JOURNAL OF MANAGEMENT AND BUSINESS SOLUTIONS

Forecasting Oil Market Volatility Using Machine Learning Models

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ABSTRACT

Forecasting oil market volatility is one of the major challenges in the global economy and financial markets, exerting broad impacts on the economic and strategic decisions of oil-producing and oil-consuming countries. This study was conducted with the aim of evaluating and forecasting oil market volatility using advanced machine learning models and analyzing the factors that influence fluctuations in oil prices. To this end, daily time-series data from macroeconomic and financial indicators—including the S&P 500 Index, the Dow Jones Index, the VIX Index, changes in unemployment claims (ICSA), and the interest rate (DGS10)—were collected and analyzed for the period from 2014 to 2024. In this research, heteroskedasticity models (GARCH and TGARCH) were first employed to extract conditional variance as a metric for volatility, and then these variables were used as inputs for machine learning models such as neural networks and random forests. The results indicated that machine learning models—especially threshold GARCH models with skewed Student-t and Johnson SU distributions—are capable of providing more accurate forecasts of oil market volatility. Moreover, variables such as stock market index volatility and the VIX Index have a positive and significant effect on oil market volatility. These findings demonstrate the effectiveness of machine learning models in analyzing the complex and nonlinear fluctuations of the oil market. The study suggests that, for improved oil market risk management, the use of machine learning models should receive greater attention, particularly during periods of market distress.

Keywords: oil market volatility, forecasting, machine learning, heteroskedasticity models, economic indicators, market fluctuations.

Introduction

The crude oil market remains one of the most strategically important and structurally complex arenas in the global economy, with price and volatility dynamics that cascade through production, trade, inflation, financial stability, and geopolitical relations (1, 2). Since the liberalization of energy markets and the sequence of oil shocks in the late twentieth century, policymakers and firms have had to adapt repeatedly to sharp swings in oil prices, which affect everything from fiscal balances in exporting countries to input costs and real income in importing economies (2, 3). In recent decades, the world oil market has become increasingly integrated with global financial cycles, derivative markets, and cross-asset investment strategies, amplifying the speed and complexity with which information and shocks are transmitted into oil price volatility (4, 5). Against this backdrop, accurate modeling and forecasting of oil market volatility are not only of academic interest but also crucial for risk management, portfolio allocation, macroeconomic policy design, and energy security planning (1, 6).

Article history:
Received 18 November 2024
Revised 11 February 2025
Accepted 18 February 2025
Published online 01 April 2025

How to cite this article:
Majdi, Z., Hanifi, F., & Fallah Shams, M. (2025). Forecasting Oil Market Volatility Using Machine Learning Models. *Journal of Management and Business Solutions, 3*(2), 1-17. https://doi.org/10.61838/jmbs.71

The macroeconomic and development consequences of oil price fluctuations are especially pronounced in oil-exporting regions such as the Middle East and North Africa (MENA), where fiscal revenues, external balances, and long-term growth paths are tightly linked to hydrocarbon markets (7, 8). Evidence for MENA economies indicates that oil price volatility can both stimulate and destabilize growth depending on the institutional structure, diversification level, and fiscal responses of each country (7). Similar vulnerabilities are observed across other oil-exporting states, where instability in global oil markets complicates efforts to implement sustainable development strategies, industrial diversification, and social spending commitments (8, 9). Even oil-importing and mixed economies are not insulated: fluctuations in oil prices significantly affect inflation dynamics, external trade balances, and real activity via cost-push channels and changes in expectations (10, 11). Studies on specific exporters such as Kuwait and Nigeria show that oil price swings are closely associated with macroeconomic variables, public health outcomes, and broader socio-economic indicators, underlining the systemic nature of oil market risk (12-14).

Oil price fluctuations also reverberate through global trade and financial networks. Shocks to crude oil prices affect trade volumes, terms of trade, and current account imbalances, as well as the pricing of related energy and commodity contracts (10). At the same time, uncertainty originating in macroeconomic, financial, and policy domains has been shown to exert powerful predictive content for oil price volatility, suggesting a bidirectional relationship between oil markets and broader uncertainty measures (15). Measures of the global financial cycle and economic policy uncertainty, for example, help explain time-varying patterns in oil volatility and its co-movement with other asset classes, including equities and currencies (5, 6, 15). This growing entanglement between oil and financial markets implies that effective forecasting frameworks must move beyond purely physical supply–demand factors and explicitly incorporate macro-financial variables, global uncertainty proxies, and market-based indicators of risk sentiment (2, 4).

From a modeling perspective, the literature on oil price and volatility forecasting spans a wide spectrum of approaches, from structural models rooted in supply–demand fundamentals to purely statistical and data-driven frameworks (2, 3). Conventional econometric techniques—such as ARIMA, VAR, and GARCH-type models—have been widely used to capture serial dependence, volatility clustering, and the impact of macroeconomic drivers on oil prices and their conditional variance (6, 15, 16). Recent contributions employ variants of GARCH-MIDAS and mixed-frequency frameworks to disentangle short- and long-run components of volatility, integrating low-frequency macro or uncertainty indicators with high-frequency oil price data (6, 15). Parallel to these advances, gray prediction models, regime-switching techniques, and other non-standard econometric tools have been proposed to handle structural breaks such as the COVID-19 pandemic, which introduced unprecedented disruptions to both energy demand and supply (17, 18).

At the same time, the global oil market has undergone structural transformation, driven by factors including financialization, shale and unconventional oil production, OPEC+ coordination, and the growing role of Asia in demand growth (4, 9). These shifts have generated dynamics that are often nonlinear, regime-dependent, and influenced by complex feedbacks between physical and financial market segments (4, 5). Traditional linear or low-dimensional volatility models may struggle to capture such features, especially when faced with jumps, heavy tails, and time-varying asymmetries in the response of volatility to positive and negative shocks (16, 18). Consequently, there is a growing recognition that purely parametric approaches, while interpretable and theoretically grounded, may be insufficient on their own for high-accuracy forecasting and risk measurement in today's oil markets (1, 15).

In response, an expanding line of research has turned to machine learning and deep learning models to forecast crude oil prices and volatility, leveraging their capacity to approximate complex nonlinear functions and to exploit high-dimensional information sets (16, 19). Feedforward neural networks, support vector regression, and ensemble methods such as random forests and gradient boosting have been applied to predict crude prices using combinations of macroeconomic, financial, and geopolitical variables, with generally promising gains in predictive accuracy compared to classical benchmarks (11, 19, 20). Recent contributions further highlight the effectiveness of deep architectures for capturing nonlinear market dynamics, long-range dependencies, and interactions among predictors that are difficult to pre-specify in traditional models (21, 22). Yet this flexibility often comes at the cost of interpretability: complex machine learning models are frequently criticized as "black boxes," complicating their use for policy analysis and risk communication (19, 23).

Beyond the oil market, advances in financial econometrics and machine learning have produced sophisticated frameworks for modeling volatility, tail risk, and systemic stress across asset classes (1, 23). For instance, hybrid models combining generalized hyperbolic GARCH processes with dynamic conditional correlation (DCC) structures and machine learning techniques have been used to design financial stress indices that fuse information from multiple markets and channels (24). In parallel, financial econometrics has refined tools for assessing model adequacy, handling non-Gaussian innovations, and evaluating risk measures such as value-at-risk (VaR) and expected shortfall under heavy-tailed distributions (15, 23). These developments suggest that hybrid architectures—where econometric volatility models are used to generate risk-sensitive features that are then fed into machine learning predictors—may offer a productive compromise between structural interpretability and predictive performance (16, 19).

Crucially, the interaction between oil markets and the broader macro-financial environment is mediated through multiple channels, including economic growth, external balances, fiscal policy, and sectoral activity, making the measurement of oil-related risk highly multidimensional (7, 8). Oil price shocks can transmit to tourism receipts and other external income sources in exporting countries, alter public health and social outcomes via income and expenditure effects, and drive shifts in investment and capital flows (13, 14). Moreover, economic policy uncertainty and global risk sentiment—as proxied by indices linked to equity market volatility and financial stress—play a pivotal role in shaping expectations and amplifying or dampening the impact of oil market shocks (5, 11, 15). These insights underscore the importance of developing volatility models that integrate information from stock indices, volatility indicators such as the VIX, interest rates, and macro-real variables into a unified risk-forecasting framework for oil (6, 15).

Despite significant progress, several gaps remain in the literature. First, much of the empirical work on oil focuses on price level forecasting rather than directly modeling volatility as a risk metric, even though volatility is more closely related to hedging decisions, VaR calculations, and capital requirements for energy-related portfolios (1, 6). Second, while GARCH-type models and their extensions are widely used to capture volatility clustering and asymmetry, relatively fewer studies exploit their conditional variance outputs as structured inputs into machine learning models that can flexibly learn nonlinear interactions with macro-financial predictors (16, 19). Third, existing machine learning applications often treat crude oil as an isolated time series, underutilizing contemporaneous information from stock market volatility, interest rate dynamics, and indicators of global uncertainty, even though such variables have been shown to be powerful drivers and forecasters of oil volatility (5, 11, 15). Finally, there is still limited evidence on how hybrid GARCH–machine learning frameworks perform when evaluated not only on statistical forecast errors but also on economically meaningful risk measures such as VaR over long panels of daily data that span multiple crisis periods (4, 17, 18).

In this context, the present study situates itself at the intersection of financial econometrics and machine learning by constructing a comprehensive, macro-financial framework for modeling and forecasting oil market volatility and associated market risk. Building on recent advances in volatility modeling, uncertainty forecasting, and data-driven prediction, the analysis combines conditional variance estimates from asymmetric GARCH-family models with machine learning algorithms such as random forests, support vector regression, decision trees, and artificial neural networks, using daily oil market data and key macro-financial indicators—including stock market indices, volatility measures, interest rates, and labor-market signals—to evaluate and compare their forecasting performance and risk implications (15, 16, 19, 21, 22, 24). Therefore, the aim of this study is to develop and empirically assess a hybrid econometric–machine learning framework for predicting crude oil market volatility and value-at-risk using high-frequency macro-financial data and advanced volatility measures.

Methods and Materials

To prepare the variables required for the models used to analyze the hypotheses of this study, Microsoft Excel spreadsheet software was utilized. Initially, the collected data were entered into different worksheets of the software, after which the necessary calculations were performed to extract and adjust the research variables. Upon completion of the calculations and extraction of all essential variables, they were consolidated into a single worksheet and prepared for transfer to the software used for the final analysis. It should be noted that all data analysis procedures in this study will be conducted using R software, version 4.3.1. The statistical population of the study consists of daily time-series data from selected macroeconomic and financial indicators covering the period from May 5, 2014, to April 26, 2024. In this research, oil price return and volatility were selected as the target variables, and a new approach was adopted to compute the value-at-risk of these variables. Table (1) presents the research variables along with their corresponding symbols. For ease of implementation in the software environment, all variables have been designated with specific symbols.

Table 1. Description of Research Variables

Variable Name	Symbol	Type	Description
Oil Price Volatility	Oil	Dependent	West Texas Intermediate (WTI) crude oil futures
VIX Volatility Index	VIX	Independent	One of the most important indicators for assessing fear and volatility levels in financial markets
S&P 500 Index Volatility	GSPC	Independent	The S&P 500 Index includes 500 major and reputable U.S. companies
Dow Jones Index Volatility	DJI	Independent	The DJIA consists of 30 major U.S. companies operating across various industries
Changes in Initial Unemployment Claims	ICSA	Independent	The “Initial Claims” (ICSA) time series, published by the Federal Reserve Bank of St. Louis, indicates the number of individuals filing for unemployment insurance for the first time. These data are provided weekly and seasonally; in the present study, they were converted from weekly to daily frequency.
Changes in Interest Rate	DGS10	Independent	Represents the market yield on 10-year U.S. Treasury constant maturity bonds

Several important points regarding the selected variables in this study should be highlighted. The primary objective of this research is to comprehensively measure oil market risk by considering its various dimensions. To examine the effects of financial markets, three major and influential financial indicators in the United States were employed: the Standard & Poor’s 500 Index (S&P 500), the Dow Jones Industrial Average (DJI), and the Fear and Greed Volatility Index (VIX). The conditional variance of the S&P 500 and Dow Jones indices was incorporated into the study's models as a measure of volatility, as the main aim of the research is to capture the risk effects of these variables for modeling oil market risk. Since the VIX itself is considered a risk indicator, it was directly included as an input variable in the model.

Furthermore, the same approach was applied to other variables. For instance, to incorporate econometric and macroeconomic dimensions, changes in two variables—initial unemployment claims and the Federal Reserve interest rate—were used. (Here, “changes” refer to the conditional variance of these variables.) This approach enables us to model and analyze all dimensions affecting oil market risk with greater precision.

Findings and Results

As shown in Table 2, the number of observations in this study, after date alignment, reached 2,495 days. For the variables “Oil,” “GSPC,” and “DJI,” logarithmic returns were calculated, and the descriptive statistics presented correspond to these returns. The range of daily return fluctuations for West Texas Intermediate (WTI) crude oil was between −33% and +32%, with an average daily return of approximately 0 to 1 percent. Its standard deviation is around 3 percent, indicating the risk associated with these returns. Moreover, the skewness and kurtosis values indicate relative symmetry and a sharper peak compared to a normal distribution. Regarding the “VIX” index, its range of variation was between 9.14 and 82.69, with an average value between 16 and 18, reflecting a relatively stable level of fear and uncertainty in the market. For the “ICSA” variable, daily fluctuations in the number of unemployment claims ranged between 245,000 and 374,988 individuals, indicating considerable volatility. Finally, the fluctuation range of U.S. Treasury bond yields (“DGS10”) was between 0.5% and 5%, which reflects moderate volatility in the returns of these securities. These analyses provide a depiction of the various volatilities and risks associated with the oil market and its related economic and financial variables.

Table 2. Summary of Descriptive Statistics for Research Variables

Variables	Observations	Minimum	Maximum	Mean	Median	Std. Dev.	Skewness	Kurtosis
Oil	2495	-0.335	0.319	-0.00007	0.0012	0.030	-0.71	26.54
VIX	2495	9.14	82.69	18.118	16.09	7.335	2.60	12.79

GSPC	2495	-0.127	0.089	0.0004	0.0006	0.011	-0.81	15.98
DJI	2495	-0.138	0.107	0.00034	0.0007	0.011	-0.96	22.81
ICSA	2495	187000	6137000	374988.376	245000	545226.161	6.95	57.69
DGS10	2495	0.52	4.98	2.361	2.29	0.945	0.42	-0.13

These characteristics emphasize the necessity of using advanced approaches—such as machine learning—in modeling and forecasting oil market risk and highlight the importance of a more precise analysis of these data as a foundation for testing the study's hypotheses.

For modeling oil market risk, the first step is transforming the research variables into features that possess risk-related characteristics. Specifically, in this study, the target variable is the volatility of oil market returns, which is directly related to market risk. To extract volatility, heteroskedasticity models (conditional variance) are employed. The same procedure is applied to the "GSPC," "DJI," and "DGS10" variables. Since the "VIX" index is inherently a volatility indicator and recognized as a risk variable, there is no need to convert it into another risk-based variable. In this regard, only the basic assumptions for the variables "Oil," "GSPC," "DJI," and "DGS10" were examined, and the results are presented in Table (3).

Table 3. Results of Preliminary Tests Prior to Modeling for Examining Basic Assumptions

Row	Variable	Jarque–Bera Test		Augmented Dickey–Fuller Test		ARCH Effects Test	
		Statistic	p-value	Statistic	p-value	Statistic	p-value
1	Oil	73,583.31	<0.01	-12.99	<0.01	848.57	<0.01
2	GSPC	26,872.29	<0.01	-13.41	<0.01	974.81	<0.01
3	DJI	54,551.29	<0.01	-13.45	<0.01	1,011.43	<0.01
4	DGS10	76.01	<0.01	-0.89	0.95	2,473.90	<0.01

As shown in Table 3, the p-values for the Jarque–Bera normality test and the ARCH heteroskedasticity effects test are all less than 0.05, indicating non-normal distribution of the data and non-constant variance. Thus, in addition to the presence of heteroskedasticity in the variables, their distributions do not follow a normal distribution. Regarding the stationarity assumption, except for the interest rate variable, all other variables are stationary at the 95% confidence level. Given that stationarity is one of the fundamental assumptions in GARCH modeling, these variables are directly included in the machine learning model. Accordingly, for the three variables "Oil," "GSPC," and "DJI," GARCH modeling was performed, and after extracting the conditional variance, these variances were used as measures of volatility in the machine learning model.

In this section, the input features and the target variable for the machine learning model are prepared for analysis. Based on the previous results, heteroskedasticity modeling was performed for the three variables "Oil," "GSPC," and "DJI," and the corresponding conditional variances were extracted as indicators of volatility for these indices. For this purpose, an appropriate GARCH model was selected and applied to the variables. The results from comparing various models in the heteroskedasticity family for each variable are presented separately in Tables (4) to (6).

Table 4. Comparison of Different Heteroskedasticity Models by Statistical Distribution for Oil

Model	Distribution	Log-Likelihood	AIC	BIC
GARCH	norm	5844.39	-4.68007	-4.66607
GARCH	snorm	5873.753	-4.70281	-4.68647
GARCH	std	5924.533	-4.74351	-4.72718
GARCH	sstd	5943.635	-4.75802	-4.73936
GARCH	ged	5908.511	-4.73067	-4.71434

GARCH	sged	5932.234	-4.74888	-4.73022
GARCH	jsu	5943.175	-4.75766	-4.73899
EGARCH	norm	5870.867	-4.70049	-4.68416
EGARCH	snorm	5900.725	-4.72363	-4.70496
EGARCH	std	5939.839	-4.75498	-4.73631
EGARCH	sstd	5960.312	-4.77059	-4.74959
EGARCH	ged	5924.085	-4.74235	-4.72368
EGARCH	sged	5949.78	-4.76215	-4.74115
EGARCH	jsu	5959.89	-4.77025	-4.74925
GJRGARCH	norm	5866.766	-4.69721	-4.68087
GJRGARCH	snorm	5893.296	-4.71767	-4.699
GJRGARCH	std	5933.71	-4.75007	-4.7314
GJRGARCH	sstd	5952.706	-4.76449	-4.74349
GJRGARCH	ged	5919.675	-4.73882	-4.72015
GJRGARCH	sged	5942.806	-4.75656	-4.73556
GJRGARCH	jsu	5952.326	-4.76419	-4.74319
TGARCH	norm	5878.99	-4.70701	-4.69067
TGARCH	snorm	5909.944	-4.73102	-4.71235
TGARCH	std	5946.504	-4.76032	-4.74166
TGARCH	sstd	5967.626	-4.77645	-4.75545
TGARCH	ged	5930.216	-4.74727	-4.7286
TGARCH	sged	5956.469	-4.76751	-4.74651
TGARCH	jsu	5967.148	-4.77607	-4.75507

Table 5. Comparison of Different Heteroskedasticity Models by Statistical Distribution for GSPC

Model	Distribution	LogLikelihood	AIC	BIC
GARCH	norm	8322.205	-6.6663	-6.6523
GARCH	snorm	8368.72	-6.70278	-6.68645
GARCH	std	8400.02	-6.72787	-6.71154
GARCH	sstd	8415.576	-6.73954	-6.72087
GARCH	ged	8394.312	-6.7233	-6.70696
GARCH	sged	8408.165	-6.7336	-6.71493
GARCH	jsu	8422.596	-6.74517	-6.7265
EGARCH	norm	8362.137	-6.6975	-6.68117
EGARCH	snorm	8407.165	-6.7328	-6.71413
EGARCH	std	8441.951	-6.76068	-6.74201
EGARCH	sstd	8458.55	-6.77319	-6.75218
EGARCH	ged	8430.392	-6.75142	-6.73275
EGARCH	sged	8446.512	-6.76354	-6.74254
EGARCH	jsu	8464.106	-6.77764	-6.75664
GJRGARCH	norm	8354.302	-6.69122	-6.67489
GJRGARCH	snorm	8396.526	-6.72427	-6.7056
GJRGARCH	std	8434.974	-6.75509	-6.73642
GJRGARCH	sstd	8449.48	-6.76592	-6.74491
GJRGARCH	ged	8423.917	-6.74623	-6.72756
GJRGARCH	sged	8438.075	-6.75677	-6.73577
GJRGARCH	jsu	8454.662	-6.77007	-6.74907
TGARCH	norm	8375.22	-6.70799	-6.69166
TGARCH	snorm	8422.082	-6.74475	-6.72609
TGARCH	std	8453.477	-6.76992	-6.75125
TGARCH	sstd	8471.84	-6.78384	-6.76284
TGARCH	ged	8440.388	-6.75943	-6.74076
TGARCH	sged	8458.25	-6.77295	-6.75194
TGARCH	jsu	8477.414	-6.78831	-6.76731

Table 6. Comparison of Different Heteroskedasticity Models by Statistical Distribution for DJI

Model	Distribution	LogLikelihood	AIC	BIC
GARCH	norm	8415.63	-6.74119	-6.72719
GARCH	snorm	8447.777	-6.76615	-6.74982
GARCH	std	8484.315	-6.79544	-6.77911
GARCH	sstd	8492.65	-6.80132	-6.78265
GARCH	ged	8485.07	-6.79605	-6.77971
GARCH	sged	8493.872	-6.8023	-6.78363
GARCH	jsu	8501.764	-6.80863	-6.78996
EGARCH	norm	8451.4	-6.76906	-6.75272
EGARCH	snorm	8475.922	-6.78791	-6.76925
EGARCH	std	8517.819	-6.8215	-6.80283
EGARCH	sstd	8528.71	-6.82943	-6.80843
EGARCH	ged	8514.025	-6.81846	-6.79979
EGARCH	sged	8525.288	-6.82668	-6.80568
EGARCH	jsu	8531.644	-6.83178	-6.81078
GJRGARCH	norm	8448.795	-6.76697	-6.75064
GJRGARCH	snorm	8474.242	-6.78657	-6.7679
GJRGARCH	std	8516.568	-6.8205	-6.80183
GJRGARCH	sstd	8526.981	-6.82804	-6.80704
GJRGARCH	ged	8512.674	-6.81737	-6.79871
GJRGARCH	sged	8524.009	-6.82566	-6.80466
GJRGARCH	jsu	8529.906	-6.83039	-6.80938
TGARCH	norm	8460.745	-6.77655	-6.76021
TGARCH	snorm	8487.239	-6.79698	-6.77832
TGARCH	std	8525.614	-6.82775	-6.80908
TGARCH	sstd	8538.488	-6.83726	-6.81626
TGARCH	ged	8521.164	-6.82418	-6.80551
TGARCH	sged	8534.148	-6.83379	-6.81278
TGARCH	jsu	8541.506	-6.83968	-6.81868

To select the heteroskedasticity model with an appropriate distribution, the criteria of log-likelihood, AIC, and BIC were used. According to the results in the corresponding tables, for the “Oil” variable, the threshold GARCH (TGARCH)-(sstd) model with a skewed Student-t distribution, and for the “GSPC” and “DJI” variables, the threshold GARCH (TGARCH)-(jsu) model with a Johnson SU distribution were selected as the optimal models. In standard GARCH models, it is assumed that positive and negative shocks have the same effect on volatility (conditional variance); however, in financial data, negative shocks (such as stock price declines) typically have a greater impact on volatility. The TGARCH model incorporates these asymmetric effects through a threshold term and explicitly accounts for the asymmetric impact of positive and negative shocks on volatility. Because this model allows negative and positive shocks to have different effects on variance, it is highly effective for calculating value-at-risk (VaR), where asymmetric volatility plays an important role.

On the other hand, the Johnson SU distribution is one of the flexible families of distributions used for modeling non-normal data. Financial asset return data typically exhibit heavier tails than the normal distribution, and the Johnson SU distribution models this property effectively. It can also better capture asymmetry in the data compared with symmetric distributions such as the normal distribution. In general, the Johnson SU distribution, with its multiple parameters, can account for a variety of shapes, including fat tails, skewness, or forms close to the normal distribution. In the next step, for volatility modeling, the threshold GARCH model with skewed t and Johnson SU distributions was used. The results of these models for the three variables “Oil,” “GSPC,” and “DJI” are presented in Tables (7) to (9) and in the plots in Figures (7) to (9). It is noteworthy that 20% of the data, equivalent to 504 observations, were considered as out-of-sample (test set), and their forecasts were computed using a rolling window. Volatility forecasts for the "Oil" variable were used to calculate value-at-risk. In addition, the forecasts for the "GSPC" and "DJI" variables were employed as inputs to the machine learning model for forecasting oil volatility and, consequently, for computing value-at-risk. In other words, in this study, oil volatility was computed using two approaches: the first based on a univariate GARCH model, and the second by modeling volatility through other variables. Then, under both approaches, value-at-risk was calculated and the results were compared using backtesting.

Table 7. Results of Fitting the Threshold GARCH Heteroskedasticity Model with Skewed t Distribution for Oil

Parameters	Estimated Coefficient	Standard Error	t-Statistic	p-value
mu	-0.0002	0.00036	-0.56	0.57
omega	0.00057	0.00013	4.21	0.00
alpha1	0.10225	0.01353	7.56	0.00
beta1	0.90113	0.0129	69.85	0.00
eta11	0.51472	0.09946	5.18	0.00
skew	0.84792	0.0261	32.49	0.00
shape	6.305	0.85432	7.38	0.00

Table 8. Results of Fitting the Threshold GARCH Heteroskedasticity Model with Johnson SU Distribution for GSPC

Parameters	Estimated Coefficient	Standard Error	t-Statistic	p-value
mu	0.00017	0.00014	1.21	0.23
omega	0.00042	0.00006	6.68	0.00
alpha1	0.14482	0.01762	8.22	0.00
beta1	0.84893	0.01653	51.37	0.00
eta11	0.93112	0.10482	8.88	0.00
skew	-0.82507	0.1706	-4.84	0.00
shape	2.00011	0.17401	11.49	0.00

Table 9. Results of Fitting the Threshold GARCH Heteroskedasticity Model with Johnson SU Distribution for DJI

Parameters	Estimated Coefficient	Standard Error	t-Statistic	p-value
mu	0.00025	0.00014	1.75	0.08
omega	0.00037	0.00006	6.15	0.00
alpha1	0.14295	0.01851	7.72	0.00
beta1	0.85261	0.01707	49.95	0.00
eta11	0.79651	0.10419	7.64	0.00
skew	-0.52982	0.1149	-4.61	0.00
shape	1.83309	0.14618	12.54	0.00

Given the p-values obtained for the parameters alpha1 and beta1, which are less than 0.05, it is clear that the heteroskedasticity effects are significant for all three variables, namely "Oil," "GSPC," and "DJI." Moreover, in all three tables, the parameter representing the asymmetric effect of shocks is also estimated as positive and statistically significant (p-value less than 0.05). This indicates that negative shocks in all three variables have a greater impact than positive shocks. In other words, investors' reactions to negative news in these markets have been more intense. By examining the estimated skewness coefficient in Table (7), it is observed that this coefficient for "Oil" is positive and significant (p-value less than 0.05). This indicates that the right tail of the distribution is heavier and that positive return values are more likely. However, for the other two variables, "GSPC" and "DJI," the situation is different, as the skewness coefficient for these variables is negative and significant, indicating that the left tail of the distribution is heavier and, in other words, that negative returns are more likely. The “shape” parameter, which pertains to the form and kurtosis of the distribution, when greater than one and significant, indicates the intensity of events in the tails of the distribution. The significance of this parameter implicitly suggests that rare events in the market are considerably likely. Considering the values of the “shape” parameter in the different tables and comparing them, it is observed that the intensity of rare events and the impact of their shocks in the oil market are greater than in the “GSPC” and “DJI” markets. The following plots clearly illustrate the distribution of residuals.

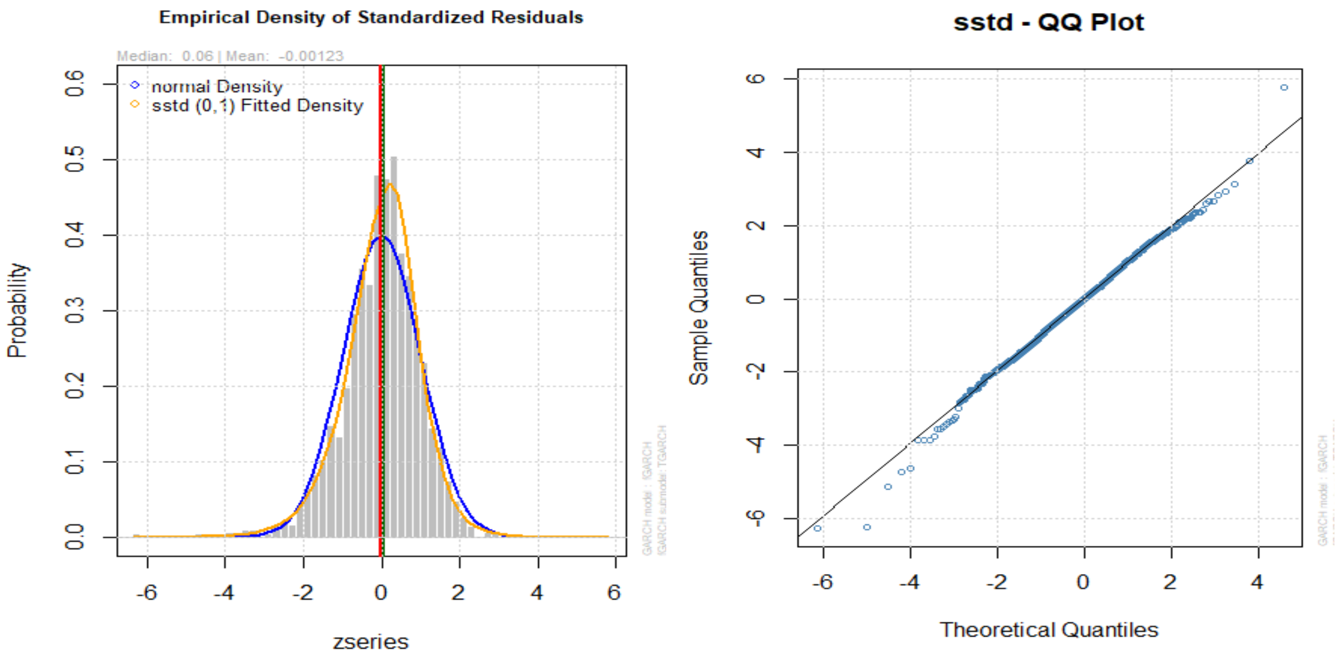

Figure 1. Distribution plots of residuals obtained from the threshold conditional heteroskedasticity model for Oil

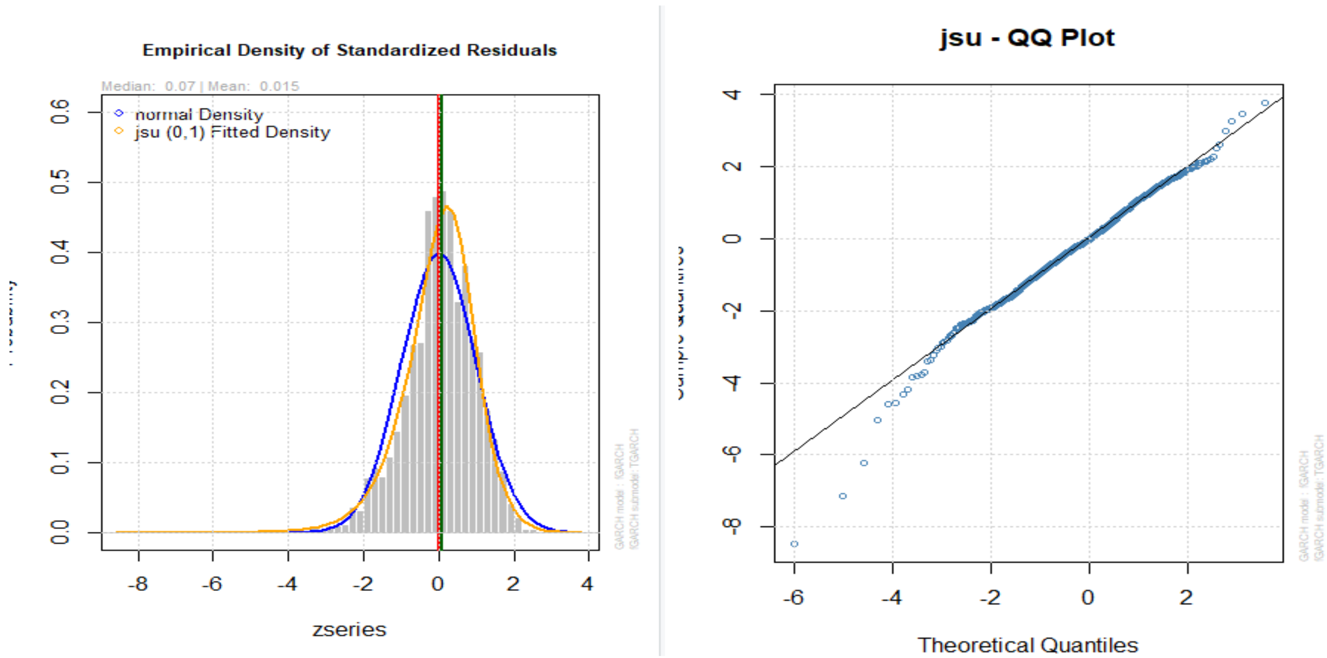

Figure 2. Distribution plots of residuals obtained from the threshold conditional heteroskedasticity model for GSPC

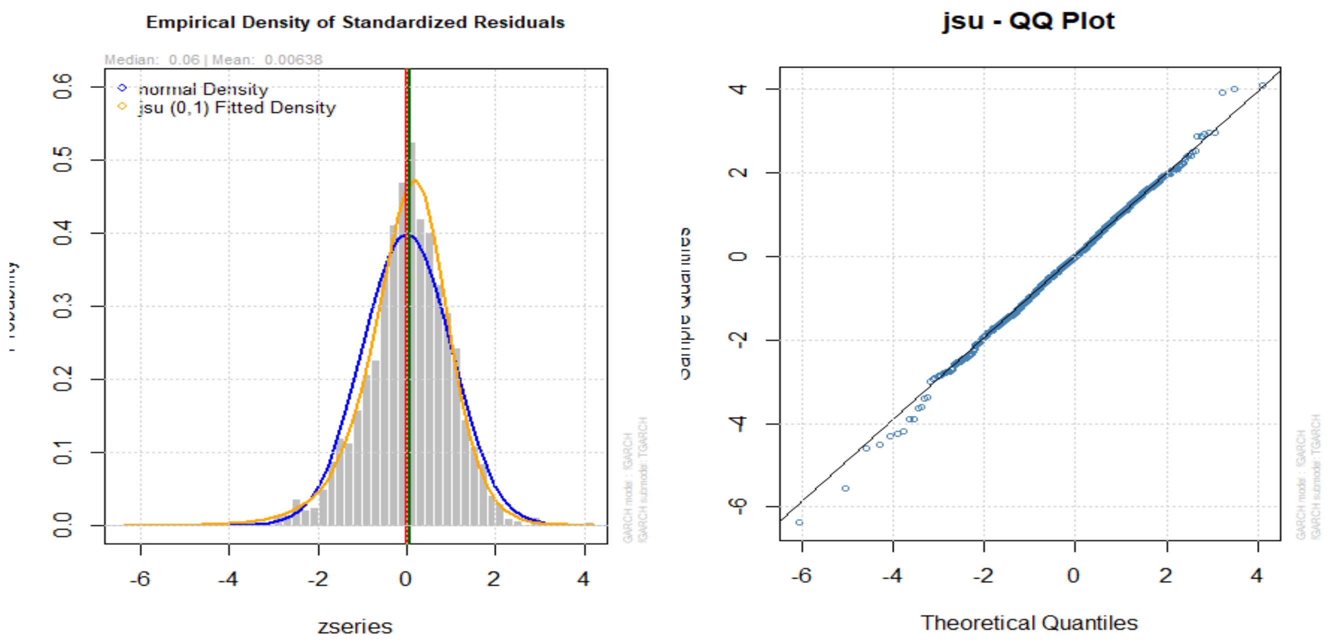

Figure 3. Distribution plots of residuals obtained from the threshold conditional heteroskedasticity model for DJI

In order to examine the effect of each variable independently on oil volatility, a multiple linear regression model was used, and its results can be seen in Table (10).

Table 10. Results of the Linear Regression Model for Testing the Significance of the Coefficients of Independent Variables on Oil Volatility

Parameters	Estimated Coefficient	Standard Error	t-Statistic	p-value
(Intercept)	0.01352	0.000646	20.93	0.00
GSPC volatility	0.588344	0.16119	3.65	0.00
DJI volatility	0.217305	0.152929	1.42	0.16
DGS10	-0.00193	0.001102	-1.75	0.08
ICSA	0.078681	0.002781	28.30	0.00
VIX	0.009124	0.004281	2.13	0.03

Adjusted coefficient of determination (R^2) of the model: 0.5727

Durbin–Watson statistic: 0.14327

Before interpreting the model results, it is essential to assess its quality. Given the adjusted coefficient of determination (R^2), which is approximately 0.57, the fitted linear model can be evaluated as having moderate quality. This means that 57 percent of the variations in the dependent variable are explained by the explanatory variables in the model. Another important point is the value of the Durbin–Watson statistic, which is approximately 0.14, reinforcing the spurious regression hypothesis proposed by Granger and Newbold (1974). According to Granger and Newbold (1974), in spurious regressions, we typically observe a high R^2 and autocorrelated disturbance terms along with a low Durbin–Watson statistic. Based on this, they suggest that when R^2 is greater than the Durbin–Watson value, regressions should be estimated in the form of first-difference functional models. Furthermore, by examining the statistical distribution of the residuals according to Figure (4), it is clearly evident that the assumption of residual normality is rejected.

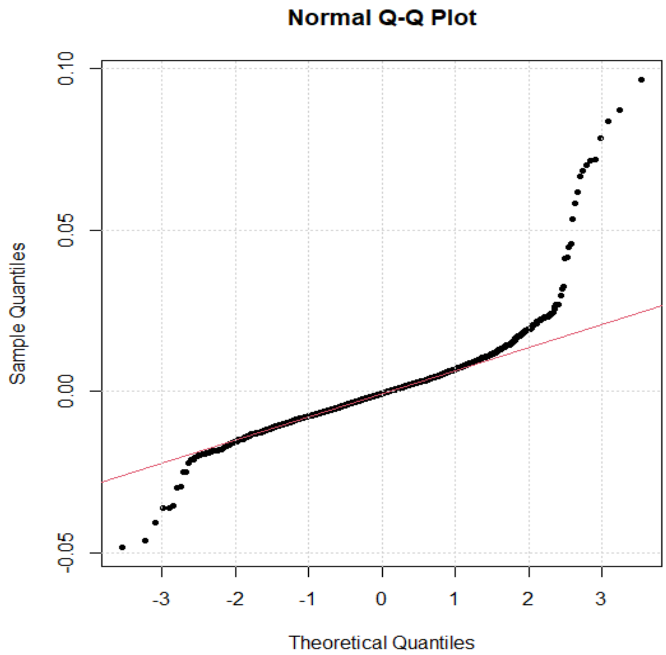

Figure 4. Normal Q–Q plot for the residuals of the linear regression model

The normal Q–Q plot displays the residuals of the model against the quantiles of the normal distribution. If the data lie on a straight line, this indicates that the distribution of the data is consistent with the normal distribution. However, as shown in the figure above, this conformity is intuitively rejected. Thus, in light of the model adequacy assessment results, the significance of the coefficients cannot be relied upon with full confidence. Nevertheless, the analyses conducted indicate that the volatility of "GSPC," changes in unemployment claims ("ICSA"), and the "VIX" index have a positive and significant effect on oil market volatility. The reasons for the significance of these variables are as follows:

GSPC: This index reflects financial market expectations, economic conditions, and the level of activity of industrial and energy-related companies, which directly affect oil demand and its price fluctuations.

Increase in unemployment claims (ICSA): Such an increase may indicate a decline in economic activity and, consequently, a reduction in energy (oil) demand. However, the effect of these changes usually occurs with a time lag and in an indirect manner.

VIX index: This index represents market expectations of future volatility in the GSPC over the next 30 days and is recognized as a measure of risk and uncertainty in financial markets. When the VIX index rises, it signals greater perceived uncertainty and higher risk in the market. In such conditions, investors tend to move towards safe assets such as bonds and exit high-risk markets (such as oil). This shift increases volatility and reduces liquidity in the oil market. Conversely, a decline in VIX indicates greater investor confidence and higher market stability, typically associated with lower oil price volatility and a more stable trend.

Overall, the linear regression model provides insights into the potential linear relationships between the independent variables and oil volatility, but due to the rejection of model adequacy, its results are not fully reliable. For this reason, in the present study, machine learning models have been used to model oil volatility, as they are more robust to the assumptions of classical models. Table (11) provides a comparison of the strengths and weaknesses of the linear regression model and machine learning models.

Table 11. Comparison of Advantages and Disadvantages of the Linear Regression Model and Machine Learning Models

Model	Advantages	Disadvantages	Suitable for
Linear regression	Simple, interpretable	Requires basic assumptions (such as normality of errors, independence of data)	When linear relationships exist between variables
Machine learning	Flexible, nonlinear modeling, robust to noise, capable of learning complex patterns	Requires substantial computation, difficulty in model interpretation ("black box")	When data are complex and patterns are nonlinear

As mentioned in Table (11), machine learning models, due to the nature of their learning-based approach, do not require basic assumptions such as normality of residuals and absence of serial correlation in the residuals. In addition, these models are capable of simulating and uncovering complex nonlinear patterns among variables. However, due to the "black box" nature of these models, interpreting their results is considerably complex and challenging. Therefore, in the next section of the study, volatility modeling will be conducted using one of the commonly used machine learning models.

In this section, after preparing the data, four common machine learning models were trained. As mentioned earlier, 80 percent of the observations were considered as training data and 20 percent as the test set. Table (12) presents the predictive accuracy results of these four models based on well-known loss functions, namely the root mean squared error (RMSE) and the mean absolute error (MAE), which are defined as follows:

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2}$$

The MAE criterion reflects the average magnitude of the errors (whether positive or negative), while the RMSE criterion indicates the dispersion of errors around zero; therefore, the smaller the values of these two criteria, the higher the predictive accuracy. Typically, the MAE value is smaller than the RMSE value.

Table 12. Comparison of Predictive Accuracy Results of Machine Learning Models for Oil Volatility

Model	Training RMSE	Training MAE	Test RMSE	Test MAE
Support Vector Regression (SVR)	0.006037	0.00349	0.00909	0.007341
Random Forest	0.002068	0.001381	0.006188	0.005011
Decision Tree	0.007355	0.005629	0.007638	0.006115
Artificial Neural Network (ANN)	0.00454	0.003604	0.009671	0.007382

As previously mentioned, the mean absolute error criterion represents the average magnitude of the errors (both positive and negative). Based on the obtained results, we find that the forecast of oil market volatility (Oil) produced by the Random Forest model has, on average, a lower error than that of the other models. Furthermore, the value of the root mean squared error for the Random Forest model also indicates that the dispersion of its forecast error values is smaller than that of the other models, which reflects its greater stability. Therefore, this model has been used to estimate the conditional standard deviation for value-at-risk.

Discussion and Conclusion

The primary objective of this study was to model and forecast crude oil market volatility using a hybrid econometric–machine learning framework that integrates conditional variance estimates derived from asymmetric GARCH-type models with nonlinear learning algorithms. The results demonstrate that the TGARCH model with skewed Student-t distribution for oil and Johnson SU distribution for GSPC and DJI produced the best volatility estimates among the tested heteroskedasticity models, consistent with the stylized facts of financial time series—namely heavy-tailed distributions, asymmetry in volatility response to shocks, and the persistence of conditional variance. These findings are aligned with previous research noting that the crude oil market exhibits strong non-Gaussian characteristics and fat tails that cannot be captured by conventional symmetric normal-based distributions (15, 18). The significant alpha and beta coefficients in all three GARCH-family models further confirm the presence of volatility clustering, a phenomenon widely reported in the literature on energy markets (6, 16).

A noteworthy pattern emerging from the results is the presence of asymmetric shock effects across all variables. The estimated positive and statistically significant threshold parameters reveal that negative shocks exert disproportionately larger impacts on volatility than positive shocks. This finding is theoretically consistent with the leverage effect documented in financial and commodity markets, wherein adverse news tends to heighten market uncertainty and risk more intensely than favorable news (5, 15). The crude oil market's sensitivity to downside pressures is also supported by evidence showing that supply disruptions, global demand contractions, geopolitical tensions, and macroeconomic uncertainty lead to amplified increases in volatility compared to periods of positive economic or supply-side developments (1, 11). Additionally, the skewness parameter for crude oil being positive and significant stands in contrast to the negative skew found in GSPC and DJI volatility. This asymmetry suggests that the distribution of oil returns carries a heavier right tail—indicating occasional large positive price movements—while equity markets display heavier left tails consistent with risk-averse investor behavior during downturns. Such divergent skewness patterns are consistent with the literature describing oil markets as being subject to sudden upward price shocks due to geopolitical pressures or supply rigidities (2, 9).

The regression analysis provides further insight into the roles of key macro-financial indicators in shaping oil volatility. Although the linear regression model was found to be statistically inadequate—due to non-normal residuals, low Durbin–Watson statistics, and the likelihood of spurious regression—the coefficient signs nonetheless reveal underlying relationships that align with economic intuition and previous empirical studies. The positive and significant effect of GSPC volatility on oil volatility is consistent with the strong financialization of the oil market, especially since the early 2000s when commodity markets became increasingly integrated with broader financial cycles (5, 6). This co-movement between oil and equity volatility is reinforced by studies showing that global financial stress, investor sentiment, and risk-on/risk-off transitions significantly influence oil price dynamics (11, 15). Similarly, the positive influence of the VIX index aligns with literature demonstrating that policy uncertainty and market fear indicators are powerful predictors of oil market volatility (15, 19). When uncertainty rises, investors often retreat into safer assets, reducing liquidity in oil markets and exacerbating volatility spikes, a finding that resonates with the broader evidence on transmission of economic policy uncertainty to commodity price dynamics (5).

The positive effect of changes in initial unemployment claims (ICSA) on oil volatility—despite the limitations of the linear model—also corresponds to macroeconomic cyclicality theories. Labor market weakening often signals broader economic slowdown, which can depress energy consumption and trigger anticipatory adjustments in oil markets, increasing uncertainty and price fluctuation. Similar findings have been reported for multiple oil-exporting economies, where macroeconomic instability and social indicators respond strongly to oil price volatility (12-14). Moreover, as unemployment claims increase, financial markets typically respond negatively, amplifying risk sentiment spillovers that affect oil market dynamics. This interdependence between labor market conditions and commodity volatility is also supported by studies linking macroeconomic slowdowns to oil demand uncertainty and elevated volatility levels (8, 10).

The comparison of machine learning models reveals robust evidence that nonlinear and ensemble-based methods outperform traditional linear approaches in predicting oil market volatility. Among the tested algorithms, the Random Forest model achieved the lowest RMSE and MAE values in both training and testing phases, indicating superior predictive accuracy and generalization capacity. This finding is consistent with extensive literature demonstrating the effectiveness of ensemble learning in handling noisy, nonlinear, and high-dimensional datasets typical of commodity and financial markets (19, 21, 22). Random Forest models are particularly advantageous because they capture nonlinear interactions and variable importance patterns without imposing parametric assumptions required by econometric models. Prior studies forecasting crude oil prices using machine learning—such as neural networks, SVM, and hybrid frameworks—report similar performance dominance over traditional forecasting models (11, 16, 20). The improved performance of ensemble learning methods in this study further confirms the argument that incorporating nonlinearity, interactions, and data-driven learning into volatility forecasting frameworks enhances predictive power in the presence of structural shifts, jumps, and complex dynamic patterns (15, 18).

Furthermore, the hybrid framework employed in this study—where conditional variances estimated from TGARCH models are used as structured features for machine learning prediction—reflects a methodological trend gaining recognition in financial econometrics. Scholars increasingly acknowledge that combining the interpretability and risk-theoretic foundations of econometric volatility models with the flexibility of machine learning can produce models that perform better than either category alone (23, 24). The strong empirical results produced by this hybrid strategy validate these claims and suggest that such combined approaches may be especially suitable for markets characterized by heavy-tailed distributions, uncertainty shocks, and nonlinear interactions—as is prominently observed in global oil markets (4, 5, 17).

Overall, the findings of this research reinforce several key insights emphasized across the literature:

1. **Oil price volatility is tightly linked to global macro-financial uncertainty**, including equity market volatility, policy uncertainty, and global financial cycles (5, 6, 15).
2. **Asymmetric and fat-tailed distributions dominate oil market behavior**, necessitating models capable of capturing extreme events and nonlinearity (16, 18).
3. **Machine learning models, particularly ensemble methods, provide superior forecasting accuracy**, supporting the argument for adopting data-driven approaches in energy market forecasting (20-22).
4. **Hybrid econometric–machine learning frameworks offer a promising avenue** for combining interpretability and predictive strength (19, 23).

Collectively, the results contribute to the ongoing shift in the energy economics literature toward integrating macro-financial indicators, econometric volatility models, and machine learning tools for more accurate and comprehensive modeling of oil price volatility and risk.

This study, despite its contributions, has several limitations. First, the dataset is restricted to daily observations and may not fully capture intraday volatility dynamics that could further improve model accuracy. Second, the study relies on a fixed set of macro-financial variables, whereas additional geopolitical, supply-side, or high-frequency sentiment indicators could provide valuable predictive content. Third, the machine learning models used—although effective—remain black-box approaches, limiting interpretability and posing challenges for policy application. Finally, the study focuses on forecasting volatility and VaR for crude oil specifically, without extending the framework to multi-asset interactions or spillover networks, which could enrich understanding of systemic risk.

Future research can extend this work in several directions. Incorporating high-frequency or intraday data may enhance volatility estimation and capture microstructural market effects. Expanding the feature set to include geopolitical risk indices, real-time news sentiment, or supply chain disruptions may increase predictive power. Researchers should also explore explainable AI (XAI) techniques to address the interpretability gap in machine learning models. Furthermore, applying this hybrid framework to a broader set of commodities or examining cross-market volatility spillovers could deepen insights into systemic risk transmission.

For practitioners, the results highlight the importance of adopting hybrid modeling approaches that combine econometric and machine learning tools to improve risk forecasting accuracy. Energy traders, risk managers, and policymakers can benefit from integrating ensemble learning methods into decision support systems to anticipate volatility spikes more effectively. The models developed here can enhance risk management strategies, improve hedging effectiveness, and support more resilient policy planning in environments characterized by uncertainty and rapid market shifts.

Acknowledgments

We would like to express our appreciation and gratitude to all those who helped us carrying out this study.

Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

Funding

This research was carried out independently with personal funding and without the financial support of any governmental or private institution or organization.

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