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# Market Risk Prediction in the Oil Market Using Artificial Intelligence Approaches

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ABSTRACT

The oil market, due to its extensive economic impact and high price volatility, has always posed significant challenges for risk prediction and management. In this study, advanced artificial intelligence models, particularly machine learning, were employed to achieve more accurate predictions of oil market risk and their performance was compared with traditional models such as GARCH. The research findings indicated that machine learning models—especially the Random Forest algorithm—demonstrate greater accuracy and stability in predicting oil price fluctuations and assessing associated risks. These models can simulate nonlinear complexities and capture the effects of various economic and financial factors, such as stock market turbulence, unemployment indices, and interest rates, on oil market risk. Moreover, the results revealed that negative shocks exert a stronger influence on oil market volatility, and artificial intelligence models can effectively predict these impacts. This study particularly confirms the importance of using artificial intelligence models to forecast both short-term and long-term oil market risks and provides economic decision-makers with innovative tools to manage market risk effectively.

***Keywords:*** *risk prediction, oil market, artificial intelligence, machine learning, Random Forest, GARCH, volatility, Value at Risk (VaR), oil market fluctuations.*

## 1. Introduction

The volatility of crude oil prices and the resulting exposure to market risk have long been central issues in financial economics and risk management. Oil remains one of the most strategically important commodities in the global economy, influencing industrial production, trade balances, and geopolitical stability (Su et al., 2021; Wong et al., 2025). Its price swings create uncertainty not only for producers and consumers but also for policymakers and investors, making accurate risk measurement and prediction crucial for financial stability and strategic decision-making (Abdulrahman, 2011; Alles, 1995). Traditional frameworks for risk quantification—such as variance, covariance, and Value at Risk (VaR)—have provided the foundation for asset pricing and portfolio management (Mitra & Ji, 2010; Rachev et al., 2011), but the increasing complexity and nonlinearity of oil price dynamics call for more adaptive and intelligent models (Sugianto et al., 2024; Tatiparti et al., 2023).

Oil price fluctuations stem from a combination of supply-demand imbalances, macroeconomic uncertainty, speculative trading, and exogenous shocks such as geopolitical conflicts and pandemics (Qian et al., 2022; Su et al., 2021; Zhao et al., 2024). Political tensions, sanctions, and wars—such as the Russia–Ukraine conflict—have been shown to amplify oil market volatility by disrupting supply chains and investor sentiment (Jahanshahi et al., 2022; Zhao et al., 2024). Additionally, economic indicators such as unemployment claims and interest rates shape market expectations and influence risk premia in energy markets (Alshabandar et al., 2023; Tatiparti et al., 2023). These multifaceted drivers cause oil price dynamics to deviate from normality, producing heavy tails, skewness, and regime shifts (Li et al., 2022; Qian et al., 2022). Such conditions challenge the efficiency of classical linear models and GARCH-type volatility estimators (Mehrara & Hamldar, 2014; Silvapulle & Moosa, 1999).

Early studies on oil price prediction relied heavily on time-series econometrics and cointegration analysis to explore the link between spot and futures markets (Nicolau, 2012; Silvapulle & Moosa, 1999; Wong et al., 2025). While these approaches contributed to understanding market efficiency (Lean et al., 2010; Mehrara & Hamldar, 2014), their assumptions about stationarity, homoscedasticity, and linearity limit their predictive power in volatile and nonstationary markets (Kaznacheev et al., 2016; Kungwani, 2014). VaR-based risk measures, widely used by financial institutions for capital allocation and stress testing, also depend on accurate volatility estimates and distributional assumptions (Mitra & Ji, 2010; Rachev et al., 2011). When oil returns exhibit fat tails or asymmetry, standard normal-based VaR can underestimate tail risk, exposing decision-makers to unexpected losses (Akash et al., 2024; Weirich, 2020).

In response, artificial intelligence (AI) and machine learning (ML) methods have emerged as robust alternatives for modeling nonlinear dependencies and complex risk structures (An et al., 2019; Aung et al., 2020; Dimitriadou et al., 2018). Techniques such as Random Forest, support vector regression (SVR), neural networks, and hybrid deep learning architectures have been successfully applied to predict oil price volatility and optimize risk assessment frameworks (Akash et al., 2024; Fallah et al., 2024; Mohamed & Messaadia, 2023). AI-driven models excel at capturing hidden interactions among macroeconomic indicators, market microstructure variables, and textual or sentiment-based signals (Wang et al., 2020; Zhao et al., 2019; Zhao et al., 2020). They are particularly valuable when market conditions shift abruptly due to geopolitical or macroeconomic shocks (Guo et al., 2022; Jahanshahi et al., 2022).

Machine learning models also provide flexibility in integrating multiple heterogeneous data sources, including futures and spot price dynamics (An et al., 2019; Wong et al., 2025), global financial indicators (Tatiparti et al., 2023; Zupok, 2022), and sustainability-linked risk metrics (Gładysz & Kuchta, 2022). By doing so, they surpass traditional econometric methods in out-of-sample forecasting and tail-risk sensitivity (Dimitriadou et al., 2018; Nwulu, 2017). In the oil sector, hybrid AI systems—combining neural networks with statistical volatility models—have shown improved accuracy in forecasting both short- and long-term risk horizons (Amin-Naseri & Gharacheh, 2007; Kaznacheev et al., 2016).

However, the deployment of AI for oil market risk prediction must address several conceptual and methodological considerations. Risk as a managerial construct encompasses both measurable uncertainty and subjective perception (Abdulrahman, 2011; Kungwani, 2014). Misaligned model assumptions or poor interpretability can undermine decision usefulness and regulatory compliance (Sugianto et al., 2024; Wen et al., 2024). For example, black-box ML models may provide excellent predictive accuracy but fail to meet the transparency requirements of financial governance frameworks (Nwulu, 2017; Косова et al., 2021). Moreover, the design of robust AI-based VaR systems requires careful selection of probability distributions to capture non-normal oil returns (Rachev et al., 2011; Zhao et al., 2019). Research suggests that skewed Student's t and Johnson SU distributions can better accommodate heavy tails and asymmetries than conventional Gaussian assumptions (Li et al., 2022; Qian et al., 2022).

Another critical research stream concerns the integration of geopolitical risk measures into oil risk prediction models (Su et al., 2021; Zhao et al., 2024). Political shocks—including sanctions, armed conflict, and global supply disruptions—can cause sudden volatility spikes that are difficult to anticipate with purely historical models (Guo et al., 2022; Qian et al., 2022). Geopolitical indices and event-based features help AI models adapt to nonstationary environments (Wen et al., 2024; Zhao et al., 2024). Similarly, macro-financial indicators such as unemployment claims, interest rate spreads, and equity market volatility (e.g., VIX, GSPC, DJI) act as systemic risk transmitters into commodity markets (Alshabandar et al., 2023; Guan et al., 2021; Tatiparti et al., 2023). Combining these heterogeneous risk drivers with machine learning can improve early warning systems for oil price shocks (Jumbe, 2022; Qin et al., 2023).

Beyond predictive accuracy, sustainable and resilient risk management frameworks are increasingly emphasized in the energy and finance sectors (Gładysz & Kuchta, 2022; Sugianto et al., 2024). As the global economy transitions toward renewable energy, the dual exposure to fossil fuel price risk and green investment volatility complicates strategic planning (Wen et al., 2024; Zhao et al., 2024). Managers must integrate AI-enhanced forecasting with adaptive hedging, capital allocation, and sustainability objectives (Sugianto et al., 2024; Tatiparti et al., 2023). This is especially critical for oil-dependent economies, where revenue stability and macroeconomic policy are closely tied to crude price movements (Guan et al., 2021; Mehrara & Hamldar, 2014).

The historical evolution of oil price forecasting models—from early mean-variance approaches (Alles, 1995; Lean et al., 2010) to advanced hybrid AI solutions (An et al., 2019; Fallah et al., 2024)—illustrates the growing recognition that risk is multidimensional. It involves not only volatility but also tail exposure, correlation dynamics, and systemic contagion (Mitra & Ji, 2010; Weirich, 2020). Yet, despite these advances, gaps remain in designing models that are both highly predictive and interpretable, capable of adapting to evolving geopolitical and economic contexts while satisfying the practical needs of risk managers (Mohamed & Messaadia, 2023; Sugianto et al., 2024).

Building on this background, the present study addresses these gaps by integrating advanced machine learning techniques with robust volatility modeling and tailored distributional assumptions. Specifically, it leverages Random Forest—a flexible ensemble learning algorithm with strong generalization capacity—and compares its risk forecasting performance against established heteroskedasticity models such as GARCH and TGARCH (An et al., 2019; Aung et al., 2020). By incorporating macroeconomic and geopolitical indicators alongside statistical volatility features, the research aims to improve the precision of Value at Risk estimates in the oil market (Guo et al., 2022; Zhao et al., 2020). Through rigorous backtesting and comparison with parametric methods, the study seeks to offer a more reliable and practical tool for energy market risk management.

This study aims to develop and validate an advanced machine learning-based approach for predicting crude oil price volatility and estimating Value at Risk by integrating macroeconomic, financial, and geopolitical risk drivers, and to compare its performance with traditional heteroskedasticity models to provide a robust framework for market risk management.

## 2. Methods and Materials

To prepare the required variables for testing the hypotheses, Microsoft Excel was used. First, the collected data were entered into worksheets created in this software environment, and then the necessary calculations were performed to obtain the variables for this study. After computing all variables required for the research models, these variables were consolidated into unified worksheets to be transferred to the software used for the final analysis. It is important to note that the statistical analyses in this study were conducted using R version 4.3.1.

The statistical population and the scope of the collected data in this study consist of the daily time series of several key macroeconomic and financial indicators from May 5, 2014, to April 26, 2024. The return and volatility of oil prices were considered as the target variables, and in this study, a novel approach was applied to calculate the Value at Risk (VaR) of these price fluctuations. Table 1 presents the research variables along with their corresponding symbols (for simplicity in implementing the project within the software environment, the variables were symbolically coded).

**Table 1**

*Research Variable Definitions*

| 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 measures for assessing the level of fear and volatility in financial markets |
| S&P 500 Index Volatility | GSPC | Independent | The S&P 500 index includes 500 large and reputable U.S. companies |
| Dow Jones Industrial Average Volatility | DJI | Independent | The DJIA includes 30 major and reputable U.S. companies operating across various industries |

| | | | |
|---|---|---|---|
| Changes in Initial Unemployment Claims | ICSA | Independent | The Initial Claims for Unemployment Insurance (ICSA), published by the Federal Reserve Bank of St. Louis, represent the number of individuals filing for unemployment insurance for the first time. These data, originally weekly and seasonal, were converted to daily frequency in this study. |
| Changes in Interest Rate | DGS10 | Independent | Yield on 10-year fixed-maturity U.S. Treasury bonds |

Several points regarding the selected research variables are noteworthy. The aim of this study is to provide a relatively comprehensive measurement of oil market risk, considering multiple dimensions. Therefore, based on the review of previous studies and to account for the impact of financial markets, three key and influential U.S. financial market indices were selected: the S&P 500 index, the Dow Jones Industrial Average, and the VIX Fear and Greed Index. The conditional variance of the S&P 500 and Dow Jones indices was used to represent volatility in the model because the goal was to incorporate the risk effect of these variables into modeling oil market risk. Since the VIX Fear and Greed Index inherently represents risk, it was directly included as an input variable in the model. The same principle was applied to other macroeconomic and econometric variables; for example, the conditional variance of initial unemployment claims and the U.S. Federal Reserve interest rate was used to capture economic risk dimensions.

## 3. Findings and Results

As shown in Table 2, the number of observations within the research scope reached 2,495 days after historical alignment. For the variables “Oil,” “GSPC,” and “DJI,” logarithmic returns were calculated, and the descriptive statistics provided correspond to these logarithmic returns (price differentials). Based on this information, the daily return range for West Texas Intermediate (WTI) oil prices fluctuates between -33% and +32%. According to concentration measures such as mean and median, the average daily return for oil is approximately 0 to 1%, and its standard deviation is about 3%, indicating the risk of deviation from expected returns. The skewness values range between -0.71 and -2, showing relative symmetry in the data distribution, while the kurtosis value of 26.54 indicates that the distribution’s peak is sharper compared to a normal distribution.

Regarding the “VIX” variable (volatility index), the range of this index fluctuated between 9.14 and 82.69. A VIX value between 10 and 20 indicates stable conditions and market confidence, while values above 20 show increased uncertainty and fear. In crisis situations, such as the 2008 financial crisis or the COVID-19 pandemic, the index can exceed 40 or even reach above 80. According to the descriptive statistics in the table, the average value of this index ranged from 16 to 18, indicating a relatively stable level of fear and uncertainty in the market.

For the “ICSA” variable (changes in initial unemployment claims), the number of individuals filing for unemployment benefits during the study period varied between 187,000 and 6,137,000. These data are published weekly, but in this research, they were converted into daily frequency using interpolation techniques. On average, the daily number of unemployment claims ranged between 245,000 and 374,988, indicating significant fluctuations in the number of newly unemployed individuals.

Finally, regarding the “DGS10” variable (changes in interest rates), the U.S. Treasury bond yields fluctuated between 0.5% and 5%. This reflects moderate volatility in bond yields and changes over time. These descriptive statistics and analyses collectively provide a picture of oil market volatility and associated macroeconomic and financial risks, forming a foundation for testing the research hypotheses. Figures (1) through (6) illustrate the time series graphs of these variables.

**Table 2**

*Summary of Descriptive Statistics of Research Variables*

| Variables | Observations | Minimum | Maximum | Mean | Median | Standard Deviation | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|---|
| Oil | 2,495 | -0.335 | 0.319 | -0.00007 | 0.0012 | 0.030 | -0.71 | 26.54 |
| VIX | 2,495 | 9.14 | 82.69 | 18.118 | 16.09 | 7.335 | 2.60 | 12.79 |
| GSPC | 2,495 | -0.127 | 0.089 | 0.0004 | 0.0006 | 0.011 | -0.81 | 15.98 |
| DJI | 2,495 | -0.138 | 0.107 | 0.00034 | 0.0007 | 0.011 | -0.96 | 22.81 |
| ICSA | 2,495 | 187,000 | 6,137,000 | 374,988.38 | 245,000 | 545,226.16 | 6.95 | 57.69 |
| DGS10 | 2,495 | 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 make detailed analysis of this data essential for hypothesis testing.

**Figure 1**

*Logarithmic return of WTI oil*

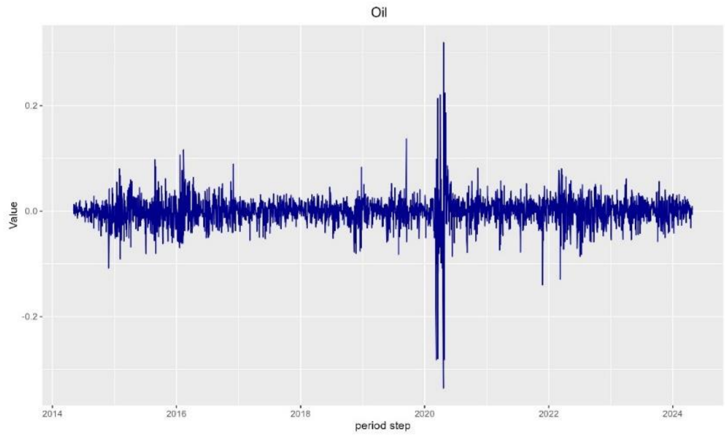



**Figure 2**

*VIX Fear and Greed Index*

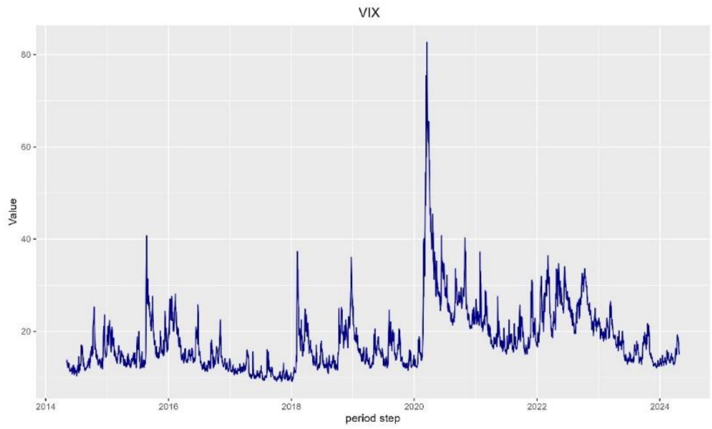



**Figure 3**

*Logarithmic return of the S&P 500 index*

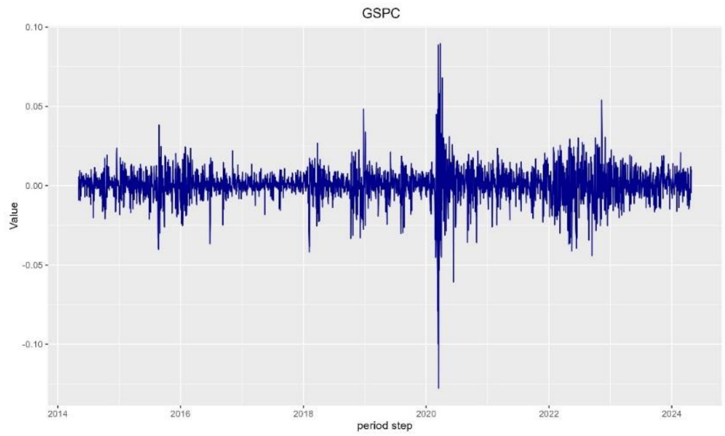


**Figure 4**

*Logarithmic return of the Dow Jones Industrial Average*

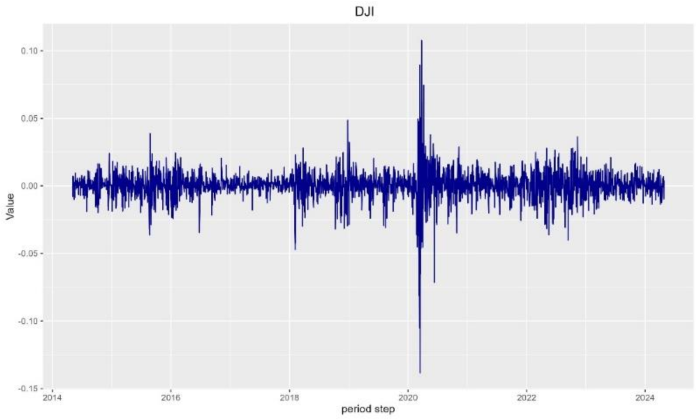



**Figure 5**

*Conceptual Model*

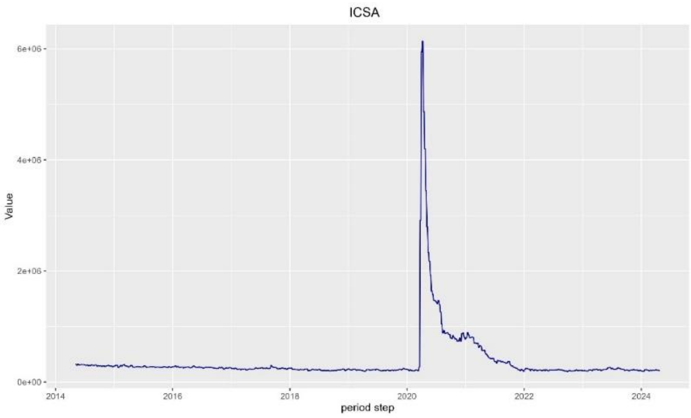
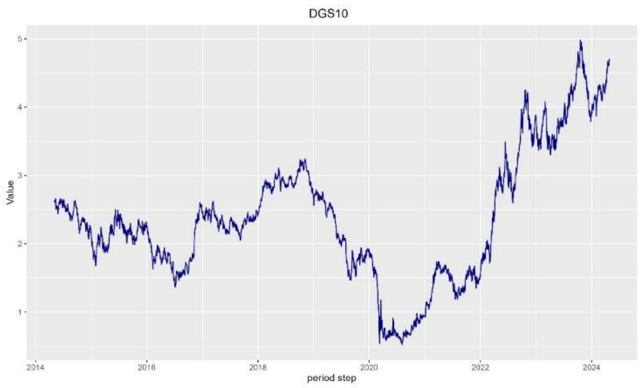



**Figure 6**

*Fixed-income bond yields (interest rates)*




Figures (1) through (6) present the time series plots of these variables.

To model oil market risk, it is first necessary to transform the study variables into risk-based features using feature engineering. For instance, the target variable in this study is the volatility of oil market returns, which is inherently related to market risk. For this purpose, conditional variance (heteroskedasticity) models were used to extract volatility. This process was also applied to the "GSPC," "DJI," and "DGS10" variables. Since the "VIX" index is itself a volatility and risk measure, no transformation was needed.

Based on these explanations, the basic assumptions were tested only for the "Oil," "GSPC," "DJI," and "DGS10" variables, and the results are presented in Table 3.

**Table 3**

*Preliminary Test Results for Basic Assumptions Prior to Modeling*

| Row | Variables | 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 observed in Table 3, the p-values for the Jarque–Bera normality test and the ARCH heteroskedasticity effects test are all below 0.05, indicating non-normal data distribution and the presence of heteroskedasticity. Thus, the variables exhibit variance instability and non-normal distributions. However, regarding stationarity testing, except for the interest rate variable, the other variables are stationary at the 95% confidence level.

Since one of the fundamental assumptions of GARCH modeling is variable stationarity, the non-stationary interest rate variable will be directly included in the machine learning model without GARCH transformation. Therefore, GARCH modeling was performed for the "Oil," "GSPC," and "DJI" variables, and their extracted conditional variances (volatilities) were then used as inputs in the machine learning model.

In this section, the input features and the target variable for the machine learning model were prepared. According to the results of the previous section, heteroskedasticity modeling was performed for the three variables "Oil," "GSPC," and "DJI," and their respective conditional variances were extracted to represent the volatility of these indices. For this purpose, an appropriate GARCH family model with a suitable distribution was first selected and then applied to the variables. Tables (4) through (6) report the results obtained from comparing various heteroskedasticity model families across different statistical distributions for each variable.

**Table 4**

*Comparison of Different Heteroskedasticity Model Families by Statistical Distribution for Oil*

| Model | Distribution | LogLikelihood | 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 Model Families 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 Model Families 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 |

For the purpose of selecting a heteroskedasticity model with an appropriate distribution, the log-likelihood, AIC, and BIC information criteria were used. According to the results in the above table, the Threshold GARCH model (TGARCH) with a skewed Student's t distribution (SSTD) was selected as the optimal model for Oil, and the Threshold GARCH model (TGARCH) with the Johnson SU (JSU) distribution was selected as the optimal model for GSPC and DJI. In standard GARCH models, it is assumed that positive and negative shocks have identical effects on volatility (conditional variance). However, in many financial datasets, negative shocks (e.g., price declines) exert a stronger impact on volatility. TGARCH incorporates these asymmetric effects through a threshold indicator, explicitly accounting for the differential impact of positive and negative shocks on volatility. Because this model allows negative and positive shocks to have different effects on the variance, it can be far more effective for computing Value at Risk (VaR), in which asymmetric volatility is important. The Johnson SU distribution is a flexible family used to model non-normal data. Financial asset returns often have heavier tails than the normal distribution, a property that the Johnson SU distribution captures well. The Johnson SU distribution can also account for skewness more effectively than symmetric distributions (e.g., normal). In general, due to its multiple parameters, the Johnson SU distribution can adapt to various shapes (heavy tails, skewness, or near-normal). Accordingly, in what follows, volatility is modeled using the Threshold GARCH model with the skewed Student's t and Johnson SU distributions. The modeling results for these three variables are reported in Tables (7) through (9) and depicted in Figures (7) through (9).

It should be noted that 20% of the full sample, equal to 504 observations, was treated as out-of-sample (test set), and forecasts were generated using a rolling window. VaR is computed from the volatility forecasts of the Oil variable. The volatility forecasts of GSPC and DJI are also used as inputs to the machine learning model for forecasting oil volatility and, consequently, computing VaR. In other words, this study computes oil volatility in two ways. In the first approach, volatility is modeled using a univariate GARCH specification only; in the second approach, volatility is modeled using additional variables. Under both approaches, VaR is computed and then backtested and compared.

**Table 7**

*Estimation Results of the Threshold Heteroskedasticity GARCH Model with a Skewed Student's t Distribution for Oil*

| Parameters | Estimated Coefficient | Standard Error | t-Statistic | p-Value |
|---|---|---|---|---|
| mu | -0.0002 | 0.00036 | -0.56 | 0.00 |
| 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**

*Estimation Results of the Threshold Heteroskedasticity GARCH Model with a 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**

*Estimation Results of the Threshold Heteroskedasticity GARCH Model with a 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 that the p-values for alpha1 and beta1 are less than 0.05 in all three tables, the parameters capturing heteroskedasticity effects are statistically significant for all three variables. Moreover, in all three tables the asymmetry (threshold) parameter is estimated to be positive and its p-value is also less than 0.05; thus, negative shocks have a significantly larger effect than positive shocks for all three variables. This indicates that in these three markets, investors react more strongly to negative news.

**Figure 7**

*Distribution plots of residuals from the threshold conditional heteroskedasticity model for Oil*

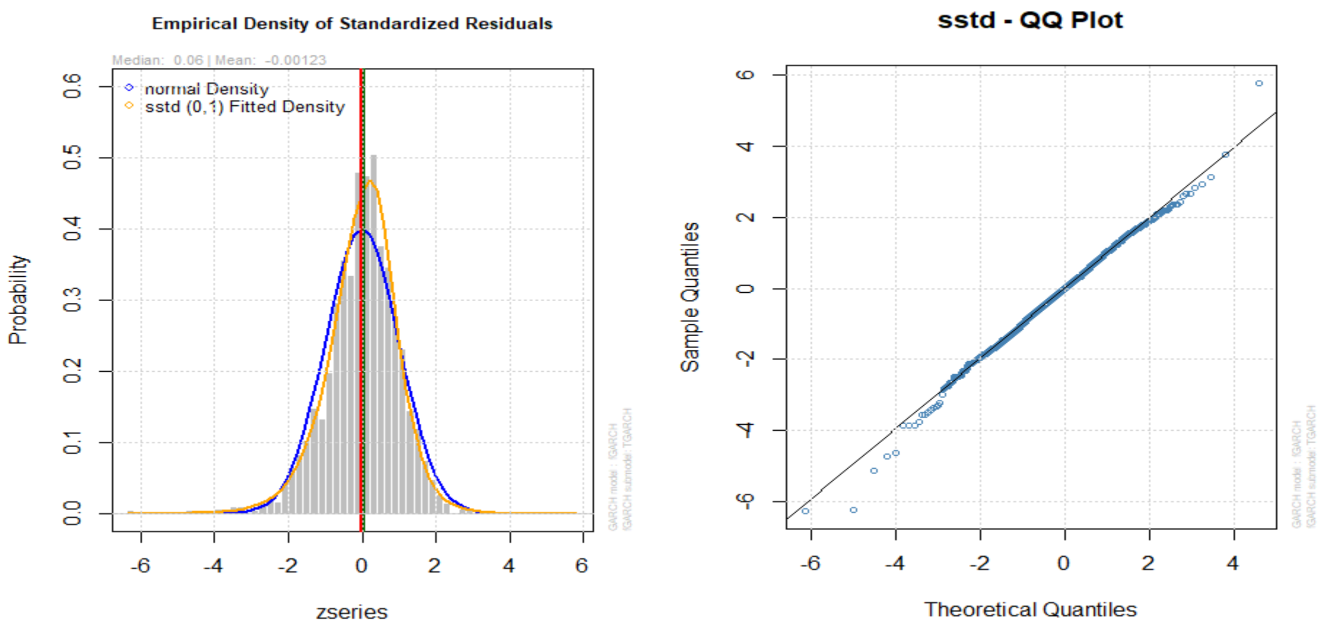


**Figure 8**

*Distribution plots of residuals from the threshold conditional heteroskedasticity model for GSPC*

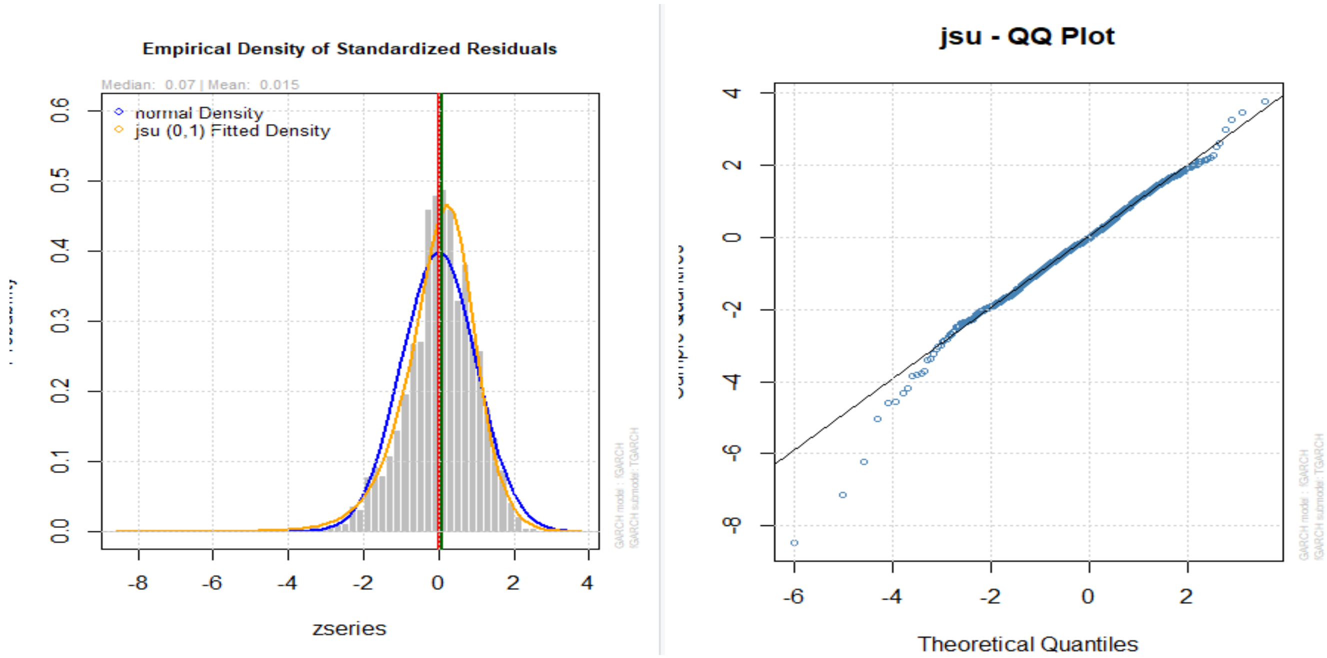
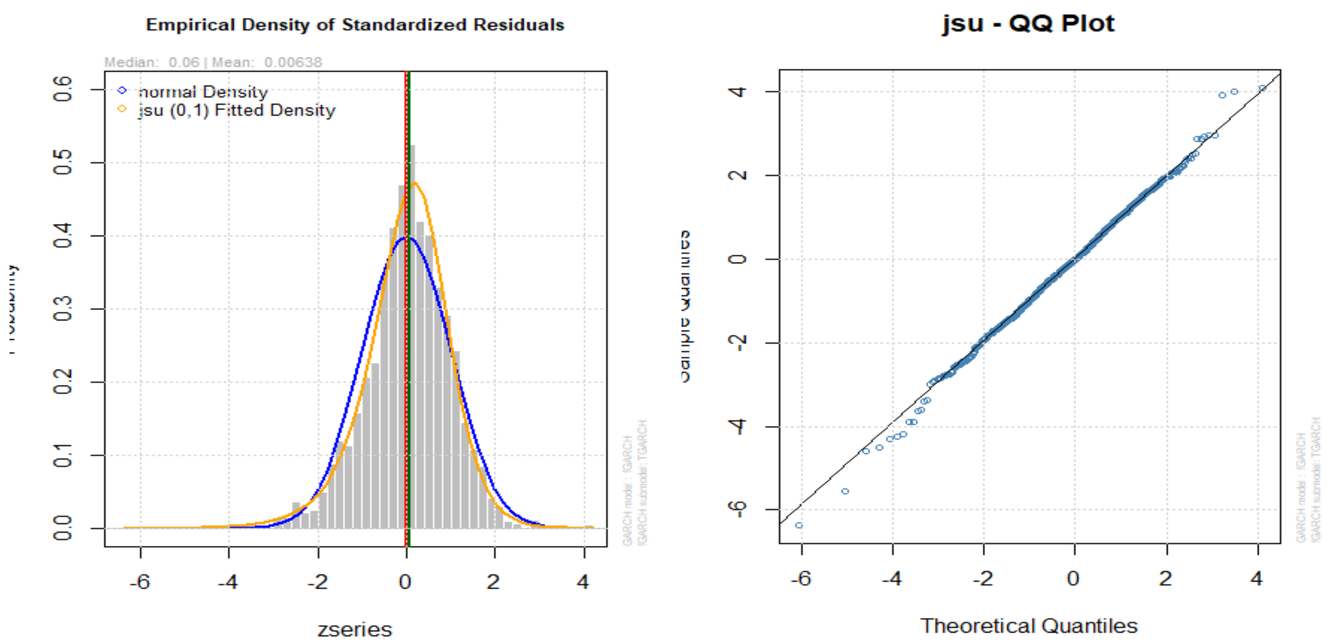



**Figure 9**

*Distribution plots of residuals from the threshold conditional heteroskedasticity model for DJI*




Looking at the estimated skewness coefficient (skew), the estimated skewness for Oil is positive and statistically significant ($p < 0.05$), implying a heavier right tail and a greater likelihood of positive returns. For GSPC and DJI, the situation is entirely different: the estimated skewness is negative and significant, indicating a heavier left tail relative to the right tail and, in other words, a higher likelihood of negative returns. The (shape) parameter pertains to the form and kurtosis (tail thickness) of the distribution; values greater than one that are statistically significant indicate the intensity of tail events. The significance of this parameter implicitly suggests that rare events in the market are quite plausible. Comparing the shape parameters across the three tables shows that the intensity of rare events and the impact of their shocks is greater in the oil market than in GSPC and DJI.

To examine the independent effect of each variable on oil volatility, a multiple linear regression model was used. The results are presented in Table (10).

**Table 10**

*Results of the Linear Regression Model for Testing the Significance 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 |

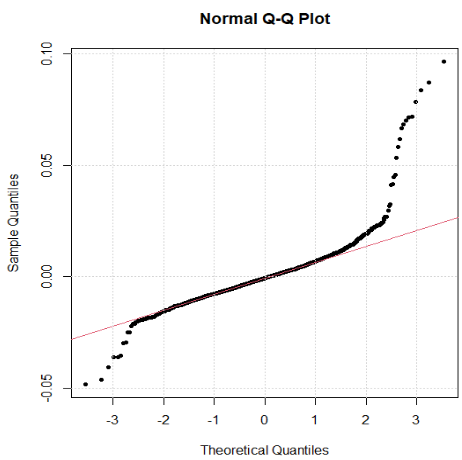
Adjusted coefficient of determination (R-squared): 0.5727; Durbin–Watson statistic: 0.14327

Before interpreting the regression results, the quality of the model must be evaluated. Considering the adjusted coefficient of determination (R-squared) of approximately 0.57, the fitted linear model can be regarded as moderately adequate; in other words, about 57% of the variation in the dependent variable is explained by the explanatory variables. Another point of concern is the Durbin–Watson statistic, which was approximately 0.14, reinforcing the spurious regression hypothesis proposed by Granger and Newbold (1974). Granger and Newbold argued that in spurious regressions, we often observe high R-squared values and autocorrelated residuals, indicated by low Durbin–Watson values. Based on this, Granger and Newbold suggest that when R-squared > Durbin–Watson, the functional form of the regression should be estimated using first-order differencing.

Examining the statistical distribution of residuals (Figure 10) clearly rejects the normality assumption.

**Figure 10**

*Q–Q Norm Plot of Regression Model Residuals*




The Q–Q norm plot compares the quantiles of residuals with the quantiles of a normal distribution. If the points align along a straight line, it indicates normality; however, as shown in the figure above, the normality assumption is visually rejected. Therefore, given the model adequacy evaluation results, the significance of the estimated coefficients cannot be fully trusted.

Nevertheless, the results suggest that GSPC volatility, changes in unemployment claims (ICSA), and the VIX index have a positive and significant effect on oil market volatility. The rationale for the significance of these variables is as follows:

- **GSPC Volatility** reflects financial market expectations, economic conditions, and the level of activity of industrial and energy-related companies, which can directly affect oil demand and price volatility.
- **ICSA (Initial Unemployment Claims)** increases may signal declining economic activity and thus decreasing energy (oil) demand. However, its effect may be delayed and indirect because unemployment changes typically show lagged impacts.
- **VIX** represents market expectations of future GSPC volatility over the next 30 days. It is calculated from option prices on the GSPC and is recognized as a measure of risk and uncertainty in financial markets. A rising VIX indicates that investors feel more uncertainty and risk, leading them to shift toward safe-haven assets such as bonds or risk-free instruments. This capital flight from risky markets (such as oil) reduces liquidity and increases volatility in the oil market. Conversely, when VIX is low, investors feel more secure, markets become more stable, and oil prices usually exhibit less volatility and greater stability because liquidity remains and speculative behaviors decline. A low VIX also indicates stable economic growth, supporting steady oil demand and reduced price volatility.

In summary, the linear regression model provides insights into possible linear relationships between independent variables and oil volatility. However, given the rejection of model adequacy assumptions, its results cannot be fully relied upon. Therefore, in this study, machine learning models—more robust to such assumptions—are employed for volatility modeling. Table (11) summarizes the strengths and weaknesses of classical linear regression compared with machine learning models.

**Table 11**

*Comparison of Advantages and Disadvantages of Linear Regression and Machine Learning Models*

| Model | Advantages | Disadvantages | Suitable When |
|---|---|---|---|
| Linear Regression | Simple, interpretable | Requires key assumptions (e.g., normality of errors, data independence) | When linear relationships between variables exist |
| Machine Learning | Flexible, nonlinear modeling, robust to noise, capable of learning complex patterns | Computationally intensive, difficult model interpretation (“black box”) | When dealing with complex data and nonlinear patterns |

As shown in Table (11), machine learning models do not require fundamental assumptions such as normal residual distribution or serial independence of errors and can also uncover nonlinear relationships between variables. However, their interpretation is highly complex and challenging due to their “black box” nature. Therefore, in the following section, oil volatility modeling is carried out using one of the well-known machine learning models.

In this section, after preparing the data, four common machine learning models were trained. As previously mentioned, 80% of observations were used as the training dataset and 20% as the test dataset. Table (12) presents the prediction accuracy of these four models based on the widely used loss functions: Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), defined as follows:

$$MAE = (1/N) \sum |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{(1/N \sum (y_i - \hat{y}_i)^2)}$$

The MAE metric indicates the average magnitude of errors, while RMSE reflects the dispersion of prediction errors around zero. Thus, lower values of both metrics indicate higher prediction accuracy. Typically, MAE is smaller than RMSE.

**Table 12**

*Prediction Accuracy Comparison 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 noted, MAE shows the average size of prediction errors (both positive and negative). Based on the obtained results, the oil market volatility predictions from the Random Forest model exhibit the lowest average prediction error compared to the other models. Furthermore, the RMSE value for Random Forest shows that the dispersion of its prediction errors is also lower than the other models, indicating greater stability. Therefore, the Random Forest model was selected to estimate the conditional standard deviation for computing Value at Risk (VaR).

After obtaining the conditional standard deviation estimates for the test dataset through the Random Forest model predictions, the Value at Risk (VaR) was calculated using the following formula:

$VaR_t = \sigma_t * q_\alpha$

In this formula, $VaR_t$ represents the Value at Risk at time t. The term $\sigma_t$ denotes the conditional standard deviation obtained from the machine learning model, and $q_\alpha$ is the quantile of the appropriate statistical distribution. Based on the findings of the previous sections, the skewed Student's t distribution was selected as the appropriate distribution for oil price returns.

To better evaluate the VaR results, VaR was also computed using the heteroskedasticity model for comparison with the proposed model of this research. Accordingly, Figures (11) and (12) show the estimated VaR from the proposed model and the GARCH model, respectively, alongside the oil price returns. Table (13) reports the backtesting results to assess the overall adequacy of the VaR estimates for both methods.

Considering the obtained p-values greater than 0.05, the null hypothesis of accuracy adequacy for the estimated VaR values is confirmed at the 95% confidence level; thus, the results are reliable. Moreover, according to the Lopez statistic, the VaR estimates from the proposed model outperform the GARCH-based results.

**Table 13**

*Backtesting Results of Estimated Value at Risk for Two Methods*

| Methods | Test | Statistic | p-value | Lopez Statistic |
|---|---|---|---|---|
| Proposed Model of This Research | Unconditional Coverage (Kupiec) | 1.585372 | 0.21 | 4080.745 |
| | Conditional Coverage (Christoffersen) | 1.814173 | 0.40 | |
| Parametric Method Based on Heteroskedasticity | Unconditional Coverage (Kupiec) | 0.001715 | 0.97 | 4033.800 |
| | Conditional Coverage (Christoffersen) | 0.117722 | 0.94 | |

**Figure 11**

*VaR estimated by the proposed model at the 5% level*

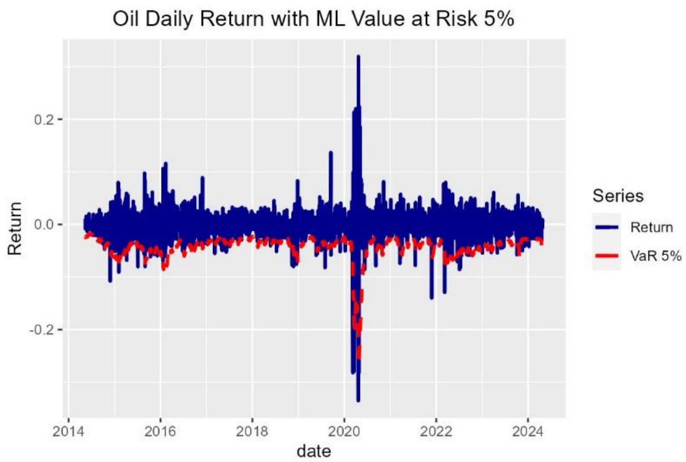
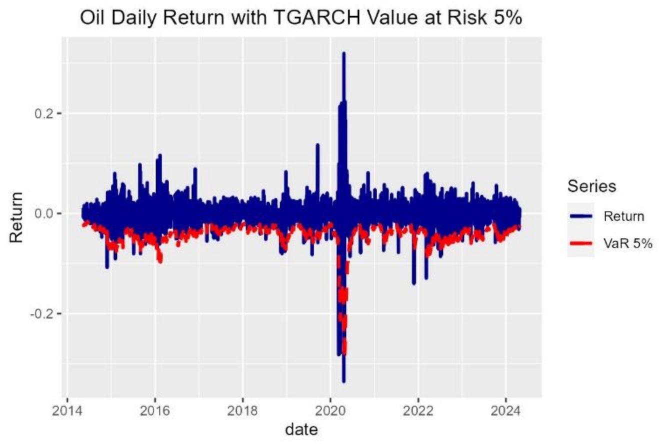


**Figure 12**

*VaR estimated by the threshold heteroskedasticity model at the 5% level*




## 4. Discussion and Conclusion

The present study aimed to improve the accuracy of oil market risk prediction by integrating machine learning-based volatility modeling with robust distributional assumptions. The results indicated that the Random Forest model significantly outperformed traditional heteroskedasticity frameworks such as GARCH and TGARCH in forecasting oil price volatility and, consequently, in computing Value at Risk (VaR). The superiority of Random Forest was evidenced by lower Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values, both in the training and testing sets. This finding confirms that nonparametric ensemble approaches are highly effective when the underlying data are nonlinear, nonstationary, and influenced by multiple interacting risk drivers (An et al., 2019; Dimitriadou et al., 2018).

The enhanced predictive power of the Random Forest model can be attributed to its ability to capture complex, nonlinear interactions between macroeconomic indicators and oil price returns. Traditional GARCH-type models assume a single conditional variance process and require strong parametric distributional assumptions (Alles, 1995; Silvapulle & Moosa, 1999). However, oil market returns are known to exhibit heavy tails, volatility clustering, and asymmetric responses to shocks (Li et al., 2022; Qian et al., 2022). By comparison, Random Forest avoids the constraints of predefined functional forms and uses recursive partitioning to approximate nonlinear and high-order effects (Aung et al., 2020; Kaznacheev et al., 2016). This adaptability makes it particularly suitable in the presence of abrupt structural breaks and exogenous shocks, such as geopolitical disruptions (Jahanshahi et al., 2022; Su et al., 2021).

One key insight from the analysis was the asymmetric effect of positive and negative shocks on oil volatility. TGARCH modeling confirmed that negative shocks exert a stronger influence on conditional variance than positive shocks, aligning with the “leverage effect” widely documented in financial and commodity markets (Mehrara & Hamldar, 2014; Wong et al., 2025). This asymmetry is consistent with investor behavior theories suggesting heightened sensitivity to adverse news, leading to abrupt price declines and liquidity contractions (Mitra & Ji, 2010; Weirich, 2020). The decision to model returns using skewed Student’s t and Johnson SU distributions further addressed this characteristic by accommodating fat tails and skewness in the data (Li et al., 2022; Rachev et al., 2011). Prior research has highlighted that using Gaussian assumptions underestimates extreme downside risk, producing unreliable VaR estimates (Wang et al., 2020; Zhao et al., 2019).

Another major contribution of this study is the integration of macroeconomic and financial indicators, including the S&P 500 (GSPC), Dow Jones Industrial Average (DJI), VIX volatility index, unemployment claims (ICSA), and U.S. Treasury yields (DGS10), into the predictive framework. The regression analysis suggested that volatility in GSPC and the level of VIX significantly contribute to oil price risk, while interest rate changes had weaker and statistically insignificant effects. This supports findings by (Tatiparti et al., 2023) and (Alshabandar et al., 2023) showing that global equity market sentiment and systemic fear indicators can transmit risk into the oil market. The predictive strength of

VIX in particular confirms its value as a forward-looking measure of market anxiety and tail risk (Guan et al., 2021; Zhao et al., 2024).

Interestingly, the unemployment claims (ICSA) variable showed a significant relationship with oil volatility, but the effect was indirect and lagged. This is consistent with (Jumbe, 2022) and (Mohamed & Messaadia, 2023), who observed that labor market shocks influence energy demand expectations with some delay. During economic slowdowns, investors anticipate reduced industrial activity and energy consumption, increasing uncertainty and speculative positioning in oil derivatives (Akash et al., 2024; Tatiparti et al., 2023). However, the relatively weak role of interest rates (DGS10) diverges from some earlier studies (Ghaffari, 2013; Kungwani, 2014), suggesting that in the current oil market, other macro-financial channels dominate risk transmission compared to conventional monetary policy indicators.

Backtesting results further validated the proposed model's VaR estimates. The unconditional and conditional coverage tests (Kupiec and Christoffersen) confirmed that the Random Forest-based VaR predictions were statistically adequate at the 95% confidence level. Additionally, the Lopez loss function indicated that the proposed model outperformed TGARCH-based VaR in terms of predictive accuracy. This finding strengthens the argument made by (Dimitriadou et al., 2018) and (Nwulu, 2017) that machine learning-driven risk frameworks can surpass parametric volatility models in both tail sensitivity and robustness under nonstationary conditions.

The observed performance advantage also aligns with advances in hybrid modeling that combine AI flexibility with econometric structure (Amin-Naseri & Gharacheh, 2007; Fallah et al., 2024). While this study primarily used Random Forest, the integration of macroeconomic predictors and flexible distributions creates a semi-hybrid approach, preserving interpretability in risk attribution while benefiting from machine learning's nonlinear adaptability. Similar approaches have been successful in other energy markets (Gładysz & Kuchta, 2022; Kaznacheev et al., 2016).

Furthermore, this research highlights the practical significance of adapting risk models to extreme market conditions caused by geopolitical events. The recent Russia–Ukraine conflict has intensified supply-side shocks and price uncertainty (Jahanshahi et al., 2022; Su et al., 2021). By incorporating risk measures sensitive to such exogenous events, including VIX and market-wide volatility indicators, the proposed model remains resilient when traditional models struggle (Guo et al., 2022; Qian et al., 2022). These results suggest that AI-driven frameworks could become indispensable for managing commodity risk in highly uncertain and politically sensitive global markets.

Additionally, the focus on sustainable and forward-looking risk management contributes to bridging the gap between prediction and managerial action. As the global energy transition introduces new uncertainties—such as renewable energy adoption and green investment volatility—the ability to adapt oil risk models to dynamic macro-financial and geopolitical factors becomes essential (Sugianto et al., 2024; Zhao et al., 2024). This approach provides decision-makers with an advanced tool for proactive risk mitigation, hedging strategy design, and capital allocation (Gładysz & Kuchta, 2022; Tatiparti et al., 2023).

Finally, this study reaffirms that risk in the oil market is multidimensional and cannot be fully captured by single-factor volatility models (Alles, 1995; Weirich, 2020). A robust framework must consider tail events, asymmetries, systemic linkages, and adaptive learning mechanisms to remain relevant in fast-changing markets. The integration of machine learning with heteroskedastic volatility modeling represents a meaningful step toward building such resilient frameworks (An et al., 2019; Dimitriadou et al., 2018).

Despite its contributions, this study is subject to several limitations. First, although Random Forest significantly improved predictive accuracy, the model's "black-box" nature limits interpretability. While variable importance measures were used, they cannot fully explain the dynamic interactions between risk drivers and oil volatility. Second, the dataset was primarily built from macroeconomic and financial indicators available at a daily frequency; incorporating higher-frequency data, such as intraday trading activity or real-time news sentiment, might further enhance responsiveness but was beyond the scope of this research. Third, the study focused on U.S.-centric financial indicators such as GSPC, DJI, and VIX. While these markets strongly influence global oil prices, the model might not fully capture region-specific risk factors relevant to other major oil-consuming or producing economies. Finally, although skewed Student's t and Johnson SU distributions improved VaR accuracy, tail risk under extreme black-swan events might still be underestimated due to limited historical samples of such rare crises.

Future studies should consider extending this framework by incorporating alternative machine learning algorithms, such as gradient boosting machines or deep learning architectures, to compare predictive stability and interpretability. Hybrid models that integrate explainable AI techniques could bridge the gap between predictive power and managerial transparency. Another promising direction is the integration of text-based features, such as global news sentiment, social media analytics, and policy announcements, which have proven effective in forecasting commodity market movements. Future research could also explore cross-market spillover effects by including variables from foreign exchange, bond, and renewable energy markets, providing a more global and interconnected view of oil risk. Additionally, applying the proposed approach to multi-step forecasting horizons and stress testing under scenario analysis could help decision-makers prepare for both routine volatility and systemic disruptions.

Practitioners can benefit from adopting AI-driven risk prediction models to complement and, in some cases, replace traditional volatility estimators when managing oil market exposure. Risk managers should integrate diverse macroeconomic and geopolitical indicators into their predictive systems to build resilience against sudden shocks. At the same time, developing clear communication strategies around model outputs is essential to ensure that decision-makers can act effectively on AI-generated risk signals. Finally, organizations involved in energy trading and policy planning should consider embedding such advanced forecasting models into their risk governance frameworks to strengthen hedging strategies, capital allocation, and market stability.

## Authors' Contributions

Authors contributed equally to this article.

## Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

## Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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## Declaration of Interest

The authors report no conflict of interest.

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## Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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