020) that are heavily used in green businesses. For example, the consumption of silver in clean energy industries has increased significantly as silver is used in photovoltaic process for the purpose of generating solar energy. Dutta (2019) argues that an upturn in silver market uncertainty could make the solar energy sector more volatile.

Based on the above-explained transmission channels, we formulate our first hypothesis as follows:

H_1: Commodity market volatility indexes have a positive impact on the volatility of green companies in India.

Therefore, our analysis explores whether an upsurge in the levels of crude oil/metal market volatility leads to a significant growth in the stock price volatility of green firms. Moreover, the application of quantile regression model allows us to examine if the transmission of risk from crude oil, gold and silver markets to Indian green equity indexes is different under diverse market conditions. This leads to the formulation of our second hypothesis:

H_2: The volatility spillovers from crude oil, gold and silver markets to Indian green equity indexes is stronger during the bearish periods compared to bullish periods.

These investigations offer important implications to investors and policymakers as this strand of research is crucial for financial planning and mitigating risk.

3. Materials and methods

3.1. Data

In this study, we use the S&P BSE GREENEX and S&P BSE CARBONEX indexes to represent the stock prices of green companies in India. The S&P BSE GREENEX tracks the performance of the top 25 green companies in terms of greenhouse gas (GHG) emissions, market cap and liquidity. Specifically, green stocks are defined as shares of a company engaging in an environmentally friendly industry and /or pursuing a product or service that is beneficial for the environment such as sustainable energy, energy efficiency, recycling and waste management, or water management. Therefore, green companies make the best precautions in preventing any direct damage to the environment in its day-to-day operations. The S&P BSE CARBONEX, on the other hand, tracks the performance of the firms within the S&P BSE 100 index based on their commitment to moderating climate risks. It was designed to address "market demand for a sophisticated approach to portfolio management incorporating climate change risk and opportunity"[8]. For comparison purpose, the S&P BSE 100 index is also considered in our empirical investigation. All these indexes are extracted from the official website of Bombay Stock Exchange (BSE). All indexes are expressed in rupees, but we convert them to US dollars using the exchange rates which are available in DataStream. Data on the implied volatility index of crude oil (OVX), gold (GVZ) and silver (VXSLV) are collected from the website of Chicago Board of Options Exchange (CBOE).

Our sample period is from 30th November, 2012 to 30th April, 2020, yielding 1,575 daily observations. Its beginning is dictated by the availability of the S&P BSE CARBONEX index. Interestingly, the sample period covers the COVID-19 pandemic, which is important given that a significant price fall and a market stress are observed in global stock market indices during the pandemic period. Fig. 1 shows that each of the indexes under study experienced a downturn. It is also evident from Fig. 2 that the volatility of Indian stock indexes increased substantially following the COVID-19 outbreak around early 2020. Moreover, Fig. 3, which depicts the commodity market implied volatility indexes, also demonstrates that during this pandemic period, the OVX in particular reached the highest level since its inception in 2007.

Table 1 displays the summary statistics for the logarithmic return series of the three Indian stock indexes under study and the fist difference of the three commodity VIXs. Of the three equity indexes, the S&P BSE GREENNEX appear to be less volatile. In addition, among the volatility indexes, OVX has a higher standard deviation than the metal sector volatility series. We further note that none of these indexes satisfies the normality assumption. Finally, the

[8] See https://www.spglobal.com/spdji/en/indices/equity/sp-bse-carbonex/#overview

augmented Dickey Fuller (ADF) and Philips Perron (PP) tests confirm the stationarity condition for the all the series. Results from the Lagrange multiplier test for autoregressive conditional heteroskedasticity (ARCH) indicate evidence of ARCH effect up to 10 lags in all series, which justifies the application of GARCH-based models.

3.2. Empirical method

We employ a GARCH-based quantile regression model to examine the risk spillovers from oil and metal sectors to Indian stock indexes. This approach consists of two phases. In the first phase, we apply univariate GARCH-based model to Indian stock indexes and extract the GARCH variance series. In the second phase, we regress these GARCH variance series on the commodity market implied volatility indexes using the quantile regression (henceforth, QR) process. A similar methodology has also been applied by Bouri et al. (2019) when studying the effect of commodity market uncertainty on the BRIC sovereign risk.

Based on different model selection criteria[9], our empirical part adopts the exponential GARCH (EGARCH) model proposed by Nelson (1991). Notably, the EGARCH process has the power to model the volatility of stock index returns while taking into account stylized facts of Indian green stock indexes such as volatility clustering, asymmetry, and fat tails (given that we estimate that the GARCH model while assuming a Student-t distribution for the residulas). This is important as we have found evidence of heteroskedasticity, as shown in the results of the ARCH effect (Table 1), which can be addressed via GARCH-based modeling. Furthermore, the choice of the asymmetry EGACH model stems from two elements: (1) the evidence from previous studies that the volatility of stock returns is higher during periods when returns are negative than during periods when returns are positive, (2) the fact that the EGARCH model ensures a positive variance given the volatility specification in terms of the logarithmic transformation (see the left side of the second equation in the below model (1)). In this paper, we employ the AR(1)-EGARCH model as follows:

$$\begin{gathered} r_{i,t} = \mu_{i,t} + \phi r_{i,t-1} + \varepsilon_{i,t} \\ log\ h_{i,t}^2 = \omega + \alpha \left| \frac{\varepsilon_{i,t-1}}{h_{i,t-1}} \right| + \gamma \frac{\varepsilon_{i,t-1}}{h_{i,t-1}} + \beta log\ h_{i,t-1}^2 \end{gathered} \tag{1}$$

[9] We choose the EGARCH model on the basis of Akaike information criterion (AIC), Bayesian information criterion (BIC) and likelihood values.

where $r_{i,t}$ is the logarithmic return on the stock index i (S&P BSE CARBONEX, S&P BSE GREENEX, or S&P BSE 100) in period *t*, which is used to estimate the mean equation of the EGARCH process; μ is the constant term, and $\varepsilon_{i,t}$ is the residuals; $h_{i,t}^2$ denotes the conditional variance of the returns of stock index i at time *t*; and α, β are the ARCH and GARCH parameters, respectively. Besides, γ captures the asymmetric term that negative shocks have a larger impact on conditional volatility than positive shocks of the same magnitude. Notably, the EGARCH process ensures that the logarithm of variance will be positive, irrespective of the sign of the coefficients on the right side of Eq. (1).

Next, we apply the QR process to the conditional variance (CV) retrieved from the EGARCH model. The QR process, proposed by Koenkar and Bassett (1978), has received considerable attention in prior literature due to the fact that unlike the ordinary least squares regression, it estimates the rates of change in all parts of the distribution of the dependent variable (Dah and Fakih, 2016; Reboredo and Uddin, 2016; Xiao et al., 2018; Das and Dutta, 2019; Dawar et al., 2021). Since one of our purposes is to examine the risk transmission from commodity markets to green stock indexes under diverse market conditions, we employ the QR model. We frame this process as follows:

$$Q_{CV_t}(\tau|CV_{t-1}, \Delta X_{t-1}) = \varphi(\tau) + \lambda(\tau)CV_{t-1} + \theta(\tau)\Delta X_{t-1} \tag{2}$$

Following Koenkar and Bassett (1978), $Q_{CV_t}(\tau|CV_{t-1}, \Delta X_{t-1})$ signifies the τ conditional quantile of CV_t, the conditional volatility series (for each of the three Indian stock indexes under study, S&P BSE CARBONEX, S&P BSE GREENEX, or S&P BSE 100) at time *t*. In addition, $\varphi(\tau)$ accounts for the unobserved effect in the quantile model, and ΔX_t refers to first-order difference of a specific commodity VIX index at time *t*.

For a given τ, we estimate Eq. (2) by minimizing the weighted absolute deviation as:

$$arg \min_{\varphi(\tau),\lambda(\tau)+\theta(\tau)} \sum_{t=1}^{T} \rho_\tau \left(CV_t - \varphi(\tau) - \lambda(\tau)CV_{t-1} - \theta(\tau)\Delta X_{t-1}\right) \tag{3}$$

where, $\rho_\tau(u) = u(\tau - I(u < 0))$ with $\mathrm{I}(\cdot)$ being the indication function.

A positive and statistically significant $\theta(\tau)$ indicates that an increase in commodity volatility index leads to an upturn in the conditional volatility of the Indian (green) stock index. However, if $\theta(\tau)$ is negative, then there is an inverse relationship between the indexes.

We consider seven quantiles, τ = (0.05, 0.10, 0.30, 0.50, 0.70, 0.90, 0.95). Note that lower quantiles (i.e. 0.05, 0.10, 0.30) reflect low volatility states in the Indian stock index, whereas higher quantiles (i.e. 0.70, 0.90, 0.95) indicate high volatility states in the Indian stock index.

4. Empirical results

4.1. Estimates of EGARCH model

Based on the model selection criteria, we choose an AR(1)-EGARCH(1,1) process for modeling the volatility of Indian stock indexes. These results of the variance equation (Table 2) reveal that the ARCH and GARCH parameters are significant at 1% level for all the series considered. The asymmetric parameter (γ) is negative and significant, indicating evidence of asymmetric effects of the so-called 'bad' or 'good' news on the Indian stock indexes. The results of the diagnostic ARCH test show that all the residual series are free of heteroscedasticity, suggesting a good-fitting model.

4.2. Impact of commodity VIX indexes

The estimated results of the quantile regressions are reported in Tables 3-8 (the estimates of the impact of commodity VIX on stock market volatility are reported in Tables 3-5, whereas the results of symmetric quantiles test for the changes in different commodity VIX indexes are exhibited in Tables 6-8). In Tables 3-5, the results are presented in three panels: Panel A shows the impact of OVX; Panel B shows the effect of GVZ; Panel C shows the impact of VXSLV.

It is evident from Table 3 that the three commodity volatility indexes (OVX, GVZ, and VXSLV) have a significant impact on the conditional volatility of the CARBONEX index. Notably, we do not find any impact of these volatility indexes at the lower quantiles of the returns of Indian stock indexes. In fact, the impacts are mainly significant when the stock index is highly volatile (see the estimates at the upper quantiles of 0.70, 0.90 and 0.95). Hence, we assume that risk significantly transmits from energy and metal markets to the Indian green stock firms during the bearish stock market periods when volatility is high. Moreover, the volatility of these stock indexes is influenced by their own lagged volatility and the coefficients are positive and significant across all the quantiles. Besides, the magnitude of these influences tends to increase as we move towards the higher quantiles. Notably, the influence of the lagged volatility is higher compared to the commodity VIX indexes.

Moving to the estimates of Table 4, we find similar impacts of commodity market VIX indexes on the conditional volatility of the GREENEX index. The impact is insignificant at lower quantiles, implying that there exists no significant impact when the Indian stock market index is less volatile. Therefore, the volatility commodity markets tend to affect Indian green firms when the stock prices of these green companies experience a downturn.

Next, Table 5 reveals that the volatility S&P BSE 100 index also reacts to the volatilities of energy and precious metal markets. The effect of gold and silver markets is higher relative to that of the crude oil market. For example, at the upper quantile of 0.90, the effects of oil, silver and gold amount to 0.0214, 0.0458 and 0.1159, respectively. One interesting finding is that while precious metal markets impact the volatility of S&P BSE 100 index at higher quantiles only, the effects of OVX are significant at both lower and higher quantiles. This result is not surprising given that this conventional stock index includes various firms (e.g., oil and gas companies, metal sector firms, and utilities firms) which could be sensitive to oil volatility shocks, irrespective of market conditions. Thus, crude oil volatility has certain predictive power for the variance of traditional stock index returns during both bearish and bullish phases. This latter outcome differs from what we have reported for green stock indexes. For green firms, we do not find any significant effect of crude oil volatility when the stock market experiences a good run (see the estimates at the lower quantiles of 0.05, 0.10 and 0.30). One would expect that both CARBONEX and GREENEX indexes comprise environmentally friendly firms which are not reliant on crude oil and related products. As these companies are committed to mitigating climate risks, they rely on renewable energies while providing products and services to the economy and society. Hence, the stock prices of these green firms are quite immune to oil volatility shocks during the moderate and low volatile stock market conditions. However, in case of the high volatility regime, the impact of crude oil VIX is significant for green stock indexes. This is because India is heavily dependent on imported oil and, therefore, its economy is largely influenced by the variations in global energy prices (Noor and Dutta, 2017). This result indicates that when the Indian stock markets become extremely volatile, firms operating in non-energy sectors (e.g., financial institutions, banks, green firms, agriculture and metal industries) are also likely to receive volatility from international oil markets due to the effect of contagious shocks (Arouri et al., 2011; Tiwari et al., 2018).

Notably, precious metal volatility impacts the three stock market indexes only when the stock markets are highly volatile. This result could be attributed to the fact that when the economy is doing well and the economic activities are stable, investor portfolio includes mainly stocks and bonds, whereas market participants shift towards precious metals during the bearish conditions as gold and silver offer hedging facility throughout the periods of high uncertainty (Hillier et al., 2006; Beckmann et al., 2015; Chkili, 2016). Such a shifting towards metal markets increases the correlations between stock and gold/silver markets.

In sum, during the periods of high stock market uncertainty, both conventional and green stock indexes are recipients of volatility from strategic commodity markets including oil, gold and silver. The findings, in general, indicate that green firms behave more or less similarly like conventional firms, although they respond differently to oil volatility shocks. Figures 4-6, which demonstrate the impact of commodity VIX indexes on different quantiles of the conditional volatility of Indian stock markets, show a similar result. Our main findings add to previous studies showing the importance of crude oil volatility to emerging stock market indexes (Maghyereh et al., 2016) and those indicating that the volatility indexes of crude oil, gold, and silver can act as an effective hedge against the downside risk of global clean energy indexes (Dutta, Bouri et al., 2020). They generally concord with mounting evidence that the commodity VIX indexes contain a valuable predictive power that stems from their forward-looking measure of future market volatility (Maghyereh et al., 2016; Raza et al., 2016; Dutta et al. 2017; Ahmad et al., 2018; Dutta, Bouri et al., 2020).

4.3. Results of symmetric quantiles tests

This section conducts the symmetric quantiles test for the changes in OVX, GVZ and VXSLV. Our objective is to investigate whether the upper quantiles (0.95, 0.90 and 0.70) have the same slopes of the lower quantiles (0.30, 0.10 and 0.05). In particular, we consider the pairs (0.05, 0.95), (0.10, 0.90) and (0.30, 0.70). The estimated results are reported in Tables 6-8, where each table consists of three panels: Panel A displays the results for GREENEX index; Panel B exhibits the findings for CARBONEX index; Panel C shows the outcomes for BSE 100 index.

The results reveal that the slope parameters do vary for upper and lower quantiles. For both gold and silver volatility indexes, all the tests appear to be significant (see the estimates shown in Tables 7 and 8), while for the crude oil volatility index seven out of nine tests reject the null hypothesis of symmetric quantiles (see the estimates given in Table 6). We can thus conclude that the effects of commodity market volatility shocks tend to vary for bullish and bearish periods. These results are consistent with those exhibited in Tables 3-5. They are in line with the academic literature showing asymmetric effects of gold and oil volatilities on the stock indices of emerging markets (Raza et al., 2016), and with recent evidence on the asymmetry in emerging markets during the COVID-19 outbreak (e.g., Shahzad et al., 2021).

4.4. Implications for sustainable development

The findings of our empirical analyses matter to investors participating in Indian green business sectors. As the stock indexes used in this study consist of firms which are committed to moderating climate risks by offering environmentally friendly products to the society, understanding the volatility dynamics of these firms is essential for ethical investors who aim at greening their portfolios by holding assets in those industries that are focused on sustainable practices[10]. Furthermore, given that investment in environmentally friendly projects is still relatively new in India, although it has recently received attention from local policymakers and eco-friendly investors, the stock prices of Indian green companies could be highly volatile and prone to risk transmission from other assets and market uncertainty. To this end, the outcomes of our methodological analyses have important implications regarding asset pricing and volatility predictability. Furthermore, thus they can be useful for quantifying the potential risk arising from other markets, such as energy and metal commodities, on the volatility of Indian green stock indexes.

Moreover, investing in green business has ecological and social impacts that can assure a certain degree of sustainability. It is, therefore, crucial for socially responsible investors to have proper knowledge on the significant risk transmission to green stock indexes to make proper inferences regarding risk management and hedging strategies. In fact, the findings of this paper have valuable information for those investors who intend to identify every possible threat associated with green stocks. In particular, our investigation offers stylized facts about green investments (part of socially responsible investments) which can be considered by investors when they swap non-green and dirty assets for green stocks to maintain a low-carbon

[10] Tables A1 and A2 show the impacts of commodity market risk on the volatility of Indian green stocks during the COVID-19 pandemic period (2 January, 2020 to 30 April, 2020). We report several interesting findings. For example, unlike the full period analyses, we find that during the pandemic period OVX impacts stock indexes at both lower and upper quantiles, while silver volatility index does not affect the volatility of green stocks. Gold VIX, on the other hand, exerts an impact during the pandemic period that is quite similar to that shown during the full period sample, confirming that its effect is significant mainly at upper quantiles. These findings could be crucial for investors looking for safe haven assets during the stress periods.

portfolio[11]. Given that eco-friendly investors not only focus on the environmental performances of a firm but consider its financial performances, the findings of this research are useful for such stakeholders.

5. Conclusions

In this paper, we employ a GARCH-based quantile regression model on daily data and find evidence that risk significantly transmits from crude oil, gold and silver markets to Indian green equity indexes. Notably, the impact of commodity market VIXs is stronger during the bearish periods compared to bullish periods, suggesting that the association between these markets tends to intensify as we move towards the upper quantiles. Hence, Indian green stock indexes are more likely to receive volatility from crude oil and precious metals during the periods of high uncertainty. These findings support our formulated hypotheses.

Our analyses offer important implications to investors and policymakers for financial planning and mitigating risk. This can be considered in light of evidence that crude oil and precious metals are often seen as effective hedges against the adverse movements in stock market returns. Sadorsky (2014) finds that these popular commodities appear as potential assets to hedge the downside risk of green equities. Since commodities like precious metals and crude oil have shown low or even negative correlation with equities over the past years, they are, therefore, useful for hedging and portfolio diversification. The recent financialization of commodity markets offers new assets for diversifying the risk linked to investor portfolios. Regulatory changes and the development of new financial instruments linked to commodities also allow investors much easily access the commodity markets. Overall, the analysis of this study extends our limited understanding on the volatility associations between green assets and commodity markets, which is important for financial institutions in their quest to measure the intensity of the interdependences between commodities and green equities and, thereby, to manage the risk of contagion in times of market distress (Iglesias-Casal et al., 2020). Other market participants can benefit from our findings by utilizing the information content of commodity VIX indexes while predicting the risk linked to the stock prices of eco-friendly firms in India. Accordingly, investors and portfolio managers should closely follow the

[11] As Dutta et al. (2020) mention: "Portfolios consisting of such assets that emit less carbon are simply less susceptible to the consequences of climate change."

volatilities of crude oil and precious metal commodities to realize the potential threats, which can help them to understand the directions of equity market risk and thereby to make precise investment and risk management decisions. Notably, this evidence is only relevant during the periods of high volatility in the Indian green stock market indexes during which the impact of commodity volatility indexes is significant, suggesting that Indian investors must have a close look at the state of stock market volatility to make more robust predictability of their investment volatility for the sake of better managing the risk of their stock portfolio. Furthermore, policymakers can benefit from our analyses while formulating appropriate policies to manage potential and harmful risk transmission during the periods of high uncertainty in order to avoid the contagious shocks stemming from energy and metal markets. For example, oil and gold futures markets can be developed to stabilize the market risk.

Our study is not without limitations. Though it captures the impacts of commodity VIX indexes on the various quantiles of the variance of green stock indexes, it possible that lower, middle, or upper quantiles of the commodity VIX index have heterogenous impacts on the quantiles of the variances of green stock indexes. Therefore, future studies can address this using a quantile-on-quantile regression model. In this regard, the information on range-based stock market volatility can be utilized. Another extension can involve the use of green firm stock level data while differentiating between the effects of positive and negative volatility shocks.

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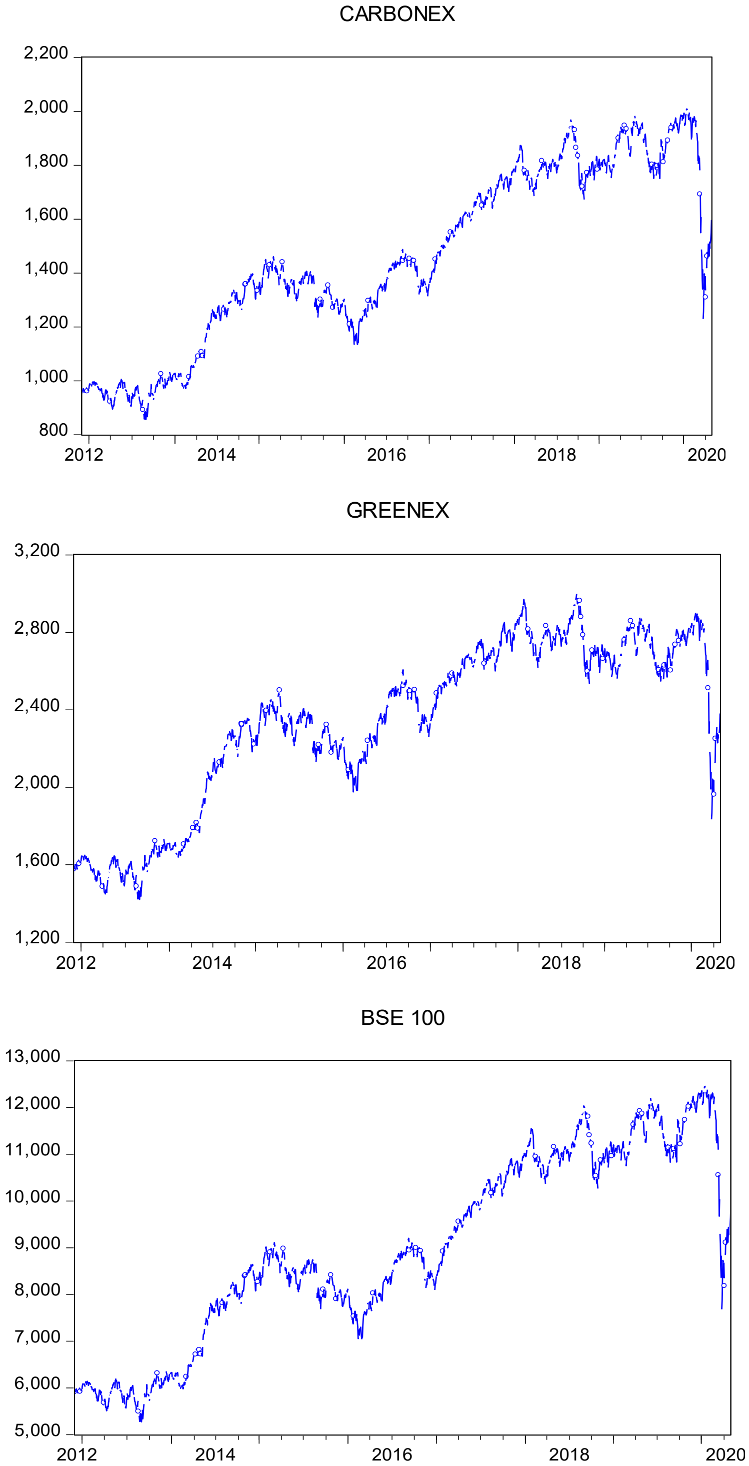


Fig. 1: Time series plot of Indian stock indexes

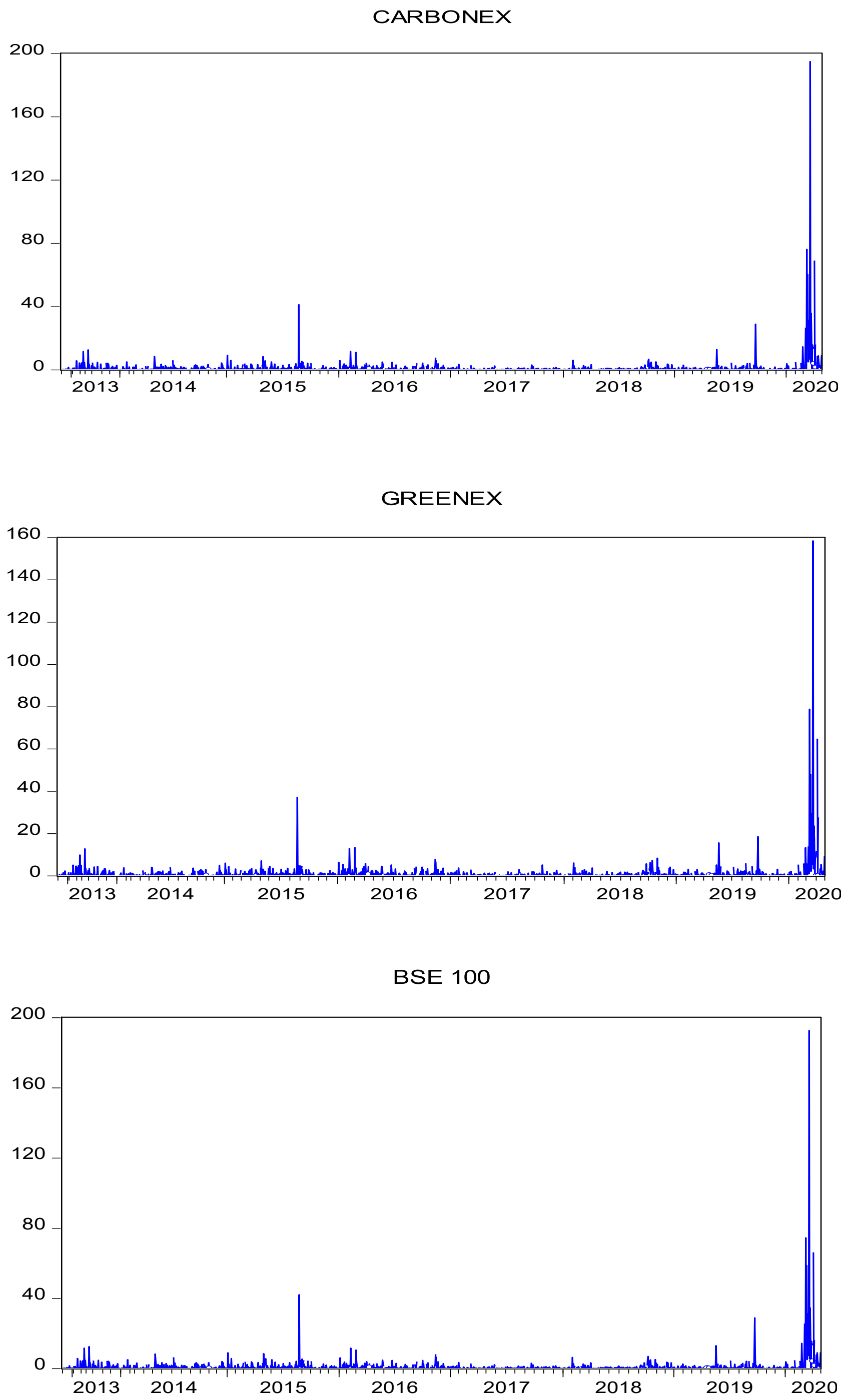


Fig. 2: Time-varying volatility of Indian stock indexes

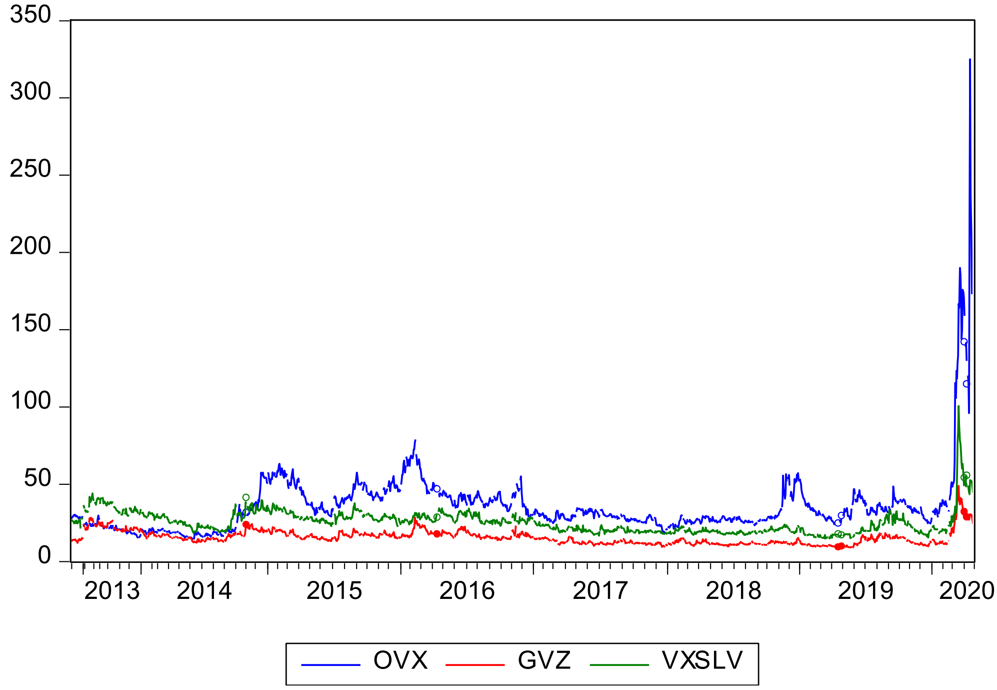


Fig. 3: Time series plot of OVX, GVZ and VXSLV

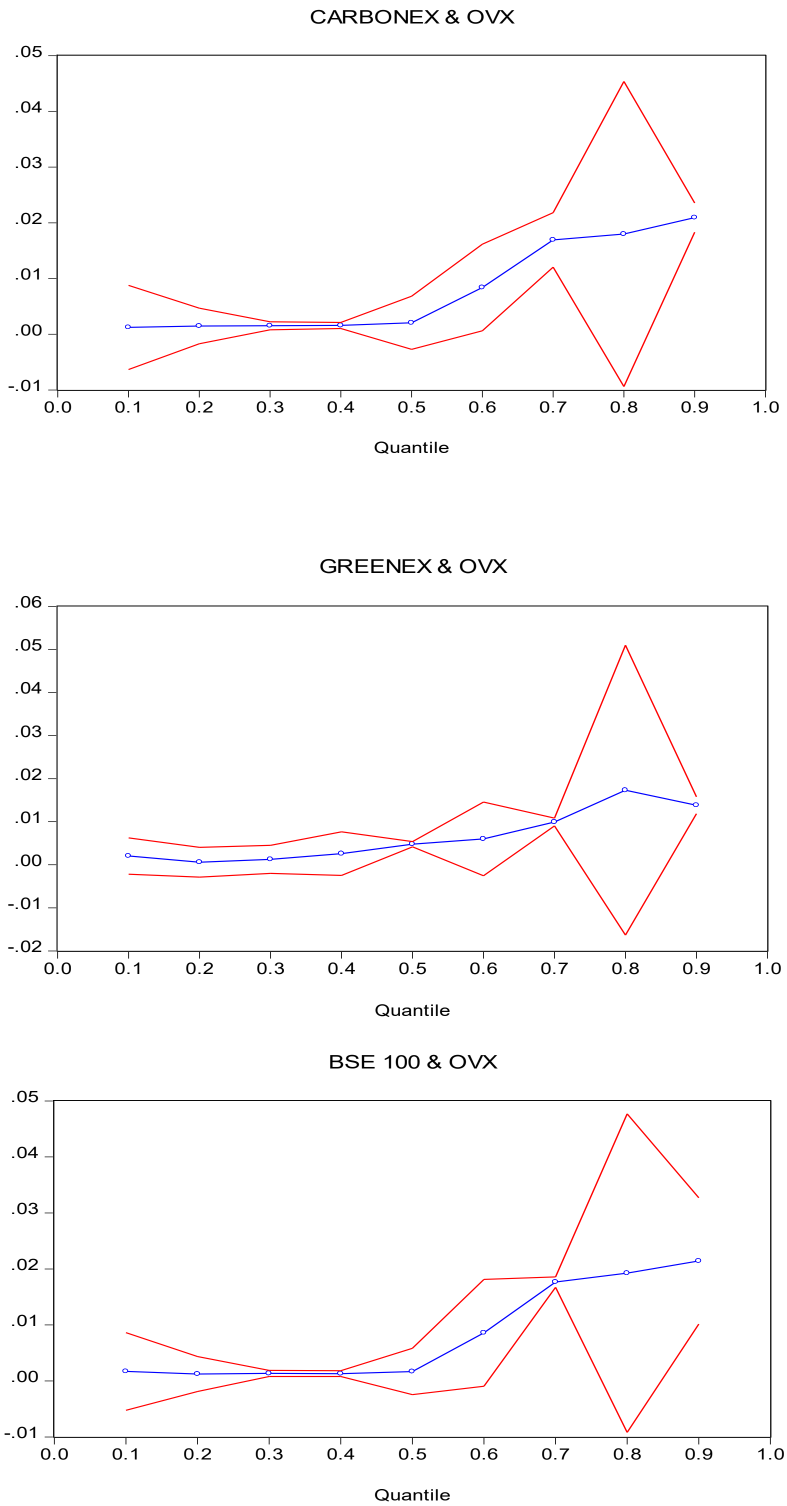


Fig. 4: Impact of OVX on different stock indexes

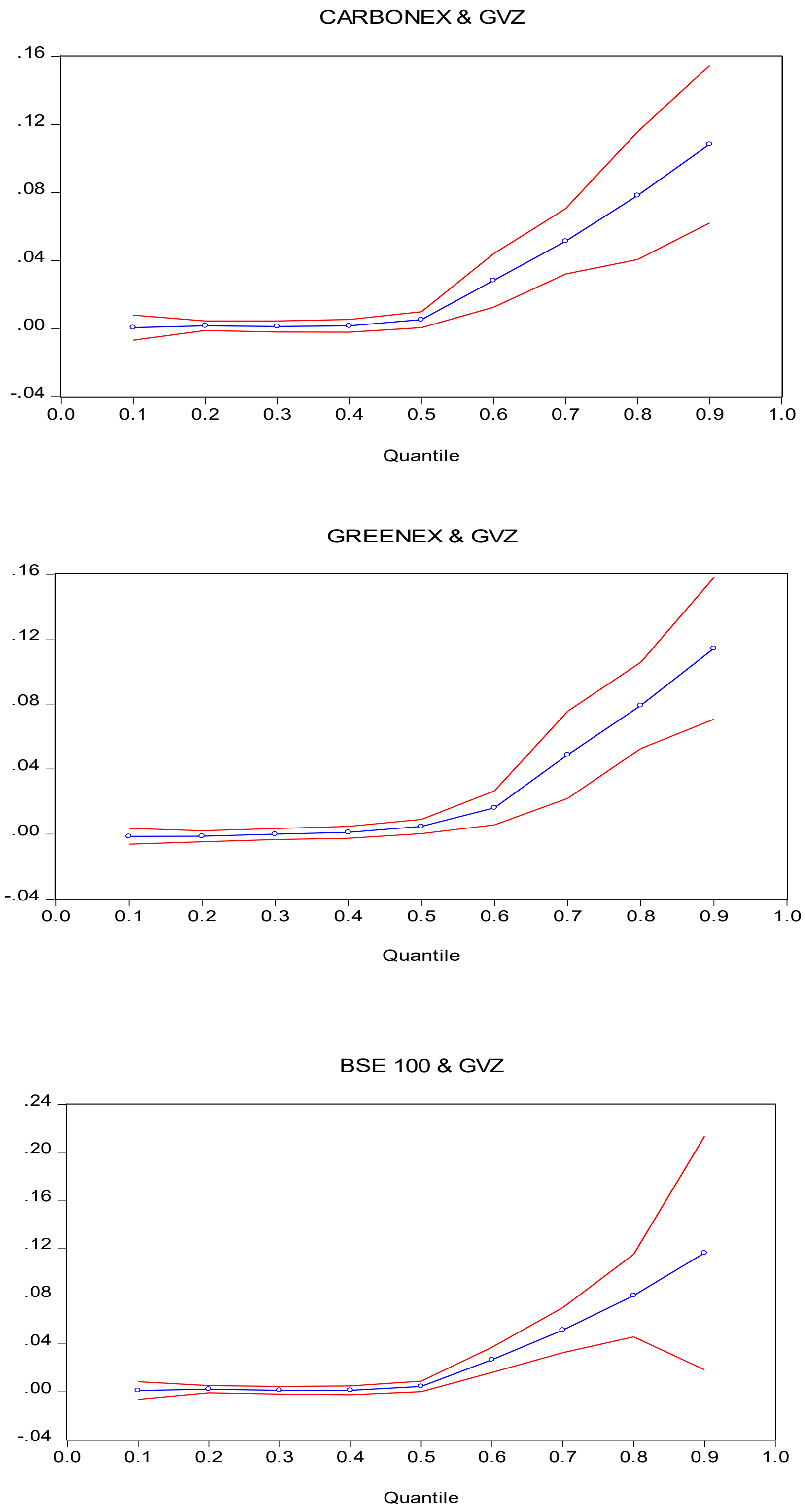
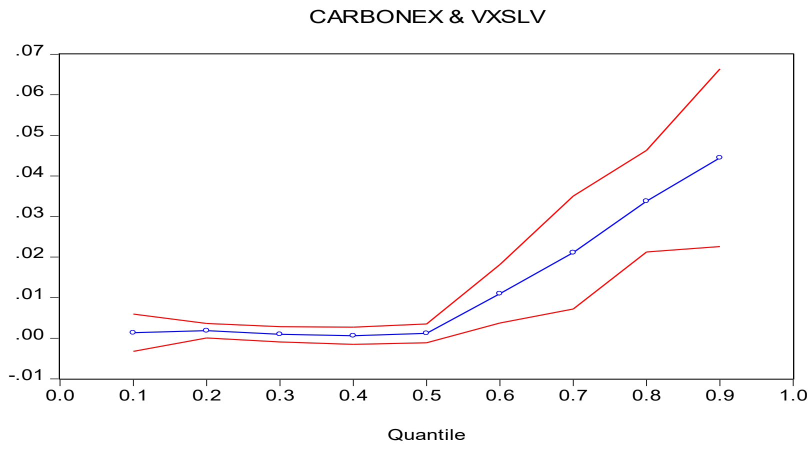
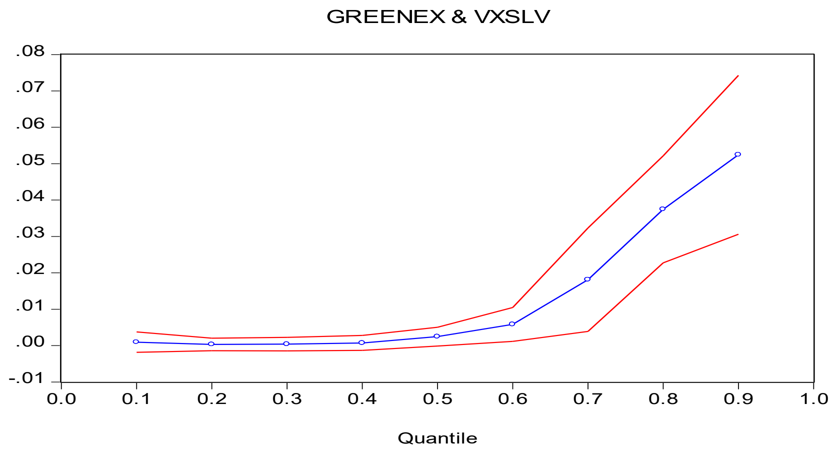


Fig. 5: Impact of GVZ on different stock indexes





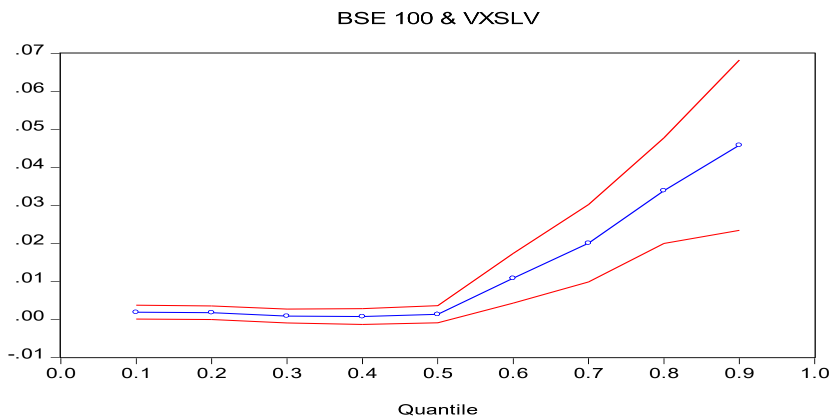


Fig. 6: Impact of VXSLV on different stock indexes

Table 1: Summary statistics

Index →	CARBONEX	GREENEX	S&P BSE 100	ΔOVX	ΔGVZ	ΔVXSLV
Mean	0.0299	0.0273	0.0308	0.0075	-0.0117	-0.0106
Std. dev.	1.0947	1.0742	1.0939	6.0808	0.9940	1.7633
Skewness	-1.65	-1.35	-1.64	5.25	0.16	2.41
Kurtosis	28.53	22.55	27.87	244.05	16.30	35.87
Jarque-Bera	**43469.97**	**25563.86**	**41296.69**	**116093.5**	**11610.97**	**72409.68**
ADF	**-13.01**	**-39.57**	**-13.09**	**-7.37**	**-42.70**	**-39.33**
PP	**-40.25**	**-39.73**	**-40.24**	**-31.58**	**-42.90**	**-40.49**
ARCH (10)	**428.69**	**383.23**	**422.74**	**657.11**	**424.68**	**577.87**

Notes: The sample period is 30th November 2012 to 30th April, 2020. ADF is the augmented Dicky Fuller test. PP is Philips Perron test. ARCH (10) is the Lagrange multiplier test for ARCH up to 10 lags. Bold indicates statistical significance at the 1% level.

Table 2: Estimates of EGARCH models

Parameter ↓	CARBONEX	GREENEX	S&P BSE 100
ω	**0.1383**	**0.1423**	**0.1456**
α	**0.1657**	**0.1740**	**0.1751**
β	**0.9493**	**0.9469**	**0.9482**
γ	**-0.1703**	**-0.1496**	**-0.1720**
ARCH (10)	1.73	2.43	1.75

Notes: This tables presents the estimate results from the variance equation of the AR-EGACH model. The last row indicates that all the residual series are free of heteroscedasticity, suggesting a good-fitting model. Bold indicates statistical significance at the 1% level.

Table 3: Risk Spillover from commodity markets to CARBONEX index

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: OVX							
Constant	**0.065**	**0.067**	**0.050**	**0.056**	0.094	**0.063**	0.002
CV_{t-1}	**0.733**	**0.751**	**0.813**	**0.816**	**0.881**	**1.218**	**1.542**
ΔOVX_{t-1}	0.004	0.001	0.002	0.002	**0.017**	**0.021**	**0.034**
Panel B: GVZ							
Constant	**0.066**	**0.068**	**0.049**	**0.055**	**0.085**	**0.107**	0.048
CV_{t-1}	**0.729**	**0.749**	**0.814**	**0.817**	**0.893**	**1.179**	**1.484**
ΔGVZ_{t-1}	0.000	0.001	0.001	**0.005**	**0.051**	**0.108**	**0.101**
Panel C: VXSLV							
Constant	**0.066**	**0.069**	**0.049**	**0.054**	**0.091**	0.081	-0.017
CV_{t-1}	**0.730**	**0.748**	**0.814**	**0.816**	**0.884**	**1.209**	**1.563**
ΔVXSLV_{t-1}	0.001	0.001	0.001	0.001	**0.021**	**0.044**	**0.046**

Notes: This table displays the estimates of Eq. (3) for the CARBONEX index. Bold indicates statistical significance at the 5% level.

Table 4: Risk Spillover from commodity markets to GREENEX index

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: OVX							
Constant	**0.066**	**0.072**	**0.058**	**0.068**	**0.104**	**0.083**	0.016
CV_{t-1}	**0.759**	**0.769**	**0.816**	**0.822**	**0.867**	**1.186**	**1.466**
ΔOVX_{t-1}	0.004	0.002	0.001	**0.005**	**0.010**	**0.014**	**0.023**
Panel B: GVZ							
Constant	**0.068**	**0.070**	**0.059**	**0.068**	**0.092**	**0.102**	0.083
CV_{t-1}	**0.760**	**0.772**	**0.814**	**0.820**	**0.895**	**1.182**	**1.411**
ΔGVZ_{t-1}	0.000	-0.001	0.000	**0.005**	**0.049**	**0.114**	**0.125**
Panel C: VXSLV							
Constant	**0.066**	**0.070**	**0.059**	**0.067**	**0.097**	**0.113**	0.011
CV_{t-1}	**0.761**	**0.773**	**0.814**	**0.821**	**0.880**	**1.146**	**1.481**
$\Delta \text{VXSLV}_{t-1}$	0.003	0.001	0.000	0.002	**0.018**	**0.052**	**0.049**

Notes: This table displays the estimates of Eq. (3) for the GREENEX index. Bold indicates statistical significance at the 5% level.

Table 5: Risk Spillover from commodity markets to S&P BSE 100 index

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: OVX							
Constant	**0.067**	**0.067**	**0.051**	**0.056**	**0.095**	0.061	0.004
CV_{t-1}	**0.730**	**0.749**	**0.810**	**0.812**	**0.875**	**1.231**	**1.554**
$\Delta\mathrm{OVX}_{t-1}$	**0.003**	0.002	**0.001**	0.002	**0.018**	**0.021**	0.034
Panel B: GVZ							
Constant	**0.068**	**0.068**	**0.050**	**0.056**	**0.086**	0.111	0.061
CV_{t-1}	**0.727**	**0.748**	**0.811**	**0.814**	**0.889**	**1.187**	**1.476**
$\Delta\mathrm{GVZ}_{t-1}$	0.001	0.001	0.001	**0.005**	**0.051**	**0.116**	**0.104**
Panel C: VXSLV							
Constant	**0.068**	**0.069**	**0.049**	**0.055**	**0.090**	0.088	-0.002
CV_{t-1}	**0.727**	**0.746**	**0.812**	**0.813**	**0.881**	**1.210**	**1.586**
$\Delta\mathrm{VXSLV}_{t-1}$	0.001	0.002	0.001	**0.001**	**0.020**	**0.046**	**0.057**

Notes: This table displays the estimates of Eq. (3) for the S&P BSE 100 index. Bold indicates statistical significance at the 5% level.

Table 6: Symmetric quantiles test for the changes in OVX

Quantiles ↓	Restricted value	Standard error	*p*-value	Decision
Panel A: CARBONEX				
0.05, 0.95	0.0337	0.0181	0.06	Significant at 10% level
0.10, 0.90	0.0180	0.0050	0.00	Significant at 1% level
0.30, 0.70	0.0143	0.0053	0.00	Significant at 1% level
Panel B: GREENEX				
0.05, 0.95	0.0175	0.0070	0.02	Significant at 5% level
0.10, 0.90	0.0063	0.0023	0.00	Significant at 1% level
0.30, 0.70	0.0016	0.0015	0.29	Insignificant
Panel C: BSE 100				
0.05, 0.95	0.0340	0.0229	0.88	Insignificant
0.10, 0.90	0.0197	0.0070	0.00	Significant at 1% level
0.30, 0.70	0.0156	0.0038	0.00	Significant at 1% level

Table 7: Symmetric quantiles test for the changes in GVZ

Quantiles ↓	Restricted value	Standard error	*p*-value	Decision
Panel A: CARBONEX				
0.05, 0.95	0.0902	0.0456	0.04	Significant at 5% level
0.10, 0.90	0.0983	0.0232	0.00	Significant at 1% level
0.30, 0.70	0.0420	0.0080	0.00	Significant at 1% level
Panel B: GREENEX				
0.05, 0.95	0.1153	0.0559	0.03	Significant at 5% level
0.10, 0.90	0.1035	0.0216	0.00	Significant at 1% level
0.30, 0.70	0.0394	0.0123	0.00	Significant at 1% level
Panel C: BSE 100				
0.05, 0.95	0.0954	0.0472	0.04	Significant at 5% level
0.10, 0.90	0.1078	0.0499	0.03	Significant at 5% level
0.30, 0.70	0.0437	0.0079	0.00	Significant at 1% level

Table 8: Symmetric quantiles test for the changes in VXSLV

Quantiles ↓	Restricted value	Standard error	*p*-value	Decision
Panel A: CARBONEX				
0.05, 0.95	0.0446	0.0119	0.00	Significant at 1% level
0.10, 0.90	0.0434	0.0109	0.00	Significant at 1% level
0.30, 0.70	0.0197	0.0064	0.00	Significant at 1% level
Panel B: GREENEX				
0.05, 0.95	0.0469	0.0238	0.04	Significant at 5% level
0.10, 0.90	0.0484	0.0108	0.00	Significant at 1% level
0.30, 0.70	0.0136	0.0065	0.03	Significant at 5% level
Panel C: BSE 100				
0.05, 0.95	0.0553	0.0138	0.00	Significant at 1% level
0.10, 0.90	0.0450	0.0109	0.00	Significant at 1% level
0.30, 0.70	0.0182	0.0044	0.00	Significant at 1% level

APPENDIX

Table A1: Risk Spillover from commodity markets to CARBONEX index during the pandemic period

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: OVX							
Constant	**0.078**	**0.084**	**0.105**	**0.075**	**0.140**	0.064	-0.098
CV_{t-1}	**0.721**	**0.732**	**0.751**	**0.805**	**0.869**	**1.217**	**1.714**
$\Delta \mathrm{OVX}_{t-1}$	**0.004**	**0.003**	**0.002**	0.004	0.014	**0.020**	**0.038**
Panel B: GVZ							
Constant	**0.078**	**0.085**	**0.105**	**0.083**	**0.086**	**0.110**	-0.004
CV_{t-1}	**0.720**	**0.729**	**0.751**	**0.819**	**0.925**	**1.209**	**1.625**
$\Delta \mathrm{GVZ}_{t-1}$	0.017	0.011	0.004	**0.042**	**0.118**	**0.273**	**0.322**
Panel C: VXSLV							
Constant	**0.081**	**0.082**	**0.104**	0.079	**0.119**	**0.160**	-0.079
CV_{t-1}	**0.720**	**0.731**	**0.750**	**0.799**	**0.901**	**1.178**	1.799
$\Delta \mathrm{VXSLV}_{t-1}$	0.005	0.008	0.008	0.003	0.049	0.132	0.082

Notes: This table displays the estimates of Eq. (3) for the CARBONEX index during the pandemic period (2 January, 2020 to 30 April, 2020). Bold indicates statistical significance at the 5% level.

Table A2: Risk Spillover from commodity markets to GREENEX index during the pandemic period

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: OVX							
Constant	**0.090**	**0.087**	**0.109**	**0.106**	**0.137**	**0.125**	-0.018
CV_{t-1}	**0.734**	**0.757**	**0.767**	**0.795**	**0.864**	**1.182**	**1.563**
ΔOVX_{t-1}	**0.006**	**0.006**	**0.005**	**0.005**	**0.009**	**0.014**	**0.026**
Panel B: GVZ							
Constant	**0.092**	**0.090**	**0.106**	**0.110**	**0.097**	**0.115**	0.043
CV_{t-1}	**0.731**	**0.751**	**0.771**	**0.795**	**0.931**	**1.144**	**1.481**
ΔGVZ_{t-1}	-0.001	-0.005	0.008	0.013	0.108	**0.241**	**0.257**
Panel C: VXSLV							
Constant	**0.092**	**0.087**	**0.103**	**0.111**	**0.125**	0.186	-0.048
CV_{t-1}	**0.731**	**0.753**	**0.772**	**0.794**	**0.903**	1.142	1.625
$\Delta \text{VXSLV}_{t-1}$	0.003	0.005	0.002	0.005	0.048	0.139	0.086

Notes: This table displays the estimates of Eq. (3) for the GREENEX index during the pandemic period (2 January, 2020 to 30 April, 2020). Bold indicates statistical significance at the 5% level.