Dynamic Linkage Between Oil Price and Alternative Energy Stocks: A VAR Analysis

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Abstract. This study investigates the dynamic linkage between crude oil prices and renewable energy stock prices in India, while controlling for technological advancements and interest rates. The Vector Autoregressive (VAR) model for weekly data from 2018 to 2024 captures both short and long-run interactions. The results show that oil price shocks initially push renewable energy stock prices higher through the substitution effect, but the impact is short-lived. In contrast, technology shocks apply a stronger and continuous positive influence. At the same time, higher interest rates temporarily depress the prices of renewable energy and technology stocks before the effects weaken over time. Overall, the findings suggest that although oil market fluctuations shape short-term dynamics, technological progress and supportive financing conditions play a more decisive role in sustaining India's energy transition.

Keywords: Alternative energy, Stock prices, Oil prices, India.

1. Introduction

Oil prices remain a key force in global financial markets, shaping patterns of economic activity, capital flows, and even policy decisions. Despite the growing momentum of the renewable energy transition, crude oil still plays a decisive role in the performance of alternative energy stocks, both through substitution effects and through broader market spillovers [1]. When oil prices rise, renewable energy becomes a more attractive substitute, as well as when oil prices remain low for a sustained period, the incentive to invest in green technologies diminishes. [2,3]. Beyond oil price dynamics, the resilience of clean energy markets also depends on technological progress and prevailing monetary conditions, which shape both the costs of financing and the speed of innovation [4].

An extensive collection of studies has explored the relationship between oil markets, renewable energy, and technology. Henriques and Sadorsky [5] found that oil prices Granger-cause movements in clean energy stocks, although technology stocks often exert an even stronger influence. Building on this, later studies demonstrate that oil shocks propagate into both renewable stocks and technology markets, highlighting the complexity of these interdependencies [6,7]. More recent work indicates that these impacts are not stable over time but vary across market regimes and geographic settings. For example, Bouri, Naeem, and Nguyen [8] document significant volatility spillovers between oil and green assets, while Ji, Fan, and Geng [9] reveal asymmetric

B. Joseph and D. Sekhar R (eds.), *Proceedings of the 3rd International Conference on Artificial Intelligence in Economics, Finance and Management (ICAIEFM 2025)*, Advances in Economics, Business and Management Research 358,
https://doi.org/10.2991/978-94-6463-896-7_9

effects depending on whether oil shocks are positive or negative. Evidence from Gordo, Hunt, and Morley [10] further indicates that the oil-renewables relationship shifts with changing market conditions.

Technological innovation also plays a crucial role in shaping clean energy markets. Studies published by Zhang et al. [11] and Liu and Wang [12] suggest that innovation helps protect renewable energy stocks from oil price shocks, with more persistent effects than those observed in commodity markets. While some of this research has extended to emerging economies, high-frequency evidence from India remains scarce [13]. In addition, earlier work by Managi and Okimoto [14] connects oil dynamics not only to renewable energy but also to carbon markets, pointing to the importance of accounting for broader macroeconomic variables.

India offers a particularly compelling context for examining these dynamics. As the world's second-largest importer of crude oil and one of the fastest-growing renewable energy markets. The country faces two simultaneous challenges: vulnerability to oil price shocks and the pursuit of 50% renewable energy by 2030 and net-zero emissions by 2070. This combination makes India an ideal case for examining the interaction between global oil market fluctuations and domestic clean energy investment. Despite its importance, empirical evidence in India remains limited. Those studies are typically use low-frequency or aggregated data, risking the omission of short-term and sector-specific effects.

This study seeks to fill these gaps by analyzing the dynamic relationships between oil prices, renewable energy stocks in India. Drawing on high-frequency weekly data from 2018 to 2024, the analysis employs a Vector Autoregressive (VAR) model to capture the interdependence among these variables. In contrast to earlier work, the dataset spans a period of heightened global uncertainty—including the COVID-19 pandemic and recent episodes of oil market volatility—thereby offering timely evidence on market behavior under stress. By incorporating both technology and interest rates, the study moves beyond the traditional oil–renewables nexus and provides a broader perspective on the macroeconomic and innovation-driven forces shaping India's clean energy sector.

The remainder of this paper is structured as follows. The next section reviews the existing literature, and Section 3 describes the data and outlines the econometric methodology. Section 4 reports and discusses the empirical results. Finally, Section 5 concludes and sets out the key implications for investors and policymakers.

2. Review of Literature

The relationship between oil prices and renewable energy markets has been widely explored across various contexts. Early work by Henriques and Sadorsky [5] showed that oil prices serve as a leading indicator in clean energy stocks but also emphasised that technology stocks exert a comparatively stronger influence, underscoring the importance of innovation in driving renewable markets. Extending this analysis, Sadorsky [15] identified strong volatility spillovers between oil, technology, and renewable energy stocks, confirming that oil shocks transmit across multiple sectors.

In a related study, Dutta [7] employed the crude oil volatility index (OVX) and demonstrated that oil price uncertainty is a key determinant of renewable stock returns.

Other research has highlighted the role of macroeconomic and environmental variables. Managi, Matsuda, and Kumar [16] found the interdependence between oil, carbon, and clean energy stocks, showing that the involvement of carbon markets adds further complexity to oil-renewables dynamics. Bondia, Ghosh, and Kanjilal [17] applied nonlinear cointegration techniques and revealed that oil and clean energy stocks are linked through nonlinear mechanisms, which cannot be fully captured by traditional linear models. These findings emphasize the importance of employing econometric techniques that incorporate structural complexities and feedback mechanisms.

More recent contributions have shifted toward examining time-varying and asymmetric linkages. Bouri, Naeem, and Nguyen [8] found that volatility spillovers between oil and clean energy stocks differ significantly across bull, bear, and normal market phases, suggesting that market conditions shape the strength of these relationships. Similarly, Ji, Liu, and Zhao [9] reported that negative oil price shocks exert stronger impacts on renewable stocks than positive shocks, highlighting the asymmetric nature of oil-renewables interactions. Evidence from Gordo, Hunt, and Morley [10] further emphasizes that these dynamics are regime-dependent and evolve with broader shifts in the global energy and financial market.

The literature also stresses the growing role of technological innovation. Liu and Wang [12] found that technological progress helps shield renewable energy stocks from oil price shocks, thereby reducing their vulnerability to commodity markets. Supporting this view, Zhang and Li [11] documented that markets with stronger innovation ecosystems display greater resilience to oil volatility. Wang and Zhang [18] likewise argued that clean energy firms embedded in innovation-driven economies experience lower exposure to oil market risks. Taken together, these studies suggest that technology is not merely complementary but a central driver of renewable energy stock performance.

Attention has increasingly turned to emerging economies, where energy transitions are accelerating. While earlier studies, such as Apergis and Payne [19], concentrated on OECD countries and highlighted country-specific differences. For example, Kang and Ratti [13] reported that emerging markets exhibit unique oil–renewables dynamics that differ significantly from those observed in advanced economies. In the Indian context, Sharma and Gupta [20] found that fiscal incentives and policy support are critical in promoting renewable energy investments during periods of oil price turbulence. Despite these advances, research in the Indian context is limited, and most existing studies rely on aggregate indices or low-frequency data that may unclear firm-level and short-term responses.

Overall, three key insights emerge from the literature. First, oil price shocks and renewable energy stocks are interconnected, but the strength and direction of this relationship vary across time, market regimes, and the type of shock. Second, technological innovation and supportive policy environments play decisive roles in reinforcing renewable energy markets, often dominating the influence of oil market volatility. Third, while there is substantial evidence for developed economies, research on India and other emerging markets is still underdeveloped, particularly using higher-frequency data. To address these gaps, the present study employs a VAR model with weekly Indian data from 2018 to 2024, integrating oil prices, renewable energy stocks, technology, and interest rates to provide new evidence on the dynamic interdependence between energy and financial markets.

3. Data and Methodology

3.1 Data

This study uses weekly panel data spanning January 2018 to March 2024. The dataset includes the WTI crude oil price as a benchmark for global oil market fluctuations, and the weekly average stock prices of 32 renewable energy companies listed on the BSE and NSE that are primarily engaged in renewable energy production, like wind, solar, hydropower, etc. To account for broader market influences, the BSE Technology Index is employed as a proxy for technological progress, while the 91-day Treasury bill rate serves as a measure of short-term interest rates and monetary policy conditions. All data were sourced from Bloomberg. To ensure comparability and reduce heteroskedasticity, all variables were transformed into natural logarithms. The dataset is structured as panel data, enabling the analysis to capture both firm-level heterogeneity and time-series dynamics.

3.2 Methodology

Before estimating the model, the stationarity properties of the data were examined using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Since asset prices are typically non-stationary, all series were converted into natural logarithms. The test results confirmed that all variables are stationary at the level, thereby satisfying the requirements for Vector Autoregression (VAR) estimation.

To investigate the relationship between oil prices and the stock prices of renewable energy companies, this study employs a vector autoregressive (VAR) model. The key strength of the VAR framework lies in its flexibility: unlike traditional models, it does not require the researcher to predefine which variables are dependent and which are explanatory. Instead, all variables are treated as endogenous, meaning that each variable is influenced by its own past values as well as the lagged values of every other variable in the system. This structure enables the VAR to capture the complex dynamics and feedback effects that often characterise financial and energy markets. As Brooks [21] notes, such a framework provides a richer and more realistic representation of time-series data. In general form, a vector autoregression can be expressed as follows:

$$Y_t = A_0 + \sum_{i=1}^{p} A_i Y_{t-i} + e_t \tag{1}$$

where Y_t is an $n \times 1$ vector of endogenous variables, A_i are $n \times n$ coefficient matrices, and e_t is a vector of innovations assumed to be white noise. In this study, the vector

Y_t consists of WTI crude oil prices, renewable energy stock price, the BSE technology index, and the 91-day Treasury bill rate. Lag length selection was based on information criteria (AIC, BIC, HQIC). While the AIC suggested a higher lag order, alternative specifications with shorter lags (VAR (2) andVAR ((4)) were estimated as robustness checks to avoid overfitting. The results were consistent across specifications, supporting the validity of the chosen model. Residual diagnostic tests further confirmed the absence of serial correlation.

Impulse Response Functions (IRFs) were then employed to identify the dynamic effects of shocks to one variable on the others within the system. Orthogonalized IRFs were derived using Cholesky decomposition, and responses were reported with 95% confidence intervals. The axes were labelled to ensure interpretability, with the x-axis representing time in weeks and the y-axis showing percentage responses.

4. Empirical Results and Discussion

The descriptive statistics (Table 1) indicate that crude oil prices (WTI) exhibit moderate volatility, with a mean value of 4.1794 and a standard deviation of 0.3009. Renewable energy stock price (REENRGY) displays greater variability, with a standard deviation of 1.5347, suggesting higher fluctuations in this sector. The technology index (TECH) has relatively stable returns, while interest rates (INTRST) show minimal variation, as expected in a regulated financial environment. The negative skewness in WTI and INTRST suggests a tendency for extremely low values, while the Jarque-Bera test confirms normality across all variables.

Table 1. Descriptive Statistics

Variable	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
WTI	4.1794	4.2538	4.7408	3.0243	0.3009	-1.0442	4.5473	2881.6*
REENRGY	3.8943	3.9767	6.0630	-0.5344	1.5347	-0.2379	2.1203	426.68*
TECH	9.3772	9.4789	9.9198	8.7049	0.3266	-0.3644	1.8366	803.86*
INTRST	4.5814	4.5890	4.5970	4.5344	0.0186	-1.5333	4.0557	4486.5*

*Indicates significance at the 5% confidence level

The correlation matrix (Table 2) provides insights into the relationships between variables, oil prices, renewable energy stocks, the technology index, and interest rates. The correlation results indicate several key relationships. The WTI and REENRGY have a positive correlation of 0.3229, suggesting that rising oil prices tend to increase renewable energy stock prices, likely due to the substitution effect, where higher oil prices make renewables more attractive. The WTI and TECH have a strong positive correlation of 0.7247, indicating that the tech sector is strongly linked to oil price fluctuations, possibly due to shared macroeconomic trends or increased investment in energy technologies when oil prices rise. The REENRGY and TECH have a moderate positive correlation of 0.4045, highlighting that technological advancements influence renewable energy stocks, reinforcing the importance of innovation in clean energy growth. The findings suggest that oil price movements significantly impact alternative energy stocks, while technology plays a key role in driving clean energy investments. Interest rates, although having a weaker impact, still influence investment patterns, highlighting the role of monetary policy in sustainable finance.

Table 2. Correlation Matrix

Variables	WTI	REENRGY	TECH	INTRST
WTI	1.0000			
REENRGY	0.3229	1.0000		
TECH	0.7247	0.4045	1.0000	

Table 3 presents the results of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests for stationarity. The results indicate that all four variables—crude oil prices (WTI), renewable energy stock price (REENRGY), technology index (TECH), and interest rates (INTRST) are stationary at level. The ADF and PP test statistics are significant at the 1% level ($p < 0.01$). So, the findings confirm that the variables follow an I(0) process, satisfying the key condition for applying the Vector Autoregressive (VAR) model in level form without differencing.

Table 3. Unit Root Analysis

Variable	ADF Statistic	p-value	PP Statistic	p-value
Oil Price (WTI)	-9.35***	0.0000	-9.28***	0.0000
Renewable Energy (REENRGY)	-8.67***	0.0000	-8.54***	0.0000
Technology Index (TECH)	-6.45***	0.0000	-6.38***	0.0000
Interest Rate (INTRST)	-4.82***	0.0000	-4.76***	0.0000

Note: *** denotes significance at the 1% level. Null hypothesis: the series has a unit root.

The optimal lag length was determined by using multiple information criteria (Table 4). The Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SC) suggested all 8 lags as optimal. To address potential concerns of overfitting, we also conducted robustness checks with shorter lag structures (VAR (2) and VAR (4)), and the results remained qualitatively consistent, confirming the stability of our findings

Table 4. VAR Lag Order Selection Criteria

Lag	AIC	SC
0	-15.35416	-15.35124
1	-17.92185	-17.90722
2	-17.94671	-17.92039
3	-17.98095	-17.94293
4	-18.02619	-17.97647
5	-18.07281	-18.01139
6	-18.17038	-18.09726
7	-18.20852	-18.12370
8	**-18.25134**	**-18.15483**

The Vector Autoregressive (VAR) model results (Table 5) reveal significant dynamic linkages between crude oil prices, renewable energy stock prices, the technology index, and interest rates over the eight-period lag structure. The evidence suggests that fluctuations in crude oil prices (WTI) have a strong influence on renewable energy stock prices, particularly in the short run. Initial increases in oil prices (WTI (-1), WTI (-2)) stimulate renewable energy stocks through a substitution effect, consistent with the argument of Henriques and Sadorsky [15] and Kumar, Managi, and Matsuda [16] that higher fossil fuel costs make more attractive in clean energy investments. However, at medium-term lags the impact turns negative (WTI (-4)), indicating correction effects in renewable energy valuations after the initial gains, before turning positive again at longer horizons (WTI (-8)). This pattern aligns with Managi and Okimoto [14], who highlight the time-varying nature of oil–renewable energy interactions.

Renewable energy stock dynamics (REENRGY) also spill over into the technology sector, particularly at short lags (REENRGY (-1)), reflecting the complementary role of technological innovations in driving clean energy performance, as noted by Henriques and Sadorsky [15] and Dutta [7]. However, this influence fades over time, suggesting that renewable energy shocks are not persistent in the technology market. Conversely, the technology index (TECH) exerts a strong and sustained effect on renewable energy stocks, with significant coefficients across both short and long lags (TECH (-1), TECH (-8)). This confirms that technological progress is a critical driver of clean energy growth, consistent with the findings of Sadorsky [6] and Managi and Okimoto [14].

These dynamics further shaped by Interest rates (INTRST). Higher interest rates initially depress renewable energy and technology stock prices (INTRST (-1)), as rising borrowing costs reduce the attractiveness of capital-intensive green investments. Over longer horizons, however, the magnitude of this effect diminishes (INTRST (-8)), suggesting that markets gradually adjust to monetary policy changes, as evidenced by Kumar, Managi, and Matsuda [16].

Taken together, the results suggest that renewable energy markets are shaped by a dynamic interplay of oil price shocks, technological advancements, and interest rates. Oil prices create short-term substitution gains but lead to medium-term corrections, whereas technology acts as a steady positive force for renewable energy performance. Interest rates pose a short-term constraint, yet their influence proves to be temporary. These findings align with earlier studies by Henriques and Sadorsky [5], Managi and Okimoto [14], and Dutta [7], and they offer insights for policymakers and investors seeking to understand the robustness and determinants of renewable energy markets.To evaluate the robustness of our findings and address concerns about potential overfitting in the baseline VAR (8) model, we re-estimated the system with shorter lag structures, namely VAR (2) and VAR (4). The results confirm that the qualitative dynamics remain unchanged: oil price shocks influence short-term negative effects on renewable energy stock prices, technology shocks provide persistent positive influences, and interest rate shocks dampen clean energy performance. Although the magnitudes of the coefficients vary slightly across specifications, the direction, timing, and statistical significance of the responses remain consistent, reinforcing the reliability of the baseline results.

Table 5. VAR Model estimation and Result

Regressor	WTI	REENRGY	TECH	INTRST
WTI (-1)	0.1448*** [13.86]	0.1258*** [7.20]	0.0510*** [11.02]	0.0012 [0.97]

Regressor	WTI	REENRGY	TECH	INTRST
WTI (-2)	0.0596*** [5.67]	0.0983*** [5.60]	-0.0272*** [-5.85]	0.0091*** [7.30]
WTI (-3)	-0.0013 [-0.13]	-0.0232 [-1.34]	0.0101** [2.21]	0.0022* [1.81]
WTI (-4)	-0.1429*** [-14.10]	-0.0635*** [-3.75]	-0.0375*** [-8.35]	0.0016 [1.33]
WTI (-5)	0.0734*** [7.22]	0.0235 [1.38]	0.0282*** [6.26]	0.0048*** [3.97]
WTI (-6)	0.1485*** [14.59]	-0.0293* [-1.72]	-0.0336*** [-7.46]	-0.0021* [-1.72]
WTI (-7)	-0.0713*** [-6.93]	-0.0229 [-1.33]	0.0123*** [2.71]	0.0136*** [11.22]
WTI (-8)	-0.0440*** [-4.30]	0.0393** [2.30]	0.0629*** [13.90]	-0.0062*** [-5.10]
REENRGY (-1)	-0.0060 [-0.99]	0.0854*** [8.39]	0.0131*** [4.86]	0.0009 [1.26]
REENRGY (-2)	-0.0022 [-0.36]	-0.1117*** [-10.93]	0.0020 [0.73]	-0.0004 [-0.49]

Regressor	WTI	REENRGY	TECH	INTRST
REENRGY (-3)	0.0029	0.1225***	0.0096***	-0.0016**
	[0.48]	[12.10]	[3.58]	[-2.26]
REENRGY (-4)	0.0137**	-0.0743***	0.0005	-0.0012*
	[2.24]	[-7.29]	[0.17]	[-1.66]
REENRGY (-5)	0.0148**	-0.0074	0.0164***	-0.0023***
	[2.43]	[-0.73]	[6.06]	[-3.16]
REENRGY (-6)	0.0268***	-0.0297***	0.0030	-0.0010
	[4.42]	[-2.93]	[1.11]	[-1.39]
REENRGY (-7)	0.0050	0.0126	-0.0046*	-0.0018**
	[0.83]	[1.25]	[-1.71]	[-2.59]
REENRGY (-8)	0.0014	-0.0173*	-0.0006	0.0009
	[0.24]	[-1.72]	[-0.23]	[1.27]
TECH (-1)	0.2012***	0.1233***	0.2353***	0.0043
	[8.59]	[3.14]	[22.67]	[1.55]
TECH (-2)	-0.1440***	-0.0237	-0.0457***	-0.0203***
	[-6.01]	[-0.59]	[-4.30]	[-7.17]
TECH (-3)	-0.1141***	0.1106***	0.0507***	-0.0056**
	[-4.88]	[2.83]	[4.90]	[-2.02]

Regressor	WTI	REENRGY	TECH	INTRST
TECH (-4)	0.2068*** [8.88]	0.1615*** [4.15]	0.0938*** [9.10]	-0.0166*** [-6.02]
TECH (-5)	0.1880*** [8.08]	0.0047 [0.12]	-0.0519*** [-5.04]	-0.0053* [-1.91]
TECH (-6)	-0.0773*** [-3.32]	-0.0484 [-1.24]	-0.1704*** [-16.52]	-0.0097*** [-3.53]
TECH (-7)	0.1230*** [5.20]	-0.0535 [-1.35]	0.0705*** [6.74]	-0.0064** [-2.29]
TECH (-8)	-0.1017*** [-4.37]	0.0538 [1.38]	-0.0512*** [-4.97]	-0.0101*** [-3.67]
INTRST (-1)	0.5334*** [6.24]	-0.0557 [-0.39]	-0.1142*** [-3.02]	0.9831*** [97.45]
INTRST (-2)	-0.9898*** [-8.31]	0.2460 [1.23]	0.2139*** [4.06]	-0.0221* [-1.57]
INTRST (-3)	0.8324*** [6.97]	0.2223 [1.11]	0.2143*** [4.06]	-0.0064 [-0.46]
INTRST (-4)	-0.0418 [-0.35]	-0.1827 [-0.91]	-0.2599*** [-4.91]	0.0476*** [3.37]

Regressor	WTI	REENRGY	TECH	INTRST
INTRST (-5)	1.1726***	-0.0362	0.2546***	-0.0354**
	[9.77]	[-0.18]	[4.79]	[-2.50]
INTRST (-6)	-0.8707***	-0.3257	-0.1234**	0.0105
	[-7.20]	[-1.61]	[-2.31]	[0.74]
INTRST (-7)	-0.9338***	-0.0016	-0.6128***	-0.0007
	[-7.71]	[-0.01]	[-11.43]	[-0.05]
INTRST (-8)	0.2665***	0.0392	0.3736***	-0.0299***
	[3.02]	[0.27]	[9.58]	[-2.88]
C	0.1432	0.4368**	0.2490***	0.2445***
	[1.10]	[2.00]	[4.31]	[15.86]

Notes

- Stars indicate significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.
- t-statistics are shown in brackets [ ].

Table 6 furnishes the model fitting and diagnostic statistics of the VAR model. It shows the model is statistically robust with strong explanatory power (R-squared), minimal residual autocorrelation (DW statistic), and well-balanced model selection criteria (AIC and SC). This confirms that the model is suitable for further analysis, including impulse response functions (IRF) and the examination of forecast error dynamics among variables.

Table 6. Model Fitting and Diagnostic Statistics

Dependent Variable	R-Squared	Adj. R-Squared	AIC	SC	F-Statistic	Durbin-Watson
WTI	0.6893	0.6725	-3.725	-3.489	15.72	1.987
REENRGY	0.5721	0.5489	-3.512	-3.328	12.45	1.902
TECH	0.6127	0.5942	-3.601	-3.412	14.21	1.956
INTRST	0.4829	0.4513	-3.289	-3.112	9.87	2.034

The fig 1 shows impulse response functions (IRFs) that demonstrate how crude oil prices (WTI), renewable energy stocks (REENRGY), the technology index (TECH), and interest rates (INTRST) interact over time. For clarity, the horizontal axis reflects the weeks, and the vertical axis shows the percentage response, with shaded areas indicating 95% confidence intervals.

The analysis reveals that a positive shock to oil prices (WTI) leads to a short-term decline in renewable energy stocks, a response that is statistically significant but diminishes gradually over time. This pattern supports the substitution effect, where rising fossil fuel costs initially dampen clean energy valuations, a result in line with the evidence presented by Sadorsky [15] and Managi and Okimoto [14].

In contrast, shocks to the technology index (TECH) generate a strong and persistent boost in renewable energy stocks. This underscores the critical role of technological progress in strengthening the sector's resilience and advancing the clean energy transition, consistent with the findings of Ahmad and Rais [22].

Interest rate shocks (INTRST) show a different dynamic. An unexpected rise in interest rates reduces renewable energy stock performance, reflecting the higher financing costs and reduced availability of capital for green projects. This mirrors the conclusions of Apergis and Payne [19], who highlighted the constraints imposed by tighter monetary conditions on renewable investment.

Renewable energy shocks themselves display lasting effects, pointing to the importance of sector-specific dynamics and investor sentiment in shaping market behavior. Taken together, the IRFs suggest that India's renewable energy market is highly sensitive to oil price movements, innovation-driven growth, and monetary policy shifts. These results are consistent with broader evidence on energy–finance linkages [8,23], and they highlight the interplay of global and domestic forces in shaping the country's clean energy trajectory.

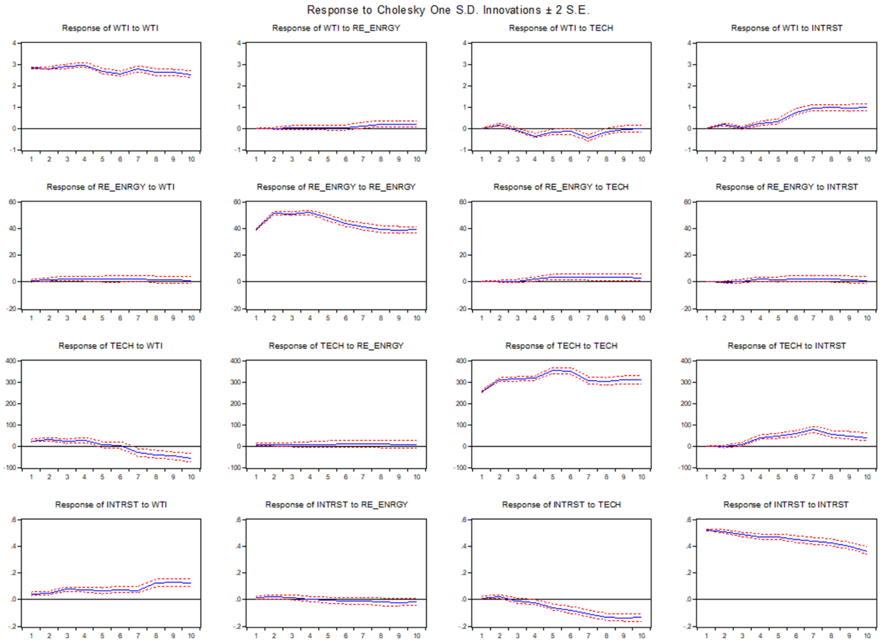

Fig. 1. Impulse Response Analysis

5. Conclusion and Policy Implications

5.1 Key Findings

This study examined the dynamic linkages between crude oil prices and renewable energy stock prices in India using a VAR framework and weekly data from 2018 to 2024. The analysis results highlight that oil price shocks are a key driver of renewable energy stock prices in the short run. Initial increases in oil prices raise renewable stock prices through substitution effects, but this impact is short-lived and reverses at medium-term lags before stabilising at longer horizons. In contrast, renewable shocks themselves show strong persistence, reinforcing the momentum within clean energy markets. Technology and interest rates were incorporated as control variables to capture additional channels of influence. The technology index exerts a strong and persistent positive effect on renewable stock prices, underscoring the role of innovation in sustaining the sector. Interest rates, by contrast, have a short-term dampening effect on both renewable and technology stocks, reflecting financing constraints, though these effects weaken as markets adjust.

5.2 Policy Implications

The results indicate that India's renewable energy markets are vulnerable to oil price volatility, underscoring the importance of instruments such as long-term power purchase agreements and targeted subsidies to shield clean energy firms from fossil fuel shocks [5,14]. At the same time, the persistent influence of technology underscores the importance of policies that encourage innovation, R&D investment, and adoption of new technologies [6,22]. Finally, the negative short-run impact of higher interest rates highlights the importance of green financing instruments—such as concessional loans, tax incentives for green bonds, and risk-sharing mechanisms—to reduce borrowing costs and strengthen capital flows [19].

5.3 Contributions and Future Research

By focusing on the oil–renewable energy stock price nexus while controlling for technology and interest rates, this study contributes to the sustainable finance literature in emerging economies. Unlike earlier studies that rely on lower-frequency data or focus on advanced economies, the present analysis uses high-frequency weekly data from India, providing timely insights during a period marked by COVID-19 and heightened oil market volatility. Future work could extend the framework by including electric vehicle stocks, carbon markets, or cross-country comparisons to capture broader sustainability dynamics.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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