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Impact of crude oil volatility jumps on sustainable investments: Evidence from India

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Abstract

This study examines the impact of crude oil volatility jumps on the realized volatility (RV) of green and dirty stocks in India. In doing so, we first estimate the time-varying jumps in oil market implied volatility index (OVX) and then augment the heterogeneous autoregressive (HAR) process with the information on such jumps. Our sample runs from December 2012 to April 2022, which includes 2328 data points. Comparing a range of HAR-type models, we find that crude oil volatility jumps provide additional information, which is not contained even in the OVX index itself. In particular, the HAR–RV model that considers both leverage effects and the information on volatility jumps produces superior forecasts compared with the existing approaches. The economic significance of these results is also supported by a simple value-at-risk analysis.

KEYWORDS

crude oil volatility jumps, dirty stocks, green stocks, HAR models, India, sustainable investing

JEL CLASSIFICATION

G1

1 | INTRODUCTION

Historically crude oil has been the leading source of primary energy despite its adverse environmental effects. Crude oil is also the largest traded commodity in the world. However, its dominance as an asset class has been fading, and clean energy has been emerging as the leading market influencer (Yahya et al., 2021). Climate change due to the burning of fossil fuels and a rise in frequent climate catastrophes have left no choice but to focus on clean energy adoption (Wang, Ma, et al., 2022). Interestingly, this metamorphosis has started reflecting in investors' sentiments, corporate strategies, and government policy formulation. The impetus is no longer limited to adopting clean energy as one of the objectives of post-COVID economic recovery (IEA, 2021). Investors' communities have also committed to diverting major investments away from dirty fossil fuels (Dordi et al., 2022; Egli et al., 2022). Corporations have started developing strategies to showcase their long-term sustainable goals to establish a green legacy (Fuente et al., 2022; Gao et al., 2022).

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The ongoing thrust has coined words like environmental, social, and governance (ESG), responsible and sustainable investing, and green and dirty investments to reflect the embedding sentiment toward a sustainable future. Despite this euphoria, experts argue that crude oil cannot be ignored soon, even in the *Net Zero* scenario by 2050 (IEA, 2022). This indicates that the crude oil price, which is intrinsically volatile, is expected to continue the trend due to supply disruptions having cascading effects on clean and dirty asset classes.[1] Pandemics like COVID-19 and geopolitical events can trigger a sudden jump in oil prices and, thereby, upsurge investors' anxiety as the safe haven properties of the oil are becoming questionable (Bourghelle et al., 2021; Corbet et al., 2021). So, the rush toward sustainable investments involves a gamut of risks causing the clean and dirty indexes to become volatile asset classes. In light of this, examining whether crude oil price volatility can predict the associated risks of clean and dirty indexes and to what extent the link has been fortified is interesting. The answers to these queries have intriguing implications for investors, corporates, and policymakers. The current work examines these research questions in the Indian context.

India, the second largest oil importer after China, is vulnerable to oil price shocks (World Energy & Climate Statistics—Yearbook 2022, 2022). India's oil import has increased from 184,795 million tons (MT) (US$ 144.293 billion) in the financial year 2012 to 211,980 MT (US$ 120,445 billion) in 2021, which imposes a significant dent in India's foreign exchange reserve. However, India has committed to reducing oil import dependence by boosting its clean energy initiatives, and sustainable green financing has a major role in propelling the transition. Since the "United Nations Framework Convention on Climate Change (UNFCCC) Paris Agreement" in 2016, sustainable and responsible investing has become immensely popular among ecofriendly investors and policymakers in India. For instance, the Indian government has set targets to minimize India's total projected carbon emission by 1 billion tonnes by 2030, decrease the carbon intensity of the nation's economy by less than 45% by the same period, achieve carbon neutrality by 2070 and increase its clean energy installed capacity to 500 GW by 2030.[2] To achieve these goals, the government aims to finance a range of green and sustainable infrastructures. Accordingly, the state has planned to invest US$ 686 billion in green sectors by 2033.

Note that while investments in environmentally friendly projects have increased significantly over the past few years, sustainable investing still represents a relatively new notion in this emerging economy (Dutta, Bouri, Dutta, et al., 2021). This could increase the risk or volatility of green equities amid the transition period, which might lower their appeal to socially responsible investors by elevating the portfolio risk. That is, the increased risk linked to green equities would affect asset allocation decisions and portfolio optimization strategies (Kuang, 2021). Hence, precise estimates of time-varying volatilities of this new asset class play a key role in understanding the potential risk of green portfolios. It is worth noting that key events including financial crises, energy price decline, or natural adversities tend to raise the volatility levels for global financial markets, and due to market integration, green equities could also receive volatility from other financial assets, such as conventional stocks, commodities, cryptos, and so forth (Mensi et al., 2017; Wang, Li, et al., 2022; Wang, Ma, et al., 2022). Moreover, the volatility of crude oil could very well impact the volatility of green equities. Although clean stocks are projected to be the substitutes for dirty stocks, experts argue for the supremacy of crude oil until 2050 (IEA, 2022). This means that dirty energy options would continue to coexist with green choices and would probably complement each other in the long run. It is, therefore, essential to study the associations between green and other potential substitute asset classes like crude oil and dirty equities to realize the underlying risk of green investments.

However, despite the growing interest in sustainable investing in India, the literature on green assets is rather scarce. Notable contributions include Tiwari et al. (2018), Dutta, Bouri, Dutta et al. (2021), Sharma et al. (2021), Shanmugam et al. (2022), and Jadiyappa and Krishnankutty (2022). For instance, Tiwari et al. (2018) find that green sectors react significantly to asymmetric oil price impacts. The authors employ quantile regression models in their empirical analyses. Dutta, Bouri, Dutta et al. (2021) show that energy and precious metal markets send volatility to Indian green sector equity markets amid high uncertainty. Applying the autoregressive distributed lag (ARDL) process, Sharma et al. (2021) document that prices of green stocks are sensitive to a number of macroeconomic variables, including industrial production, wholesale price index, economy money supply, crude oil prices, and real effective exchange rate. More recently, Jadiyappa and Krishnankutty (2022) analyzed the effects of green operations (measured using the energy intensity of its operations) on the value of corporate firms in stock markets. The study reports a positive association between energy efficiency (firms that consume less energy per unit of sale) and stock returns.

[1]Green and clean stocks or equities refer to similar asset classes.
[2]See https://www.investindia.gov.in/sector/renewable-energy.

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The present study joins this scarce literature to investigate the volatility dynamics of green equities in India. Our study differs from earlier studies in many aspects, making several significant contributions to the existing literature. First, unlike the study by Dutta, Bouri, Dutta et al. (2021), which examines the impact of the crude oil volatility index (OVX) on the volatility levels of Indian green stocks, we aim to assess whether the time-varying jumps occurring in OVX offer useful contents for predicting the risk linked to such equities.[3] Note that OVX jumps could be defined as unexpected shocks, which might cause rapid increments in the volatility levels of global crude oil prices. These jumps also tend to raise the number of potential outliers in crude oil prices. In addition to structural oil shocks or oil volatility shocks, the jump component of OVX represents another form of oil shock, which usually indicates the abnormal increase in risk perceptions in energy markets (Das et al., 2022). Since volatility jumps can capture the effects of rare events including market crashes or downturns, identifying such jumps would help market participants make proper investment decisions during the periods of oil market uncertainty. Moreover, as the global oil market is closely linked to other financial assets, such as stock, foreign exchange, metal, or agricultural markets, detecting the sudden movements or jumps in oil price volatility would be useful for investors in adjusting their portfolios precisely. It is also worth noting that both dirty and green stocks are highly significant to OVX shocks (Das et al., 2022; Dutta et al., 2020). Therefore, large jumps in OVX could introduce large abrupt price variations in these markets. It is thus important to mitigate the adverse impact of oil volatility jumps by designing dynamic portfolios which can hedge such risk. In sum, analyzing the impact of oil volatility jumps could be crucial for portfolio optimization and risk management.

Second, while prior studies (e.g., Dutta, Bouri, Dutta, et al., 2021; Sharma et al., 2021; Tiwari et al., 2018) explain the impact of oil price changes or oil volatility shocks on green equities within the sample only, this study investigates how accurately OVX or its jumps can forecast the realized volatility (RV) of these assets out of the sample. In addition, the current work also evaluates the sensitivity of green stocks to different volatility components realized over different time horizons. Precise out-of-sample forecast results tested over multiple time horizons provide insight into the means of developing accurate asset pricing models. Thus, our analysis is critical from a risk management perspective.

Third, we investigate the impacts of crude oil volatility jumps in the market risk for both green and oil sector assets. The motivation behind this inspection is that depending on the nature of oil volatility shocks, the responsiveness of green and dirty equities to such shocks might be heterogeneous. Our analysis is thus crucial to understand the effect of oil volatility jumps on industry-specific volatility, which could be useful for hedging oil market shocks. Besides, due to the fact that green and dirty stocks act as possible substitutes, sudden oil price shocks, which would have a direct effect on oil firms, might also influence green equities (Henriques & Sadorsky, 2008; Kumar et al., 2012; Kocaarslan & Soytas, 2019; Managi et al., 2012; Saeed et al., 2021). To this end, our analysis would assist market participants in making proper asset allocation decisions during periods of significant jumps in oil market volatility. Hence, this strand of research offers important implications to socially responsible investors who include dirty and green sector assets in the same portfolio or swap dirty assets with ecofriendly assets to keep a green portfolio.

Methodologically, we employ the HAR process to model the RV of the assets under study. To do so, we first detect the time-varying jumps in OVX using the generalized autoregressive conditional heteroskedasticity (GARCH)-jump process and then extend the standard HAR process using the information on such jumps. In our empirical part, we apply several extensions to the baseline RV model and find that the process, which considers the information on both leverage effects[4] and jumps, outperforms all other models by providing the best forecast results. Note that we report similar outcomes for both green and dirty stocks. These findings offer key implications to socially responsible investors given that they could utilize the information on jump-induced oil market volatility to predict the risk linked to green investments.

The remainder of the article has five more sections. Section 2 surveys the literature briefly. Sections 3 and 4 describe data and methodology, respectively. Empirical results are discussed in Section 5 before concluding the study in Section 6.

[3]Note that the significance of crude oil volatility jumps has recently received considerable attention in finance literature (Das et al., 2022; Dutta, Bouri, & Roubaud, 2021). Dutta, Bouri, and Roubaud (2021), for example, show that when predicting energy price volatility, crude oil volatility jumps offer additional information beyond what is contained in the OVX index. Das et al. (2022) also provide evidence that the jump component of OVX plays a pivotal role in predicting metal market volatility. However, unlike these two studies, we investigate the impact of oil volatility jumps on green investments. Since oil and green assets are intertwined, our analysis has key implications for asset pricing and portfolio management. It is also worth mentioning that Dutta, Bouri, and Roubaud (2021) and Das et al. (2022) consider the intensity of jumps, while we utilize the information on jump-induced volatility. Hence, we propose a novel extension to the standard heterogeneous autoregressive (HAR) process.

[4]In this context, the leverage effect refers to the higher influence of negative returns on the future volatility than the positive returns (Rodriguez & Ruiz, 2012).

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2 | LITERATURE REVIEW

Recently the relationship between crude oil markets and sustainable investing received much attention in the academic literature. This section briefly reviews several notable contributions. We begin with the study by Reboredo (2013), which reveals that sustainable assets such as European Union Allowance can hedge the downside risk of crude oil prices. Using multivariate GARCH models, Sadorsky (2014) examines the risk transmission relationship between oil/gold and the Dow Jones Sustainability Index. The author finds that oil and precious metal can be used to hedge the underlying risk of green firms. In addition, de Oliveira et al. (2017) state that West Texas Intermediate oil prices significantly impact the Brazilian corporate sustainability index. Mensi et al. (2017) employ the DECO-FIAPARCH process to estimate the dynamic connections between commodity and green asset prices. The study documents significant correlations among the markets, which tend to increase during the 2008 global financial crisis. Furthermore, using a range of GARCH models, Dutta (2018) finds that the European Union (EU) emission asset is highly sensitive to oil volatility shocks. Besides, two recent studies Zheng, Yin et al. (2021) and Ren et al. (2022), reveal that different sources of oil market shocks, such as supply, demand, and volatility shocks explain the carbon price dynamics.

Moreover, using the multiscale wavelet decomposition, Andersson et al. (2022) find a short-run causality between ESG investment and crude oil returns. A recent study by Dutta et al. (2020) investigates the effects of energy market volatility shocks on green investments. The authors employ regime-switching models to study a number of MSCI sustainable indexes. The results show that while these indexes are sensitive to OVX shocks, they are not affected by global oil price fluctuations. These findings thus demonstrate the significance of using oil market VIX instead of traditional energy price series in this line of academic research. More recently, Arif et al. (2021) employed the network connectedness approaches to investigate the linkage between green assets and different conventional assets, including commodities. The authors document that green stocks and commodity index are nonconnected, indicating some hedging benefits. Using the GARCH-MIDAS approach, Wang, Li et al. (2022) show that oil market uncertainty plays a pivotal role in recognizing the time-varying dynamic associations among several green assets, including the EU carbon market, green bond, and sustainable index.

Few recent studies have also investigated the linkage between crude oil prices and the carbon market in China. For instance, Zheng, Zhou et al. (2021) examine such links using the nonlinear ARDL approach and find a long-term association between the two markets. They conclude that both oil supply shock and oil demand shock lead to an increase in carbon allowance prices, while the oil risk shock causes a drop in emission prices. In addition, Guo et al. (2022) assess if energy prices can predict the emission markets in Beijing, Guangdong, Hubei, and Shanghai. The study concludes that crude oil has some predictive contents only for the Hubei market.

It is worth noting that inspecting the effects of oil volatility jumps on sustainable investments has not received any attention in prior studies, even though such investigations have important implications for hedging strategies and risk analysis. This study attempts to fill this void in the existing literature for the Indian context.

3 | DATA

In line with Tiwari et al. (2018), Dutta, Bouri, Dutta et al. (2021), and Dutta, Bouri, and Roubaud (2021), this study also considers the S&P BSE GREENEX and S&P BSE CARBONEX indexes to study the equity prices of socially responsible firms in India. These indexes track the performance of those organizations which are engaged in an ecofriendly business 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 (Dutta, Bouri, Dutta, et al., 2021; Dutta, Bouri, & Roubaud, 2021; Sharma et al., 2021).[5] For comparison purposes, we also employ the S&P BSE OIL and GAS index in this research, representing the dirty index (see Bouoiyour et al., 2022; Saeed et al., 2021).

We use daily observations in our analysis, and the sample runs from December 2012 to April 2022, yielding a total of 2328 observations. The stock price data are retrieved from the Bombay Stock Exchange (BSE) official website. Furthermore, the OVX data are extracted from the website of Chicago Board of Options Exchange (CBOE).

[5]The S&P BSE CARBONEX, the first index of its kind in India, tracks the performance of the companies within the S&P BSE 100 index based on their commitment to mitigating risks arising from climate change. The index has been launched to address the market demand for a sophisticated approach to portfolio management incorporating climate change risk and opportunity. The S&P BSE GREENEX, on the other hand, is designed to measure the performance of the top 25 "green" companies in terms of greenhouse gas emissions, market cap, and liquidity.

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TABLE 1 Summary statistics of all the stock indexes.

Index	CARBONEX	GREENEX	OIL&GAS
Mean	0.0005	0.0004	0.0003
Standard deviation	0.0110	0.0109	0.0143
Skewness	−1.3399	−1.0692	−0.9404
Kurtosis	21.1335	16.2446	13.4663
Jarque–Bera test	31,556.66***	16,904.42***	10,620.30***
ADF test	−16.53***	−46.58***	−47.43***
PP test	−47.05***	−46.66***	−47.44***

Notes: This table shows the summary statistics for both green and dirty stock indexes. ADF and PP tests refer to different unit root tests.

Abbreviations: ADF, augmented Dickey–Fuller; PP, Phillips–Perron.

***Indicates statistical significance at 1% level.

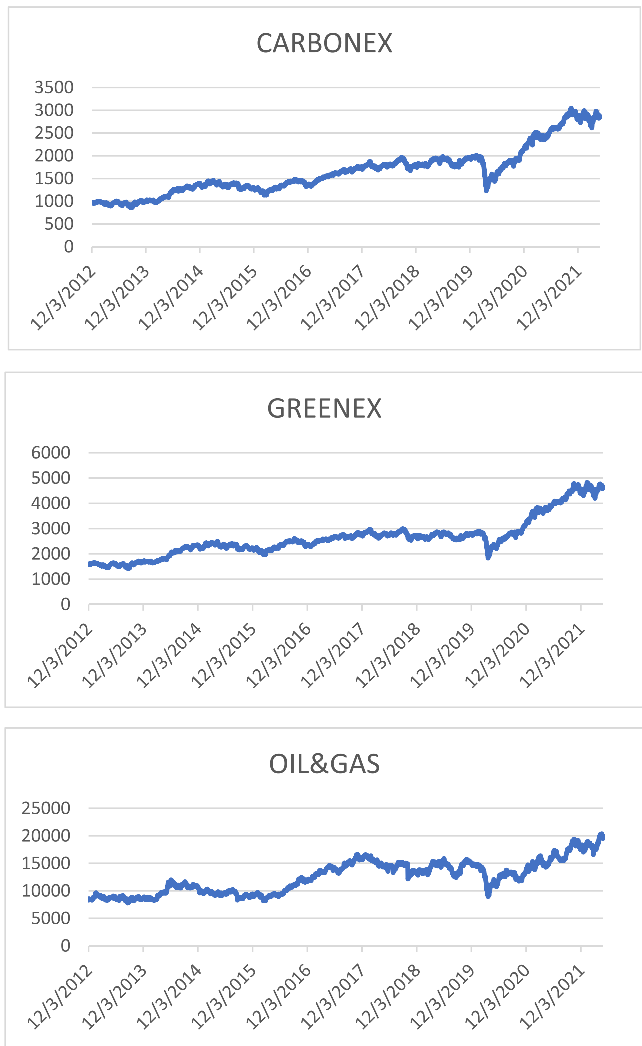

FIGURE 1 Time series plots of different stock indexes.

Table 1 exhibits the summary statistics for different stock indexes. Of these series, the OIL&GAS index is more volatile than the green indexes. Each of these series shows negative skewness and appears to be leptokurtic. Besides, the Jarque–Bera test rejects the normality assumption for each index. Figure 1 depicts the price evolution for all the equity indexes. We notice similar features for both green and dirty stocks. For instance, the stock prices of both sectors

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experience a significant fall during the COVID-19 pandemic period. Such a drop could be attributed to the oil price decline during the same period.

4 | METHODOLOGY

4.1 | GARCH-jump approach

The GARCH-jump approach, proposed by Chan and Maheu (2002), is a robust method for finding time-varying jumps in financial asset classes (Chiang et al., 2019; Gronwald, 2012; Zhou et al., 2019). Some recent studies, for example, Dutta, Bouri, and Roubaud (2021) and Das et al. (2022), have employed this process to detect jumps in OVX.[6] We also apply the same model as discussed below[7]:

$$X_t = \pi + \mu X_{t-1} + \epsilon_t, \tag{1}$$

where X_t indicates the first difference for the OVX index at time t, and ϵ_t refers to the innovation term which is specified as

$$\epsilon_t = \epsilon_{1t} + \epsilon_{2t}, \tag{2}$$

where ϵ_{1t} will follow the GARCH (1, 1) specification:

$$\epsilon_{1t} = \sqrt{h_t} z_t, \quad z_t \sim NID(0,1),$$

$$h_t = \omega + \alpha \epsilon_{1t-1}^2 + \beta h_{t-1}. \tag{3}$$

In addition, ϵ_{2t} denotes a jump innovation defined as

$$\epsilon_{2t} = \sum_{l=1}^{n_t} J_{tl} - \theta \lambda_t, \tag{4}$$

where J_{tl} is the jump size with a mean value θ and a variance ϑ^2, $\sum_{l=1}^{n_t} J_{tl}$ refers to the jump factor, and n_t represents the jump frequency at time t, following a Poisson distribution given by

$$P(n_t = j | I_{t-1}) = \frac{e^{-\lambda_t} \lambda_t^j}{j!}, \quad j = 0, 1, 2, \ldots \tag{5}$$

with

$$\lambda_t = \lambda_0 + \rho \lambda_{t-1} + \gamma \xi_{t-1}. \tag{6}$$

In Equation (6), λ_t indicates the time-varying autoregressive conditional jump intensity (ARJI) parameter, λ_0 is the constant jump intensity, and ξ_{t-1} denotes the intensity residual. Chan and Maheu (2002) assume that $\lambda_t > 0$, $\lambda_0 > 0$, $\rho > 0$, and $\gamma > 0$.

We outline the log-likelihood as

[6]Several recent studies employ the HAR process to model the volatility of green financial markets. Liu (2022), for instance, investigates the volatility structure of green bond returns using the HAR approach. Besides, Herrera et al. (2022) apply the HAR model to examine the impact of investor sentiment on the volatility levels of clean energy stock returns. However, unlike these studies, we make a novel extension to the HAR process by adding the oil volatility jumps.

[7]The choice of the AR(1) specification is based on the Akaike information criterion and Bayesian information criterion values.

$$L(\Theta) = \sum_{t=1}^{T} \log f(X_t | I_{t-1}; \Theta),$$

where $\Theta = (\pi, \mu, \omega, \alpha, \beta, \theta, \vartheta, \lambda_0, \rho, \gamma)$ and I_{t-1} is the information set.

Note that the variance of the jump component is defined as $(\theta^2 + \vartheta^2)\lambda_t$, which is also known as jump-induced variance (Gronwald, 2012). Then the jump-induced volatility (henceforth, JV) is given as

$$JV_t = \sqrt{(\theta^2 + \vartheta^2)\lambda_t}\,. \tag{7}$$

4.2 | HAR models

The HAR-type process for modeling the RV of financial markets has recently received ample attention among researchers (Dutta & Das, 2021; Kambouroudis et al., 2021). This increasing popularity could be attributed to the fact that it often outperforms the standard volatility approaches when forecasting the RV of financial assets (see Andersen et al., 2007, 2011; Corsi & Renò, 2012; Dutta & Das, 2022; Forsberg & Ghysels, 2007; Giot & Laurent, 2007; Ma et al., 2014).

Note that the HAR approach considers different volatility components realized over different time horizons by separating the RV into short-term, medium-term, and long-term volatility components (Corsi, 2008; Corsi et al., 2010; Kambouroudis et al., 2021). Using this approach, we model the RV of stock returns as follows:

$$\mathrm{HAR-RV}: RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \varepsilon_t \tag{8}$$

with h being equal to 1, 5, and 22 depending on the daily, weekly, and monthly volatility components, respectively, and

$$RV_{t_1,t_2} = \frac{1}{t_2 - t_1} \sum_{t=t_1+1}^{t_2} RV_t. \tag{9}$$

To estimate the RV for different stock indexes, we employ the range-based volatility measure proposed by Parkinson (1980), which is given as

$$RV_t = \frac{1}{4 \ln 2} (\ln H_t - \ln L_t)^2\,, \tag{10}$$

where H_t and L_t refer to the highest and lowest prices on a trading day t.

In this study, we consider several extensions to the HAR–RV model.[8] To do so, we first use leverage effects to extend the baseline HAR approach. Corsi and Renò (2012) demonstrate that the HAR process with leverage effects (known as the LHAR process) offers additional information which improves the accuracy of the baseline HAR–RV model. We define this process as follows:

$$\mathrm{LHAR-RV}: RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \psi_d r_t^- + \psi_w r_{t-5,t}^- + \psi_m r_{t-22,t}^- + \varepsilon_t, \tag{11}$$

where $r_t^- = \min(r_t, 0)$ with r_t being the log-return for GREENEX/CARBONEX/OIL&GAS index at time t. In addition, $r_{t-5,t}^- = \min((r_{t-4} + r_{t-3} + \cdots + r_t)/5, 0)$ and $r_{t-22,t}^- = \min((r_{t-21} + r_{t-20} + \cdots + r_t)/22, 0)$.

[8]A number of studies (Andersen et al., 2007; Busch et al., 2011; Corsi et al., 2010; Dutta & Das, 2022) have documented that separating RV into a continuous and a jump component improves the forecasting power of the HAR–RV models. Buncic and Gisler (2017), however, find that considering these components is advantageous only for the US equity indexes, not for the non-US markets. We, therefore, have not considered these components in our study.

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Next, we extend Equation (11) considering the information content of crude oil implied volatility index or OVX. This model, termed LHAR–RV–IV, takes the following form[9]:

$$\begin{aligned}\text{LHAR}-\text{RV}-\text{IV}: RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \psi_d r_t^- + \psi_w r_{t-5,t}^- + \psi_m r_{t-22,t}^- + \delta_d\, \Delta OVX_t \\ + \delta_w\, \Delta OVX_{t-5,t} + \delta_m\, \Delta OVX_{t-22,t} + \varepsilon_t.\end{aligned} \tag{12}$$

Finally, we insert the JV term, defined in Equation (7), into the LHAR–RV model as follows:

$$\begin{aligned}\text{LHAR}-\text{RV}-\text{JV}: RV_{t,t+h} = \tau_0 + \tau_d RV_t + \tau_w RV_{t-5,t} + \tau_m RV_{t-22,t} + \psi_d r_t^- + \psi_w r_{t-5,t}^- + \psi_m r_{t-22,t}^- + \phi_d JV_t + \phi_w \\ JV_{t-5,t} + \phi_m JV_{t-22,t} + \varepsilon_t.\end{aligned} \tag{13}$$

It is worth noting that as options expire at a monthly frequency, our study aims to predict 1-month ahead volatility only. Hence, h is equal to 22 in our analysis. Busch et al. (2011) also conduct a similar analysis in their empirical work. Following them, we construct each monthly realized measure using a value of h, exactly matching the number of trading days covered by the crude OVX.

4.3 | Forecast evaluation

4.3.1 | Root mean-squared error

To compare the out-of-sample forecasting performance of the different models, we evaluate the heteroskedasticity adjusted root mean square error (HRMSE) proposed by Bollerslev and Ghysels (1996). This statistic is defined as

$$HRMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{RV_t - \hat{RV_t}}{RV_t}\right)^2} \tag{14}$$

with T indicating the number of observations to be forecasted, whereas RV_t and $\hat{RV_t}$ specify the actual and estimated RV on day t, respectively.

Additionally, we employ the Diebold and Mariano (hereafter, DM) test (1995) to examine the null hypothesis of no difference in accuracy associated with different approaches. To do so, let $e_{it} = RV_t - \hat{RV_t}$ $(i = 1{,}2)$ denote the forecast errors. Now, suppose that $d_t = f(e_{1t}) - f(e_{2t})$, where $f(\cdot)$ indicates a function of forecast errors. We then test for the following null hypothesis:

$$H_0: E(d_t) = 0.$$

DM (1995) computes the approximate asymptotic variance of $\bar{d}$ as follows:

$$Var(\bar{d}) \approx k^{-1}\left[\eta_0 + 2\sum_{l=1}^{p-1}\eta_l\right], \tag{15}$$

where η_l implies the lth autocovariance of d_t estimated as

$$\hat{\eta} = k^{-1}\sum_{t=l+1}^{k}(d_t - \bar{d})(d_{t-l} - \bar{d}). \tag{16}$$

[9]Recent literature (e.g., Liang et al., 2022) shows that considering the heterogeneous structure of OVX improves the forecast accuracy of HAR-type models. We, therefore, consider such structures for both OVX and its jump component in our analysis.

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We then define the DM test statistic as

$$\mathbf{DM} = (\widehat{\boldsymbol{Var}}(\bar{\boldsymbol{d}}))^{-1/2}\bar{\boldsymbol{d}}. \tag{17}$$

Assuming that $\boldsymbol{H_0}$ is true, the DM statistic is normally (asymptotically) distributed.

4.3.2 | Mincer–Zarnowitz regression

In our analysis, we also consider applying the Mincer and Zarnowitz (1969) (MZ) regression technique to verify whether the proposed models provide incremental information relative to the baseline HAR–RV model. The main benefit of this procedure is that it will directly give an indication of the differences between the approaches under evaluation. Using this process, we first regress the true volatility on the forecast volatility over the out-of-sample period and then examine the R^2 values. The forecast model that produces the highest R^2 is preferred. The MZ regression technique gains immense popularity in the literature due to its simplicity (Kambouroudis et al., 2021).

We define the MZ regression approach as follows:

$$RV_t = \varphi_0 + \varphi_1 \hat{RV_t} + \epsilon_t, \tag{18}$$

where RV_t and $\hat{RV_t}$ are the true and estimated volatility for day t, respectively.

5 | EMPIRICAL FINDINGS

5.1 | Estimates of the GARCH–ARJI model

The outcomes of the GARCH–ARJI specification are presented in Table 2. These figures confirm the occurrence of time-varying jumps in OVX, which seem time-dependent as the ARJI parameters ρ and γ are statistically significant at 1% and 5% levels, respectively. Note that both ρ and γ take positive values, satisfying the restrictions of the ARJI process. Moreover, the significance of the parameter ρ also indicates the persistence in

TABLE 2 Estimates of the GARCH–ARJI model.

Variables	Estimates	Standard errors	*t* Statistics	*p* Values
π	−0.0628**	0.0262	−2.39	0.02
μ	−0.0397*	0.0224	−1.77	0.08
ω	0.0613***	0.0122	4.99	0.00
α	0.1233***	0.0156	7.87	0.00
β	0.8201***	0.0165	49.53	0.00
θ	4.7729***	1.1153	4.27	0.00
ϑ^2	7.0042***	1.2909	5.42	0.00
λ_0	0.0130*	0.0077	1.69	0.09
ρ	0.7248***	0.1566	4.62	0.00
γ	0.2244**	0.1052	2.13	0.03
Log-likelihood	−4509.36			

Notes: This table presents the estimates of the GARCH–ARJI process for the OVX index. In particular, the estimates of Equations (1)–(6) are shown in this table.

Abbreviations: ARJI, autoregressive conditional jump intensity; GARCH, generalized autoregressive conditional heteroskedasticity.

***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

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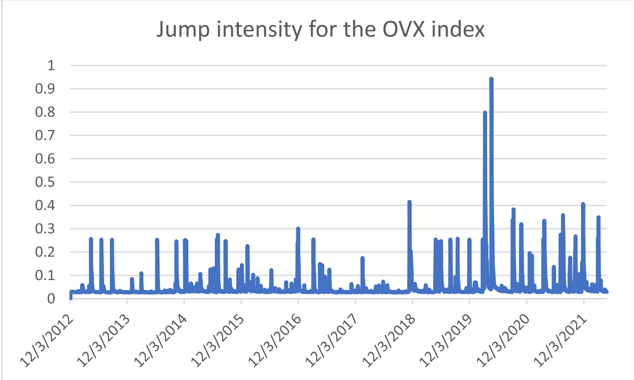

FIGURE 2 Jump intensity for the oil volatility index (OVX).

TABLE 3 Estimates of different HAR–RV models for the CARBONEX index.

Models	HAR–RV	LHAR–RV	LHAR–RV–IV	LHAR–RV–JV
τ_0	0.00005*** (0.000002)	0.00004*** (0.000003)	0.00004*** (0.000003)	−0.000024* (0.000014)
τ_d	0.0568*** (0.0143)	0.0452*** (0.0139)	0.0426*** (0.0139)	0.0374** (0.0138)
τ_w	0.2460*** (0.0251)	0.0761*** (0.0288)	0.0706** (0.0289)	0.0697** (0.0290)
τ_m	−0.0107 (0.0256)	0.0018 (0.0291)	0.0115 (0.0292)	−0.0391 (0.0313)
ψ_d		−0.0014*** (0.0004)	−0.0012*** (0.0004)	−0.0015*** (0.0004)
ψ_w		−0.0086*** (0.0012)	−0.0079*** (0.0012)	−0.0074*** (0.0011)
ψ_m		−0.0097*** (0.0026)	−0.0107*** (0.0027)	−0.0106*** (0.0026)
δ_d			0.000001** (0.0000005)	
δ_w			0.000004*** (0.000001)	
δ_m			−0.000003 (0.000004)	
ϕ_d				0.000024*** (0.000006)
ϕ_w				0.000001*** (0.0000002)
ϕ_m				0.0000095 (0.0000099)
R^2 (%)	16.22	21.51	22.81	24.34
HET test	0.27	0.58	0.63	0.68
Log-likelihood	16,938.58	17,004.82	17,014.57	17,042.67

Notes: This table presents the estimates of the HAR models for the CARBONEX index. The sample period runs from December 2012 to April 2022. We estimate four HAR–RV models and the R^2 statistics are reported accordingly. We also provide the p values for testing heteroscedasticity (HET). Standard errors are in parentheses.

Abbreviations: HAR, heterogeneous autoregressive; IV, integrated variance; JV, jump-induced volatility; LHAR, leverage HAR; RV, realized volatility.

***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

the conditional jump intensity. These findings are consistent with Dutta, Bouri, Dutta, et al. (2021), Dutta, Bouri, and Roubaud (2021), and Das et al. (2022), given that these authors also detect such jumps in crude oil volatility series.

Now, Figure 2 plots the jump intensity parameter (λ_t) for the OVX series, where we observe several spikes due to the COVID-19 pandemic. This is because the novel coronavirus causes the oil price to drop significantly, which lifts the volatility levels.

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TABLE 4 Estimates of different HAR–RV models for the GREENEX index.

Models	HAR–RV	LHAR–RV	LHAR–RV–IV	LHAR–RV–JV
τ_0	0.00006*** (0.000002)	0.00005*** (0.000003)	−0.000016 (0.000012)	0.00005*** (0.000003)
τ_d	0.0567*** (0.0139)	0.0486*** (0.0138)	0.0433*** (0.0116)	0.0473*** (0.0137)
τ_w	0.2306*** (0.0247)	0.0864*** (0.0286)	0.0800*** (0.0287)	0.0770** (0.0286)
τ_m	−0.0024 (0.0263)	−0.0183 (0.0290)	−0.0742** (0.0317)	−0.0037 (0.0294)
ψ_d		−0.0009*** (0.0003)	−0.0095*** (0.0036)	−0.0076** (0.0037)
ψ_w		−0.0042*** (0.0010)	−0.0033*** (0.0011)	−0.0037*** (0.0011)
ψ_m		−0.0131*** (0.0022)	−0.0140*** (0.0024)	−0.0140*** (0.0024)
δ_d			0.00002*** (0.000005)	
δ_w			0.000002 (0.000007)	
δ_m			0.00002** (0.00001)	
ϕ_d				0.000001** (0.0000005)
ϕ_w				0.000004*** (0.000001)
ϕ_m				−0.000004 (0.000004)
R^2 (%)	15.27	19.35	23.32	24.71
HET test	0.26	0.61	0.66	0.70
Log-likelihood	17,257.59	17,305.99	17,335.22	17,391.54

Notes: This table presents the estimates of the HAR models for the GREENEX index. The sample period runs from December 2012 to April 2022. We estimate four HAR–RV models and the R^2 statistics are reported accordingly. We also provide the p values for testing heteroscedasticity (HET). Standard errors are in parentheses.

Abbreviations: HAR, heterogeneous autoregressive; IV, integrated variance; JV, jump-induced volatility; LHAR, leverage HAR; RV, realized volatility.

***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

5.2 | Estimates of HAR–RV models

Tables 3–5 present the estimates of the HAR–RV models within the sample. Tables 3 and 4 exhibit the results for the green stocks, while the same for the oil and gas stocks is shown in Table 5. Looking at the estimates in Table 3, we find that the long-term volatility component appears to be statistically insignificant for the baseline HAR–RV model. However, both the short-term and medium-term components have a positive (and significant) effect on the future monthly volatility. It is also noteworthy that the impact of the weekly volatility component on monthly RV is four times higher than that of the daily volatility component. These findings suggest that the RV of these green stocks is sensitive to different volatility components realized over different time horizons.

For the LHAR–RV model, we document negative and significant estimates for the negative returns at all the daily, weekly, and monthly aggregation frequencies. This finding is consistent with Corsi and Renò (2012). Their analysis also detects a heterogeneous structure in the leverage effect, which indicates that the market might aggregate daily, weekly, and monthly memory, responding to price declines that occurred over the past week and month. The results thus confirm a persistent leverage effect. We further find that the R^2 statistic increases substantially from 16.22% to 21.51%.

Next, the estimates of the LHAR–RV–IV model reveal that OVX exerts a positive impact on the RV of the CARBONEX index.[10] In particular, we find that only daily and weekly components of OVX have significant effects on the RV. Hence, the changes in OVX do not have any long-term impact on the RV of the CARBONEX index. We also observe an increment, though tiny, in the R^2 statistic. Turning to the LHAR–RV–JV model, we notice several

[10]India is the second largest oil importer in the world preceded by China. As this emerging economy is booming, the consumption of crude oil has increased substantially in recent years. Therefore, oil has a key role to play in the Indian national economy (Dutta, Bouri, Dutta, et al., 2021; Dutta, Bouri, & Roubaud, 2021). Our findings also indicate that oil and green assets are possible substitutes and hence an increase in the OVX brings a positive influence on the volatility levels of green stocks. So, the aspect of oil volatility cannot be ignored for sustainable investments in India.

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TABLE 5 Estimates of different HAR–RV models for the OIL&GAS index.

Models	HAR–RV	LHAR–RV	LHAR–RV–IV	LHAR–RV–JV
τ_0	0.00011*** (0.000004)	0.00010*** (0.000004)	0.0001*** (0.00001)	0.00008*** (0.00002)
τ_d	0.0320*** (0.0113)	0.0230** (0.0114)	0.0214* (0.0115)	0.0211* (0.0114)
τ_w	0.1410*** (0.0239)	0.0469* (0.0264)	0.0391 (0.0214)	0.0431 (0.0269)
τ_m	0.0900*** (0.0289)	0.0731** (0.0312)	0.0840*** (0.0323)	0.0765** (0.0335)
ψ_d		−0.0006 (0.0004)	−0.0004 (0.0004)	−0.0006 (0.0004)
ψ_w		−0.0046*** (0.0011)	−0.0044*** (0.0012)	−0.0043*** (0.0011)
ψ_m		−0.0125*** (0.0026)	−0.0122*** (0.0027)	−0.0119*** (0.0026)
δ_d			0.000001 (0.000001)	
δ_w			0.000005*** (0.000001)	
δ_m			−0.000002 (0.000006)	
ϕ_d				0.00002** (0.00001)
ϕ_w				0.00007** (0.00003)
ϕ_m				−0.00001 (0.00001)
R^2 (%)	9.89	13.00	14.56	15.23
HET test	0.17	0.44	0.51	0.54
Log-likelihood	16,325.71	16,358.58	17,356.97	17,398.41

Notes: This table presents the estimates of the HAR models for the OIL&GAS index. The sample period runs from December 2012 to April 2022. We estimate four HAR–RV models and the R^2 statistics are reported accordingly. We also provide the *p* values for testing heteroscedasticity (HET). Standard errors are in parentheses.

Abbreviations: HAR, heterogeneous autoregressive; IV, integrated variance; JV, jump-induced volatility; LHAR, leverage HAR; RV, realized volatility.

***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

interesting findings. First, crude oil volatility jumps, like, the OVX index, also have short-term and midterm positive effects on the RV as the daily and weekly components appear to be significant at conventional levels. Second, the R^2 statistic increases noticeably from 22.81% to 24.34%. This output suggests that crude oil volatility jumps offer additional information which is not contained in the OVX index. Hence, the LHAR–RV–JV process outperforms all other specifications implying that using leverage effects and the information on crude oil volatility jumps would improve the accuracy of the HAR-type models. Our finding aligns with the work of Guo et al. (2022), which established the predictive content of crude oil prices for the emission market of Hubei.

The results for the GREENEX index, shown in Table 4, are consistent with what is reported in Table 3. For instance, the jump component provides additional information, which is quite handy for improving the HAR–RV model. Besides, the LHAR–RV–JV model wins the battle in this case as well. The only exception is that the changes in OVX now have long-term impacts on the RV of the GREENEX index. It is also important to note that although introducing the jump component improves the accuracy of the HAR-type models, the R^2 statistics still seem to be low. Previous studies, however, argue that obtaining low R^2 is very common in this strand of research (see, e.g., Busch et al., 2011; Corsi et al., 2010; Corsi & Renò, 2012; Kambouroudis et al., 2020; Dutta & Das, 2022).

Next, the estimates in Table 5 show that all the volatility components have predictive information for the baseline HAR–RV model. In Tables 3 and 4, however, we do not find any significant impact for the long-term volatility component, suggesting that the long-memory behavior of volatility is more common for dirty stocks. Looking at the estimates of the LHAR–RV model, we document negative and significant estimates for the negative returns at weekly and monthly aggregation frequencies. In contrast, the impact (with a negative sign) is insignificant at a daily frequency. Notably, when compared with the weekly volatility component, the magnitude of the impact is higher for the monthly component. Hence, a heterogeneous structure in the leverage effect is also observed for the dirty stocks. We further find that, like, the green stocks, crude oil volatility jumps offer extra information for the dirty stocks as well, confirming the superiority of the LHAR–RV–JV process over other specifications.

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Note that our findings differ from the standing literature in several aspects. First while previous studies (Dutta, 2017; Dutta et al., 2020; Pham, 2019; Pham & Do, 2022, and others) document that OVX exerts a significant impact on green investments, we show that its jump component contains more information than the OVX index itself when predicting the risk linked to such investments. Therefore, identifying the potential jumps in OVX could be crucial for portfolio optimization and risk management. Second, unlike Dutta, Bouri, and Roubaud (2021) and Das et al. (2022), who consider the intensity of oil volatility jumps, we utilize the information on JV. Hence, we propose a novel extension to the standard HAR process which outperforms the conventional approaches.

5.3 | Out-of-sample forecasts

Table 6 displays the out-of-sample forecast results based on the HMSE statistic and DM tests. We consider the in-sample estimation period from December 2012 to December 2020 and the out-of-sample period from January 2021 to April 2022. The findings suggest that for all the stock indexes under study, the LHAR–RV–JV approach produces the lowest HRMSE statistics. For example, when looking at the results for the GREENEX index, the HRMSE statistics amount to 0.000248, 0.000246, 0.000244, and 0.000239 for the HAR–RV, LHAR–RV, LHAR–RV–IV, and LHAR–RV–JV models, respectively. The DM test also supports these results by rejecting the null hypothesis of no difference in accuracy. Therefore, we can conclude that our proposed approach produces superior forecasts compared with the existing frameworks.

Next, Table 7 exhibits the R^2 (%) statistics obtained from the MZ regression models. For each of the stock indexes, we find that the LHAR–RV–JV process outclasses the competing models by producing higher R^2 values. These results, in brief, suggest that inserting the JV factor into the HAR model yields higher R^2 values for the MZ regression approach.

In sum, the out-of-sample forecast results reveal that considering the information content of crude oil volatility jumps is important for increasing the precision of the HAR–RV model. Hence, investors should not ignore the jumps occurring in crude oil implied volatilities when predicting the RV of the green and dirty assets under investigation.

5.4 | Forecasting value-at-risk (VaR)

We will now perform the VaR analysis to obtain the best forecast model. In particular, we test for all the HAR–RV models with a VaR estimated under the quantile level ψ. To serve our purpose, we apply the likelihood ratio (LR) test proposed by Kupiec (1995). Now, let us define a hit sequence as follows:

$$Hit_t = \begin{cases} 1 & \text{if } r_t < VaR_t, \\ 0 & \text{if } r_t \geq VaR_t, \end{cases} \tag{19}$$

where r_t refers the return on day t and VaR_t is specified as

TABLE 6 HRMSE statistics and DM test results.

	CARBONEX		GREENEX		OIL&GAS	
	HRMSE	DM statistic	HRMSE	DM statistic	HRMSE	DM statistic
HAR–RV	0.000242	2.60***	0.000248	2.54***	0.000271	3.01***
LHAR–RV	0.000241	2.46***	0.000246	2.12***	0.000268	2.16***
LHAR–RV–IV	0.000238	1.73**	0.000244	1.99***	0.000264	1.72**
LHAR–RV–JV	**0.000235**		**0.000239**		**0.000261**	

Notes: This table shows the HRMSE statistics and the results of Diebold–Mariano (DM) tests based on the range-based volatility measure proposed by Parkinson (1980). We consider the in-sample estimation period from December 2012 to December 2020 and the out-of-sample period from January 2020 to April 2022. The numbers in bold imply the lowest out-of-sample forecast errors for the HAR models.

Abbreviations: HAR, heterogeneous autoregressive; HRMSE, heteroskedasticity adjusted root mean square error; IV, integrated variance; JV, jump-induced volatility; LHAR, leverage HAR; RV, realized volatility.

*** and ** indicate statistical significance at 1% and 5% levels, respectively.

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TABLE 7 R^2 statistics based on the Mincer and Zarnowitz (MZ) regression approach.

Models ↓	R^2 (%)		
	CARBONEX	GREENEX	OIL&GAS
HAR–RV	14.21	13.59	12.33
LHAR–RV	21.09	20.33	14.82
LHAR–RV–IV	23.76	22.93	16.71
LHAR–RV–JV	25.98	25.58	18.44

Notes: This table reports the R^2 (%) statistics provided by the Mincer and Zarnowitz (MZ) regression approach: $RV_t = \varphi_0 + \varphi_1 R\hat{V}_t + \epsilon_t$, where RV_t and $R\hat{V}_t$ specify the true and estimated volatility for day t, respectively. The RV is computed using the range-based volatility measure proposed by Parkinson (1980). We consider the in-sample estimation period from December 2012 to December 2020 and the out-of-sample period from January 2020 to April 2022.

Abbreviations: HAR, heterogeneous autoregressive; IV, integrated variance; JV, jump-induced volatility; LHAR, leverage HAR; RV, realized volatility.

TABLE 8 VaR failure rate results.

Models ↓	LQ = 10%	LQ = 5%	LQ = 1%	RQ = 10%	RQ = 5%	RQ = 1%
Panel A: CARBONEX						
HAR–RV	0.368	0.311	0.271	0.483	0.523	0.639
LHAR–RV	0.510	0.473	0.422	0.598	0.619	0.718
LHAR–RV–IV	0.574	0.535	0.511	0.680	0.714	0.822
LHAR–RV–JV	**0.619**	**0.579**	**0.554**	**0.722**	**0.776**	**0.858**
Panel B: GREENEX						
HAR–RV	0.351	0.299	0.265	0.443	0.492	0.549
LHAR–RV	0.471	0.428	0.441	0.532	0.620	0.688
LHAR–RV–IV	0.539	0.491	0.491	0.655	0.729	0.802
LHAR–RV–JV	**0.595**	**0.540**	**0.579**	**0.711**	**0.761**	**0.854**
Panel C: OIL&GAS						
HAR–RV	0.387	0.361	0.293	0.477	0.501	0.588
LHAR–RV	0.486	0.481	0.401	0.538	0.594	0.639
LHAR–RV–IV	0.612	0.581	0.530	0.690	0.729	0.779
LHAR–RV–JV	**0.646**	**0.631**	**0.569**	**0.710**	**0.765**	**0.817**

Notes: In this table, we present the p values of the likelihood ratio test specified in Equation (21). Four different HAR models are considered in our analysis. The accuracy of the HAR models increases with the increment in p values. Numbers in bold indicate the highest p values.

Abbreviations: HAR, heterogeneous autoregressive; HRMSE, heteroskedasticity adjusted root mean square error; IV, integrated variance; JV, jump-induced volatility; LHAR, leverage HAR; LQ, left quantile; RQ, right quantile; RV, realized volatility; VaR, value-at-risk.

$$VaR_t = Z_q \sqrt{g_t}, \tag{20}$$

where Z_q indicates the quantile at $100 \times q\%$ of the standardized probability distribution and g_t denotes the volatility predicted by the HAR–RV approaches under study (see Giot, 2005; Giot & Laurent, 2003, 2004).

We then assume that N computes the frequency of VaR violations and T refers the data points. To investigate $H_0: f = q$, with f measuring the failure rate, we use the following LR test statistic proposed by Kupiec (1995):

$$LR = -2\ln\{(1-q)^N q^{T-N} / \left(1 - \frac{N}{T}\right)^{T-N} \left(\frac{N}{T}\right)^N\} \sim \chi^2(1). \tag{21}$$

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TABLE 9 Robustness test using the MZ regression model.

Models ↓	R^2 (%) CARBONEX	GREENEX	OIL&GAS
HAR–RV	14.03	13.76	12.56
LHAR–RV	20.72	20.42	14.78
LHAR–RV–IV	23.81	22.54	17.02
LHAR–RV–JV	26.08	24.91	18.68

Notes: This table reports the R^2 (%) statistics provided by the Mincer and Zarnowitz (MZ) regression approach: $RV_t = \varphi_0 + \varphi_1 \hat{RV}_t + \epsilon_t$, where RV_t and $\hat{RV}_t$ specify the true and estimated volatility for day t, respectively. The RV in this case is computed using the range-based volatility measure proposed by Rogers and Satchell (1991). We consider the in-sample estimation period from December 2012 to December 2020 and the out-of-sample period from January 2020 to April 2022.

Abbreviations: HAR, heterogeneous autoregressive; IV, integrated variance; JV, jump-induced volatility; LHAR, leverage HAR; RV, realized volatility.

TABLE 10 HRMSE statistics and DM test results based on the Rogers and Satchell RV measure.

	CARBONEX		GREENEX		OIL&GAS	
	HRMSE	DM statistic	HRMSE	DM statistic	HRMSE	DM statistic
HAR–RV	0.000244	3.12***	0.000247	2.14***	0.000270	3.02***
LHAR–RV	0.000242	2.98***	0.000247	2.13***	0.000269	2.68***
LHAR–RV–IV	0.000237	2.18***	0.000244	1.79**	0.000264	1.67**
LHAR–RV–JV	**0.000233**		**0.000240**		**0.000261**	

Notes: This table shows the HRMSE statistics and the results of Diebold–Mariano (DM) tests based on the range-based volatility measure proposed by Rogers and Satchell (1991). We consider the in-sample estimation period from December 2012 to December 2020 and the out-of-sample period from January 2020 to April 2022. The numbers in bold imply the lowest out-of-sample forecast errors for the HAR models.

Abbreviations: HAR, heterogeneous autoregressive; IV, integrated variance; JV, jump-induced volatility; LHAR, leverage HAR; RV, realized volatility.

*** and ** indicate statistical significance at 1% and 5% levels, respectively.

We present the p values of this test in Table 8. Our findings show failure rates for both left and right quantiles. Given that the accuracy of the HAR models increases with the increment in p values, the VaR analysis confirms the superiority of the LHAR–RV–JV approach over other competing models. The results hold for both green and dirty stocks. To summarize, leverage effects and jumps are vital for predicting the VaR more precisely.

5.5 | Robustness check

So far, we have used the range-based volatility measure, proposed by Parkinson (1980), to estimate the true volatility of both green and dirty stocks. To check the robustness of our findings, we now employ the volatility measure proposed by Rogers and Satchell (1991). This measure is defined as

$$RV_t = \ln\left(\frac{H_t}{O_t}\right)\ln\left(\frac{H_t}{C_t}\right) + \ln\left(\frac{L_t}{O_t}\right)\ln\left(\frac{L_t}{C_t}\right), \tag{22}$$

where O_t and C_t indicate the opening and closing prices on a trading day t, respectively. The advantage of applying the above estimator is that it considers the opening and closing prices in addition to the high and low prices to capture any jumps during the nontrading times.

Next, Table 9 presents the results of our robustness test based on the RV measure of Rogers and Satchell (1991). These numbers are the R^2 (%) statistics obtained from the MZ regression models. For both green and dirty stock

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indexes, we find that the LHAR–RV–JV model outperforms the others as it generates higher R^2 values than the rest. For example, when considering the CARBOEX index, the R^2 statistics are equal to 14.03%, 20.72%, 23.81%, and 26.08% for the HAR–RV, LHAR–RV, LHAR–RV–IV, and LHAR–RV–JV models, respectively.

Moreover, Table 10 displays the out-of-sample forecast results based on the HMSE statistic and DM tests based on the Rogers and Satchell (1991) RV measure. These results are also consistent with those reported in Table 6. In sum, our proposed approach produces superior forecasts compared with the existing approaches.

6 | CONCLUSIONS

Although there has been a growing interest in green investments among investors and policymakers in India over the past few years, empirical studies on the dynamics of environmentally friendly assets are scant. This is unexpected given that understanding the time-varying features of this emerging asset plays a pivotal role in risk management and hedging strategies. Sustainable investments being relatively new in asset classes, they are more risk-prone. Besides, exploring the relationship between green stocks and crude oil price is essential to recognize the underlying risk of sustainable investing as such equities are highly sensitive to crude oil volatility shocks. This study aims to extend this scarce literature where we examine the predictive ability of crude oil price volatility to influence the green asset classes.

In particular, our objective is to assess the impact of crude oil volatility jumps on the RV of green and dirty stocks in India. In doing so, we first estimate the time-varying jumps in the OVX index and then extend the HAR process using the information on such jumps. We apply several extensions to the baseline RV model using the information content of the crude OVX and leverage effects. Comparing these extended HAR–RV models, we find that crude oil volatility jumps provide additional information, which is not contained even in the OVX index itself. More specifically, the HAR–RV model that considers both leverage effects and the information on volatility jumps produces more accurate forecasts than the existing models. A simple VaR analysis further supports the economic significance of these results.

Given that concerns about climate change encourage investors and policymakers to shift toward green investments, our results have important implications for market participants. For instance, we find that green and dirty stocks react similarly to crude oil volatility jumps, indicating that these assets are substitutes. Therefore, investors should closely observe these equities since information in one sector might flow to the other. In addition, financial market analysts should not ignore the time-varying jumps in crude oil volatilities as the results reveal that such jumps have more information content compared with the OVX itself in explaining both green and dirty stocks. It is also worth noting that as large volatility jumps may create immediate chaos in energy markets, risk can transmit from oil market to its allied markets including stock, commodity, or foreign exchange markets. Hence, sudden jumps in OVX could introduce high economic uncertainty in global financial markets. It is thus important to mitigate the adverse impact of oil volatility jumps by designing dynamic portfolios which can hedge such risk. In sum, analyzing the impact of oil volatility jumps could be crucial for portfolio optimization and risk management.

On the other hand, policymakers should encourage ethical or sustainable investments to mitigate the adverse impact of dirty energy on the global environment. To this end, the government could substantially finance ecofriendly services and trades to attract socially responsible investors in India. Introducing higher carbon taxes could also promote the use of sustainable products. Since India cannot get rid of crude oil dependence soon, the government should also focus on enhancing the current "strategic petroleum reserve"[11] to hedge the risk exposure of sustainable investments from future oil price volatility.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

[11]Indian strategic petroleum reserve limited maintains a contingency crude stock pile of 5.3 million metric tonnes to sustain 9.5 days of crude oil requirement. However, the IEA recommends to hold an emergency oil stocks equivalent of at least 90 days of net import for major oil importing countries.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data that support the findings of this study are openly available at the BSE website (https://www.bseindia.com/indices/IndexArchiveData.html) and in the website of CBOE (https://www.cboe.com/tradable_products/vix/vix_historical_data/).

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