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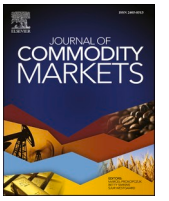

Regular article



Geopolitical risk and energy market tail risk forecasting: An explainable machine learning approach

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ABSTRACT

This study develops a forecasting model for energy market tail risk, with a focus on the predictive role of geopolitical risk factors. Using daily energy commodities data spanning from 2000 to 2024, this study evaluates the performance of machine learning models. Results indicate that the Light Gradient Boosting Machine (LGBM) consistently outperforms other models based on key metrics. Robustness tests across different tail risk levels affirm LGBM as the optimal choice for energy market tail risk forecasting. Furthermore, model interpretability reveals that geopolitical risk indicators contribute significantly, with a 19.15 % impact on the forecasting model. Notably, the foreign exchange market, influences predictions by 15 %, while the monetary policy, contributes 12.19 %. Our findings have significant implications for regulators, industry practitioners, and investors seeking optimal tail risk forecasting during geopolitical conflicts.

1. Introduction

Energy is an essential strategic resource crucial for ensuring nationwide social and economic development (Chishti et al., 2023a; Gong et al., 2023). It serves as the foundation for the survival and advancement of human society, driving global economic growth (Luo et al., 2023; Peña et al., 2020). In a country's development journey, energy is seen as the backbone of the national economy. The share of energy consumption within global consumption is on the rise. According to the BP Statistical Review of World Energy, primary energy consumption grew by 2.9 % in 2018, marking the highest growth rate since 2010 and nearly doubling the average growth rate (1.5 %) over the past decade. However, the inherent volatility of energy markets presents significant challenges for policymakers, investors, and other stakeholders (Bouri et al., 2023; Luo et al., 2023; Tiwari et al., 2024). This volatility is often heightened by geopolitical risks, which have become more prominent in recent years.

Geopolitical risks refer to the risks associated with terrorist acts, tensions, and wars between countries (Caldara and Iacoviello, 2022; Chishti et al., 2023b; Creti, 2017), which are considered extreme risks. Their impact on the energy market is mainly reflected in

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expectation differences about future energy supply and demand (Gong and Xu, 2022; Li et al., 2022; Yang et al., 2023). Events such as the Russian-Ukrainian war, the Syrian conflict, and heightened tensions in the Middle East exemplify how geopolitical instability can lead to significant disruptions in energy supply chains (Chowdhury et al., 2025; Sulong et al., 2023; Zhang et al., 2023). These disruptions often result in sharp fluctuations in energy prices, reflecting the market's sensitivity to geopolitical developments. For instance, oil prices have historically shown a strong reaction to geopolitical tensions in major oil-producing regions, such as the Persian Gulf, where conflicts can lead to immediate concerns over supply security and potential shortages (Ben Cheikh and Ben Zaied, 2024; Liu et al., 2024b; Mignon and Saadaoui, 2024). Given the critical impact of geopolitical risks on energy markets, it is essential to examine how these risks influence energy market tail risk forecasting.

Tail risk, which refers to the risk of extreme price movements, forecasting is crucial for effective investment management, yet it has received limited attention. Traditional methods like ARIMA (Autoregressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) have been widely used for predicting energy prices and volatility based on historical data and statistical patterns (Beyca et al., 2019; Costa et al., 2021; Ghoddusi et al., 2019). However, the growing complexity of the energy market, driven by technological advancements, policy changes, and geopolitical risks, has underscored the limitations of these approaches. Traditional models often struggle to capture non-linear relationships and the impact of external shocks, fueling interest in advanced forecasting techniques (Abdullah et al., 2024; Chowdhury et al., 2023; Niu et al., 2023). Machine learning models, capable of handling large datasets and complex relationships without rigid assumptions about data distribution, have gained popularity in energy market forecasting (Abdullah et al., 2024).

However, ML models are not without limitations. They are often criticized for their "black-box" nature, which can obscure the causal mechanisms behind predictions—a challenge when transparency is crucial for policy and regulatory decisions (Abdullah et al., 2024). Additionally, overfitting, lack of interpretability, and dependence on large labeled datasets can limit their practical utility. These concerns have led to growing interest in explainable machine learning (e.g., SHAP values), which aims to make model outputs more interpretable and actionable (Lundberg et al., 2020). Recent literature has started to bridge this gap by combining ML's predictive strengths with interpretability tools, applying them to critical areas like tail risk forecasting in energy markets. Nevertheless, most studies remain focused on point forecasting or volatility estimation (Beyca et al., 2019; Costa et al., 2021; Ghoddusi et al., 2019; Guo et al., 2023; Zhao et al., 2017), with relatively fewer exploring the extreme ends of risk distributions where financial and policy implications are most severe. This study contributes to this emerging field by systematically evaluating the role of geopolitical and macro-financial factors in ML-based tail risk forecasting, offering both methodological and practical insights for managing uncertainty in the energy sector.

Theoretically, geopolitical risk is closely related to energy market tail risk through several mechanisms. Firstly, geopolitical risks encompass events such as wars, terrorist attacks, political instability, and diplomatic conflicts, all of which can disrupt the supply and demand dynamics of global energy markets (Bouoiyour et al., 2019; Chishti et al., 2025; Yang et al., 2023). These disruptions often lead to significant volatility in energy prices, as markets react to sudden changes in supply availability or anticipate potential supply constraints. For instance, conflicts in major oil-producing regions can lead to concerns over oil supply security, causing sharp price spikes or drops, thereby increasing market volatility (Mignon and Saadaoui, 2024). This heightened volatility, or tail risk, reflects the probability of extreme price movements, which can have severe economic consequences.

Secondly, geopolitical events can influence investor sentiment and risk perceptions, prompting abrupt shifts in investment flows into or out of energy assets. Such movements can exacerbate price fluctuations, further contributing to tail risk. Thirdly, supply disruptions caused by geopolitical events can lead to immediate spikes in energy prices, as markets anticipate reduced availability of key commodities such as oil and natural gas. These price spikes can be severe, leading to tail risk events where prices move far beyond typical ranges. Finally, geopolitical risks often have broader economic implications, including impacts on inflation, currency stability, and overall economic growth, which can indirectly affect energy markets (Yang et al., 2023; Zhang et al., 2024). As geopolitical risks induce uncertainty and instability, they create an environment where the likelihood of extreme negative outcomes in the energy market.

As far as we know, empirical studies related to tail risk have mostly focused on spillover and portfolio management (Bouri et al., 2023; Gong and Xu, 2022; González-Pedraz et al., 2014; Qin et al., 2020). Moreover, studies related to energy market forecasting have primarily concentrated on oil price and volatility forecasting (Beyca et al., 2019; Costa et al., 2021; Ghoddusi et al., 2019; Guo et al., 2023; Ivanovski and Hailemariam, 2021; Li et al., 2024; Zhao et al., 2017). Surprisingly, studies have yet to be conducted to forecast energy market tail risk and examine the role of geopolitical risk. To this end, considering the theoretical linkage, novelty of the issues, and gaps in the literature, this study aims to: (i) forecast energy market tail risk using machine learning, and (ii) examine the role of geopolitical risk in energy market tail risk forecasting.

For empirical analysis, we utilize the S&P Goldman Sachs Commodity Index (GSCI) Energy spot price index to represent the energy market, covering commodities such as WTI Crude Oil, Brent Crude Oil, Heating Oil, Gasoil, and Natural Gas. Additionally, alternative proxies including the S&P GSCI Crude Oil, Gas Oil, Heating Oil, and Natural Gas spot price indices are considered for robustness testing. We employ the novel Geopolitical Risk index proposed by Caldara to proxy geopolitical risk. Our dataset spans from January 1, 2000, to March 26, 2024 daily observations. Methodologically, we estimate energy market tail risk using Conditional Autoregressive Value at Risk (CAViAR), and forecast using ARIMAX and various machine learning models such as Lasso, Ridge, Random Forest, ExtraTrees, AdaBoost, K-Nearest Neighbors, and Light Gradient Boosting Machine (LGBM). Model performance is evaluated using mean square error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). Finally, we employ explainable artificial intelligence techniques to explore the influence of geopolitical risk on energy market tail risk forecasting.

Our finding shows that LGBM emerges as the standout performer in forecasting energy market tail risk, consistently exhibiting the lowest MAE, MAPE, and MSE values across both training and testing phases. This superior performance underscores LGBM's efficacy

compared to other benchmark models in accurately predicting tail risk within the energy market. In our baseline analysis, we conducted examination using a 70:30 training-testing split. Robustness tests further substantiated our initial findings across various scenarios, including adjustments in sample size splits and different risk thresholds such as the 1 % CAViaR. Even under more extreme risk conditions, LGBM consistently demonstrated superior forecasting accuracy, reinforcing its reliability and robustness.

Additionally, our study extended its robustness analysis to encompass major energy commodities—Crude Oil, Gas Oil, Heating Oil, and Natural Gas—beyond the aggregate market level. Across these commodities, minimal variance was observed between actual and forecasted tail risk, affirming the generalizability of LGBM's performance across diverse segments of the energy market. Furthermore, employing Explainable AI technique we explore further into the factors influencing our forecasts. Geopolitical risk indicators emerged as key contributors, accounting for 19.15 % of the explanatory power in the LGBM model. Notably, changes in the dollar index, reflecting foreign exchange market stability, exerted a 15 % influence. Moreover, the US_SSR indicator, serving as a proxy for monetary policy, contributed 12.19 %.

This study makes several significant contributions. Firstly, it expands the scope beyond traditional forecasting methods focused on oil price, volatility, and returns, by integrating machine learning techniques. Previous research has mostly focused on forecasting oil prices, volatility, and returns (Beyca et al., 2019; Ghoddusi et al., 2019; Guo et al., 2023). This study extends this literature by specifically investigating the impact of geopolitical risk on energy market tail risk using advanced machine learning techniques. Second, our approach builds upon the work of Niu et al. (2023), who examined the influence of geopolitical risk categories on stock volatility using monthly data. In contrast, we analyze the role of geopolitical risk in forecasting energy market tail risk using daily data, offering a more granular perspective and enhancing the applicability of our findings to real-time market dynamics. Furthermore, we also extend the study by Salisu et al. (2022) who employed heterogenous autoregressive realized volatility model for oil tail risk forecasting using geopolitical risk data.

Third, in addition to forecasting accuracy, this study utilizes explainable AI to illuminate the contributions of individual variables. Given that machine learning models are often viewed as black boxes, our use of explainable AI contributes significantly to understanding how geopolitical risk, alongside other factors, shapes energy market tail risk. Finally, our analysis identifies not only geopolitical risk but also the significant roles played by foreign exchange market stability and monetary policy in influencing energy market tail risk. These results provide insights for policymakers, regulators, and investors seeking to develop strategies that mitigate tail risk effectively in the energy markets.

2. Literature review

The effect of geopolitical factors on energy market and forecasting is extensively documented by industry and academia. Our study is closely related with three strand of studies: i) geopolitical risk and energy market; ii) tail risk in energy market; and iii) application of machine learning in energy market.

The influence of geopolitical risk on energy markets has been extensively debated by scholars. Bouoiyour et al. (2019) emphasize the nonlinear nature of the oil market, where the impacts of geopolitical risks—both threats and acts—are differentiated. Qin et al. (2020) extend this by highlighting asymmetric effects across different market conditions, revealing significant negative impacts on crude oil returns during bearish periods and positive effects on volatility. Gong and Xu (2022) contribute by illustrating how geopolitical risks, particularly geopolitical acts, influence the interconnectedness among energy and other commodity markets, indicating varied net spillover effects. Another study by Li et al. (2022) explores nonlinear Granger causality and spillover effects among geopolitical risks, crude oil prices, and Chinese sectoral stock markets, considering sector-specific transmission dynamics. Yang et al. (2023) underscores the dynamic relationship between geopolitical risks, oil price shocks, and inflation across global economies.

Recently, Zhang et al. (2023) demonstrate that the Russia-Ukraine War significantly affects crude oil prices through channels like speculative activities and supply-demand dynamics, necessitating intervention strategies. Bouri et al. (2023) documented how crude oil volatility and geopolitical risk influence stock sector returns and volatility. Moreover, Mignon and Saadaoui (2024) find that US-China political relations and geopolitical risks both drive oil prices, with political tensions affecting consumer expectations and geopolitical risks influencing supply disruption fears. Liu et al. (2024b) documented geopolitical threats and acts exert significant long-run effects on natural resource prices and correlations.

In the strand of geopolitical risk and energy market several studies focused on clean energy. Sohag et al. (2022) uncovers that various forms of geopolitical risk influence green investments positively in bearish market conditions but negatively in bullish states. Hille (2023) explores how geopolitical risks in fossil fuel supplier countries stimulate renewable energy adoption in importing countries. Cheikh and Zaied (2023) find that crude oil markets remain largely unresponsive to geopolitical events unless risks escalate significantly, while clean energy sectors exhibit adverse reactions during heightened geopolitical uncertainty, suggesting a decoupling between traditional and renewable energy responses. Another study Ben Cheikh and Ben Zaied (2024) documented that geopolitical uncertainty positively affects renewable energy deployment in advanced economies but fails to drive similar transitions in emerging markets. Recently, Liu et al. (2024a) demonstrate that green bond prices fluctuate in response to geopolitical risk, acting both as a hedge asset and a barometer for market sentiment during geopolitical turmoil.

Regarding the tail risk several studies are conducted focusing on spillover and portfolio management. González-Pedraz et al. (2014) analyze energy price risk using a multivariate approach and found heavy tails and positive asymmetry in risk distributions. Mensi et al. (2017) investigate risk spillovers between oil and currency markets, identifying significant downside and upside risk transmissions. Zhu et al. (2020) explore extreme risk spillovers among global energy firms. Lian et al. (2020) extend studies on oil stock returns to include tail behavior influenced by diverse risk factors from asset pricing literature. Ahmed et al. (2022) applied extreme value theory to assess tail risk and systemic spillovers of oil prices to precious metals. Chatziantoniou et al. (2022) introduce a framework combining

CAViaR and TVP-VAR models to analyze dynamic tail risk transmission mechanisms across crude oil and refined petroleum products, revealing changing roles amid energy market developments and crise.

Moreover, Gong et al. (2023) constructs a volatility spillover network using QVAR models, revealing significant long-term tail risk spillovers among international energy markets, with clean energy sectors acting as net receivers and traditional energy markets as net transmitters. Lucey and Ren (2023) analyze dynamic risk transmission among sustainability equities, energy assets, and financial indices, and uncovered ESG and green equities as persistent risk transmitters and green bonds and renewable energy stocks as ambiguous in their risk roles. Naeem et al. (2024) study tail risk spillovers between Shanghai oil and global stock and commodity markets, identifying Shanghai oil as a net risk receiver with heightened connectedness during crises such as the COVID-19 pandemic and geopolitical conflicts. Chowdhury et al. (2025) documented that geopolitical risk not only transmits risk but also receives it from the food commodity, energy, and stock markets.

With regards to application of machine learning in energy market forecasting, Zhao et al. (2017) propose a deep learning ensemble approach combining stacked denoising autoencoders and bootstrap aggregation for oil price forecasting and found superior performance over traditional methods. Beyca et al. (2019) assess natural gas consumption forecasting in Istanbul using multiple linear regression, artificial neural networks (ANN), and support vector regression (SVR), with SVR showing significant accuracy advantages. Nguyen et al. (2021) utilize machine learning to predict corporate carbon emissions, achieving up to 30 % improvement in accuracy by integrating Meta-Elastic Net learners and additional predictors. Another study by Costa et al. (2021) explore 23 machine learning models for oil price forecasting, highlighting their effectiveness in short-term predictions and substantial gains over traditional approaches, particularly with lasso-based models and forecast combinations.

Furthermore, Guo et al. (2023) forecasted crude oil futures price in China's newly established market using machine learning, and they uncovered the GRU model's superior performance. Diebold et al. (2023) evaluate forecasting methods for Arctic sea ice using feature-engineered machine learning, they showed improved accuracy over traditional linear regression models. Spandagos et al. (2023) explore AI's potential to predict energy poverty across European countries, using Random Forest to identify predictors beyond income for effective targeting of vulnerable households. Guan and Gong (2023) propose a Mod-VMD-BiLSTM hybrid model for crude oil price forecasting, highlighting its robustness and accuracy compared to benchmark models. Recently, Saädaoui and Ben Jabeur (2023) investigate multiresolution cross-correlation and causality between European energy markets and geopolitical risk using VMD-M-CNN, demonstrating its effectiveness in forecasting electricity prices under varying geopolitical conditions. A detailed literature review on implication of machine learning in energy economics and finance can be found in study by Ghoddusi et al. (2019).

Up to now, several studies have explored the role of geopolitical risk in the energy market, while others have focused on tail risk. Moreover, machine learning models are increasingly employed for forecasting energy price volatility and returns. However, none of the above studies have used machine learning to forecast energy market tail risk using geopolitical risk factors. We aim to fill this gap by employing machine learning and explainable AI to examine the role of geopolitical risk in forecasting energy market tail risk.

3. Methodology

For our methodological approach, we first employ Conditional Autoregressive Value at Risk to estimate the energy market tail risk. Next, we utilize several machine learning and traditional benchmark models to forecast energy market tail risk incorporating geopolitical risk and other related variables. Finally, we explore the role of geopolitical risk in energy market tail risk forecasting using explainable artificial intelligence techniques.

3.1. Conditional Autoregressive Value at risk

First, we use the Conditional Autoregressive Value at Risk (CAViaR) model to measure the likelihood of extreme losses—known as tail risk—for semiconductor companies, building on the approach of Chatziantoniou et al. (2022). Unlike traditional methods that estimate tail risk in two steps—first modeling the overall return distribution and then calculating the risk level—CAViaR directly estimates the Value-at-Risk (VaR), making it more efficient and targeted. Specifically, we employ the asymmetric slope version of the model, developed by Engle and Manganelli (2004), which is particularly useful in capturing how risk can behave differently during market downturns compared to upswings. This added flexibility allows us to better account for the uneven, or asymmetric, nature of financial data—something simpler models like the symmetric absolute value CAViaR or the standard GARCH(1,1) method may overlook. By doing so, we provide a more accurate view of downside risk, especially in turbulent market conditions. Moreover, the asymmetric slope CAViaR model stipulates that VaR at a given quantile follows an autoregressive process, mathematically defined as follows:

$$f_{\alpha,t}(\beta) = \beta_0 + \beta_1 f_{\alpha,t-1}(\beta) + \beta_2 x_{t-1}^{+} + \beta_3 x_{t-1}^{-} \tag{1}$$

In this model, $f_{\alpha,t}$ represents the VaR at the α level on day t. The model includes a constant term denoted by β_0. The parameter β_1 represents the weight assigned to lagged VaRs, specifically $f_{\alpha,t-1}(\beta)$. Additionally, β_2 and β_3 capture the effects of positive and negative returns on the VaR, respectively.

3.2. Forecasting methodologies

To forecast energy market tail risk, we start with the ARIMAX model as our baseline for multivariate forecasting. This selection is

grounded in extensive literature that highlights ARIMAX's robustness in handling multivariate time series data (Abdullah et al., 2024). However, to avoid the pitfalls of model selection bias, we expand our analysis by incorporating a diverse array of machine learning models, each with unique strengths and parameters (Chowdhury et al., 2023; Ghosh et al., 2023; Niu et al., 2023; Tiwari et al., 2023). These models include Lasso, Ridge, Random Forest (RF), ExtraTrees, AdaBoost, K-Nearest Neighbors (KNN), and Light Gradient Boosting Machine (LGBM). The rationale behind employing multiple models is to ensure a comprehensive evaluation and comparison of performance, enabling us to select the most suitable model for forecasting energy market tail risk.

3.2.1. Autoregressive integrated moving average exogenous (ARIMAX)

Traditional series forecasting models often rely on univariate approaches, which overlook the influence of other variables. To address this limitation, we use the ARIMAX model, incorporating the effects of the geopolitical risk, additional related variables on energy market tail risk. The ARIMAX model is defined as follows (Abdullah et al., 2024; Box et al., 2015):

$$y_t = \frac{\theta_q(B)\Theta_Q(B^S)a_t}{\Phi_p(B^S)\varphi_p(B)(1-B)^d(1-B^S)^D} + X \tag{2}$$

here, y_t represents the predicted value; $\Theta_Q(B^S)$ stands for the seasonal moving average; $\varphi_p(B)$ denotes the autoregressive coefficients; $\Phi_p(B^S)$ indicates the seasonal autoregressive component; $(1-B)^d$ signifies the ordinary differencing; $(1-B^S)$ represents the seasonal differencing; X denotes the exogenous variables; and a_t represents the white noise time series with a mean of zero. Similar to ARMA models, " p" and " q" represent the autoregressive (AR) and moving average (MA) lags, respectively. The integration order " d" indicates the number of differences needed to achieve stationarity in the time series. The terms P, D, and Q refer to the seasonal orders of AR, differencing, and MA. Based on the AIC value of −1912.914, this study adopts the $ARIMA(0,1,0)(0,0,0)_0$ model, where (0,1,0) refers to the orders (p,d,q) and $(0,0,0)_0$ refers to the seasonal orders $(P,D,Q)_S$.

3.2.2. LARS Lasso and Ridge regression

In addition to machine learning models, this study incorporates Lasso and Ridge regression as benchmark linear models to assess performance. Lasso, or Least Absolute Shrinkage and Selection Operator, is a linear regression technique that employs shrinkage to penalize the absolute size of regression coefficients. This shrinkage process moves data values towards a central point, often the mean, effectively reducing the influence of less important variables and encouraging sparsity in the model. Lasso is particularly useful in scenarios with high multicollinearity among predictors or when automated variable selection is desired (Santosa and Symes, 1986). In contrast, Ridge regression also addresses multicollinearity but uses a different approach by adding a penalty equivalent to the square of the magnitude of coefficients (L2 regularization). This penalty ensures that coefficients are shrunk towards zero but not eliminated entirely, which can help improve the stability and performance of the model, especially when dealing with correlated predictors. These models can be expressed as:

$$\frac{arg}{\beta_0}, \frac{min}{\beta} \parallel Y - X\beta \parallel_2^2 + \gamma\left((1-\alpha) \parallel \beta \parallel_2^2 + \alpha \parallel \beta \parallel 1\right) \tag{3}$$

here, Y represents a vector consisting of the outcome variable in the training dataset. X represents a matrix of predictors with dimensions $(n \times p)$. Lastly, $(\beta_1, \beta_2, \ldots, \beta_p)$ represents a vector of regression beta coefficients.

3.2.3. Random Forest

Random Forest is constructed using a subset of the training data and a random selection of features, ensuring diversity among the trees. The final prediction of the Random Forest is typically the average (for regression tasks) or the majority vote (for classification tasks) of all individual tree predictions. This ensemble approach helps mitigate overfitting and enhances generalization performance compared to single decision tree models. Random Forest model can be expressed as:

$$\widehat{y}(X) = \frac{1}{N_{trees}} \sum_{i=1}^{N_{trees}} f_i(X) \tag{4}$$

where N_{trees} is the number of trees in the forest, and $f_i(X)$ represents the prediction of the i-th decision tree in the forest for input X. This averaging process helps smooth out individual tree predictions, leading to improved stability and forecasting accuracy.

3.2.4. ExtraTrees

ExtraTrees, an extension of the Random Forest algorithm, was introduced to further enhance the robustness and diversity of ensemble learning models. Proposed as a variation by Geurts et al. (2006), ExtraTrees introduces additional randomness in the tree construction process compared to Random Forests. Specifically, ExtraTrees selects random thresholds for each feature rather than searching for the best possible thresholds, as done in traditional decision trees and Random Forests. This randomization reduces computational costs and can lead to faster training times. Like Random Forests, ExtraTrees aggregates predictions from multiple decision trees to make final predictions, averaging for forecasting tasks.

3.2.5. AdaBoost

Freund and Schapire (1997) created the boosting technique as a classification algorithm, but it has since been successfully applied to regression analysis as well. Boosting improves prediction accuracy by using decision trees in an ensemble modeling strategy, aiming to build a strong classifier from multiple weak learners. Initially, a model is built using the training data. Subsequent models are then created to correct the errors of the previous models. This process continues until the training data is accurately predicted or the maximum number of models is reached. The Adaptive Boosting (AdaBoost) algorithm can be defined as:

$$\widehat{g}(\chi) = \widehat{\beta}^{\hat{\delta}} \chi^{\hat{\delta}},$$

$$\widehat{\beta}(j) = \sum_{i=1}^{n} X_i^{(j)} U_i \Big/ \sum_{i=1}^{n} \left(X_i^{(j)}\right)^2,$$

$$\widehat{\delta} = \arg\min_{1 \le j \le p} \sum_{i=1}^{n} \left(U_i - \widehat{\beta}^{(j)} X_i^{(j)}\right)^2,$$

$$\widehat{\beta}^{[m]} = \widehat{\beta}^{[m-1]} + \upsilon . \widehat{\beta}^{[\hat{\delta} m]} \tag{5}$$

The AdaBoost technique generates multiple training samples and assigns weights to each sample. Here, $\widehat{\delta}$ represents the index of each predictor within each sample, and $\widehat{\beta}^{[m]}$ denotes the updated coefficient estimates. This method involves fitting small trees sequentially to gradually improve performance as needed.

3.2.6. *k*-Nearest Neighbors

k-Nearest Neighbors (KNN) regression is a nonparametric approach which aggregate data points within the same neighborhood. This method divides the observation space into *k* closest points from the training dataset to make predictions. The size of this neighborhood, *k*, can be selected using cross-validation to minimize mean-squared error (Altman, 1992). The forecasting algorithm based on k-NN is defined as:

$$\widehat{f} = \frac{1}{k} \sum_{x_i \in N_k(x)} y_i \tag{6}$$

The variable *k* represents the closest observations in the training dataset, while $N_{k(x)}$ refers to the nearest group of predictors *x*.

3.2.7. Light gradient boosting machine (LGBM)

The extreme gradient boosting (XGBoost) model, proposed by Friedman (2001), mitigates overfitting with high-dimensional sparse data and difficulty handling missing values issues by incorporating a regularization term to prevent overfitting and effectively managing missing data, though it still struggles with high-dimensional features. LightGBM, developed by Chen and Guestrin (2016), enhances XGBoost by employing the gradient one-sided sampling algorithm, exclusive feature bundling algorithm, and leaf-wise growth strategy with depth restrictions, improving forecasting accuracy. LightGBM, an advanced version of the Gradient Boosting Decision Tree algorithm, uses decision tree learners to fit gradients in a supervised learning setup. The basic formulation of gradient boosting is as follows:

$$F(X) = \sum\nolimits_{m=0}^{M} f_m(X) \tag{7}$$

In the model, $F(X)$ represents the "base learner," specifically a decision tree. The loss function, designed as mean square loss L, is formulated as follows:

$$L = (y_i - F_{m-1}(x_i))^2 \tag{8}$$

In gradient descent, the goal is to minimize $f_m(X)$. The model uses a greedy approach to ensure $L(y, F_m(X)) < L(y, F_{m-1}(X))$. Treating $F_m(X)$ as parameters, derivatives are taken to learn $f_m(X)$ using square loss. The learning process formulations are as follows:

$$F_m(X) = F_{m-1}(X) + f_m(X) \tag{9}$$

$$\widetilde{y}_i = -\partial_{F_{m-1}(x_i)} L(F_{m-1}(x_i), y_i) \tag{10}$$

$$f_m(X) = \underset{f(X)}{\operatorname{argmin}} \sum\nolimits_{i=1}^{n} (f(x_i) - \widetilde{y}_i)^2 \tag{11}$$

Overall, boosting updates $F_m(X)$ using gradient descent by fitting new models to the residuals, which correspond to the negative gradient.

3.3. Hyperparameter tuning

Hyperparameters play a crucial role in determining the performance and generalization ability of machine learning models (Abdullah et al., 2024; Tiwari et al., 2023). Unlike parameters, which are learned during training, hyperparameters are set before the learning process begins and govern aspects such as model complexity, learning rate, and regularization strength. In this study, hyperparameter tuning is essential to optimize the performance of the models. Grid search, a common technique for hyperparameter tuning, systematically evaluates different combinations of hyperparameters to identify the set that yields the best model performance based on predefined evaluation metrics. To ensure robust evaluation and mitigate issues related to time series data, such as temporal dependencies and potential data leakage, the TimeSeriesSplit function from the scikit-learn package is employed. This function performs cross-validation by splitting the dataset into a specified number of folds, preserving the chronological order of observations. In this study, a TimeSeriesSplit with 5 splits and a testing dataset batch size of 100 is used. Table 1 presents the grid search range of each hyperparameter.

3.4. Forecasting performance evaluation

To assess the accuracy of the aforementioned models, we employed three key performance metrics: mean square error (MSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). These metrics provide insights into different aspects of model accuracy and reliability. MSE measures the average squared difference between predicted values and actual values. MAE calculates the average absolute difference between predicted and actual values. MAPE, expressed as a percentage, evaluates the average magnitude of errors relative to the actual values, making it particularly useful for understanding the predictive performance in terms of relative error. The three metrics are:

$$MSE = \frac{1}{\mathrm{N}} \sum_{t=1}^{N} (A_t - F_t)^2 \tag{12}$$

$$MAE = \frac{1}{\mathrm{N}} \sum_{t=1}^{N} |A_t - F_t| \tag{13}$$

Table 1
Hyperparameters of models.

Model	Parameter	Description	Grid Search Value
Lasso	alpha	The alpha parameter in the LARS Lasso model controls the regularization strength, influencing the sparsity of the solution by penalizing the absolute size of coefficients.	Sequence of 0.00–0.99 with the interval of 0.01.
Ridge	alpha	The alpha parameter in Ridge regression controls the regularization strength, balancing the fit of the model to the data against the penalty for large coefficients.	Sequence of 0.00–0.99 with the interval of 0.01.
RF	bootstrap	A Boolean parameter indicating whether bootstrap samples are used when building trees.	True
	max_depth	The maximum depth of each decision tree in the forest.	80, 90, 100, 110
	max_features	The maximum number of features considered for splitting a node.	'auto', 'sqrt', 'log2'
	min_samples_leaf	The minimum number of samples required to be at a leaf node. Higher values prevent the model from learning overly specific patterns, reducing overfitting.	3, 4, 5
ExtraTrees	min_samples_split	The minimum number of samples required to split an internal node. This parameter ensures that each split is made only if it improves model performance by more than a certain threshold, thus controlling tree growth and model complexity.	8, 10, 12
	n_estimators:	The number of trees in the forest. Increasing the number of trees generally improves model performance up to a certain point, balancing computational cost with model accuracy.	100, 200, 300, 1000
AdaBoost	n_estimators	The number of base estimators used in the ensemble.	Sequence of 2–20 with the interval of 1
	learning_rate:	A hyperparameter that scales the contribution of each base estimator. Lower values make the model more robust by shrinking the contribution of each tree, while higher values can lead to overfitting.	Sequence of 0.97–1.04 with the interval of 0.01
KNN	n_neighbors	Specifies the number of neighbors used for prediction.	2,3,4,5,6,7,8,9,10
	weights	Determines how neighbors are weighted when making predictions	'uniform','distance'
LGBM	max_depth	Maximum depth of the tree.	3, 4, 6, 5, 10
	num_leaves	Maximum number of leaves in a tree.	10, 20, 30, 40, 100, 120
	learning_rate	Shrinks the contribution of each tree.	Sequence of 0.97–1.04 with the interval of 0.01
	n_estimators	Number of boosting iterations (trees) to be performed.	50, 100, 300, 500, 700, 900, 1000
	colsample_bytree	Fraction of features to consider when building each tree. Helps in controlling overfitting by introducing randomness.	0.3, 0.5, 0.7, 1

Note: All models are trained and tested using scikit-learn Python package.

$$MAPE = \frac{1}{N} \sum_{t=1}^{N} \left| \frac{A_t - F_t}{A_t} \right| \tag{14}$$

The equation represents the relationship between the actual value A_t and the forecast value F_t at a specific time t for a certain number of observations N. We assess the predictive accuracy of each model by employing the aforementioned measures on both the training and testing datasets.

3.5. Explainable artificial intelligence

Explainable Artificial Intelligence (XAI) is an emerging area of research that focuses on making complex machine learning models more transparent and understandable. As these models are increasingly used in high-stakes areas like finance, healthcare, and energy, it becomes essential not only to make accurate predictions but also to understand how and why those predictions are made. In this study, we use a popular tool from the XAI toolkit called SHapley Additive exPlanations (SHAP) to interpret our machine learning results (Lundberg et al., 2020). SHAP is based on concepts from cooperative game theory, where each "player" contributes to an outcome—in this case, each feature (or input variable) contributes to the model's prediction. SHAP assigns each feature a value that reflects its role in pushing the prediction higher or lower, relative to a baseline (Lundberg et al., 2020). For example, if geopolitical risk is one of the inputs in our model for forecasting tail risk in energy markets, SHAP can tell us not just that it's important, but whether it increases or decreases risk in a specific prediction—and by how much.

SHAP provides individual-level explanations, which distinguishes it from conventional feature importance techniques. Rather than simply ranking which variables are generally important, SHAP helps us understand how each feature affects a single prediction in context (Ghosh et al., 2023; Niu et al., 2023). This allows us to capture both the direction (positive or negative effect) and magnitude (how strong that effect is) of each variable's influence. By doing so, SHAP enhances trust in machine learning models, turning them from black boxes into interpretable tools that can inform decision-making with greater confidence. SHAP values are introduced as a reliable metric for determining the importance of features be defined as follows:

$$f(x) \approx g(z^*) = \phi_0 + \sum_{i=1}^{M} \phi_i z_i^* \tag{15}$$

here, the contribution of a feature ϕ_i to the prediction process is denoted by the binary value z_i^*. A value of 1 indicates that the feature M is included in the prediction process, while a value of 0 indicates otherwise. The contribution of feature i can be represented as:

$$\phi_i = \sum_{S \subseteq N \setminus i} \frac{|S|!(M - |S| - 1)!}{M!} [f_x(S \cup \{i\}) - f_x(S)] \tag{16}$$

SHAP values leverage a set of input features M, where C represents a subset of these features S, and the prediction model $f_x(C)$ computes how each feature influences the prediction of a given sample x. This capability enables SHAP values to uncover both the positive and negative impacts of each feature on the prediction outcome.

4. Data and sample

We use the S&P Goldman Sachs Commodity Index (GSCI) Energy spot price index to represent the energy market (Gong and Xu, 2022). This index tracks the performance of various energy commodities and is weighted by global production. It includes physical energy commodities that have active and liquid futures markets. The S&P GSCI Energy spot price index encompasses future contracts for WTI Crude Oil, Brent Crude Oil, Heating Oil, Gasoil, and Natural Gas. We also consider S&P GSCI Crude oil spot price index (Crude_Oil), S&P GSCI Gas oil spot price index (Gas_Oil), S&P GSCI Heating oil spot price index (Heating_Oil), and S&P GSCI Natural Gas spot price index (Natural_Gas) as alternative proxy for robustness test.

Next, we use Geopolitical Risk index (GPRI) developed by Caldara and Iacoviello (2022) to proxy daily geopolitical risk. GPRI measures the impact of adverse geopolitical events on the global economy. GPRI is constructed from automated text searches of ten major newspapers' electronic archives, the index tracks the frequency of articles related to geopolitical tensions. The GPRI captures spikes during significant historical events such as the world wars, the Korean War, the Cuban Missile Crisis, and post-9/11, indicating periods of heightened geopolitical risk. Higher values of the GPR index are predictive of lower investment, declining stock prices, and reduced employment, as well as increased chances of economic disasters. The index is organized into eight categories, covering various threats and acts of geopolitical significance, and includes two subindexes: the Geopolitical Threats (GPRI_THREAT) and Geopolitical Acts (GPRI_ACT) indexes, which focus on different types of geopolitical content. Moreover, we also consider geopolitical risk index measured using Number of articles based on 10 recent newspapers which is denoted as N10D.

Following earlier studies (Abdullah et al., 2023; Tiwari et al., 2023), we consider several economic, financial market, and sentiment factors as additional predictive variables of energy market tail risk. Specifically, we use changes in the Economic Policy Uncertainty (EPU) index, which tracks shifts in economic policy uncertainty (Baker et al., 2016), and the CBOE Implied Volatility Index (VIX), representing changes in market volatility. We also include the Risk Aversion Index (RAI), indicating levels of investor risk aversion (Bekaert et al., 2022), and changes in the USA's monetary policy (US SSR) (Krippner, 2020). Further, we account for the Financial Stress Index (FSI), capturing fluctuations in financial stress, and the Dollar Price Index (DXY), tracking changes in the value of the

dollar. The changes in gold prices are measured by the S&P GSCI Gold Spot Price Index (Gold). Sentiment variables are derived from the American Association of Individual Investors (AAII) Sentiment Survey, which provides insights into individual investor attitudes (Tiwari et al., 2023): Sent_Neu indicates the proportion of investors with neutral attitudes, Sent_Pos reflects those with optimistic sentiments, and Sent_Neg represents the proportion expressing pessimistic views.

We collected data covering the period from January 1, 2000, to March 26, 2024. This sample period includes significant economic and geopolitical events such as 9/11, the global financial crisis, COVID-19, and the Russia-Ukraine war. Considering these events allows us to forecast energy market tail risk more rigorously and identify the best model capable of handling significant upsurges in tail risk during turbulent times. Table A.1 presents the variable specifications along with their data sources. For our forecasting analysis, we split our sample into training and testing datasets, allocating 70 % of the data to the training dataset (January 1, 2000, to December 19, 2016) and the remaining 30 % to the testing dataset (December 21, 2016, to March 26, 2024).

After data collection, we measured the tail risk of the energy market using the CAViaR method. First, we calculated the changes in the spot price index and estimated downside tail risk at the 5 % CAViaR level. Fig. 1 illustrates the historical tail risk series of the energy market, showing significant upsurges during events such as 9/11, the global financial crisis, COVID-19, and the recent Russia-Ukraine war. Fig. A1 depicts the historical tail risk series for robustness proxies, including Crude Oil, Gas Oil, Heating Oil, and Natural Gas.

Table 2 presents summary statistics for all variables. Among the energy market components, Natural Gas exhibits the highest downside tail risk with a mean of −5.099. Variance values are highest for Crude Oil (2.871) and notably lower for Gas Oil (1.439), Heating Oil (1.577), and Natural Gas (1.916). Skewness values indicate a negative skew for the energy variables, with Crude Oil having the most pronounced negative skew (−4.458), suggesting a longer left tail in the distribution. Excess kurtosis is notably high, particularly for Crude Oil (34.842) and the Geopolitical Risk Index (GPRI_ACT) (58.144), indicating heavy tails in their distributions. The Jarque-Bera (JB) test statistics are all highly significant, suggesting non-normality in the distributions. The Elliott-Rothenberg-Stock (ERS) test values are negative and significant, confirming stationarity in the series. For the GPRI variables, the means hover around 115, with variances indicating substantial fluctuations, especially in GPRI_ACT (11052.669). Skewness and kurtosis for these variables indicate extreme values and heavy tails, as supported by their high JB statistics. Fig. 2 illustrates the correlation matrix, revealing notable patterns of correlation among the variables.

5. Empirical results and discussion

5.1. Forecasting results

In forecasting energy market tail risk, we employed ARIMAX as a traditional benchmark and tested seven machine learning models to determine the optimal performer. Model performance was evaluated using MAE, MAPE, and MSE metrics, with all models trained and validated on a 70:30 split of training and testing datasets. Table 3 summarizes the results of energy market tail risk forecasting. The findings indicate that LGBM achieved the lowest MAE, MAPE, and MSE values during both training and testing phases, suggesting superior forecasting performance compared to other models. Fig. 3 illustrates the actual and forecasted values of energy market tail risk for training and testing datasets. Notably, ARIMAX exhibited the poorest performance in energy market tail risk forecasting. The variance between actual and forecasted values was lowest for LGBM, whereas the Lasso model exhibited significantly higher variance. Overall, Table 3 and Fig. 3 underscore that LGBM outperforms other benchmark models in forecasting energy market tail risk.

Next, we evaluate the bias-variance trade-off of the models to mitigate issues of overfitting or underfitting. These problems arise due to models being either too complex or too simple to adequately capture the underlying patterns in the data. To assess this, we employed Wilcoxon signed-rank test (Wilcoxon, 1945), Kolmogorov-Smirnov test (Marsaglia et al., 2003), and Cramér–von Mises criterion test (Cramér, 1928). The results are summarized in Table 4. The null hypotheses were not rejected for all models except LGBM, as their p-values exceeded 5 %. Models with p-values less than 5 % indicate poor fit, suggesting that their residuals significantly deviate from the expected distribution in both training and testing datasets. Overall, LGBM demonstrates good fit model in forecasting energy market tail risk using geopolitical risk factors. This finding aligns with earlier studies (Ding et al., 2022; Fu et al., 2024; Sun et al., 2020) also highlighted LGBM's superior forecasting accuracy.

5.2. Robustness test results

In our baseline analysis, we utilized energy market tail risk based on a 70:30 split for training and testing. In this section, we assess the robustness of our findings across different scenarios, including variations in sample size splits, levels of CAViaR, and components of energy markets. Firstly, we evaluate the robustness of our results across different sample size splits. Earlier, we employed a 70 % training dataset and 30 % testing dataset split. For robustness testing, we explore three additional splits: i) 60:40, ii) 80:20, and iii)



Fig. 1. Historical tail risk series of energy market.

Table 2
Summary statistics results.

	Mean	Variance	Skewness	Ex.Kurtosis	JB	ERS
Energy	−3.156	1.772	−2.719***	12.828***	48851.972***	−5.944***
Crude_Oil	−3.562	2.871	−4.458***	34.842***	325467.227***	−8.130***
Gas_Oil	−3.147	1.439	−1.382***	3.114***	4363.536***	−3.736***
Heating_Oil	−3.345	1.577	−1.467***	3.550***	5336.760***	−5.733***
Natural_Gas	−5.099	1.916	−1.032***	1.107***	1380.752***	−8.342***
GPRI	114.837	4551.064	4.401***	35.570***	337853.838***	−7.374***
GPRI_ACT	115.385	11052.669	6.005***	58.144***	886955.297***	−7.787***
GPRI_THREAT	115.777	4466.868	2.599***	13.567***	53113.845***	−10.212***
N10D	0.111	0.030	1.822***	4.974***	9565.255***	−20.572***
GPRI_MA30	105.157	2673.454	4.879***	37.032***	369035.868***	−7.204***
GPRI_MA7	104.732	3201.078	5.238***	44.341***	522337.137***	−7.754***
EPU	0.185	0.803	7.117***	124.076***	3924694.556***	−11.607***
VIX	0.002	0.005	2.005***	16.402***	71742.873***	−34.425***
RAI	0.002	0.006	13.518***	400.750***	40595030.261***	−34.378***
US_SSR	−0.013	0.225	−3.378***	529.447***	70545541.540***	−32.568***
FSI	−0.041	17.569	−20.650***	1699.286***	727014854.861***	−35.148***
DXY	0.007	0.020	6.671***	113.294***	3274558.401***	−27.643***
Gold	0.010	0.029	8.376***	139.886***	4994425.338***	−33.173***
Sent_Neu	29.201	55.828	0.097***	−0.199***	19.518***	−4.748***
Sent_Pos	32.594	96.590	0.431***	−0.098	189.279***	−5.934***
Sent_Neg	38.208	101.400	0.440***	−0.077	196.470***	−3.279***

Note: Kurtosis: Anscombe and Glynn (1983) test; ERS: Elliott et al. (1996) unit-root test.; Skewness: D'Agostino (1970) test; JB: and Jarque and Bera (1980) normality test; ***,**,* denote significance at 1 %, 5 % and 10 % significance level.

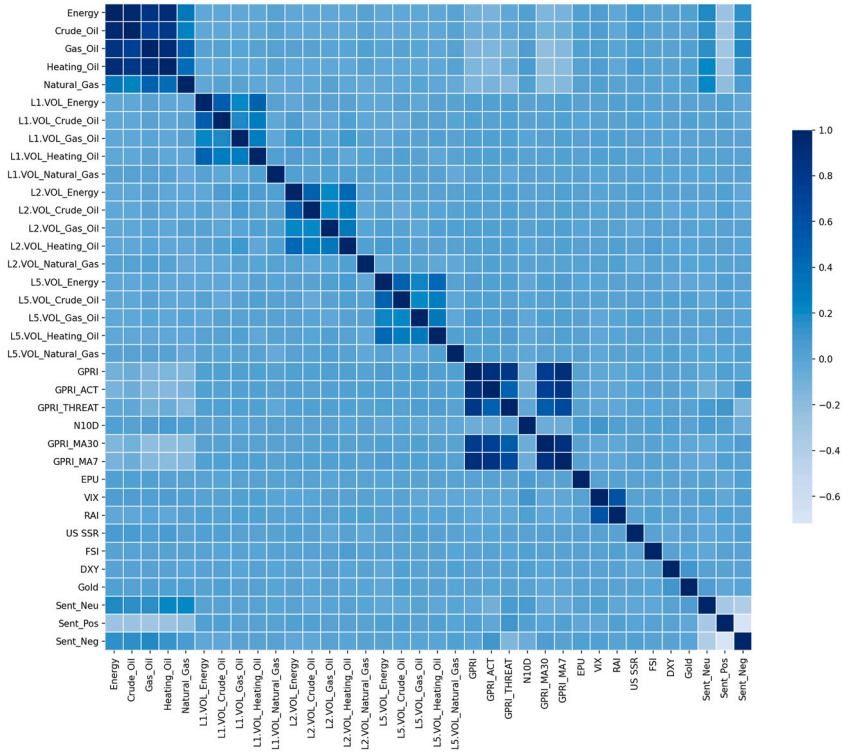

Fig. 2. Correlation matrix.

90:10 and results are presented in Table 5. Across all sample size splits, LGBM consistently exhibits the lowest MAE, MAPE, and MSE values. This consistency across different splits indicates that our results are not contingent on a specific choice of sample split.

Next, we explore the impact of changing the quantile level in the CAViaR model on our analysis. In our initial baseline analysis, we estimated the downside tail risk using a 5 % quantile CAViaR model. To ensure the robustness of our findings, we conduct a robustness test using a 1 % quantile CAViaR model. Table 6 provides the results of this robustness test using the 1 % CAViaR model. Once again, the findings demonstrate that the LGBM model consistently outperforms others across all performance metrics. Figure A.2 illustrates

Table 3
Forecasting results.

	Training			Testing		
	MAE	MAPE	MSE	MAE	MAPE	MSE
ARIMAX	0.862	0.33	1.36	1.057	0.342	2.811
Lasso	0.799	0.287	1.24	0.926	0.27	2.655
Ridge	0.802	0.285	1.2	0.875	0.249	2.511
RF	0.285	0.094	0.176	0.84	0.249	2.034
ExtraTrees	0.564	0.195	0.629	0.843	0.251	2.099
AdaBoost	0.74	0.284	0.804	0.887	0.284	1.943
KNN	0.66	0.23	0.885	0.953	0.267	2.765
LGBM	0.035	0.013	0.003	0.841	0.25	1.939

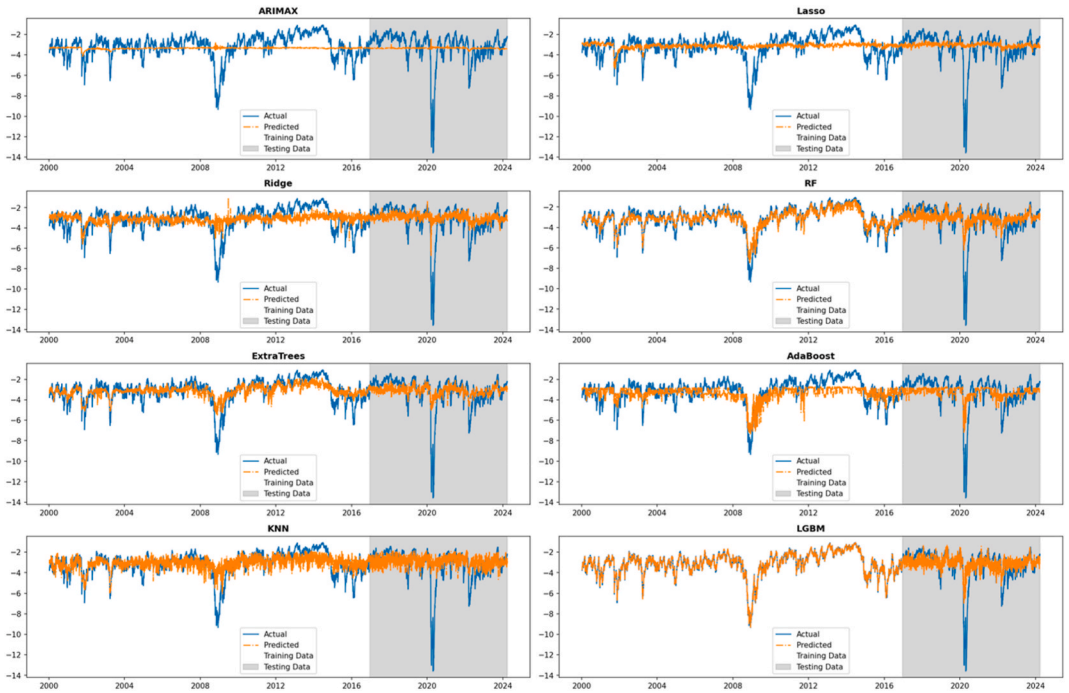

Fig. 3. Actual vs predicted results.

Table 4
Bias variance trade off results.

	KS	Wilcoxon	Cramér-von
ARIMAX	0.607 (0.000)	25.447 (0.000)	204.916 (0.000)
Lasso	0.401 (0.000)	10.467 (0.000)	108.718 (0.000)
Ridge	0.303 (0.000)	9.253 (0.000)	64.584 (0.000)
RF	0.116 (0.000)	4.323 (0.000)	8.946 (0.000)
ExtraTrees	0.196 (0.000)	7.355 (0.000)	32.261 (0.000)
AdaBoost	0.383 (0.000)	19.12 (0.000)	74.048 (0.000)
KNN	0.164 (0.000)	2.934 (0.003)	22.519 (0.000)
LGBM	0.011 (0.970)	0.191 (0.849)	0.045 (0.907)

Note: Null hypothesis for all test is two samples have the similar variance.

actual vs fitted values of tail risk at 1 % CAViaR, which again shows similar pattern of prediction for LGBM model. This indicates that even when the quantile level is adjusted to a more extreme risk threshold (1 % CAViaR), LGBM continues to exhibit the lowest MAE, MAPE, and MSE values compared to alternative models.

Finally, we conduct robustness tests using alternative proxies for the energy market. In our baseline model, we used the overall energy market tail risk for forecasting. For this robustness test, we focus on major commodities within the energy market: Crude Oil, Gas Oil, Heating Oil, and Natural Gas. We estimate the 5 % CAViaR downside tail risk for each of these proxies. Subsequently, we use

Table 5
Robustness test based on sample size.

	60:40			80:20			90:10		
	MAE	MAPE	MSE	MAE	MAPE	MSE	MAE	MAPE	MSE
ARIMAX	1.602	0.473	3.845	1.356	0.389	3.018	1.096	0.296	2.763
Lasso	0.743	0.267	1.155	0.78	0.283	1.164	0.858	0.295	1.667
Ridge	0.743	0.263	1.101	0.778	0.279	1.122	0.864	0.295	1.622
RF	0.259	0.086	0.156	0.282	0.095	0.17	0.311	0.100	0.242
ExtraTrees	0.505	0.171	0.558	0.556	0.194	0.61	0.615	0.204	0.878
AdaBoost	0.731	0.294	0.795	0.735	0.291	0.783	0.829	0.321	1.022
KNN	0.598	0.209	0.792	0.644	0.227	0.837	0.715	0.238	1.232
LGBM	0.034	0.012	0.002	0.044	0.016	0.004	0.051	0.018	0.005

Note: 60:40, 80:20, 90:10 denotes train test sample split.

Table 6
Robustness test using 1 % CAViaR.

	Training			Testing		
	MAE	MAPE	MSE	MAE	MAPE	MSE
ARIMAX	1.266	0.336	2.903	1.549	0.346	5.947
Lasso	1.163	0.287	2.606	1.325	0.263	5.516
Ridge	1.165	0.285	2.535	1.269	0.246	5.306
RF	0.411	0.093	0.368	1.223	0.248	4.338
ExtraTrees	0.815	0.194	1.321	1.219	0.247	4.426
AdaBoost	1.114	0.295	1.818	1.275	0.279	4.072
KNN	0.957	0.230	1.870	1.385	0.265	5.845
LGBM	0.053	0.013	0.006	1.211	0.245	4.089

geopolitical risk and other variables to forecast the tail risk for each commodity. The results are presented in Table A.2 and Fig. 4. The findings show minimal variance between the actual and forecasted tail risk for each commodity. This further corroborates our initial results, demonstrating that the LGBM model remains the most optimal for forecasting energy market tail risk across various commodities.

5.3. Explainable AI results

To this end, our results clearly indicate that LGBM is the most suitable model for forecasting energy prices using geopolitical risk. However, it remains uncertain how geopolitical risk specifically contributes to the model's forecasting ability. Traditionally, machine learning models are considered "black box" models, making it difficult to explain their results (Abdullah et al., 2024). To address this, we employed the Explainable AI method using SHAP values to understand the influence of geopolitical risk on the forecasts.

Fig. 5 illustrates the variable importance for all models, showing that geopolitical risk indicators contribute 19.15 % to the LGBM model. Geopolitical events such as conflicts, wars, and political instability in key energy-producing regions can disrupt the supply chains of crucial energy commodities like oil and natural gas (Bouoiyour et al., 2019; Yang et al., 2023). For example, tensions in the Middle East, a major oil-producing region, can lead to fears of supply shortages, driving up prices and increasing market volatility. Such disruptions can cause sudden spikes in energy prices, reflecting increased tail risk in the market. Economic sanctions, trade restrictions, and diplomatic disputes can also play a role (Ngo et al., 2022). For instance, sanctions on a major oil-exporting country can reduce global supply, leading to price increases and heightened volatility. Similarly, trade disputes can impact the global flow of

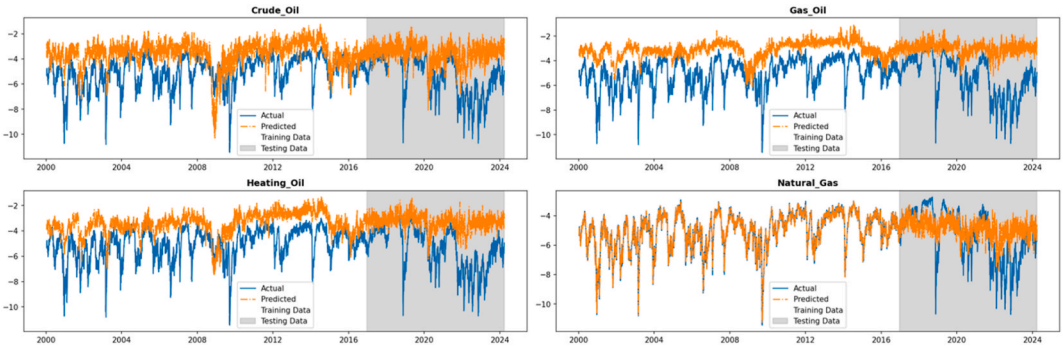

Fig. 4. Robustness test results based on alternative proxy.

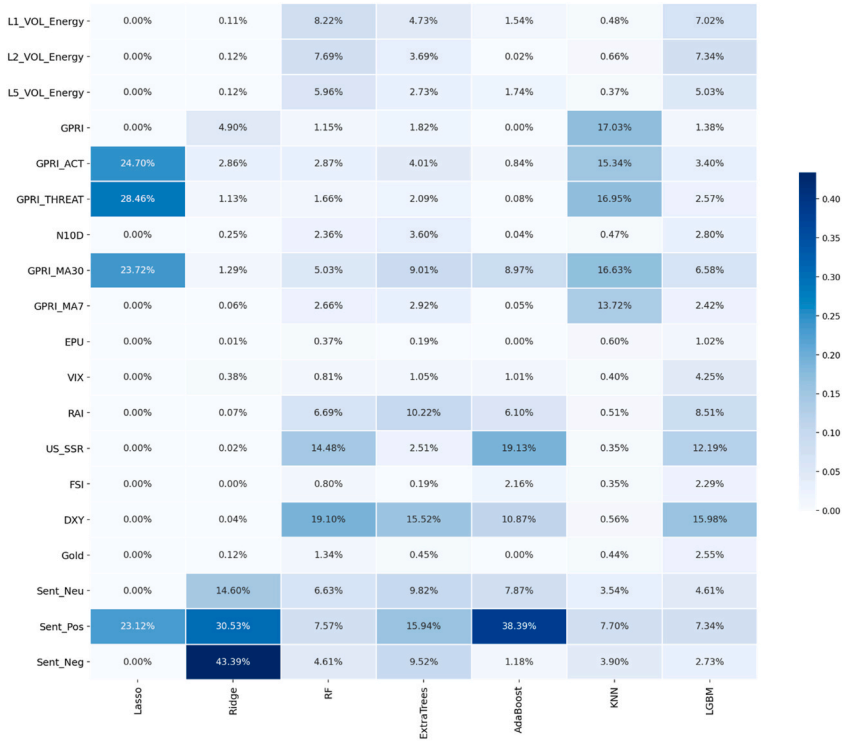

Fig. 5. Variable importance.

energy commodities, affecting prices and market stability.

To better visualize this contribution, the variable importance of the LGBM model is illustrated in Figure A.3. Among other indicators, changes in the dollar index, which represent foreign exchange market stability, show a 15 % contribution. Foreign exchange market stability is closely related to energy market tail risk due to the global nature of energy trade, which is predominantly conducted

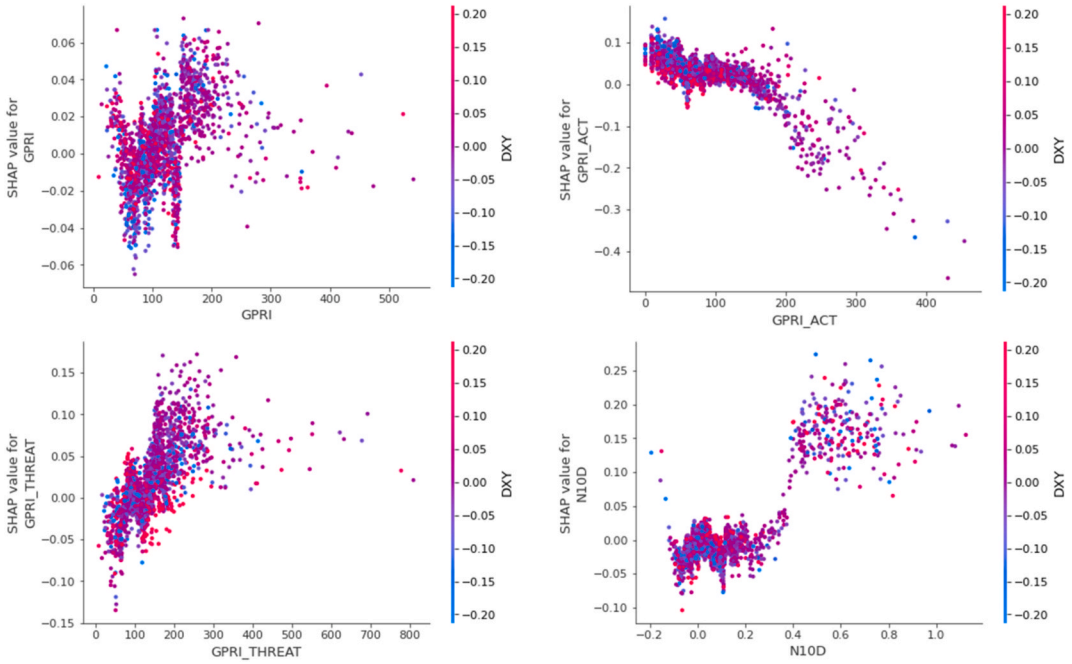

Fig. 6. Dependence plot of LGBM model for geopolitical risk and foreign exchange market.

in US dollars. When the foreign exchange market is unstable, particularly when there are significant fluctuations in the value of the dollar, it can lead to volatility in energy prices (Salisu et al., 2022). For example, if the dollar strengthens, energy prices in other currencies become more expensive, potentially reducing demand and causing price drops. Conversely, a weaker dollar makes energy cheaper in other currencies, potentially boosting demand and increasing prices. This volatility can create extreme price movements or tail risks in the energy market. Furthermore, US_SSR, which proxies monetary policy, contributes 12.19 %. Monetary policy is complexly related to energy market tail risk through its influence on economic activity, interest rates, and inflation, all of which affect energy demand and prices (Hammoudeh et al., 2015). Moreover, monetary policy affects inflation expectations, which can lead to changes in energy prices. High inflation may prompt central banks to tighten monetary policy, leading to the aforementioned effects on energy demand and prices.

Next, we analyze the interaction between features using a SHAP dependence plot. Fig. 6 demonstrates this, highlighting the interaction between geopolitical risk, the foreign exchange market, and the model's predictions. Figures A.4 and A.5 illustrate results for geopolitical risk indicators with risk aversion and monetary policy, respectively. In the plot, the x- and y-axes show the feature values, while the color indicates model predictions. SHAP interaction plots reveal how predictions change with varying feature values, helping to identify data patterns the model uses. These plots are useful for understanding how feature combinations, rather than individual features, affect predictions. They also help pinpoint feature combinations that may have unexpected effects on the model's forecasts. Results indicate that higher GPRI combined with lower DXY generally leads to higher model predictions, with a stronger impact of GPRI at lower DXY levels.

Finally, we analyze the SHAP value heatmap to visually depict each feature's significance in the LGBM model's predictions. Fig. 7 presents this heatmap, with square sizes reflecting the magnitude of each feature's impact and colors indicating whether the impact is positive or negative. SHAP heatmaps illustrate how the model generates predictions and can uncover data patterns. They also help identify features that might have unexpected or undesirable effects on predictions. The results indicate that DXY has the highest contribution, followed by US_SSR. $f(x)$ shows a linear trend in average SHAP values, while DXI and RAI show some negative contributions to the model.A similar pattern is observed for geopolitical risk indicators, suggesting that geopolitical risk significantly impacts energy market tail risk. This relationship highlights how geopolitical events and uncertainties are reflected in the fluctuations and extreme risks within the energy markets. Geopolitical tensions can disrupt supply chains, affect commodity prices, and create market instability, leading to heightened tail risk.

5.4. Additional analysis results

In this section, we analyze how the forecasting models perform during significant economic and geopolitical events. Understanding model behavior under conditions of heightened uncertainty is crucial, as these periods often introduce abrupt market shifts that challenge the robustness and reliability of predictive systems. Our sample includes several key geopolitical and economic crises that have had intense impacts on global markets: the September 11 attacks in the United States on September 11, 2001; the Iraq War (also known as Gulf War II), which began on March 20, 2003, and officially ended on December 15, 2011; the Global Financial Crisis (GFC), spanning from 2007 to 2009; the European Debt Crisis (EDC) from 2009 to 2010; the COVID-19 pandemic, beginning in January 2020 and lasting through the end of 2021; and the ongoing Russia–Ukraine war, which began on February 24, 2022. To assess how our models respond to these periods of turmoil, we examine the SHAP values of the input variables during each event.

The results of the SHAP analysis, as presented in Fig. 8, provide valuable insights into how various economic and geopolitical events influence the model's predictions. The analysis reveals that during the 9/11 attacks, certain geopolitical measures, such as GPRI_MA30, GPRI_ACT, and GPRI_MA7, were the top contributors to the model's predictions. Notably, these variables were negatively associated with the predictions during the 9/11 event, suggesting that geopolitical risk indicators had a significant but adverse impact on energy market forecasts at that time. These indicators, which capture geopolitical risk through different moving averages and activity measures, reflect the heightened uncertainty and risk aversion following the attacks.

For other significant events, such as the Global Financial Crisis (GFC) and the Russia-Ukraine war, the US_SSR, a proxy for monetary policy, played a key role in the model's predictions. Alongside the geopolitical risk indicators, the US_SSR contributed substantially to

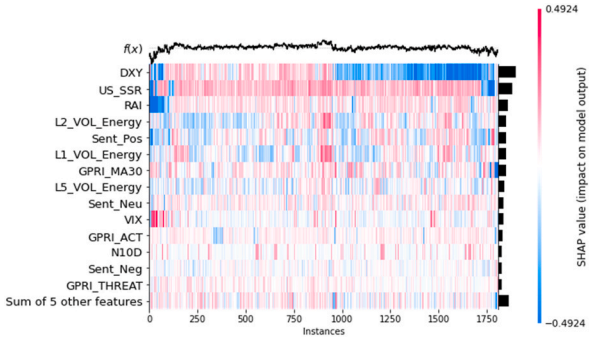

Fig. 7. SHAP values heatmap.

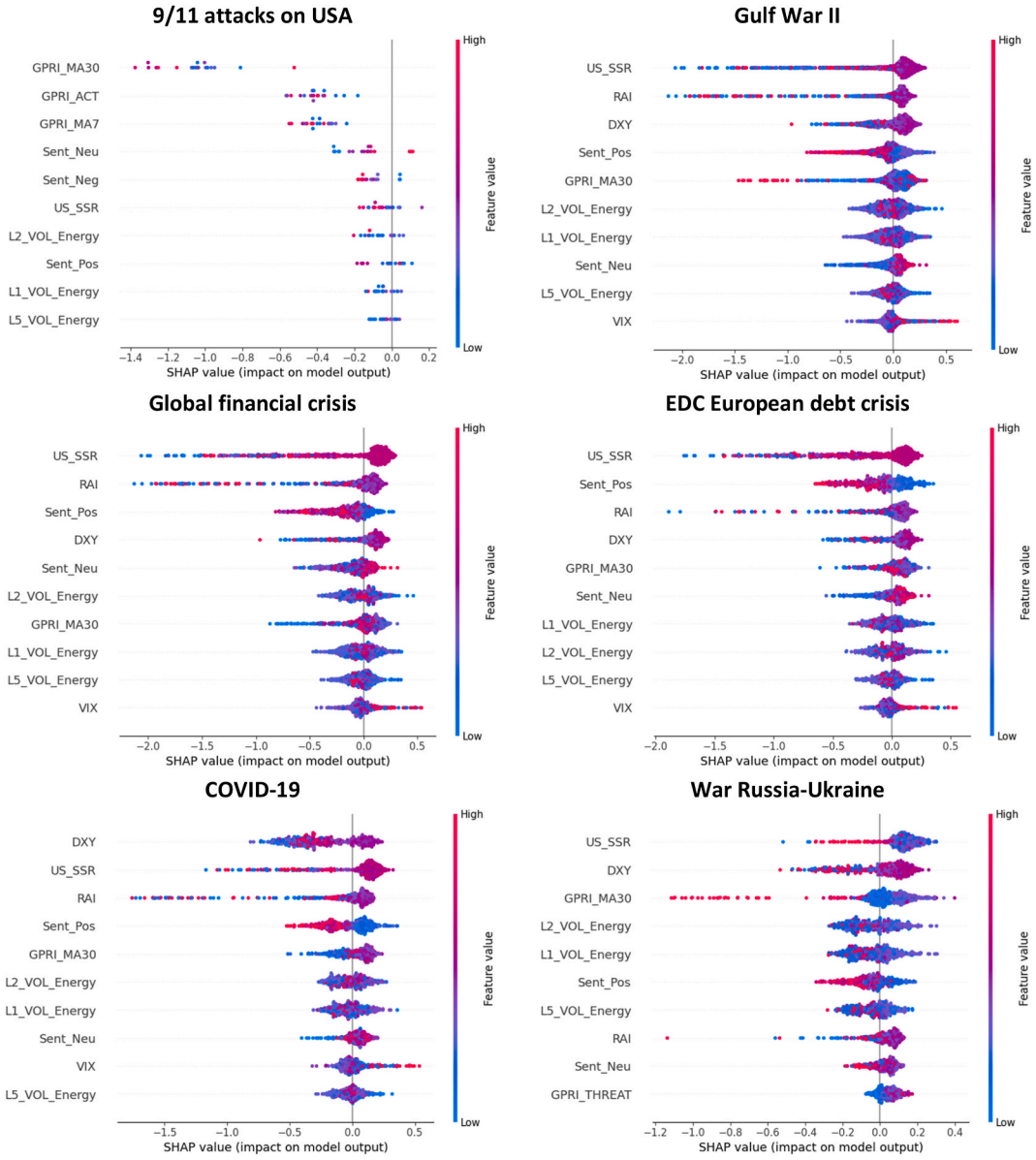

Fig. 8. SHAP values during different economic events. Note: The top 10 most important variables are illustrated for each event. SHAP values are based on data from different event windows.

the model's forecasting ability, highlighting the importance of monetary policy in shaping energy market dynamics during times of economic distress. In addition to these factors, sentiment indicators like RAI, Sent_Pos, and Sent_Neu also exhibited notable contributions, reflecting how shifts in market sentiment during periods of crisis can influence energy price forecasts. These indicators, which capture the market's collective outlook—whether positive, negative, or neutral—demonstrated a similar pattern of contribution, reinforcing the idea that investor sentiment plays a crucial role in predicting extreme price movements during turbulent times.

6. Conclusion

In this study, we explored the impact geopolitical factors on energy market tail risk. Given the significant economic and geopolitical events from 2000 to 2024, such as 9/11, the global financial crisis, COVID-19, and the Russia-Ukraine war, it is essential to understand how these factors affect the energy market. We employed several forecasting methods, including the ARIMAX model as a traditional benchmark and seven machine learning models, to determine the optimal model for predicting energy market tail risk. The performance of these models was evaluated using mean absolute error (MAE), mean absolute percentage error (MAPE), and mean squared error (MSE) metrics. The models were trained and validated using a 70:30 split of the dataset.

Our results indicated that the LightGBM (LGBM) model outperformed other models, exhibiting the lowest MAE and MAPE values during both training and testing phases. This suggests that LGBM is the most suitable model for forecasting energy market tail risk. Further analysis using SHAP values revealed that geopolitical risk indicators contribute significantly to the model's predictions, accounting for 19.15 % of the LGBM model's performance. This underscores the crucial role of geopolitical risk in influencing energy market dynamics. Our result suggests, geopolitical events such as conflicts, wars, and political instability in key energy-producing regions can severely disrupt the supply chains of essential energy commodities like oil and natural gas. Geopolitical risks also influence investor sentiment, leading to uncertainty and risk aversion, prompting shifts from riskier assets like commodities to safer investments like government bonds. Additionally, economic sanctions, trade restrictions, and diplomatic disputes can reduce global supply and increase price volatility, impacting the stability of energy markets.

From the regulatory perspective, our result suggests critical need for regulatory frameworks that can effectively manage and mitigate the risks posed by geopolitical events on energy markets. Regulators should consider implementing measures to enhance the resilience of energy supply chains, such as diversifying energy sources and investing in infrastructure that can withstand geopolitical shocks. From the investor perspective, they should consider the significant influence of geopolitical risks on energy markets and incorporate this understanding into their risk management strategies. Diversification of investment portfolios to include a mix of asset classes can help mitigate the impact of sudden geopolitical shocks.

Moreover, investors should closely monitor geopolitical developments and consider using hedging instruments, such as futures and options, to protect their investments against potential adverse movements in energy prices. Given the predictive power of geopolitical risk indicators demonstrated in the study, investors should leverage such data to make more informed investment decisions, balancing potential returns with the associated risks. Form the policymaker's point of view, they should focus on enhancing energy security by reducing the vulnerability of energy markets to geopolitical risks. This includes fostering international cooperation to reduce geopolitical tensions and promote stable energy trade relations. Policymakers should also support research and development in alternative energy sources to reduce dependency on politically unstable regions. Furthermore, strategic reserves of key energy commodities can be maintained to cushion the economy against sudden supply disruptions.

Our study primarily focuses on forecasting energy market tail risk using machine learning models and examining the impact of geopolitical risk. Future studies may expand upon our research. One potential direction is to explore the role of geopolitical risk in forecasting oil price shocks, rather than broader energy market tail risk.

CRediT authorship contribution statement

Mohammad Ashraful Ferdous Chowdhury: Writing – original draft, Software, Project administration, Methodology, Conceptualization. **Mohammad Abdullah:** Writing – original draft, Software, Methodology, Investigation, Conceptualization. **Emmanuel Joel Aikins Abakah:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Conceptualization. **Aviral Kumar Tiwari:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A.1
Variable Specifications

Variables	Description	Data Source
Energy	S&P GSCI Energy spot price index	Datastream
Crude_Oil	S&P GSCI Crude oil spot price index	Datastream
Gas_Oil	S&P GSCI Gas oil spot price index	Datastream
Heating_Oil	S&P GSCI Heating oil spot price index	Datastream
Natural_Gas	S&P GSCI Natural Gas spot price index	Datastream
L1.VOL_Energy	1 day lag of changes in volatility of Energy spot price index estimated using GARCH model	Authors Calculation
L2.VOL_Energy	2 days lag of changes volatility of Energy spot price index estimated using GARCH model	Authors Calculation
L5.VOL_Energy	1 day lag of changes volatility of Energy spot price index estimated using GARCH model	Authors Calculation
GPRI	Geopolitical risk index measured using news data	Caldara and Iacoviello (2022)
GPRI_ACT	Geopolitical risk act index measured using news data	Caldara and Iacoviello (2022)
GPRI_THREAT	Geopolitical risk threat index measured using news data	Caldara and Iacoviello (2022)
N10D	Geopolitical risk index measured using Number of articles (10 recent newspapers)	Caldara and Iacoviello (2022)

(*continued on next page*)

Table A.1 (*continued*)

Variables	Description	Data Source
GPRI_MA30	Geopolitical risk index 30 days moving average	Caldara and Iacoviello (2022)
GPRI_MA7	Geopolitical risk index 7 days moving average	Caldara and Iacoviello (2022)
EPU	Changes in economic policy uncertainty	Baker et al. (2016)
VIX	Changes in CBOE implied volatility index	Datastream
RAI	Risk aversion index	Bekaert et al. (2022)
US SSR	Changes in USA monetary policy	Krippner (2020)
FSI	Changes in financial stress index	Office of Financial Research
DXY	Changes in dollar price index	Datastream
Gold	Changes in gold price measured by S&P GSCI gold spot price index	Datastream
Sent_Neu	The American Association of Individual Investors (AAII) Sentiment Survey offers insights into the viewpoints of individual investors, specifically indicating the proportion of polled investors who hold neutral attitudes.	Datastream
Sent_Pos	The AAII Sentiment Survey offers insights into the viewpoints of individual investors, namely indicating the proportion of surveyed investors that hold optimistic emotions.	Datastream
Sent_Neg	The AAII Sentiment Survey offers valuable insights into the viewpoints of individual investors, specifically indicating the proportion of polled individuals expressing pessimistic attitudes.	Datastream

Table A.2
Alternative proxy results

	Training			Testing		
	MAE	MAPE	MSE	MAE	MAPE	MSE
Crude_Oil	1.631	0.306	3.937	1.896	0.318	5.827
Gas_Oil	1.919	0.363	4.943	2.322	0.392	7.932
Heating_Oil	1.648	0.31	3.954	2.044	0.341	6.567
Natural_Gas	0.048	0.01	0.005	1.154	0.21	2.499

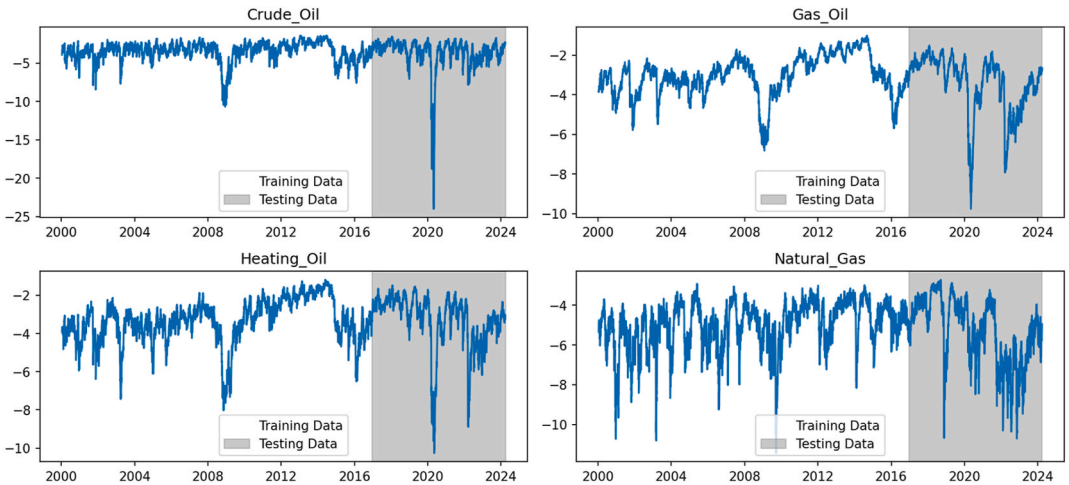

Fig. A.1. Historical tail risk series of robustness dataset.

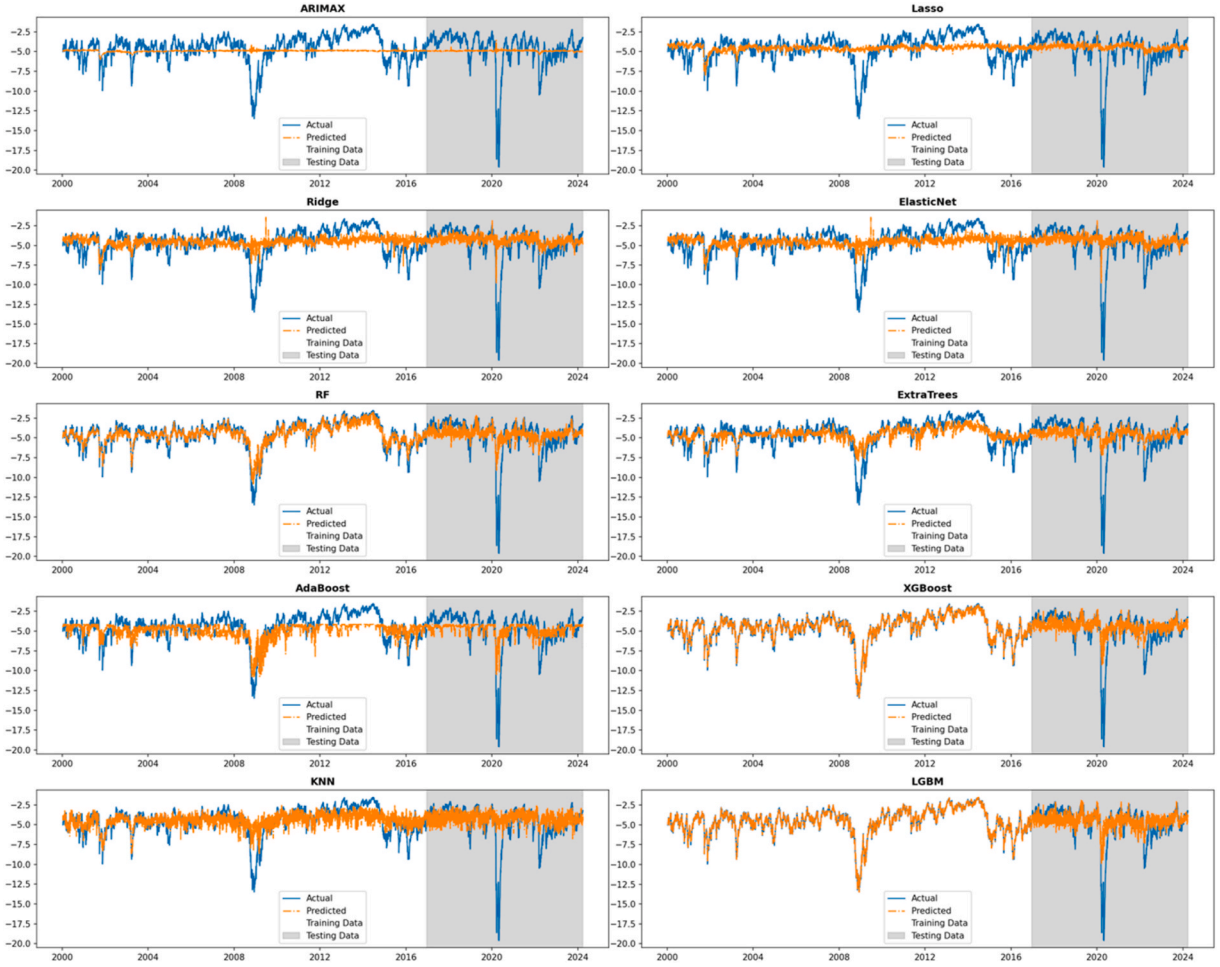

Fig. A.2. Actual vs. fitted values based on 1 % CAViaR.

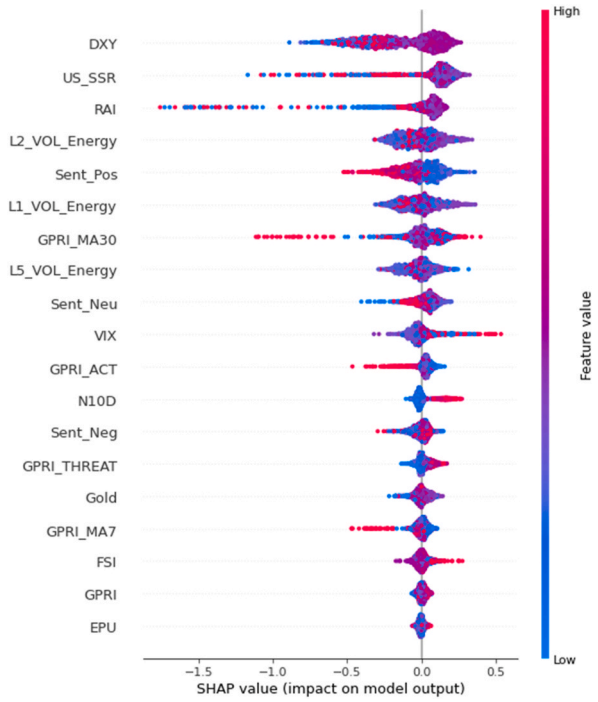

Fig. A.3. LGBM model SHAP summary.

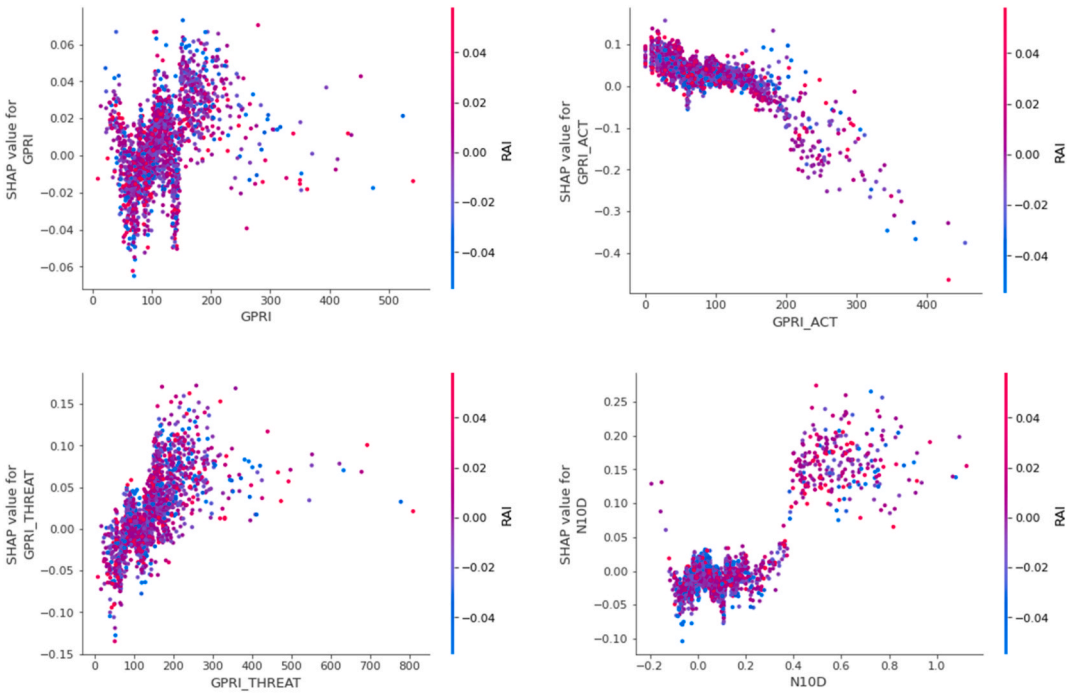

Fig. A.4. Dependence plots of LGBM model with geopolitical risk indicators and risk aversion.

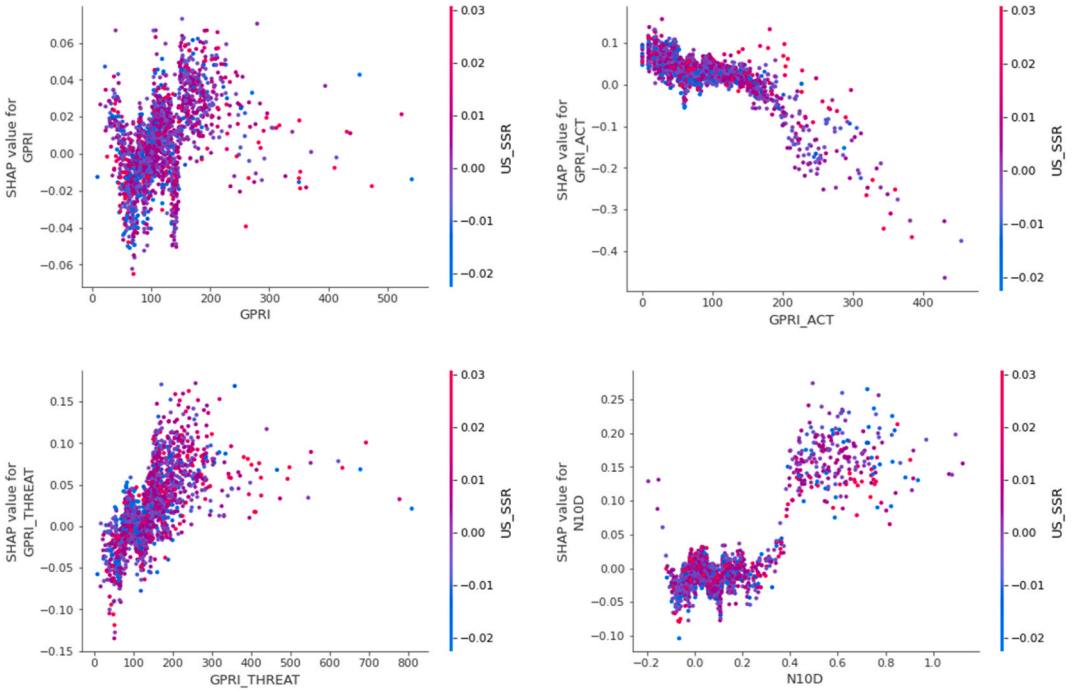

Fig. A.5. Dependence plots of LGBM model with geopolitical risk indicators and monetary policy.

Data availability

The data that has been used is confidential.

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