“Asymmetric transmission of AI and renewable energy equity shocks to U.S. oil sector performance: A regime-dependent analysis for sustainable investment”

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ASYMMETRIC TRANSMISSION OF AI AND RENEWABLE ENERGY EQUITY SHOCKS TO U.S. OIL SECTOR PERFORMANCE: A REGIME-DEPENDENT ANALYSIS FOR SUSTAINABLE INVESTMENT

Abstract

This study empirically examines the dynamic and regime-dependent asymmetric effects of Artificial Intelligence (AI) and Renewable Energy (RE) equity returns on the performance of the U.S. oil sector. Utilizing daily closing prices from December 1, 2017 to October 31, 2025, we employ regime-dependent Vector Autoregression (VAR) models, supplemented by an illustrative Bayesian Time-Varying Parameter (TVP) VAR, to capture heterogeneous transmission mechanisms across bullish and bearish market regimes. The empirical findings show that the individual lagged effects of RE returns on oil returns emerge earlier during bearish markets – a pattern consistent with loss aversion and defensive sectoral rebalancing – whereas the cumulative contribution of RE shocks to oil return variation is larger during bullish phases. In contrast, the relationship between AI and oil shifts direction depending on the market: it is driven by growth when markets are up. Still, it acts as a direct risk transmitter during downturns. Notably, AI and oil equities co-move positively in both regimes, suggesting that their potential diversification benefits as hedges against one another may be limited, although hedge effectiveness is not formally tested here. Collectively, our results underscore that effective investment strategies and policy interventions must be explicitly conditioned on the prevailing market state. Future research avenues are suggested, including subsector-specific analysis and the use of direct technological adoption metrics, such as patent data.

Keywords AI, renewables, oil, US stocks, asymmetry, Bayesian-TVP-VAR, portfolio hedge

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INTRODUCTION

The return interdependence among oil, clean energy, and technology stocks has become a key focus area in energy finance (Ahmad, 2017). Empirical studies provide strong evidence of significant linkages; most document a positive relationship between oil and clean energy, with higher oil prices often making clean energy stocks more attractive to investors. Furthermore, clean energy and technology stocks display a strong interdependence that often exceeds their linkage with oil prices, as they act as both suppliers and strategic partners (Ferrer et al., 2018; Shahbaz et al., 2021). A substantial body of literature continues to document significant spillovers from oil to renewables (Ahmad, 2017; Ansaram & Petitjean, 2024). These effects are notably asymmetric, meaning that oil price increases exert a different magnitude or direction of impact than price declines, particularly during high-volatility periods (Zhang et al., 2023).

Previous research has frequently utilized quantile regression models to examine the impact of AI and RE shocks on oil stocks across different market quantiles (Sen & Chakrabarti, 2024). While the Q-ARDL approach is useful for identifying impacts under extreme bearish or bullish conditions, it may not fully capture the continuous, time-evolving nature of these relationships across the entire energy system. To address the identified research gaps, especially the need for disaggregated analysis and a more robust understanding of temporal shifts, this study moves beyond static quantile models. Instead, we employ an asymmetric Vector Autoregression (VAR) and Time-Varying Parameter VAR (TVP-VAR) framework. This approach allows us to first investigate how AI and RE shocks exert asymmetric effects on oil stocks and how these effects evolve over time, rather than just across quantiles. Second, the magnitude and significance of these impacts during periods of market exuberance versus stress, capturing structural breaks in the coefficients. Finally, helps decide which force – AI-driven innovation or RE expansion – dominates the oil equity narrative under both bullish and bearish market conditions.

1. LITERATURE REVIEW

The global energy economy is undergoing a profound and complex structural change driven simultaneously by innovation and sustainability (Hossain et al., 2024). Traditional oil firms face intense competition from new market entrants as renewed climate commitments, coupled with the Paris Agreement and the decreasing cost of renewable energy (RE) sources, disrupt established markets. For instance, solar PV and onshore wind have seen cost reductions of 85% and 56%, respectively, over the last decade (Zahid et al., 2025). At the same time, the adoption of Artificial Intelligence (AI) as an "all-purpose technology" has begun improving energy value chains across the board. AI applications now enhance the precision of hydrocarbon exploration results by 20–30%, facilitate predictive maintenance in refineries, and optimize real-time drilling operations, thereby reshaping productivity paradigms in the oil and gas sector (Chen et al., 2025). Paradoxically, these same AI capabilities stimulate innovative shifts in renewable energy through faster-than-real-time demand forecasting algorithms, grid management breakthroughs, and materials science innovations (Aslam et al., 2025; Yousaf et al., 2024).

AI and renewables are increasingly perceived as a unified "future-oriented" sector, emerging as a distinct investment class that attracts capital inflow from innovation-driven ESG and technology-driven portfolios (Ahmad, 2017; Ansaram & Petitjean, 2024; Raggad & Bouri, 2025). The nexus between these sectors reflects both "competitive substitution and complementary integration", leading to dynamic cross-market spillovers driven by investor sentiment, technological advancement, and macroeconomic shocks (Zhang et al., 2023). As the global economy advances toward a sustainable, technology-driven future, the linkage between energy and the technology sector is becoming more noticeable (Ma et al., 2025). These segments, though distinct, are interconnected through financial linkages, economic fundamentals, and technological spillovers (Ghaemi Asl et al., 2024).

AI and big data reinforce this relationship by optimizing renewable production, storage, and efficiency, even as their high energy demands create a dual challenge for the sector (Gubareva et al., 2025; Urom et al., 2024). While some evidence suggests a gradual "decoupling" between clean energy and crude oil markets – implying that sector-specific fundamentals like technological innovation and policy incentives are beginning to drive the performance of renewables (Ghaemi Asl et al., 2024a; Pham & Nguyen, 2021) – a substantial body of literature continues to document significant spillovers from oil to renewables (Ahmad, 2017; Ansaram & Petitjean, 2024). Rising oil prices may boost renewable equity valuations by enhancing their relative competitiveness, whereas falling oil prices can dampen investor sentiment by reducing the immediate economic rationale for alternative energy adoption.

Linkages within the AI-RE-oil nexus intensify during extreme market conditions, such as the 2008 financial crisis, the COVID-19 pandemic, or the Russia-Ukraine war. During these periods, systemic shocks amplify risk transmission across fossil fuel and renewable markets, with

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tail-risk spillovers proving more dominant than median effects (Benlagha et al., 2022; Demiralay et al., 2021; Ghaemi Asl et al., 2024). Uncertainty, whether economic, financial, or geopolitical, plays a critical role in shaping these dynamics, often amplifying volatility and altering interdependencies (Benlagha et al., 2022). Different types of uncertainty have heterogeneous impacts (Nie et al., 2022). For instance, financial uncertainty, proxied by indices such as the VIX, consistently heightens cross-market connectedness by raising correlations between energy, technology, and general stock markets (Reboredo & Uddin, 2016). During the COVID-19 pandemic, AI stocks acted as "net transmitters of risk", with their interdependence with energy markets deepening as AI adoption accelerated (Ghaemi Asl et al., 2024b). Conversely, traditional safe-haven assets such as government bonds, the US dollar, and gold often absorbed these spillovers, functioning as buffers (Gubareva et al., 2025). This highlights that technology and AI sectors emerge as consistent net transmitters of shocks during systemic stress, while traditional commodities like crude oil often function as net receivers.

Despite the growing body of research, three persistent gaps remain. First is the disaggregation deficit. Much of the literature treats clean energy firms as homogeneous units, ignoring research documenting asymmetric reactions among subsectors such as wind, solar, and biofuels to identical oil shocks (Zhang et al., 2023; Reboredo, 2018; Reboredo & Ugolini, 2015). Furthermore, AI has a divergent impact: while machine learning may temporarily elevate fossil fuel profitability in extraction (Wang et al., 2025), AI innovations in battery storage may permanently diminish oil's supremacy in transportation (Rajaperumal & Columbus, 2025). Second, the temporal dynamics of these relationships are often overlooked. Renewable stocks are subject to oil price shifts, but Climate Policy Uncertainty (CPU) tends to have a longer-term impact on valuations (Özdurak, 2021; Borozan & Pirgaip, 2024). Previous models have yet to fully integrate daily oil price data with monthly CPU indices while accounting for the influence of AI. Third, there is an absence of empirical evidence for the 'theoretical switch' between oil and renewable prices. While negative oil supply shocks often encourage investment in alternative energy, oil-specific demand shocks can suppress renewable returns as capital shifts back toward fossil-fuel infrastructure (Ozkan et al., 2023). Additionally, AI's deflationary impact on the renewables industry could undermine oil's competitiveness in ways not yet considered in prior studies (Li et al., 2025).

Hence, this study is devoted to empirically examining the dynamic and regime-dependent asymmetric effects of Artificial Intelligence (AI) and Renewable Energy (RE) equity returns on the performance of the U.S. oil sector.

2. METHOD

2.1. Data

This study employs daily return series derived from three prominent indices to analyze short- to medium-term market dynamics and gauge investor sentiment. The indices are the S&P 500 Energy Index (Oil), the FR Global Renewable Energy Index (Renewable Energy), and the NASDAQ CTA US AI & Robotics NTR Index (AI). The dataset covers the timeframe from December 1, 2017 to October 31, 2025, a period characterized by increased technology adoption, implementation of energy transition policies, and notable market fluctuations, including those caused by the COVID-19 pandemic. Data were sourced from Bloomberg Terminal, ensuring high-frequency information with institutional-grade reliability.

To align the analysis with U.S. market activity, all series are synchronized to U.S. trading days. For the construction of the return series, daily closing prices are first converted into continuously compounded returns, calculated as the logarithmic difference of successive closing prices:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right). \quad (1)$$

This transformation ensures stationarity and mitigates the scale effects inherent in price levels. Returns are expressed in decimal (unscaled) log-return units throughout, so that the descriptive statistics in Table 1 and all VAR estimates are reported on the same scale.

Prior to return calculation, the original price series are pre-processed to account for non-trading days. Any missing values due to holidays or asynchronous trading sessions are treated using linear interpolation or, where appropriate, by carrying forward the most recently available closing price. After the return series are generated, no further interpolation is applied, thereby preserving the integrity of the return-generating process. This methodological approach ensures that all empirical analyses – including causality analysis, correlation dynamics, and impulse-response functions – are based on stationary and statistically consistent inputs, free from spurious trends often present in raw price data.

2.2. Model

The study uses three VAR frameworks to analyze the effects of RE and AI stock returns on oil return performance in the US. The first framework establishes a baseline by estimating the relationship under general conditions without partitioning the data into regimes. To proceed to the next two frameworks, we follow a two-step procedure: first, we apply a non-parametric sign-based filter for data partitioning, and then we estimate VARs within each partition. This distinction makes it clear that the time-ordering assumption is maintained for the dynamic estimation. There are two separate models for this framework.

$$O_t = \alpha + \sum_{k=1}^{n} \beta_k O_{t-k} + \sum_{k=1}^{n} \lambda_k X_{t-k} + \varepsilon_t, \quad (2)$$

where O_t – Oil returns at time t. X_{t-k} – Lagged returns of the explanatory variable, which is either Renewable Energy (RE) or Artificial Intelligence (AI), α – constant term, and β_k, λ_k – coefficients for the lagged oil and explanatory variables, respectively

The second framework partitions the model based on the market state of renewable energy to uncover asymmetric effects.

$$O_t = \alpha^{(\delta)} + \sum_{k=1}^{n} \beta_k^{(\delta)} O_{t-k} + \sum_{k=1}^{n} \lambda_k^{(\delta)} RE_{t-k} + \varepsilon_t, \quad (3)$$

where (δ) represents the regime, where $\delta \in$ {Bullish (RE positive), Bearish (RE negative)}.

The third specification similarly conditions the analysis on the market state of the AI sector.

$$O_t = \alpha^{(\delta)} + \sum_{k=1}^{n} \beta_k^{(\delta)} O_{t-k} + \sum_{k=1}^{n} \lambda_k^{(\delta)} AI_{t-k} + \varepsilon_t, \quad (4)$$

where (δ) represents the regime, where $\delta \in$ {Bullish (AI positive), Bearish (AI negative)}.

The regime is determined by the sign of the returns of the explanatory variable (RE > 0 or AI > 0 for bullish; or RE < 0 or AI < 0 for bearish), evaluated on the observation date t of the dependent variable.

Importantly, the sign filter is applied to the estimation sample and not to the time series themselves, so that the temporal structure of the original data is preserved. All lagged regressors, O_{t-k} and X_{t-k}, are constructed from the full, contiguous series of U.S. trading days before partitioning; the filter only determines which observation dates t enter each regime-specific equation. Consequently, a lag of order k always refers to the observation k trading days before t, irrespective of the regime prevailing on those earlier days. (In EViews, which was used for estimation, lagged values in a sample restricted by a logical condition are taken from the preceding workfile observations rather than from the preceding observations within the restricted sample.) The bullish and bearish equations are therefore equivalent to a single threshold-type equation, with a zero threshold, in which every coefficient is interacted with the regime indicators $I(X(t) > 0)$ and $I(X(t) < 0)$:

$$O_t = \Sigma_\delta I_t^{(\delta)} \cdot \begin{bmatrix} \alpha^{(\delta)} + \Sigma_k \beta_k^{(\delta)} \cdot O_{t-k} \\ + \Sigma_k \lambda_k^{(\delta)} \cdot X_{t-k} \end{bmatrix} + \varepsilon_t. \quad (5)$$

This is an established regime-dependent specification that keeps the original time ordering intact. Because the regime may change from one day to the next, the regime-specific impulse responses and variance decompositions are interpreted as conditional responses that would hold if the prevailing regime persisted over the forecast horizon. Accordingly, statements about the number of days required for propagation refer to the lag order of the statistically significant coef-

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ficients, not to a full regime-switching propagation path; a Markov-switching or threshold VAR with endogenous regime transitions is left for future research.

The adoption of a sign-filtered subsample VAR approach is formally justified by the inherent regime-dependent nature of the transmission mechanisms between AI/renewable energy equity shocks and U.S. oil sector performance. A growing body of evidence demonstrates that the volatility links and spillover effects between oil and renewable energy markets are intrinsically regime-dependent, with high-volatility states amplifying shock transmission while low-volatility regimes exhibit muted or stabilizing effects. Moreover, oil price shocks are widely documented to exert asymmetric and state-contingent impacts on financial and macroeconomic variables, where the magnitude and persistence of responses vary systematically across market regimes. The sign-filtered subsample VAR directly addresses this nonlinearity by partitioning the sample according to empirically identified regimes – distinguished by the sign of the explanatory variable's returns – and estimating regime-specific VAR systems that retain a recursive identification of shocks within each regime. This approach circumvents the infeasibility of deriving closed-form impulse responses in fully specified nonlinear VAR models with endogenous regime switching and sign restrictions, while remaining more transparent and computationally tractable than fully parametric alternatives such as Markov-switching or smooth transition VARs. Consequently, the sign-filtered subsample VAR provides a rigorous and empirically grounded framework for recovering regime-dependent impulse responses without imposing restrictive parametric assumptions on the regime-switching process itself. However, it is very important to note that our sign-based subsampling is not intended as a standalone classification algorithm but as a robust non-parametric sieve to isolate directional asymmetries in shock transmission. This approach effectively circumvents the distributional assumptions of traditional threshold models, ensuring that our identified 'bullish' and 'bearish' states are purely data-driven reflections of the sign of observed sector returns, rather than arbitrary percentile splits.

2.3. Bayesian TVP-VAR framework

A Bayesian TVP-VAR is an extension of the models described earlier. While the specified models use partitioned regimes to capture asymmetric transmission and structural shifts, a TVP-VAR allows these relationships to evolve continuously over every time period. This captures the state-contingent connectedness of the market without requiring us to pre-define specific regimes. A TVP-VAR model with a lag length of order p is expressed as:

$$y_t = \alpha + A_1 y_{t-1} + \ldots + A_p y_{t-p} + \varepsilon_t, \quad (6)$$

where y_t is the vector of log returns of oil stocks, α is the intercept vector, $A_{1\ldots}$. A_p, are the coefficient matrices and ε_t is the error vector. The components are independent and identically distributed.

Let β_t = vector (a, A_1, ⋯, Ap) and $x_t = I \otimes$ (1, y_{t-1}, ⋯, y_{t-p}). Let us assume that the coefficients β_t follow a random walk process:

$$y_t = \beta_t x_t + \varepsilon_t, \quad \beta_t = \beta_{t-1} + \delta_t, \quad (7)$$

where δ_t is a (p + 1) – dimensional vector of innovations in the coefficients, indicating the state innovation or transition noise in the random walk model for the time-varying coefficients.

3. RESULTS

3.1. Summary statistics

Table 1 documents the statistical moments of the stock returns considered for this study. The range of the distribution is maximum for Oil stock returns (Oil), whereas the variability (relative to the mean) is higher for RE and lower for AI. No extreme skewness is observed in any of the return variables, with values close to zero for the RE sector. All the variables are leptokurtic, as their kurtosis coefficients are significantly higher than 3, indicating that extreme events (large, unexpected gains or losses) occur more frequently than a standard bell curve (Gaussian distribution) would predict. The occurrence of such events is more pronounced in oil sector stocks.

Table 1. Descriptive statistics

Statistic	Oil	RE	AI
Mean	0.00051	0.00048	0.00037
Minimum	–0.29581	–0.11422	–0.09949
Maximum	0.16843	0.12089	0.09528
Median	0.00100	0.00055	0.00091
SD	0.02385	0.02127	0.01376
Skewness	–0.37279	0.12942	–0.33817
Kurtosis	14.38316	6.84765	8.41692

3.2. Correlation results

The correlation results in Table 2 reveal positive relationships among the variables. Oil sector stock returns show a moderately high positive correlation with AI (r = 0.395) and RE (r = 0.337), while AI and RE are strongly correlated (r = 0.643). The positive direction of the Oil-RE and Oil-AI relationships suggests that, in this context, higher AI and RE sector stock returns are associated with increased, rather than decreased, Oil sector performance, warranting further examination of underlying drivers. Such a relationship could also be inferred from Figure 1.

Table 2. Correlation between Oil, RE and AI sectors

Variable	Oil	RE	AI
Oil	1.000	0.337	0.395
RE	0.337	1.000	0.643
AI	0.395	0.643	1.000

3.3. Unit root tests

Results from Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests (Table 3) indicate that all return variables are stationary in levels [I (0)]. This integration underlines the appropriateness of the VAR framework that considers variables integrated at I (0) only.

Table 3. Unit root test results

Variable	ADF Test		PP Test	
	Level	First Difference	Level	First Difference
Oil	–13.3949	–17.1512	–41.4753	–272.4548
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
RE	–12.6635	–20.6629	–39.0591	–625.1792
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
AI	–12.9992	–20.5032	–39.0409	–234.0984
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***

Note: *** denotes significance at the 1% level.

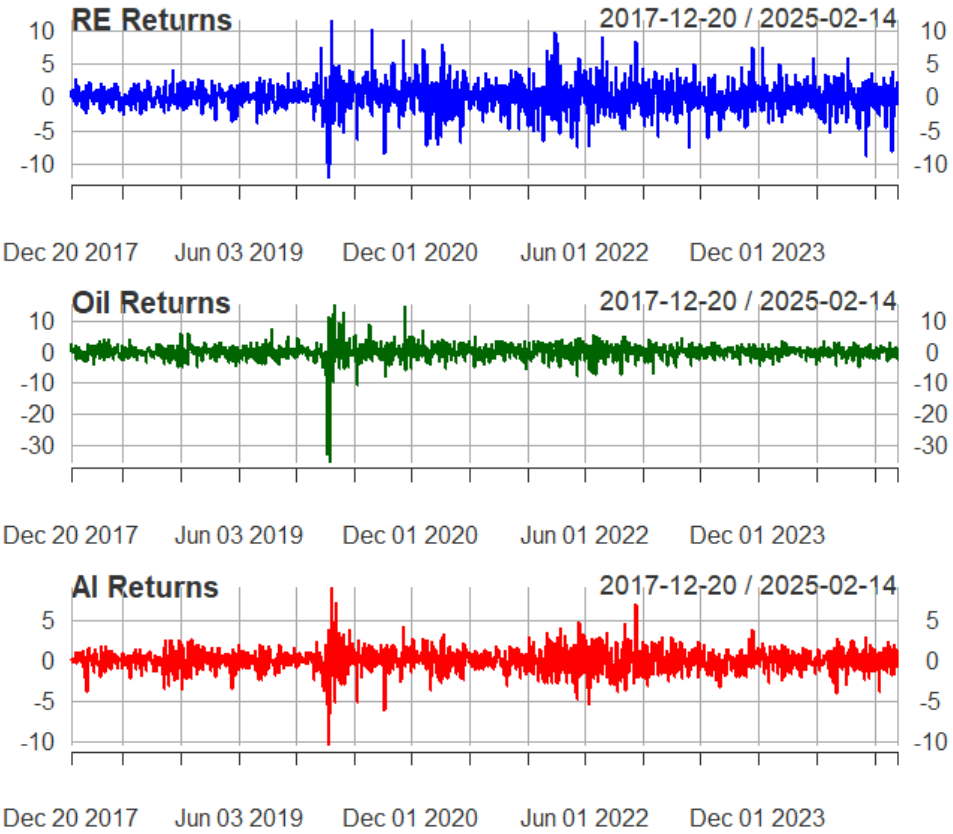


Figure 1. Oil, RE, and AI stock returns

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3.4. Lag selection

Our lag selection followed the standard approach of estimating each regime-specific VAR with a common maximum lag order, and allowing the AIC and BIC to determine the optimal lag for each subsample. The lag selection analysis reveals that optimal lag lengths vary across market regimes and variable pairs. In overall and bullish conditions, longer lags (4 or 5) are consistently preferred, suggesting more persistent dynamic linkages. Bearish regimes exhibit more heterogeneity, with

Table 4. Lag selection criteria

Lag	LogL	LR	FPE	AIC	SC
Oil to RE: Overall market conditions					
0	15237.1	NA	1.8E–10	–16.76029	–16.75423*
1	15246.29	18.35	1.8E–10	–16.76431	–16.74783
2	15248.77	4.93224	1.8E–10	–16.76432	–16.73404
3	15251.4	5.25038	1.8E–10	–16.76482	–16.72042
4	15257.34	11.81024	1.79e–10*	–16.76495*	–16.71044
5	15259.18	3.658424	1.8E–10	–16.76257	–16.69595
6	15264.15	9.875021	1.8E–10	–16.76364	–16.6849
Oil to AI: Overall market conditions					
0	2206.823	NA	0.000306	–2.417569	–2.411528
1	2223.414	33.12809	0.000301	–2.431375	–2.413254
2	2238.511	30.11056	0.000298	–2.443542	–2.413341*
3	2250.253	23.39518	0.000295	–2.452032	–2.40975
4	2255.513	10.46655*	0.000295*	–2.453413*	–2.39905
Oil to RE: Bullish market conditions					
0	8069.602	NA	1.23E–10	–17.14687	–17.13657
1	8117.606	95.70119	1.12E–10	–17.2404	–17.20949
2	8128.247	21.16829	1.1E–10	–17.25451	–17.203
3	8157.87	58.80499	1.04E–10	–17.30897	–17.23686
4	8172.894	29.76073	1.02E–10	–17.35240*	–17.23968*
5	8182.669	19.32129	1.01E–10	–17.34467	–17.23135
Oil to AI: Bullish market conditions					
0	9010.621	NA	1.76E–11	–19.08606	–19.07578
1	9062.047	102.5264	1.59E–11	–19.18654	–19.15571
2	9075.414	26.59242	1.56E–11	–19.20639	–19.15501
3	9114.575	77.73998	1.45E–11	–19.28088	–19.20895
4	9128.609	27.80068	1.42E–11	–19.30214	–19.20966*
5	9136.561	15.71931*	1.41e–11*	–19.31051*	–19.19748
Oil to RE: Bearish market conditions					
0	7460.703	NA	6.93E–11	–17.71664	–17.70539
1	7484.729	47.87901	6.61E–11	–17.7642	–17.73045*
2	7494.942	20.30592*	6.51E–11	–17.77896	–17.72272
3	7498.951	7.951408	6.51e–11*	–17.77898*	–17.70024
4	7500.5	3.064851	6.55E–11	–17.77316	–17.67192
5	7501.586	2.142751	6.6E–11	–17.76624	–17.6425
6	7503.849	4.45751	6.62E–11	–17.76211	–17.61588
7	7505.444	3.13199	6.66E–11	–17.7564	–17.58767
8	7508.03	5.068415	6.68E–11	–17.75304	–17.56181
Oil to AI: Bearish market conditions					
0	8055.118	NA	1.31E–11	–19.38175	–19.37039*
1	8063.007	15.72105	1.3E–11	–19.39111	–19.35701
2	8075.222	24.28304	1.27E–11	–19.41088	–19.35405
3	8078.868	7.229653	1.27E–11	–19.41003	–19.33047
4	8085.078	12.28707	1.27E–11	–19.41535	–19.31306
5	8086.931	3.65583	1.27e–11*	–19.41618*	–19.28516

Note: * indicates lag order selected by the criterion. Values transcribed from the source image.

lags ranging from 3 to 5 depending on the dependent variable. While the selected lags vary across regimes, this variation is a direct consequence of the data-generating process under different market conditions, which is precisely the rationale for conducting regime-dependent analysis.

3.5. Vector Autoregression Results

To empirically investigate the return dynamics among Oil, RE, and Oil sectors, we test the causal linkages between these return series. Specifically, we test whether RE and AI stock returns significantly explain US Oil stock returns. For this purpose, we employ a Vector Autoregression (VAR) framework, which is well-suited to analyzing bidirectional causality between time-series variables. As mentioned earlier, our empirical methodology utilizes three distinct VAR frameworks to investigate the complex, non-linear linkages between oil returns and the RE and AI sectors.

Table 5 presents the estimation results from two bivariate vector autoregressions (VARs) examining the predictive relationship between oil returns and two distinct explanatory variables – renewable energy (RE) and artificial intelligence (AI) indices – under overall market conditions. Each column corresponds to a separate VAR model: the first includes lags of oil and RE, the second includes lags of oil and AI. In the first model, none of the RE lag coefficients are statistically significant at conventional levels, indicating that past renewable energy index returns do not predict oil returns. Oil's own lags are mostly insignificant, with only the fourth lag showing marginal significance at the 10% level. The constant is essentially zero and not significant. The model explains very little variation in oil returns, with an adjusted R^2 of 0.0799.

In the second model, the constant is positive and highly significant (t = 4.94), implying a positive baseline drift in oil returns. All four oil lag coef-

Table 5. Oil responses to RE and AI: VAR results during overall market conditions

Dependent Variables	RE	AI
Constant	0.00001	1.47661***
	(0.00000)	(0.29899)
	[1.25268]	[4.93868]
$OilR_{t-1}$	0.00919	0.09754***
	(0.02462)	(0.02403)
	[0.37365]	[4.05932]
$OilR_{t-2}$	–0.00970	0.07560**
	(0.02463)	(0.03270)
	[–0.39455]	[2.31226]
$OilR_{t-3}$	0.00309	0.08811***
	(0.02463)	(0.02401)
	[0.12574]	[3.66933]
$OilR_{t-4}$	0.045816*	0.053175**
	(0.02463)	(0.02405)
	[1.86025]	[2.21090]
RE_{t-1}	–0.00629	–0.00546
	(0.01713)	(0.05163)
	[–0.36746]	[–0.10581]
RER_{t-2}	0.01414	0.04871
	(0.01719)	(0.05169)
	[0.82218]	[0.94230]
RER_{t-3}	–0.013875	0.077684
	(0.01719)	(0.05165)
	[–0.80735]	[1.50398]
RER_{t-4}	0.03082*	0.09354*
	(0.01712)	(0.05162)
	[1.80008]	[1.81276]
Adjusted R^2	0.0799	0.1418

Note: Standard errors are in parentheses, and t-statistics in brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. In the AI column, the rows labelled RE refer to the corresponding lags of AI returns.

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ficients are positive and statistically significant, pointing to moderate persistence in oil returns. AI lag coefficients are positive at lags two to four (the first-lag coefficient is negative and negligible), and only the fourth lag is significant at the ten percent level. The model's explanatory power (adjusted R^2 = 0.1418) is slightly higher than the RE model but still not high.

During overall market conditions, oil returns exhibit weak predictability. Renewable energy returns have no discernible predictive content for oil prices. Artificial intelligence returns show a modest positive association, particularly at longer lags, but the evidence is not robust at standard significance levels. Both models account for only a small fraction of the variability in oil returns, suggesting that other factors not included in these bivariate VARs are the primary drivers of oil price movements.

We order AI and renewable energy equity returns first, followed by U.S. oil sector equity returns, in our Cholesky decomposition (Figure 2). This ordering is justified by the economic premise that AI and renewable energy sectors function as leading indicators of technological disruption, regulatory shifts, and long-term energy transition trends, conveying forward-looking information that is rapidly incorporated into broader equity markets. As such, innovations originating in these dynamic growth sectors are plausibly transmitted contemporaneously to the traditional oil sector, as investors reprice incumbent energy assets in response to emerging climate-tech and automation signals. Conversely, ordering oil equities last reflects the rationale that shocks specific to the oil sector – largely tied to legacy supply conditions, geopolitical events, or conventional inventory cycles – are less likely to instantaneously dictate the valuation of AI and renewable energy equities, given the latter's stronger emphasis on intangible capital, innovation potential, and partial decoupling from physical commodity dynamics. This recursive structure aligns directly with our research objective of tracing the transmission from technological and green equity shocks to oil sector performance, ensuring that the identified impulse responses are economically coherent and consistent with the directional causality implied by our empirical framework.

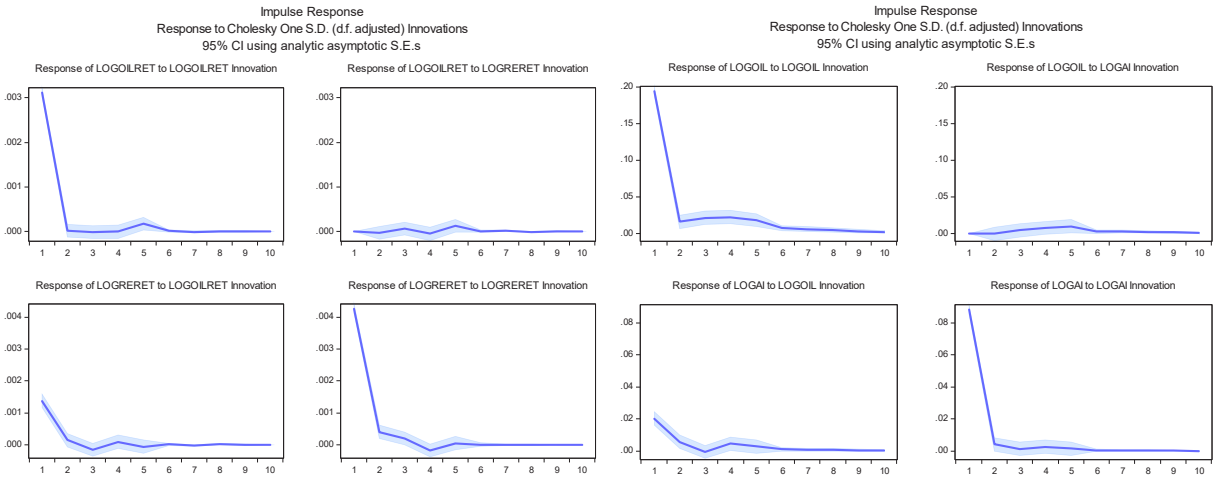
The sensitivity of the main conclusions to this identifying assumption is limited for two reasons. First, the VAR coefficients (Tables 5, 7 and 9), the Wald asymmetry tests (Table 11) and the Granger-causality tests (Table 12) are reduced-form results and are invariant to the ordering of the variables; only the impulse responses and variance decompositions depend on it. Second, in a bivariate VAR, the generalized impulse responses of Pesaran and Shin (1998) to a shock in RE or AI coincide exactly with the orthogonalized responses obtained when RE or AI is ordered first, so the oil responses shown in Figure 2 are unchanged under the generalized approach. Under the reverse ordering (oil first), the impact effect of AI/RE shocks on oil is restricted to zero, and the contemporaneous comovement is attributed to oil-specific shocks; this changes the allocation of the contemporaneous covariance but not the lagged predictive relationships on which our conclusions mainly rest.

Responses to Cholesky on SD Innovations in RE and Responses to Cholesky on SD Innovations in AI are shown in Figure 2.

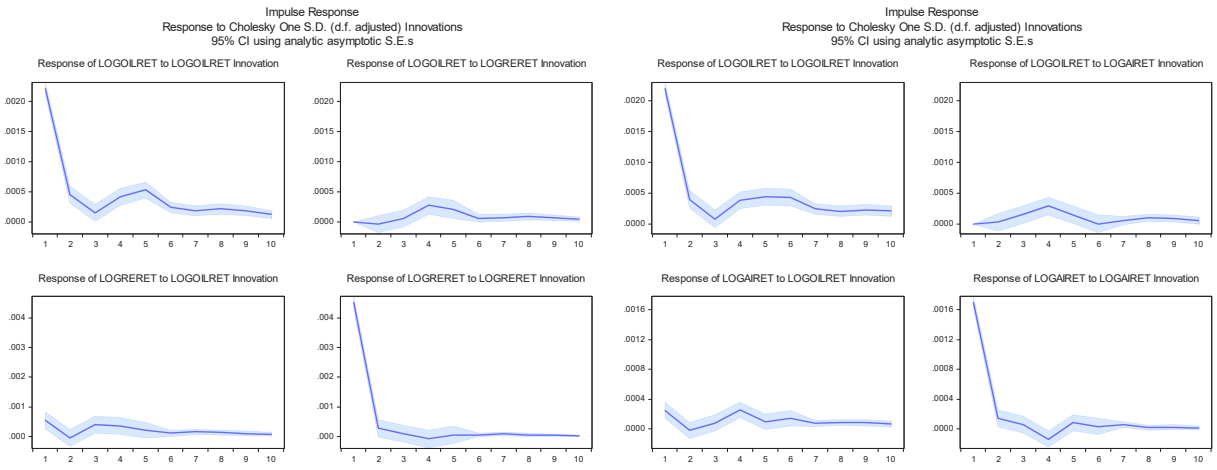
Table 6. Oil responses to RE and AI: Variance decomposition during overall market conditions

Period	OIL to RE		OIL to AI	
	OIL	RE	OIL	AI
1	100.0000	0.000000	100.0000	0.000000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
2	99.99256	0.007438	99.99939	0.000613
	(0.03313)	(0.00040)	(0.03289)	(0.00012)
3	99.95844	0.041562	99.95264	0.047356
	(0.06624)	(0.00095)	(0.06570)	(0.00101)
4	99.92843	0.071575	99.81433	0.185674
	(0.09934)	(0.00124)	(0.09863)	(0.00207)
5	99.75889	0.241105	99.58168	0.418325
	(0.13224)	(0.00228)	(0.13190)	(0.00326)
6	99.75835	0.241654	99.56683	0.433171
	(0.16528)	(0.00228)	(0.16577)	(0.00339)
7	99.75720	0.242802	99.55254	0.447455
	(0.19837)	(0.00230)	(0.19994)	(0.00351)
8	99.75648	0.243516	99.54204	0.457957
	(0.23147)	(0.00231)	(0.23434)	(0.00360)
9	99.75595	0.244055	99.53765	0.462346
	(0.26459)	(0.00232)	(0.26891)	(0.00365)
10	99.75594	0.244059	99.53632	0.463679
	(0.29773)	(0.00233)	(0.30358)	(0.00369)

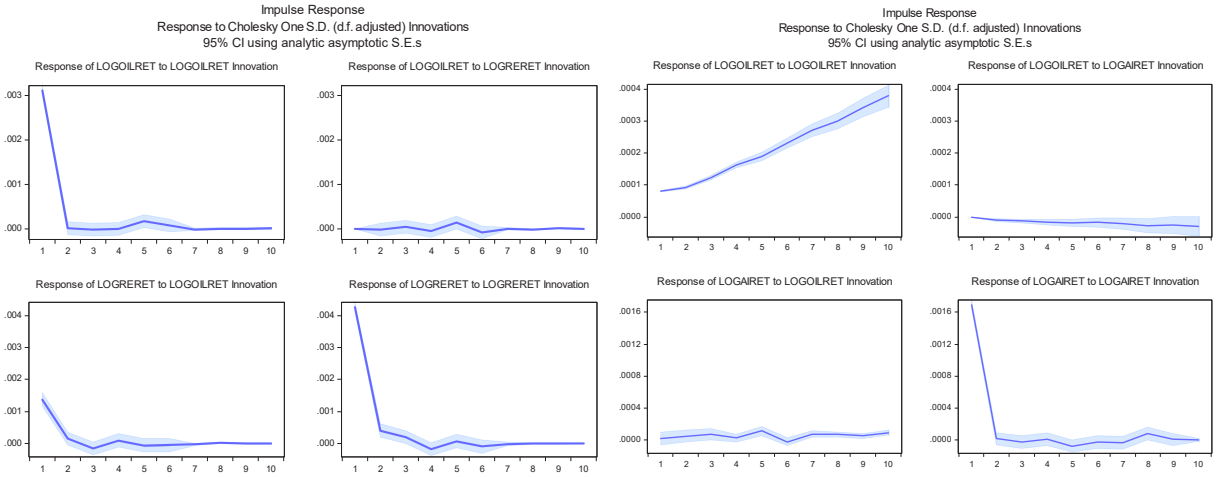
The variance decomposition presented in Table 6 and the Impulse Response Function in Figure 2



a) Overall market conditions



b) Bullish market conditions



c) Bearish market conditions

Figure 2. Impulse response functions

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provide a comparative assessment of spillover effects from renewable energy (RE) and artificial intelligence (AI) sectors to oil stock returns, revealing a clear and economically meaningful hierarchy of cross-market transmission. The left panel demonstrates that RE innovations account for a measurable, albeit modest, portion of oil price variation over the ten-period horizon. This pattern suggests a stable yet economically constrained transmission channel from traditional asset markets to commodity prices, consistent with gradual portfolio rebalancing effects and wealth-channel spillovers. Importantly, the RE-oil linkage exhibits near-complete stabilization by period six, with virtually no incremental contribution beyond this threshold, implying that the full transmission of RE disturbances to oil markets occurs within a relatively compressed window.

The right panel presents a strikingly different profile for AI-to-oil spillovers. While the initial impact at period two is an order of magnitude smaller than the corresponding RE effect, the AI contribution subsequently demonstrates substantially stronger accumulation dynamics. At period ten, the explanatory power of AI shocks reaches 0.46 percent, nearly double that of renewable energy shocks at 0.24 percent. The standard errors again confirm statistical significance across all horizons, with the AI estimates exhibiting precision comparable to that of the RE coefficients despite their smaller initial magnitudes. This crossover pattern – wherein a sector with negligible contemporaneous impact ultimately contributes more to forecast error variance – has important implications for understanding the evolving structure of cross-market interconnectedness. The findings suggest that while renewable energy has a marginally larger immediate influence on oil returns, the transmission of AI shocks exhibits greater persistence and cumulative force. This is consistent with the interpretation that AI represents a more slowly diffusing technological shock whose implications for energy demand, productivity, and industrial transformation are incorporated into oil prices with considerable lag but ultimately exert greater explanatory power. Collectively, these results demonstrate that the relative importance of competing spillover sources is horizon-dependent, and assessments of cross-market connectedness that focus exclusively on short-run dynamics would erroneously conclude that RE dominates AI, when in fact the reverse holds over longer horizons.

Table 7. Oil responses to RE: VAR results during Bullish vs Bearish market conditions

Variable	Bullish	Bearish
Constant	0.00086***	–0.00146***
	(0.00012)	(0.00012)
	[7.07678]	[–12.16667]
$OilR_{t-1}$	0.20848***	0.18124***
	(0.03241)	(0.03289)
	[6.43292]	[5.51087]
$OilR_{t-2}$	0.02253	–0.00484
	(0.03253)	(0.03314)
	[0.69294]	[–0.14606]
$OilR_{t-3}$	0.15879***	0.15168***
	(0.03265)	(0.03257)
	[4.86412]	[4.65715]
$OilR_{t-4}$	0.15989***	0.13244***
	(0.03226)	(0.03314)
	[4.95580]	[3.99662]
$OilR_{t-5}$	–	0.11926***
		(0.03278)
		[3.63856]
RER_{t-1}	–0.00766	0.01666
	(0.01593)	(0.04216)
	[–0.48087]	[0.39529]
RER_{t-2}	0.01580	0.08634**
	(0.01595)	(0.04226)
	[0.99074]	[2.04309]
RER_{t-3}	0.05774***	0.14604***
	(0.01589)	(0.04194)
	[3.63346]	[3.48177]
RER_{t-4}	0.03087*	0.041815
	(0.01597)	(0.04237)
	[1.93277]	[0.98691]
RER_{t-5}	–	–0.03192
		(0.04226)
		[–0.75522]
Adjusted R^2	0.1839	0.1972

Note: Standard errors are in parentheses, and t-statistics are in brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The VAR results presented in Table 7 offer compelling evidence of asymmetric transmission dynamics from the RE sector to oil stock returns conditional on bullish versus bearish market states. The model is partitioned into two distinct regimes – RE positive (bullish) and RE negative (bearish) – with the dependent variable being oil stock returns. Several notable patterns emerge from the coefficient estimates that speak to the

state-dependent nature of cross-market spillovers. The autoregressive structure of oil returns exhibits considerable stability across market regimes, with the first, third, fourth, and fifth lags exerting positive and statistically significant predictive power regardless of market condition.

The coefficients of primary interest – the lagged renewable energy return variables – reveal fundamentally asymmetric transmission mechanisms across market states. During bullish market conditions, renewable energy shocks exhibit a delayed positive effect on oil returns that becomes statistically significant only at the third lag. The fourth lag is marginally significant at conventional levels. This pattern indicates that during rising markets, the predictive effect of renewable energy returns on oil returns becomes statistically significant only at the third lag (i.e., three trading days before the observation date), consistent with gradual portfolio rebalancing, wealth-effect transmission, or delayed revisions in growth expectations. During bearish market conditions, however, the transmission profile is both quantitatively and qualitatively distinct. The second lag of negative RE shocks exerts a positive and statistically significant effect on oil returns. In contrast, the third lag coefficient is substantially larger than its bullish counterpart and highly significant. This pattern suggests that, during downturns, the first significant individual lag effect of RE returns emerges earlier – at lag two rather than lag three – and that the individual lag coefficients are larger than during expansions. This concerns the timing and size of individual coefficients; as shown in Table 8, it does not imply a larger cumulative contribution of RE shocks to oil return variation. The economic interpretation is highly relevant here. The positive coefficient on negative RE shocks indicates that declines in renewable energy returns are associated with increases in oil returns in subsequent periods. This counterintuitive sign pattern may reflect defensive sector rotation, in which capital flight from distressed oil markets is reallocated to RE equities as a perceived haven during bearish phases. This asymmetry in the timing of individual lag effects aligns with prospect theory and loss aversion frameworks, wherein negative shocks receive disproportionate weight in investor decision-making and cross-asset reallocation.

Table 8. Oil responses to RE: Variance decomposition during Bullish and Bearish market conditions

Period	Bullish		Bearish	
	OIL	RE	OIL	RE
1	100.0000	0.000000	100.0000	0.000000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
2	99.97629	0.023709	99.99417	0.005829
	(0.04411)	(0.00099)	(0.03314)	(0.00036)
3	99.90059	0.099408	99.96640	0.033598
	(0.09072)	(0.00186)	(0.06626)	(0.00086)
4	98.47031	1.529690	99.94171	0.058294
	(0.13558)	(0.00807)	(0.09938)	(0.00113)
5	97.77379	2.226206	99.75508	0.244924
	(0.17982)	(0.01068)	(0.13228)	(0.00230)
6	97.72139	2.278607	99.69967	0.300329
	(0.22716)	(0.01118)	(0.16528)	(0.00256)
7	97.65018	2.349820	99.69964	0.300356
	(0.27640)	(0.01177)	(0.19834)	(0.00256)
8	97.51963	2.480371	99.69838	0.301618
	(0.32683)	(0.01269)	(0.23144)	(0.00258)
9	97.45076	2.549244	99.69718	0.302822
	(0.37873)	(0.01345)	(0.26456)	(0.00260)
10	97.42326	2.576741	99.69708	0.302923
	(0.43209)	(0.01411)	(0.29769)	(0.00261)

The forecast error variance decomposition reveals striking asymmetries in the transmission of renewable-sector shocks to traditional oil stock prices across different market regimes (Table 8). During bullish market conditions, the contribution of RE innovations to oil price variation increases markedly and is economically meaningful over the forecast horizon. This monotonic upward trajectory suggests that during expansionary phases, return spillovers from renewable energy to the oil sector operate with measurable delay, propagating through the system gradually before stabilizing at non-trivial magnitudes. In stark contrast, variance decomposition under bearish market conditions shows that the renewable energy sector's influence on oil stocks is economically negligible throughout the entire ten-period horizon. This divergence provides compelling evidence of state-dependent transmission mechanisms, wherein renewable energy market disturbances transmit to oil sector returns during rising markets but remain largely compartmentalized during market downturns. The findings are consistent with asymmetric information diffusion, heightened investor attention during bullish phases, or differential responses of capital-constrained firms across business cycle conditions. Collectively,

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these results underscore the importance of conditioning cross-market spillover analyses on prevailing market states and suggest that failure to account for such regime-specific dynamics may substantially understate or mischaracterize the true interconnectedness of these energy sectors.

Read together with Table 7, these results distinguish the timing of individual lag effects from their cumulative economic importance. In the bearish regime, individual lagged RE coefficients become significant earlier, yet at horizon 10 RE shocks account for only about 0.30% of the forecast-error variance of oil returns, compared with about 2.58% in the bullish regime. The bearish asymmetry is therefore one of earlier timing, whereas the economically larger cumulative transmission of RE shocks to the oil sector occurs in bullish markets.

Table 9. Oil responses to AI: VAR Results during Bullish vs Bearish market conditions

Variable	Bullish	Bearish
Constant	0.00003	0.00000
	(0.00002)	(0.00002)
	[1.50000]	[0.58903]
$OilR_{t-1}$	1.05234***	1.127253***
	(0.02150)	(0.02227)
	[48.94558]	[50.62860]
$OilR_{t-2}$	0.18560***	0.23900***
	(0.03100)	(0.03221)
	[5.98710]	[7.42147]
$OilR_{t-3}$	0.07812***	0.04244
	(0.02950)	(0.02977)
	[2.64814]	[1.42583]
$OilR_{t-4}$	−0.21145***	−0.33318***
	(0.02280)	(0.02314)
	[−9.27412]	[−14.39830]
$OilR_{t-5}$	0.09876***	0.06524**
	(0.02580)	(0.02620)
	[3.82791]	[2.50943]
$OilR_{t-6}$	−0.05432**	−0.09388***
	(0.02390)	(0.02428)
	[−2.27280]	[−3.86698]
$OilR_{t-7}$	−0.14287***	−0.18321***
	(0.01580)	(0.01609)
	[−9.04241]	[−11.38372]
AIR_{t-1}	0.00389***	−0.00575***
	(0.00110)	(0.00113)
	[3.53636]	[−5.10618]
AIR_{t-2}	0.00152	−0.00089
	(0.00112)	(0.00113)
	[1.35714]	[−0.79417]
AIR_{t-3}	−0.00123	−0.00018
	(0.00113)	(0.00113)
	[−1.08850]	[−0.15752]
AIR_{t-4}	−0.00287***	0.00171
	(0.00111)	(0.00112)
	[−2.58559]	[1.52539]
AIR_{t-5}	0.00421***	0.00314***
	(0.00110)	(0.00112)
	[3.82727]	[2.79500]
AIR_{t-6}	0.00097	−0.00054
	(0.00112)	(0.00113)
	[0.86607]	[−0.47816]
AIR_{t-7}	−0.00178	−0.00205*
	(0.00112)	(0.00113)
	[−1.58929]	[−1.81846]
Adjusted R^2	0.3512	0.3992

Note: Standard errors are in parentheses, and t-statistics are in brackets. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The VAR results reported in Table 9 reveal a fundamental transformation in oil return dynamics conditional on AI market regimes. During AI Positive (bullish) conditions, oil returns exhibit moderate persistence consistent with prior specifications, with significant coefficients at different lags. During AI Negative (bearish) conditions, however, the oil return process undergoes a dramatic structural shift: the first-lag coefficient, already close to unity in the bullish regime, rises further, indicating near-random walk behavior characteristic of highly stressed markets. In contrast, the fourth lag exhibits sharp mean reversion. The adjusted R-squared is higher (0.3992 versus 0.3512), indicating that autoregressive dynamics explain substantially more of the oil variation during AI-negative phases, as external fundamental signals are discounted and internal price dynamics dominate.

The coefficients on lagged AI returns provide the most compelling evidence of state-contingent transmission and reveal a complete sign reversal in the AI-oil relationship across market states. During AI Positive regimes, the pattern mirrors conventional spillover specifications (significant positive coefficients at lags one and five, partly offset by a significant negative coefficient at lag four), indicating that positive AI innovations during bull markets generate delayed positive spillovers consistent with technological optimism translating into revised energy demand expectations.

During AI Negative regimes, however, the transmission mechanism is fundamentally inverted. This qualitative transformation – positive coefficients on positive shocks in bullish regimes versus negative coefficients on negative shocks in bearish regimes – demonstrates that linear, symmetric models of AI-oil interconnectedness are fundamentally mis-specified.

Table 10. Oil responses to AI: Variance decomposition during Bullish and Bearish market conditions

Period	Bullish		Bearish	
	OIL	AI	OIL	AI
1	100.0000	0.000000	100.0000	0.000000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)
2	99.98384	0.016162	99.36674	0.633256
	(0.04453)	(0.00082)	(0.01452)	(0.00248)
3	99.50714	0.492861	99.15716	0.842842
	(0.09089)	(0.00470)	(0.03285)	(0.00458)
4	97.92323	2.076767	99.06429	0.935707
	(0.13542)	(0.00993)	(0.05544)	(0.00674)
5	97.58553	2.414470	99.02645	0.973552
	(0.17995)	(0.01139)	(0.08478)	(0.00889)
6	97.66536	2.334644	99.18108	0.818925
	(0.22566)	(0.01152)	(0.11866)	(0.01045)
7	97.64138	2.358623	99.23817	0.761830
	(0.27343)	(0.01205)	(0.15699)	(0.01210)
8	97.49496	2.505039	99.21968	0.780315
	(0.32280)	(0.01309)	(0.20105)	(0.01390)
9	97.37777	2.622226	99.28157	0.718426
	(0.37337)	(0.01414)	(0.24962)	(0.01535)
10	97.35175	2.648250	99.31008	0.689919
	(0.42535)	(0.01496)	(0.30288)	(0.01683)

The variance decomposition of oil sector stock returns with respect to artificial intelligence sector shocks reveals starkly asymmetric spillover dynamics across bullish and bearish market regimes. During bullish market conditions, the contribution of AI innovations to oil price variation shows a substantial, economically meaningful accumulation over the forecast horizon (Table 10). This pattern suggests that during expansionary phases, innovations in the AI sector exert delayed but persistent spillover effects on oil markets, consistent with the gradual incorporation of technological shocks into energy price discovery and the increasing materiality of AI-related energy demand expectations. The bearish market regime presents a fundamentally different and theoretically intriguing transmission profile. While the initial impact of AI shocks on oil stocks appears marginally larger at early horizons, this effect subsequently fails to sustain momentum. The contribution peaks by period five before entering a sustained decline. This inverted U-shaped pattern, wherein explanatory power first increases modestly then gradually dissipates, stands in sharp contrast to the monotonic accumulation observed during bullish regimes. This divergence provides compelling evidence of regime-dependent transmission mechanisms that are not merely quantitative but also qualitative.

Table 11. Wald tests for regime-dependent coefficient asymmetry (βBear = βBull)

Dependent variable	Shock origin (restrictions tested)	Wald statistic	p-value [$\chi^2(q)$]
Oil Returns	Renewable Energy Returns (λ1 – λ4; q = 4)	14.202	0.007***
Oil Returns	AI Returns (λ1 – λ7; q = 7)	22.401	0.002***

Notes: H0: λk(Bear) = λk(Bull) for all lags k common to both regime-specific specifications; q = number of restrictions (degrees of freedom); V = V(Bull) + V(Bear). *** denotes significance at the one percent level.

The formal Wald coefficient-difference tests offer direct statistical evidence that the transmission of AI and renewable energy shocks to the U.S. oil sector is inherently asymmetric across market regimes (Table 11). Specifically, we test the null hypothesis that the estimated VAR coefficients in the bearish regime are jointly equal to those in the bullish regime, i.e., *H0*: $\boldsymbol{\beta}^{Bear} = \boldsymbol{\beta}^{Bull}$. The Wald statistics decisively reject this null across our key transmission channels, with particularly strong rejections for RE-to-oil returns and AI-to-oil returns, confirming that the magnitude and even the directional nature of spillovers differ significantly between expansionary and contractionary market states.

The test is constructed as follows. Let λ(Bull) and λ(Bear) denote the vectors of estimated coefficients on the lagged explanatory variable (RE or AI) in the oil-return equation of the bullish and bearish VARs, respectively. The restrictions tested are *H0:* λk(Bear) = λk(Bull) for k = 1, …, q, where q is the number of lags common to both regime-specific specifications. Where the selected lag orders differ between regimes, coefficients on lags that appear in only one specification (e.g., RE(t–5) in the bearish RE model) are excluded from the restriction

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set, so that only like-for-like coefficients are compared. Hence q = 4 for the RE model (lags 1-4) and q = 7 for the AI model (lags 1-7). Because the bullish and bearish subsamples contain non-overlapping observation dates, the two sets of estimates are treated as independent, and the covariance matrix of the coefficient difference is V = V(Bull) + V(Bear), where each term is the estimated coefficient covariance matrix of the corresponding regime-specific VAR. The Wald statistic,

$$W = \left[\lambda\left(Bear\right) - \lambda\left(Bull\right)\right]' V^{-1}\left[\lambda\left(Bear\right) - \lambda\left(Bull\right)\right], \quad (8)$$

is asymptotically $\chi^2(q)$ under *H0*. Restrictions, degrees of freedom, and p-values are reported in Table 11.

3.6. Granger causality

Table 12 reports the Granger causality test results between RE, AI, and Oil returns. The empirical results reveal a nuanced, state-dependent relationship between technological and energy-transition factors and oil stock valuations. In the full-sample analysis, we find that Artificial Intelligence (AI) factors Granger-cause oil stock prices at the 5% significance level ($p < 0.05$), suggesting that shocks to AI development and adoption have predictive power for movements in oil-related equities. Conversely, Renewable Energy (RE) factors do not exhibit a significant causal relationship with oil stock prices in the baseline model, implying that, over the entire sample period, renewable energy trends have not consistently preceded or predicted fluctuations in oil stock valuations.

However, this relationship is highly contingent on the prevailing market regime. In bullish market conditions, both RE and AI emerge as highly significant predictors of oil stock prices, indicating that during periods of broad market optimism, technological shocks in both the renewable and AI sectors strongly influence expectations for oil firms. This could reflect market sentiment that oil firms will either be disrupted by these technologies or successfully integrate them. Critically, during bearish market conditions, the causal influence diverges sharply: RE ceases to Granger-cause oil stock prices, while AI retains its strong predictive power with overwhelming significance ($p < 0.01$). This suggests that in downturns, AI's role as a driver of efficiency, demand destruction, or competitive advantage for oil firms remains a dominant pricing factor. In contrast, broader market dynamics overshadow the impact of renewable energy trends. These findings underscore that the financial materiality of AI for the oil sector is robust across market cycles. At the same time, the influence of renewables is context-dependent and most pronounced in bullish environments.

3.7. Bayesian time-varying parameter vector autoregression (TVP-VAR)

The Bayesian time-varying parameter vector autoregression (TVP-VAR) framework is particularly well-suited for this analysis as it allows parameters to evolve flexibly over time, capturing structural shifts in the oil-stock nexus that constant-parameter models would obscure. In this paper, however, the TVP-VAR plays a supplementary and illustrative role only; the main conclusions rest on the regime-dependent VAR estimates and the Granger-causality and Wald tests reported above. Figures 3-6 display the posterior medians of the time-varying VAR coefficients on the indicated lags (coefficient paths); they are not impulse response functions. Because posterior credible intervals are not reported, the figures are not used to infer statistical significance. To illustrate, Figures

Table 12. Granger causality results

Causality	Chi square	p-values
RE does not Granger-cause OIL stock prices	4.4912	0.3436
AI does not Granger-cause OIL stock prices	8.8586	0.0362**
RE does not Granger-cause OIL stock prices in a bullish market	19.6006	0.0011***
AI does not Granger-cause OIL stock prices in a bullish market	20.3181	0.0001***
RE does not Granger-cause OIL stock prices in a bearish market	5.5402	0.3536
AI does not Granger-cause OIL stock prices in a bearish market	43.5648	0.0000***

Note: *** – significance at the 1% level, and ** – significance at the 5% level.

3 and 4 present distinct transmission dynamics of oil price shocks to RE and AI stocks during the bullish period.

The time-varying coefficient paths for RE stocks (Figure 3) are close to zero at lag 1, whereas the posterior median coefficients at lags 2 and 3 are positive, rising later in the sample before fading, which is suggestive of oil price increases pushing portfolio switches towards clean energy sectors in risk-on regimes. However, a strikingly different relationship for AI stocks is captured in Figure 4, where the posterior median coefficients point to a faster and more enduring positive association with oil shocks across several lags. In line with the time-varying nature of the two sets of coefficients, these coefficient paths appeared to strengthen around the same time that the energy transition narrative matured. At the same time, AI-related capital expenditures ballooned, suggesting that sectoral exposures to macro-energy shocks were becoming increasingly differentiated by relative technological and thematic positioning amid market hyperactivity.

Next, the study estimates the dynamic impact of renewable energy (RE) and artificial intelligence (AI) stock returns on oil stock returns during bearish market conditions with a Bayesian Time-varying parameter Vector Autoregression (TVP-VAR) model. Figures 5 and 6 report the posterior medians of the time-varying coefficients estimated from the model (not impulse responses). The Bayesian framework with time-varying parameters permits the estimated coefficients to reflect the structural changes and adapt to different market regimes.

By dividing periods of market stress, the analysis concentrates on how these relationships deepen or change during downturns. Figure 5 incorporates five lags to capture the medium-term dynamics and persistence in the transmission from RE returns to oil prices, which may be particularly noticeable in bear markets due to flight-to-quality effects, shifts in investor sentiment, or changing macroeconomic connections. Figure 6 extends this analysis by including eight lags, thereby modeling the prolonged, compound adjustment process by which AI sector growth influences oil stock performance. This extensive lag structure is crucial for sectors like oil, where the impact of technological innovations – a key factor in long-

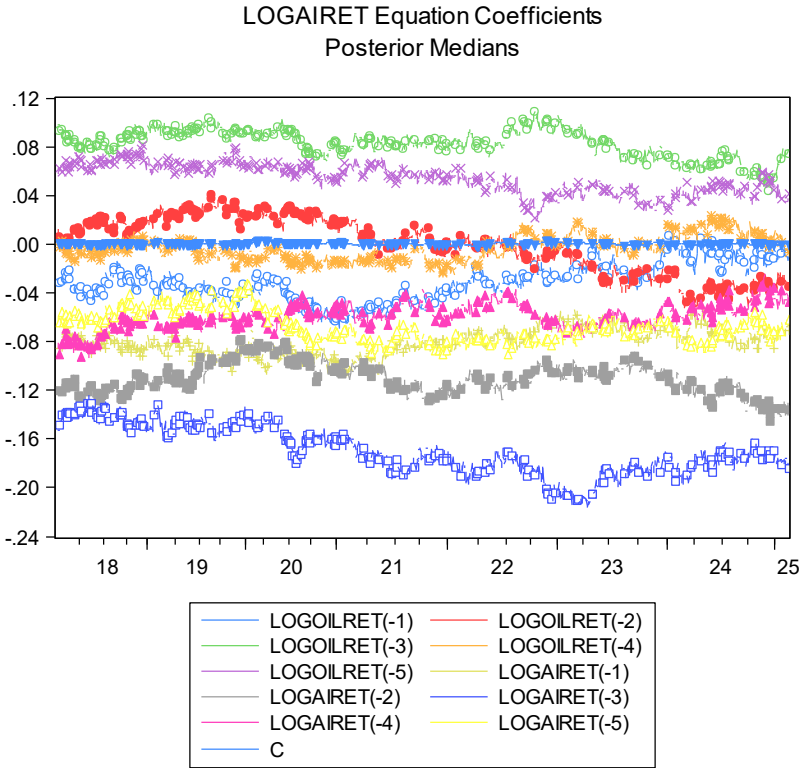


Figure 3. Oil to RE stock returns in Bullish markets: Bayesian TVP-VAR (posterior medians of time-varying coefficients)

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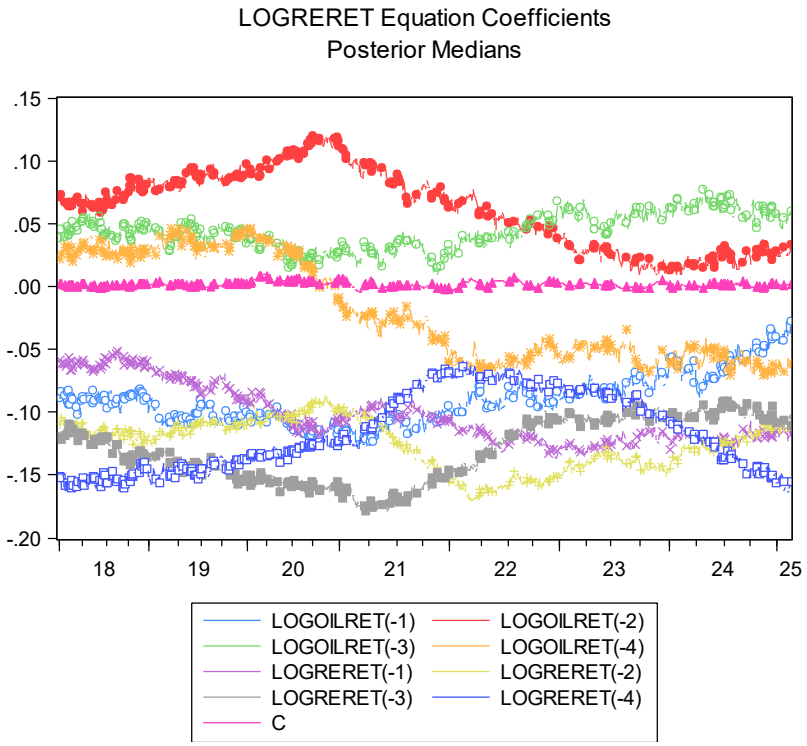


Figure 4. Oil to AI stock returns in Bullish markets: Bayesian TVP-VAR (posterior medians of time-varying coefficients)

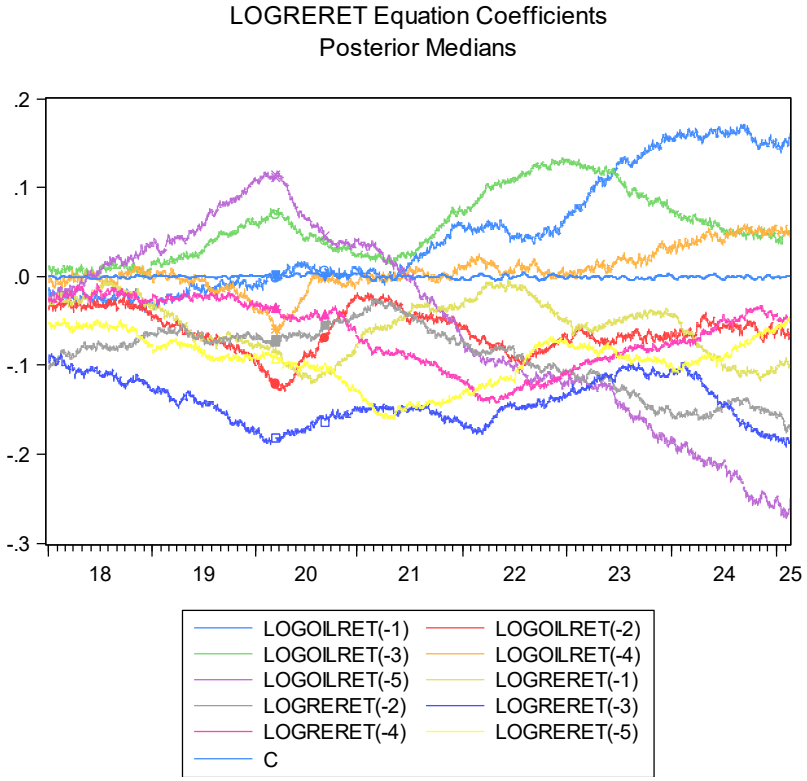


Figure 5. Oil to RE stock returns in Bearish markets: Bayesian TVP-VAR (posterior medians of time-varying coefficients)

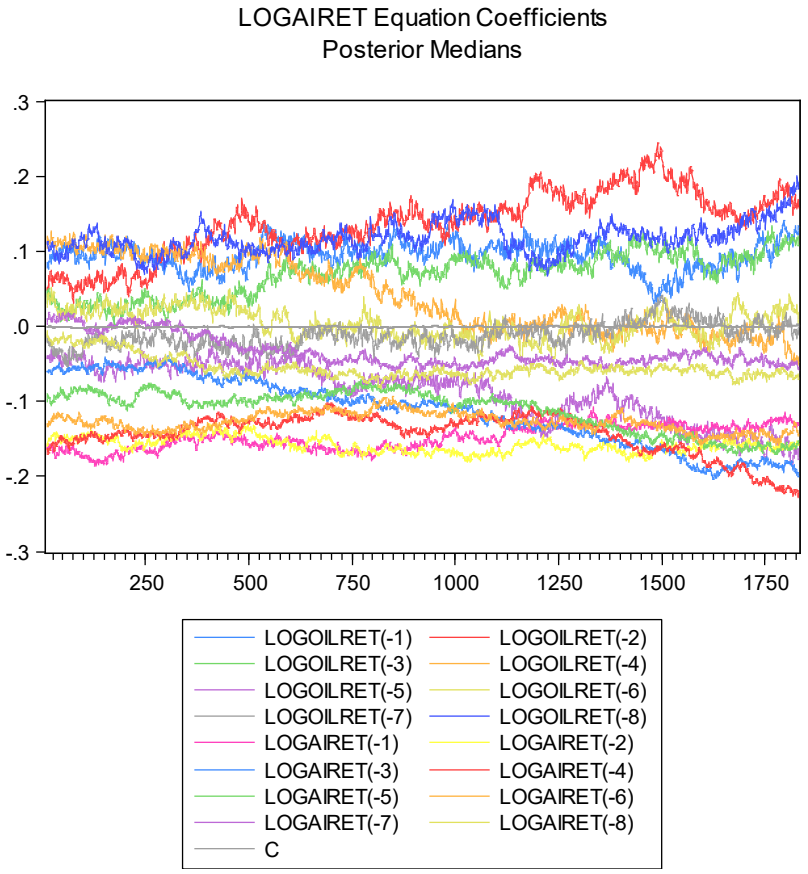


Figure 6. Oil to AI stock returns in Bearish markets: Bayesian TVP-VAR (posterior medians of time-varying coefficients)

term demand forecasts – can take considerable time to be fully incorporated into stock valuations due to factors such as corporate hedging strategies, operational rigidities, and delays in earnings realizations.

It is important to acknowledge a methodological limitation concerning our Bayesian TVP-VAR analysis. While we present these results only as supplementary, illustrative evidence that complements our baseline VAR findings, the TVP-VAR methodology is documented here only at a summary level, with the main results shown graphically. A full replication of these time-varying parameter estimates would require a more detailed exposition of the prior specifications, the MCMC algorithm, and the convergence diagnostics, which is beyond the scope of this paper. This limitation suggests that the TVP-VAR results should be interpreted as indicative rather than definitive, and they are not used as independent support for the paper's main conclusions. Future research could provide a more comprehensive documentation of the TVP-VAR estimation, potentially including the full code and data for replication purposes.

4. DISCUSSION AND LIMITATIONS

This asymmetric VAR analysis reveals significant heterogeneity in the stock return distribution of US oil firms while they respond to AI and RE firms' returns. Furthermore, empirical evidence shows that conventional linear, regime-invariant models materially misrepresent the true nature of interactions between the energy and technology sectors. By averaging across fundamentally distinct transmission regimes, such models overlook the state-contingent linkages that define contem-

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porary asset markets. Under general market conditions, renewable energy returns appear to have no discernible predictive content for oil stock returns, and AI exhibits only a modest, non-robust association. It is only by partitioning these relationships into bullish and bearish phases that the asymmetric transmission dynamics become clear, revealing that the predictive power of these sectors is not only present but highly sensitive to market sentiments.

The relationship between the RE and Oil sectors particularly highlights this state-dependency, demonstrating a shift in both timing and direction. In expansionary phases, RE returns become significant predictors of oil returns only at the third lag (three trading days), likely driven by wealth effects or delayed revisions to growth expectations. However, during contractionary phases, the first significant individual lag effect of RE returns emerges earlier, by the second lag, although the cumulative contribution of RE shocks to oil forecast-error variance remains smaller than in bullish phases (about 0.30% versus 2.58% at horizon 10). This earlier response to negative signals aligns with prospect theory and loss aversion, suggesting that investors prioritize downside risks in RE as a more informative signal for oil price movements. Moreover, the observed pattern in which declining RE returns predict increasing oil returns suggests a defensive sector rotation, in which capital is reallocated between these assets during periods of market distress.

In contrast, the AI-Oil relationship undergoes a fundamental structural shift and a complete sign reversal depending on the market regime. During AI-positive periods, the linkage reflects a fundamental mechanism in which technological optimism translates into expectations of increased energy demand for future computing and productivity. This finding aligns with Shobanke et al. (2025). This results in positive spillovers where AI gains lead to higher oil returns. Conversely, during AI-negative periods, the mechanism switches to a 'classic contagion channel'. In these stressed states, negative AI shocks trigger broad risk-off sentiment and cross-asset liquidation, causing AI and oil prices to decline simultaneously through portfolio balance channels, as rightly pointed out by Cui and Maghyereh (2026). This transformation from fundamental linkage to contagion acknowledges that AI has emerged as a systemic risk factor capable of altering the market's correlation structure. These findings carry potential implications for portfolio management, as they suggest that AI and oil equities may be of limited value as hedges for one another. Because the two sectors appear to co-move positively in both regimes – driven by growth expectations in bull markets and contagion-induced liquidation in bear markets – the pair may offer weaker diversification benefits when hedging is most valuable. Since hedge ratios and hedge effectiveness are not estimated in this study, these implications remain to be confirmed by formal portfolio and hedging analysis. Ultimately, any effective investment strategy or policy intervention must be explicitly conditioned on the prevailing market state, acknowledging that the mechanisms driving these cross-market spillovers are fundamentally different in times of prosperity than in times of crisis.

One of the main limitations of this study concerns the investment and hedging volatility spillovers implications. While our empirical results reveal significant return linkages and predictive (Granger) causality between AI, renewable energy, and oil markets – with potential implications for diversification – we do not formally test these implications through portfolio optimization or hedging effectiveness analysis. Such analyses would require constructing optimal portfolios (e.g., minimum variance portfolios, tangency portfolios) and computing optimal hedge ratios and hedge effectiveness measures, which are beyond the scope of the current paper. Consequently, our discussion of investment and hedging implications should be interpreted as suggestive rather than definitive. Future research could extend our findings by conducting a formal portfolio analysis using the dynamic conditional correlations or volatility spillovers estimated in this study to quantify the actual economic value of including AI and RE assets in a diversified portfolio alongside oil.

Another limitation of our empirical specification is the omission of potentially important common market factors. Specifically, we do not control for broad U.S. equity market movements (e.g., S&P 500 returns) or for a direct crude-oil price factor (WTI or Brent returns). Our oil variable, the S&P 500 Energy Index, is an equity-sector index;

although it is related to crude oil prices, it cannot substitute for direct oil-price returns, which also reflect commodity-market supply and demand conditions. The absence of these factors means that some of the spillovers we attribute to AI and RE stocks could, in part, reflect general market sentiment rather than sector-specific transmission channels. This concern is particularly relevant given the high correlation between technology stocks and broader equity indices during periods of market stress. Consequently, our results should be interpreted as reduced-form evidence of interconnectedness rather than structural causal relationships. Future research could address this by employing a factor-augmented VAR (FAVAR) framework or by including S&P 500 and WTI/Brent returns as exogenous control variables, which would help distinguish sector-specific transmission from general market co-movement and direct oil-market effects.

CONCLUSION

This research examined the dynamic and regime-dependent asymmetric effects of Artificial Intelligence (AI) and Renewable Energy (RE) equity returns on the performance of the U.S. oil sector under novel econometric frameworks. The ultimate aim is to capture heterogeneous transmission mechanisms across these sectors in distinct bullish and bearish market regimes. Our VAR results provide econometric support for state-contingent asymmetric connectedness between renewable energy and oil, and between AI and the oil market, meaning that shocks transmit with varying intensity depending on direction and market conditions.

Positive RE shocks during expansions influence oil returns with a moderate delay and modest positive coefficients but account for a larger cumulative share of oil forecast-error variance. Negative RE shocks during contractions show earlier and larger individual lag effects, with a positive sign consistent with defensive capital rotation rather than contagion, although their cumulative contribution to oil return variation is small. During AI-positive phases, the mechanism reflects a fundamental linkage, acknowledging that positive AI innovations offer productivity gains and future computing-related energy demand, leading investors to revise oil price expectations upward with a moderate lag. In contrast, negative AI shocks induce broad risk-off sentiment and cross-asset liquidation, reducing oil prices contemporaneously through portfolio balance channels. Collectively, these results underscore that financial interconnectedness between the AI and oil sectors is state-contingent and that unconditional assessments of cross-market spillovers would materially misrepresent the true nature of this relationship.

This study also outlines critical future research pathways to understand how artificial intelligence and renewable energy affect the valuation of oil firms. In this research, which analyses the influence of AI and RE stock returns on the price of conventional oil firms, the RE sector is considered as a single unit. However, further studies should move beyond general categories by analyzing specific subsectors such as solar or hydrogen and distinguishing between software-driven and hardware-focused firms. To improve accuracy, future studies should utilize direct metrics of technological adoption, such as robotic deployment and patent data, rather than relying solely on stock indices. There is also a call to examine firm-level differences between major integrated corporations and independent explorers to see how they react uniquely to market shifts. Finally, the source emphasizes the need to uncover the underlying drivers of these trends, including investor sentiment and regulatory changes. Together, these recommendations aim to provide a more granular and causal understanding of the evolving energy landscape.

AUTHOR CONTRIBUTIONS

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Supervision: Bhasura Valsan K.
Validation: Saji Thazhungal Govindan Nair, Ratheesh K. Nair.
Visualization: Kanakachandran C. R., Sivaprasad G.
Writing – original draft: Saji Thazhungal Govindan Nair, Ratheesh K. Nair, Kanakachandran C. R., Bhasura Valsan K.
Writing – review & editing: Saji Thazhungal Govindan Nair, Sivaprasad G.

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