Heliyon 10 (2024) e34437

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Do OPEC+ policies help predict the oil price: A novel news-based predictor

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ARTICLE INFO

Keywords:
Crude oil price
Forecast
OPEC+ policy
Text mining
Econometric and machine learning models

ABSTRACT

The OPEC+, composed of the Organization of the Petroleum Exporting Countries (OPEC) and non-OPEC oil-producing countries, exerts considerable influence over the global crude oil market. However, existing literature lacks a comprehensive application of this factor in oil price forecasting, primarily due to the complexity of measuring such policy evolutions. To address this research gap, this study develops a news-based OPEC+ policy index based on text mining methods for comprehensive analysis and forecasting of the oil price. First, by crawling and mining news headlines related to OPEC+ production decisions, a dynamic and high-frequency (weekly) OPEC+ policy index is established. Second, the linear and nonlinear relationship between the proposed OPEC+ policy index and the WTI crude oil futures price is thoroughly examined, assessing the potential predictive power of the index in explaining the movements of the crude oil price. Third, the forecasting efficacy of the constructed index on the oil price is rigorously evaluated across eight econometric and machine learning models. Key findings include: (1) The proposed weekly OPEC+ policy index demonstrates strong concordance with OPEC+ production change decisions, exhibiting notable peaks and troughs corresponding to OPEC+ Ministerial Meetings. (2) The relationship analysis demonstrates a strong linear and nonlinear association between the proposed OPEC+ policy index and the crude oil price. (3) For oil price prediction, models incorporating our proposed OPEC+ policy index demonstrate superior performance compared to models without this index. In particular, the index exhibits a more significant predictive effect within three-week forecasting horizons and performs exceptionally well during periods of pandemic and the Russia-Ukraine conflict. In addition, the OPEC+ policy index also exhibits a significant predictive effect on the daily crude oil price and natural gas price, further confirming the robust and powerful forecasting capability of this index within the energy system.

1. Introduction

Recent years have witnessed drastic fluctuations in the crude oil price, attributable to an interplay of numerous complex factors. Specifically, the oil price sharply declined to as low as $27 in 2014, driven by an oversupply of oil resulting from OPEC's decision to

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https://doi.org/10.1016/j.heliyon.2024.e34437
Received 29 February 2024; Received in revised form 14 May 2024; Accepted 9 July 2024
Available online 14 July 2024
2405-8440/

maintain production levels. Subsequently, the COVID-19 pandemic triggered a historic drop in global oil demand and prices in 2020, with prices plummeting to negative territory unprecedentedly [1], followed by a gradual recovery in early 2021 due to production cuts, vaccine rollouts, and a return to normal demand patterns. Moreover, on February 24, 2022, the outbreak of the Russia-Ukraine conflict resulted in a surge in global oil prices [2]. The oscillations of the oil price underscore the importance of comprehending the multifaceted drivers of price movements and the challenge of promoting accurate crude oil price forecasting.

Using complex factors to promote crude oil price forecasting is a pressing concern for governments, companies, and investors, and has therefore become a promising research focus in academia [3]. In this regard, some fundamental and simple factors, such as supply-demand, economic and financial variables, have been successfully applied to crude oil price forecasting models [4–6]. However, there are other complex indicators(e.g., emergencies, weather, and changes in global energy policies) that have not received sufficient attention due to the difficulties associated with their quantification. Among these factors, the OPEC (and OPEC+) policy stands out as one of the most influential elements.

OPEC member countries, accounting for 38% of total world oil production,[1] have shown significant influence on global oil market supplies and prices since the first oil crisis in the 1970s. The OPEC+, which includes both OPEC and 13 non-OPEC nations, collectively contributing 59% of global oil production, further strengthens this influence. Over time, OPEC+ has emerged as a pivotal determinant of crude oil prices, surpassing the individual impact of OPEC. Since the establishment of OPEC+ in December 2016, OPEC concluding statements (which are released one day before the OPEC+ statement) have become less informative, reflecting the rise of OPEC+'s decisions and the pivotal role played by Russia within this reconfigured coalition of oil-producing nations [7].

The most direct way OPEC+ policy affects the oil price is through production quotas. When OPEC+ members decide to increase or decrease oil production, it can lead to a corresponding increase or decrease in the global oil supply. Higher production can lead to lower prices, while production cuts can lead to higher prices. Another avenue OPEC+ policy wields influence over the oil price is through market sentiment. Announcements of production cuts or increases can lead to anticipations in the market. For example, if OPEC+ decides to cut production, it can signal to the market that they are attempting to support higher oil prices, which can lead to price increases. Both of the mechanisms — the direct impact of production quotas and the subtler, yet equally significant, influence on market sentiment — underscore the pivotal role of OPEC+ policies in shaping the oil price.

However, it is worth noting that existing studies have often overlooked OPEC+ in oil price forecasting. Actually, there are extensive studies working on the impact of OPEC and OPEC+ on oil prices, but there are relatively few studies using them for oil price prediction. This is because existing studies focusing on their effects typically use dummy variables or OPEC (OPEC+) production to indicate OPEC (OPEC+) policies. However, these methods have some limitations, such as binary dummy variables and low-frequency production data performing poorly in oil price prediction, as analyzed in the subsequent literature review. Therefore, it is essential to develop a dynamic, high-frequency OPEC+ policy index to assist in oil price forecasting.

Traditional data platforms encounter challenges in effectively capturing and quantifying the OPEC+ policies. Fortunately, the emergence of big data technology offers a promising solution to address these limitations, particularly by leveraging text mining tools and techniques. For example, based on text mining techniques, Baker et al. [8] devised a novel economic policy uncertainty (EPU) index by quantifying the frequency of newspaper coverage. Likewise, Caldara and Iacoviello [9] created an indicator of geopolitical risk by tallying the frequency of articles on geopolitical risks in prominent international newspapers. Moreover, text mining is also widely used to quantify another complex factor, namely market sentiment, which represents the expectations of participants in the markets [10–13]. All of these successful studies have presented valuable insights for measuring the OPEC+ policy in this paper, by using powerful text mining techniques.

Accordingly, this paper aims to develop a novel indicator to measure OPEC+ policy and utilize it to enhance oil price forecasting. The key endeavors encompass: (1) constructing a dynamic and high-frequency OPEC+ policy index using text mining techniques on a vast corpus of OPEC+ related news; (2) examining the linear and nonlinear relationship between the OPEC+ policy and oil price; and (3) forecasting the oil price based on the newly introduced OPEC+ policy index and eight econometric and machine learning models. The principal contributions of this paper are noteworthy since it represents the first attempt to quantify a dynamic and high-frequency OPEC+ policy index, examine its linear and nonlinear influence on the crude oil price quantitatively, and employ it to enhance oil price forecasting. In addition, we also examine the predictive ability of the OPEC+ policy index for the natural gas futures price, to further demonstrate the powerful predictive capability of this index.

The subsequent sections of this paper are structured as follows: Section 2 presents a literature review of prior studies relevant to this research. Section 3 outlines the general framework, including the methodology employed in developing the OPEC+ policy index, methods utilized to investigate the relationship, and techniques applied to crude oil price forecasting. Experimental designs are described in Section 4. The empirical results of oil price forecasting are presented in Section 5. Section 6 presents the application results of our index for the daily crude oil price and natural gas market. Lastly, Section 7 concludes this paper with a summary of the key findings and suggestions for future research in this area.

2. Literature review

This paper aims to forecast the crude oil price by creating a novel predictor, i.e., the OPEC+ policy index. As for the forecasting methods for crude oil prices, econometric models and machine learning models are widely used. First, econometric models such as

[1] Data source: U.S. Energy Information Administration, Short-Term Energy Outlook, April 2023.

Table 1
Typical research on predicting the oil price based on various predictors (i.e., exogenous variables).

Authors	Predictors
Fang et al. [34]	Market sentiment
Li et al. [31]	Geopolitical risk
Zhang et al. [32]	Geopolitical risk
Li et al. [12]	Market sentiment
Hao et al. [4]	Changes in global oil production; Real global economic activity; Percent changes in petroleum consumption; Changes in oil inventory; Percent changes of oil import; Non-energy commodity index
Li et al. [11]	Market sentiment
Zhang and Wang [36]	MSCI World Index; S&P 500 Index; AMEX Oil Index; FTSE 100 Index
Zhang et al. [38]	18 macroeconomic variables and 18 technical indicators
Chai et al. [33]	Demand factors; Supply factors; Stock factors; Financial market factors; Technology indicators
Zhao et al. [35]	198 exogenous variables
Miao et al. [5]	Supply factors; Demand factors; Financial factors; Commodity market factors; Speculative factors; Political factors
Wei et al. [30]	Fundamental (supply and demand); Speculation (the ratio of OECD petroleum stocks over U.S. petroleum stocks); Uncertainty (EPU)
Naser [3]	149 variables related to macroeconomic, financial, and geographic flow and stock forces
Yin and Yang [37]	18 macro variables and 18 technical indicators

linear regression (LR) [14,15], autoregressive integrated moving average (ARIMA) [16], generalized autoregressive conditional heteroskedasticity (GARCH) [17,18], random walk (RW) [19], and vector autoregression (VAR) [20–22] have been widely applied to oil price prediction, and perform well in capturing the linear component of the oil price. Second, considering the nonlinear patterns and irregularities hidden within the oil price series, machine learning models like support vector machine (SVM) [23,24] and artificial neural networks (ANN) have also been used for forecasting the oil price. In the realm of ANN, various types such as Extreme Learning Machine (ELM) [25], Back-Propagation Neural Network (BPNN) [14], Random Vector Functional Link (RVFL) [26], Long-Short Term Memory (LSTM) [27,28], and Gated Recurrent Unit (GRU) [29] have been extensively employed and have shown significant effectiveness.

As for predictive factors, an array of distinct drivers of crude oil price was utilized to promote forecasting performance, as exemplified in Table 1. Generally, the predictors utilized in prior literature can be classified into four categories: (1) Supply and demand factors, including factors such as global oil production, petroleum consumption, oil inventory and oil import [4,30]; (2) Geopolitical and macroeconomic factors, including factors such as political factors [5], geopolitical risk [31,32], economic growth and GDP changes [3], economic policy uncertainty [30], etc.; (3) Market sentiment and speculative factors, including factors such as speculation [33] and investor sentiment [11,12,34]; (4) Financial and technological factors, including exchange rate [35], futures price [3], stock index [36] and technological based on trading rules [37], etc. Among these predictors, the supply factor is one of the fundamental drivers of the crude oil price, the level of which is largely determined by OPEC+ policy. Thus, the decision of OPEC+ (i.e., OPEC+ policy) may be a promising predictor for crude oil price and deserves further research.

This paper is not the first to examine OPEC's (or OPEC+'s) impact on the crude oil price. Actually, there is extensive literature analyzing this influence by employing event study techniques and regression methods. On the one hand, since OPEC (or OPEC+) meetings and announcements are discrete events that occur at specific times, event study is commonly used to evaluate the impact of OPEC announcements on the oil price [7,39–42]. On the other hand, regression methods (e.g., OLS and VAR) are popular tools in investigating the influence of OPEC (or OPEC+) on crude oil prices. For instance, Wirl and Kujundzic [43] investigated how far OPEC (measured by dummy variables) influences world oil markets based on the OLS regression method. Similarly, Schmidbauer and Rösch [44] applied the OLS regression to evaluate the influence of OPEC announcements on the oil market's expectation and price, where OPEC is identified as a modified dummy variable. Further, Derbali et al. [45] used a conditional quantile regression method to explore the impact of OPEC news (measured by dummy variables) on oil futures. Quint and Venditti [46] assessed the effectiveness of OPEC+ in sustaining oil prices based on two complementary structural vector autoregression (SVAR) models, where the OPEC+ behaviors are indicated by the monthly OPEC+ production. Using the SVAR model, Ratti and Vespignani [47] estimated the interrelationship between seasonal OPEC production and oil price.

However, existing studies (including the ones abovementioned) mainly introduce OPEC or OPEC + policy as a dummy variable or a sequence of OPEC or OPEC+ production, which may cause some limitations. First, dummy variables may fail to capture the temporal dynamics and strength of production policy. While the impact of OPEC+ policy is not static but rather time-varying. For instance, the impact may not only occur immediately after a policy decision is made, but also before the OPEC+ conferences, during which there is often widespread speculation about what oil production decisions the member countries will ultimately agree upon [44]. These speculative activities are difficult to capture using simple dummy variables, but are likely to extracted from various news reports. Further, dummy variables are often binary (0 or 1), which may ignore the strength of the OPEC+ policy. In contrast, the news-based index may mitigate this shortcoming, since we find that a big OPEC+ production adjustment often leads to larger new reports and consequently a larger OPEC+ policy index. Second, OPEC or OPEC+ production is a feasible proxy, but it may be limited in terms of data frequency and information lag. Most of the literature tends to use monthly and seasonal production data [46,47], and may result in limitations in sample size, particularly in oil price forecasting. Moreover, OPEC+ production may lag behind policy or meetings, as some of OPEC's production adjustment policies do not commence on the second day of the meeting. Additionally, certain member countries may require time to adjust their production facilities. Thus, this study endeavors to develop a novel dynamic and

Table 2
The dictionary developed for OPEC+ policy index construction.

Panel A: Keywords		
Allotment/Allotments	Output/Outputs	Supply/Supplies
Export/Exports	Produce/Producing	Quota/Quotas
Inventory/Inventories	Production/Productions	Reserve/Reserves
Panel B: Positive modifiers		
Ail/Ailed/Ailing/Ails		Fall/Fallen/Falling/Falls
Alleviate/Alleviated/Alleviating/Alleviates		Lessen/Lessened/Lessening/Lessens
Alleviation/Alleviations		Limit/Limited/Limiting/Limits
Collapse/Collapsed/Collapsing/Collapses		Low/Lower/Lowered/Lowest/Lows
Constrain/Constrained/Constraining/Constrains		Plummet/Plummeted/Plummeting/Plummets
Constraint/Constraints		Plunge/Plunged/Plunging/Plunges
Cut/Cutting/Cuts		Recede/Receded/Receding/Recedes
Decline/Declined/Declining/Declines		Reduce/Reduced/Reducing/Reduces
Decrease/Decreased/Decreasing/Decreases		Reduction/Reductions
Deflate/Deflated/Deflating/Deflates		Restrict/Restricted/Restricting/Restricts
Depress/Depressed/Depressing/Depresses		Shortfall/Shortfalls
Descend/Descended/Descending/Descends		Shrink/Shrank/Shrinking/Shrinks
Down/Downs		Slash/Slashed/Slashing/Slashes
Drop/Dropped/Dropping/Drops		Slip/Slipped/Slipping/Slips
Fade/Faded/Fading/Fades		Stop/Stopped/Stopping/Stops
Panel C: Negative modifiers		
Add/Added/Adding/Adds		Increase/Increased/Increasing/Increases
Ample/Ampler/Amplest		Inflate/Inflated/Inflating/Inflates
Arise/Arisen/Arising/Arises		Jump/Jumped/Jumping/Jumps
Ascent/Ascents		More
Boom/Boomed/Booming/Booms		Peak/Peaked/Peaking/Peaks
Boost/Boosted/Boosting/Boosts		Raise/Raised/Raising/Raises
Climb/Climbed/Climbing/Climbs		Rise/Risen/Rising/Rises
Expand/Expanded/Expanding/Expands		Soar/Soared/Soaring/Soars
Expansion/Expansions		Spike/Spiked/Spiking/Spikes
Extend/Extended/Extending/Extends		Surge/Surged/Surging/Surges
Heighten/Heightened/Heightening/Heightens		Top/Tops
High/Higher/Highest/Highs		Up/Upped/Upper/Ups
Hike/Hiked/Hiking/Hikes		Upgrade/Upgraded/Upgrading/Upgrades
Improve/Improved/Improving/Improves		Uptrend

high-frequency index (weekly and daily) for OPEC+ policy for oil price forecasting.

The text mining method is applied in this paper to quantify the novel OPEC+ policy index. Text mining has attracted growing attention in the field of oil price forecasting, with news and social media (e.g., Twitter, Weibo, and forums) serving as the main sources of target text [48–52]. Among these, online news stands out as a more effective source of information compared to other social media platforms due to its lower noise level and higher persuasiveness [15]. Leveraging the capabilities of text mining, complex factors impacting crude oil, such as market sentiment [53], geopolitical risks [54], and economic policy uncertainty [55], have been successfully quantified, leading to improvements in oil price forecasting. However, to the best of our knowledge, effective text mining methods have not yet been applied to quantify the OPEC+ behavior. Therefore, this paper aims to develop and apply a dictionary-based text mining method to quantify the OPEC+ policy index, utilizing a novel dictionary tailored to the policy types of OPEC+ (i.e., increase, decrease, and maintain).

Although extensive studies have been conducted on oil price forecasting, this paper makes several novel contributions. Firstly, we have developed a novel OPEC+ policy index for oil price forecasting. In contrast to existing research that utilizes dummy variables (which fail to capture policy evolution and strength) or OPEC+ production (which suffers from limitations in sample size and information lag) to measure the OPEC+ policy, we have developed a dynamic and high-frequency (weekly and daily) OPEC+ policy index based on text mining method. To the best of our knowledge, this is the first application of text mining in investigating OPEC+ behavior. For this purpose, we have developed a new dictionary (shown in Table 2) according to the policy types of OPEC+. Secondly, we have explored the relationship between the OPEC+ policy and the oil price. Unlike existing research that uses VAR and linear Granger causality tests [45–47], we have explored both linear and nonlinear Granger causality between the OPEC+ policy and crude oil price. Thirdly, we have verified the effectiveness of the OPEC+ policy index for oil price forecasting across eight different techniques, including both econometric and machine learning methods. A wide range of model selections contributes to verifying the robustness of the predictive performance of the proposed OPEC+ policy index.

3. Methodology

3.1. General framework

The general framework of incorporating the OPEC+ policy index into oil price forecasting is presented in Fig. 1. Four main steps are

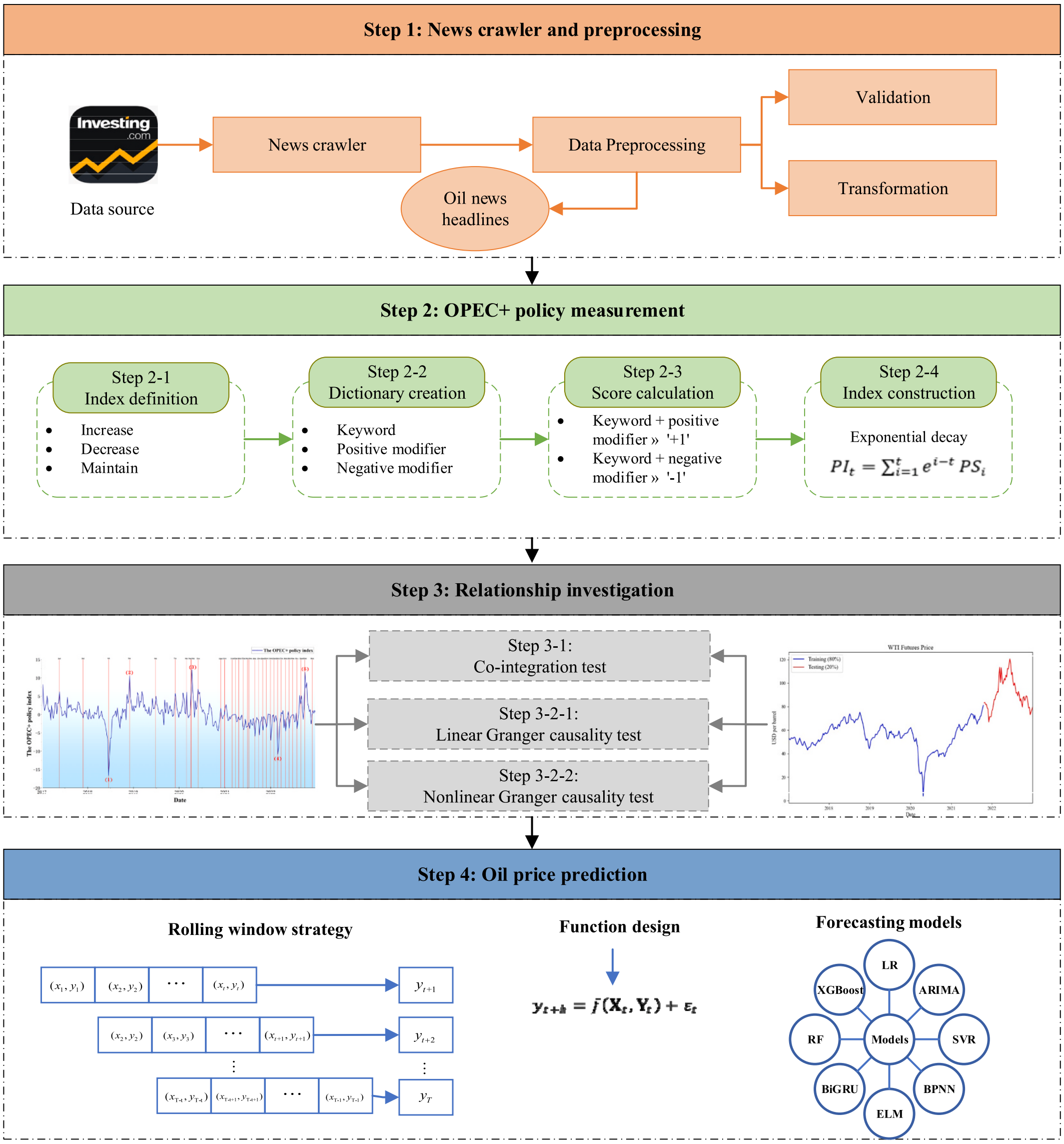

Fig. 1. General framework of incorporating the OPEC+ policy index into oil price forecasting.

designed to achieve the global objective, namely news crawler and preprocessing, OPEC+ policy measurement, relationship investigation, and oil price prediction. The specific sub-goals for each step are outlined as follows:

(1) **News crawler and preprocessing** aim to collect oil-related news headlines, use the text data preprocessing method to screen out the correct headlines, and convert them into a suitable format for analysis.
(2) **OPEC+ policy measurement** strives to develop a novel news-based index to reflect the production decisions made by OPEC+ countries. This index not only captures OPEC+'s output policy, but also reflects investor sentiment's reaction to such policy changes. This objective is accomplished through the following four processes: index definition, dictionary creation, score calculation, and index construction.
(3) **Relationship investigation** seeks to explore the association between the proposed OPEC+ policy index and the crude oil price. This investigation encompasses two important aspects: examining the persistence of a long-term interrelation and assessing the existence of statistically significant causal relationships. To comprehensively assess the causal relationship, this paper employs both linear and nonlinear Granger causality tests.

(4) **Oil price prediction** aims to predict the crude oil price by introducing the proposed OPEC+ policy index to various forecasting techniques, based on the function $y_{t+h} = f(X_t, Y_t) + \varepsilon_t$, where y_t is the prediction result of oil price at period *t.* The parameter *h* denotes the prediction horizon, $X_t = \{x_t, x_{t\text{-}1}, \ldots\}$ and $Y_t = \{y_t, y_{t\text{-}1}, \ldots\}$ denote the available observations during period *t* for the

OPEC+ policy index and the historical oil price, and ε_t represents the error term. A rolling window strategy is adopted for the out-of-sample predictions.

3.2. News crawler and preprocessing

The news crawler and preprocessing procedures are firstly designed to collect news headlines related to oil markets and transform them into a suitable format for analysis.

In the news crawler, the news headlines are crawled from Investing.com, which is a widely recognized financial website that provides real-time market data, news, analysis, and tools for investors and traders. Our investigation employs news headlines as opposed to complete articles, as headlines are more readily accessible and typically serve as concise summaries of the content, encompassing adequate key information. Additionally, brief headlines exhibit diminished redundancy and fewer extraneous words compared to the entirety of the document [11]. To enable a comprehensive evaluation of the impact of the OPEC+ coalition on the global oil market since its inception at the end of 2016, news headlines were collected from the beginning of 2017 to the end of 2022.

In terms of data preprocessing, two main data cleaning techniques (i.e., data validation and transformation) are adopted to analyze the news headlines. First, data validation aims to select accurate news headlines that are highly related to the crude oil price. To achieve this goal, we select specific keywords relevant to the domain of crude oil (e.g., 'Oil', 'Crude', 'OPEC+', 'Brent', 'WTI'), considering news headlines containing these keywords as valid, while discarding those that did not meet this criterion. Second, data transformation seeks to convert valid news into a suitable format for analysis. To attain this objective, we convert all valid news titles into lowercase, and delete stop words unrelated to the text.

3.3. OPEC+ policy measurement

In this step, a dictionary-based method is applied to construct the OPEC+ policy index. Compared with machine learning methods, dictionary-based methods are more intuitive and interpretable (Loughran and McDonald, 2016). In this dictionary-based quantification framework, four sub-steps, i.e., index definition, dictionary creation, score calculation, and index construction, are involved.

In the index definition step (i.e., step 2–1), OPEC+ policy is defined as a set of agreements and decisions (i.e., increase, decrease, and maintain) made by the OPEC and its non-OPEC allies (collectively known as OPEC+), regarding oil production levels to manage global oil supply and prices.

In the dictionary creation step (i.e., step 2–2), we develop a novel dictionary based on the existing one developed by Loughran and McDonald [56]. The dictionary (as listed in Table 2) involves a panel of keywords and two panels of positive and negative modifiers. Specifically, the keywords are utilized to select the news headlines that are related to OPEC+ policy focus, including supply, production, allotment, reserve, quota, etc. And the positive and negative modifiers listed in panels B and C, signal "an increase in" crude oil price and "a decrease in" crude oil price, respectively. Positive modifiers are linked with a decrease in production made by OPEC+, while negative modifiers are linked with an increase in production.

In the score calculation step (i.e., step 2–3), news headlines related to the OPEC+ policy are assigned specific scores based on the presence of keywords in conjunction with negative or positive modifiers. Headlines with keywords and positive modifiers receive a '+1' tag, while those with keywords and negative modifiers receive a '-1' tag. News headlines that contain two types of modifiers or lack any modifiers are deemed to have an indeterminate meaning and are discarded. The weekly OPEC+ policy score is obtained by summing all tags in the week.

In the index construction step (i.e., step 2–4), the final index is developed by considering the exponential decline impact of online news. This approach is supported by the findings of Xu and Berkely [57], which indicate that the influence of news on stock prices is contingent upon both current and previous news. Specifically, the impact of current news is robust, while the impact of previous news is comparatively weaker. This combined influence can be modeled as an exponential decay process. Consequently, the news-based OPEC+ policy index is formulated as:

$$PI_t = \sum_{i=1}^{t} e^{i-t} PS_i \tag{1}$$

where PS_i denotes the policy score in week i, and PI_t denotes the cumulative policy score in week t, i.e., the final OPEC+ policy index. This equation suggests that the impact factor of a certain OPEC+ policy news is initially at its maximum value of $e^0 = 1$ when the news is released in a specific week. However, this influence gradually decreases over time. Specifically, one week later, the impact factor reduces to $e^{-1} = 36.79\%$ of the original value, and after four weeks (equivalent to one month), it diminishes to $e^{-4} = 1.83\%$ of the original value.

3.4. Relationship investigation

In order to examine the association between the crude oil price and the newly devised OPEC+ policy index in this study, two widely utilized correlation analysis tools, specifically the co-integration test and the Granger causality tests (both linear and nonlinear versions), are utilized. The subsequent sections provide a brief overview of these relevant methodologies.

3.4.1. Co-integration test

Co-integration test is a widely used econometric technique that can assess the long-run relationship between two or more time series variables. In this study, the Johansen co-integration test [58] is employed to assess the long-term relationship between the crude oil price and the OPEC+ policy index. The test estimates a vector autoregression (VAR) model:

$$\mathrm{Y}_t = \alpha_{1,1}\mathrm{Y}_{t-1} + \cdots + \alpha_{1,p}\mathrm{Y}_{t-p} + \beta_{1,1}\mathrm{X}_{t-1} + \cdots + \beta_{1,p}\mathrm{X}_{t-p} + \mu_{1,t} \tag{2}$$

$$\mathrm{X}_t = \alpha_{2,1}\mathrm{Y}_{t-1} + \cdots + \alpha_{2,p}\mathrm{Y}_{t-p} + \beta_{2,1}\mathrm{X}_{t-1} + \cdots + \beta_{2,p}\mathrm{X}_{t-p} + \mu_{2,t} \tag{3}$$

where X_t and Y_t denote the OPEC+ policy and the crude oil price at time t, respectively; α and β are coefficient matrices that capture the impact of the lagged levels of Y and X, respectively; $\mu_{1,t}$ and $\mu_{2,t}$ denote the error terms or residuals at time t, which are assumed to follow a normal distribution and be independent.; and p is the lag order.

The null hypothesis of no co-integration, i.e., $\beta_{1,i} = \alpha_{2,i} = 0\ (i = 1, \cdots, p)$, is tested against the alternative hypothesis of co-integration, suggesting that at least one of the $\beta_{1,i}$ or $\alpha_{2,i}$ coefficients is not equal to zero. Rejection of the null hypothesis implies the existence of a long-term relationship or co-integration between the OPEC+ policy and the crude oil price.

3.4.2. Linear granger causality test

The linear Granger causality test [59] is utilized in this paper to assess the linear causal association between the OPEC+ policy and the crude oil price, denoted as X_t and Y_t, respectively. It should be noted that the Granger causality does not establish a definitive causal relationship, but rather provides evidence of statistical association between variables. The underlying concept is that if X_t exhibits Granger causality on Y_t, then the historical values of X_t should encompass informative content that enhances the forecasting of future values of Y_t, surpassing the explanatory power solely attributed to past values of Y_t. Thus, Granger causality can be regarded as a powerful tool to verify the predictiveness of the OPEC+ policy index on the crude oil price. Similar to the Johansen co-integration test, the Granger causality test is also conducted within a VAR framework, as presented in equations (2) and (3). Take Eq. (2) for example, the null hypothesis is that the OPEC+ policy index (i.e., X_t) does not Granger cause the crude oil price (i.e., Y_t), which means that the coefficients of X_t are all zero, i.e., $\beta_{1,1} = \beta_{1,2} = \beta_{1,p} = 0$. If the null hypothesis is rejected according to the statistical test, it provides evidence in favor of the alternative hypothesis that the OPEC+ policy index Granger causes the crude oil price.

3.4.3. Nonlinear granger causality test

The nonlinear Granger causality is developed for certain cases where the relationship between variables is nonlinear. In this study, the nonparametric test introduced by Diks and Panchenko [60] is specifically employed to investigate the nonlinear causal relationship between the crude oil price and the OPEC+ policy.

Assume the variables of X_t and Y_t are stationary, X_t does not strictly Granger cause Y_t if:

$$\mathrm{H}_0 : Y_{t+1}|(X_t, Y_t) \sim Y_{t+1}|Y_t \tag{4}$$

This hypothesis relates to the invariant distribution of the invariant distribution of the $(Lx + Ly + 1)$-dimensional vector $W_t = \left(X_t^{Lx}, Y_t^{Ly}, Z_t\right)$, where $Z_t = Y_{t+1}$. For simplicity, we drop the time index and assume $Lx = Ly = 1$. Under the null hypothesis, the conditional distribution of Z given $(X,Y)=(x,y)$ is expected to be the same as the conditional distribution of Z given $Y = y$. In terms of ratios of joint distributions, the null hypothesis in Eq. (4) can be changed into that the joint probability density function $f_{X,Y,Z}(x, y, z)$ and its marginals must satisfy the following relationship:

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)} = \frac{f_{X,Y}(x,y)}{f_Y(y)} \cdot \frac{f_{Y,Z}(y,z)}{f_Y(y)} \tag{5}$$

Accordingly, X and Z are independent conditionally on $Y = y$ for each fixed value of y. Thus, the revised null H_0 shows:

$$q \equiv E\left[f_{X,Y,Z}(X, Y, Z)f_Y(Y) - f_{X,Y}(X, Y)f_{Y,Z}(Y, Z)\right] = 0 \tag{6}$$

Here, we denote the local density estimator of a d_W-variate random vector W at W_i as:

$$\widehat{f}_w(W_i) = \frac{(2\varepsilon_n)^{-d_W}}{(n-1)} \sum_{j,j\neq i} I_{ij}^W \tag{7}$$

where $I_{ij}^W = I\left(\left\| W_i - W_j < \varepsilon_n \right\|\right)$ with the indicator function $I(\cdot)$ and the bandwidth ε_n depending on the sample size n. Finally, the test statistic can be formulated in terms of a scaled sample version of q:

$$T_n(\varepsilon_n) = \frac{n-1}{n(n-2)} \cdot \sum_i \left(\widehat{f}_{X,Y,Z}(X_i, Y_i, Z_i)\widehat{f}_Y(Y_i) - \widehat{f}_{X,Y}(X_i, Y_i)\widehat{f}_{Y,Z}(Y_i, Z_i)\right) \tag{8}$$

For $Lx = Ly = 1$, when $\varepsilon_n = Cn^{-\beta}$, $(C > 0,\ 1/4 < \beta < 1/3)$, the test statistic $T_n(\varepsilon_n)$ satisfies:

$$\sqrt{n}\ \frac{(T_n(\varepsilon_n) - q)}{S_n} \xrightarrow{D} N(0,1) \tag{9}$$

where $\xrightarrow{D}$ denotes convergence in distribution, and S_n is an estimator of the asymptotic variance of $T_n(\cdot)$. Ultimately, a one-tailed test is conducted based on Eq. (9).

3.5. Oil price prediction techniques

To rigorously evaluate the predictive efficacy of the OPEC+ policy index on the crude oil price, eight representative models are selected for consideration. These models include a range of techniques, such as linear regression (i.e., LR and ARIMAX), support vector regressions (i.e., SVR), and ANNs (i.e., BPNN, ELM and bidirectional gated recurrent units (BiGRU)), as well as ensemble learning models (i.e., Random Forest (RF) and eXtreme Gradient Boosting (XGBoost)). This comprehensive selection of models enables us to test the effectiveness of the OPEC+ policy index across a variety of different techniques and to identify which models are most effective for predicting the crude oil price concerning this index. The brief descriptions of these models are presented as follows, with their corresponding parameters listed in the Appendix.

3.5.1. LR

LR is a traditional econometric model that uses linear relationships between variables to make predictions. In this paper, LR assumes a linear relationship between the OPEC+ policy and the crude oil price, which can be expressed by:

$$\mathrm{Y}_t = \beta_0 + \beta_1 \mathrm{X}_t + \mu_{,t} \tag{10}$$

where Y_t is the crude oil price, X_t is the OPEC+ policy index, β_0 denotes the constant term, β_1 represents the regression coefficient of X_t, and $\mu_{,t}$ is the error term.

3.5.2. ARIMAX

ARIMAX, an extension of the ARIMA model, is a linear forecasting model that incorporates exogenous variables [61]. ARIMAX is widely used in econometrics, finance, and other fields for modeling and forecasting time series data that may be influenced by external factors. The ARIMAX (p, d, q, k) model can be mathematically represented as:

$$\mathrm{Y}_t = \gamma + \sum\nolimits_{i=1}^{p} \alpha_i Y_{t-i} + \sum\nolimits_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum\nolimits_{m=1}^{k} \beta_m X_{t-m} + \varepsilon_t \tag{11}$$

where Y_t is the crude oil price, X_t is the OPEC+ policy index; p, d, q and k are the order parameters of the ARIMA component of the model, representing the number of autoregressive terms, differences to achieve stationary time series and moving average terms, and the number of exogenous variables (i.e., the OPEC+ policy index), respectively; $\alpha_i(i = 1, \cdots, p)$ are the AR coefficients, $\theta_j(j = 1, \cdots, q)$ are the MA coefficients, $\beta_m(m = 1, \cdots, k)$ are the coefficients of the exogenous variables; γ denotes the constant term and μ_t is the error term at time t. In this paper, the Akaike information criterion (AIC) is adopted to find the optimal lag values of p, d, q, and k.

3.5.3. SVR

SVR specifically uses support vector machines (SVM), a widely utilized machine learning approach proposed in Ref. [62], to identify the optimal hyperplane that minimizes the discrepancy between predicted and observed values. SVR has advantages in dealing with small-sample, noise, nonlinear, and high-dimensional problems [63]. Given a training dataset of N input-output pairs $\{(z_1, y_1), (z_2, y_2), \ldots, (z_N, y_N)\}$, where $z_N \in R^d$ represents the input features of dimension d (the lagging information of oil price and the OPEC+ policy), and $\mathrm{y}_i \in R$ represents the corresponding output variable (i.e., the crude oil price), the goal of SVR is to determine the optimal hyperplane $\omega \cdot \phi(z) + b = 0$ that minimizes the following optimization problem:

$$\min \quad \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{N}(\xi_i + \xi_i^*) \mathrm{s.t.} \begin{cases} \omega * \phi(z_i) + b \ - y_i \leq \varepsilon + \xi_i^*(i = 1, 2, \ldots, N) \\ y_i - (\omega * \phi(z_i) + b\ ) \leq \varepsilon + \xi_i(i = 1, 2, \ldots, N) \\ \xi_i, \xi_i^* \geq 0(i = 1, 2, \ldots, N) \end{cases} \tag{12}$$

where ω is the weight vector, b is the bias term, $\phi(\bullet)$ is a function that maps the training sample to a higher dimensional space, ε is the tolerance for prediction errors, ξ_i and ξ_i^* are the slack variables that allow for points to be outside the margin or on the wrong side of the hyperplane, and C is the regularization parameter that governs the balance between minimizing the training error and maximizing the margin.

3.5.4. BPNN

BPNN, proposed by Rumelhart et al. [64], is a typical feedforward neural network that consists of multiple interconnected layers of artificial neurons, organized in input, hidden, and output layers. The input layer receives the input data, which is typically represented as a vector of features denoted as $\mathrm{Z} = (z_1, z_2, \cdots, z_N)$, which is composed of the lagging information of the crude oil price and the OPEC+ policy index. The hidden layer is responsible for processing the input data through a series of weighted connections and applying an

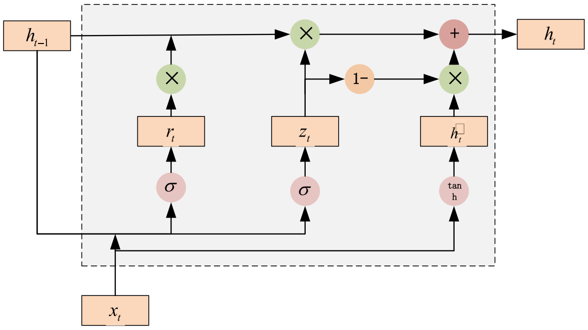

Fig. 2. The gate structure of GRU.

activation function to produce output values. The output layer is responsible for producing the final output values of the network based on the inputs and weights learned during the training process.

$$h_j = f_1\left(b_j + \sum_{i=1}^{N} \omega_{i,j} z_i\right), \left(b_j \geq 0, \omega_{i,j} \leq 1\right) \tag{13}$$

$$y = f_2\left(\theta_k + \sum_{j=1}^{M} w_{j,k} h_j\right), \left(\theta_k \geq 0, w_{j,k} \leq 1\right) \tag{14}$$

where $\omega_{i,j}$ is the weight of the connection between neuron i in the input layer and neuron j in the hidden layer, z_i is the input feature from the input layer, b_j is the bias of neuron j in the hidden layer, $f_1(\cdot)$ denotes the activation function; $w_{j,k}$ is the weight of the connection between neuron j in the hidden layer and neuron k in the output layer, h_j is the feature from the hidden layer, θ_k is the bias of neuron k in the output layer, $f_2(\cdot)$ denotes the activation function.

3.5.5. ELM

ELM, first proposed by Huang et al. [65], is a type of single-hidden-layer feedforward neural network that employs random weight and biases initialization for the hidden layer. The hidden layer neurons compute a linear combination of input features followed by an activation function. In the output layer, a linear regression approach is employed to calculate the optimal weights and biases for the connections linking the hidden layer and the output layer:

$$\widehat{y}_k = \sum_k \beta_{j,k} s\left(\sum_j \omega_{i,j} * z_i + b_j\right) + c_k \tag{15}$$

where $\widehat{y}_k$ is the output of neuron k in the output layer, $\beta_{j,k}$ is the weight of the connection between neuron j in the hidden layer and neuron k in the output layer, s(•) is the activation function applied to the net input of the neurons in the hidden layer, $\omega_{i,j}$ is the weight of the connection between neuron i in the input layer and neuron j in the hidden layer, z_i denotes the input feature from the input layer, b_j and c_k represent the bias of neuron j in the hidden layer and neuron k in the output layer, respectively. Compared with traditional learning schemes, ELM offers several benefits, including reduced computational complexity, ease of implementation, scalability, and high learning performance [66].

3.5.6. BiGRU

BiGRU is a variant of the traditional GRU by extending the architecture with bidirectionality [67]. The GRU is a variant of recurrent neural network (RNN) that incorporates gating mechanisms to selectively update and forget information at each time step. Similar to other gating mechanisms, GRU addresses the challenge of vanishing gradient and facilitates the model in capturing long-term dependencies within the input sequence. By selectively updating and forgetting information, GRU enhances its ability to capture and retain important patterns over time. The gate structure of GRU is depicted in Fig. 2.

In Fig. 2, x_t is the input data, h denotes the output of GRU, r and z represent the rest and update gate, respectively. h_{t-1} represents the hidden state at the previous time step t-1, and h_t represents the hidden state at the current time step t. The main process of GRU can be described by the following equations.

$$\text{The update gate}: z_t = \sigma(W_z(h_{t-1}, x_t) + b_z) \tag{16}$$

$$\text{The reset gate}: r_t = \sigma(W_r(h_{t-1}, x_t) + b_r) \tag{17}$$

$$\text{The candidate activation}: \widetilde{h}_t = tanh(W_h(r_t h_{t-1}, x_t) + b_h) \tag{18}$$

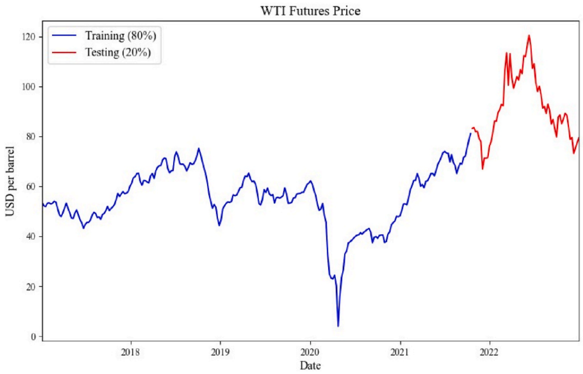

Fig. 3. The WTI futures price.

$$\text{The output}: h_t = (1 - z_t)h_{t-1} + z_t\widetilde{h}_t \tag{19}$$

where W denotes the gate weight and b is the bias, σ is the Sigmoid activation. The update gate equation (16) controls the flow of information from the previous time step to the current time step; the reset gate equation (17) decides how much of the past information to forget and how much of the new information to consider for the new memory $\widetilde{h}_t$; the candidate activation equation (18) generates a new memory candidate that incorporates information from both the current input and the previous hidden state; the output equation (19) computes the updated hidden state h_t.

In a standard GRU, information flows in only one direction through the recurrent connections, typically from front h_{t-1} to h_t. However, in a BiGRU model, there are two sets of recurrent connections: one set processes the input sequence in the forward direction, while the other set processes it in the backward direction [68]. BiGRU, with its ability to capture bidirectional context and model complex dependencies in sequential data, can be used as a powerful tool for crude oil price forecasting [10,29,34].

3.5.7. RF

RF, proposed by Breiman [69], is a powerful ensemble learning technique that amalgamates the principles of bagging with decision trees, resulting in the creation of a highly accurate and robust predictive model. The key idea behind RF is to build a collection of decision trees and combine their predictions to obtain a more accurate and robust result compared to using a single decision tree (Zhang et al., 2023). Assuming the sample size of the oil price is N, with a sample feature dimension of M, and the number of decision trees in the artificially designated random forest is denoted as K. The specific modeling steps of RF are outlined as follows:

- Use the bootstrap method to draw M-sized subsets from a dataset of N oil price data, a total of K draws are made.
- Select m features in the M dimension as training for different decision trees, where $m < M$.
- The decision trees continue to grow with a constant feature value.
- Aggregate predictions from all decision trees as the final forecast results.

By aggregating predictions from multiple trees and using techniques like bagging and random feature selection, RF is less prone to overfitting compared to individual decision trees. In addition, it can effectively handle datasets with a large number of features without feature selection or dimensionality reduction techniques.

3.5.8. XGBoost

XGBoost, developed by Chen and Guestrin [70], is an ensemble learning technique that combines the principles of boosting with decision trees to create a more accurate and robust predictive model. The main idea behind XGBoost is to iteratively build a series of weaker base learners (decision trees) that correct the errors of previous trees. Each tree is added to the model in a way that minimizes the overall prediction error. According to Mo et al. [71], the output function of XGBoost is calculated as follows:

$$\widehat{Y}_i^T = \sum_{k=1}^{T} f_k(x_i) = \widehat{y}_i^{T-1} + f_T(x_i) \tag{20}$$

where $\widehat{Y}_i^T$ is the generated decision tree, $f_T(x_i)$ denotes the newly created decision tree, and T is the tree size. XGBoost elevates accuracy by employing a differentiable loss function, typically the mean squared error, and employing the gradient descent optimization algorithm. This algorithm follows the first and second-order terms of the Taylor series expansion, thereby refining the model's prediction through iterative updates. The addition of a regularization term effectively limits the complexity of the expanded term, thereby mitigating overfitting [72]. XGBoost's combination of boosting, regularization, and efficient implementation makes it a highly effective algorithm for oil price forecasting.

4. Experimental designs

4.1. Data description

In this paper, two sets of original data, namely the WTI crude oil futures price and crude oil news headlines, are collected. As for crude oil price, the futures price is selected instead of the spot price because futures prices are forward-looking and react more quickly to OPEC+ policy changes. The weekly WTI futures price (as shown in Fig. 3) is collected from US Energy Information Administration (https://www.eia.gov/), with the sample interval ranging from the beginning of 2017 to the end of 2022. This interval, with 313 weeks, covers the entire period since the establishment of OPEC+ in December 2016. As for crude oil news headlines, 26,282 OPEC+ related news headlines are crawled from Investing.com. These headlines reflect public attention to the crude oil market and are further screened to specifically select those capturing adjustments in OPEC+ production policies for index construction. Both the weekly oil price data and the OPEC+ policy index are partitioned into two parts: a training dataset encompassing the initial 80% of the sample period and a testing dataset comprising the remaining 20%.

In addition, weekly data are utilized for two compelling reasons. Firstly, in order to comprehensively understand the influence of OPEC announcements on the oil price, it is imperative to have a minimum frequency of weekly data [44]. Secondly, weekly data tends to exhibit superior data quality compared to daily data, as it can effectively mitigate noise, volatility, and missing values, thereby enhancing the reliability and accuracy of our analysis. Nevertheless, to mitigate the potential issues of overfitting and instability caused by insufficient sample size, we also collected daily data (totaling 1516 data points) to validate the robustness of the OPEC+ policy index we constructed in enhancing oil price predictions.

4.2. Model evaluation

To assess the precision of different forecasting models, three widely used criteria are chosen, namely, mean absolute error (MAE), root mean squared error (RMSE), and Theil's U (TU), which are presented below:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{y}_t - y_t\right| \tag{21}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_t - y_t\right)^2} \tag{22}$$

$$\mathrm{TU} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_t - y_t\right)^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_t\right)^2} + \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_t\right)^2}} \tag{23}$$

where $\hat{y}_t$ denotes the predicted value of oil price and y_t is the true value at time t, respectively. The data size of the testing data is represented as N.

To verify the policy-enhanced models are superior to the benchmark models without the policy predictor in terms of accuracy and reliability, this paper employs the model confidence set (MCS) test (Hansen et al., 2011) to examine the significance of prediction disparities. The MCS test involves comparing multiple models through equivalence tests and elimination rules. Subsequently, the optimal model set can be determined within a specified confidence level, which is set as 0.25 according to Refs. [13,73]. The MCS test, combined with the Bootstrap method, calculates two statistics: TR and TMAX, which are calculated as:

$$\mathrm{TR} = \max_{i,j\in M}\frac{\left|\overline{d}_{i,j}\right|}{\sqrt{Var\left(d_{i,j}\right)}} \tag{24}$$

$$\mathrm{TMAX} = \max_{i\in M}\frac{\left(\overline{d}_{i,.}\right)^2}{\sqrt{Var\left(\overline{d}_{i,.}\right)}} \tag{25}$$

where $\overline{d}_{i,j} = \frac{1}{N}\sum_{t=1}^{N} d_{i,j,t}$, $d_{i,j,t}$ is the loss difference of model i and j at time t, $\overline{d}_{i,.} = \frac{1}{M}\sum_{j\in M}\overline{d}_{i,j}$, and Var denotes the variance operator.

5. Empirical results

5.1. Behavior of the OPEC+ policy index

By mining a mass of news headlines that relate to OPEC+'s production decision, a news-based OPEC+ policy index is constructed,

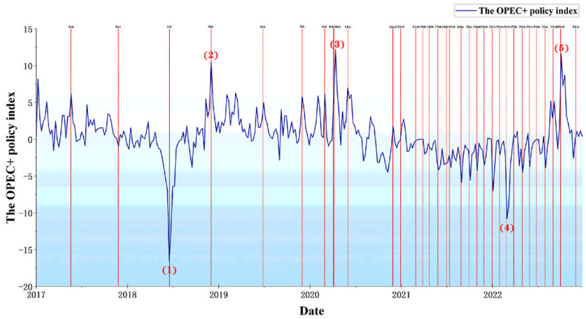

Fig. 4. The news-based OPEC+ policy index.

Table 3
Statistical description of our proposed OPEC+ policy index.

Statistics	Values	Statistics	Values
Mean	0.3602	Kurtosis	7.4472
Median	0.2338	Jarque-Bera	265.0832
Maximum	12.1905	Probability	0.0000
Minimum	−16.5765	Sum	112.7452
Std. Dev.	3.1460	Sum Sq. Dev.	3087.9170
Skewness	−0.3703	Observations	313

as exhibited in Fig. 4, with its descriptive statistics presented in Table 3.

From Fig. 4 and Table 3, two intriguing findings can be inferred. First, the occurrence of extreme values in the OPEC+ policy index coincides closely with the timing of OPEC+ Ministerial Meetings (i.e., OPEC and non-OPEC Ministerial Meetings). Since its inception at the end of 2016, OPEC+ has held 36 OPEC+ Ministerial Meetings to discuss and coordinate oil production policies. The specific times of the 33 meetings (since 2017) are indicated with red vertical lines in Fig. 4. It is obvious that the specific time of the meetings is highly associated with the extreme value of our proposed OPEC+ policy index. Take the five most apparent extreme values for example (marketed in Fig. 4):

(1) In the 4th OPEC+ Ministerial Meeting (held on June 23, 2018), OPEC+ countries declared that they have exceeded the required level of production cuts outlined in the 'Declaration of Cooperation', reaching 147% in May 2018. Therefore, OPEC+ decided that as of July 1, 2018, it will ensure all member countries adhere to production cuts at 100% starting from July 1st, which will result in an increase in crude oil output from the current levels. Correspondingly, our OPEC+ policy index has released a significant negative signal, indicating that this policy may have a negative impact on the oil price.
(2) In the 5th OPEC+ Ministerial Meeting (held on 7 December 2018), OPEC+ decided to reduce the overall production by 1.2 mb/d, effective as of January 2019. Accordingly, our OPEC+ policy index has emitted a noteworthy positive signal, signifying that this production reduction policy may have a positive effect on the oil price.
(3) In the 10th OPEC+ Ministerial Meeting (held on 12 April 2020), OPEC+ decided a biggest-ever oil cut to support prices amid the coronavirus pandemic. Accordingly, our OPEC + policy index peaked around this week, indicating a strong signal to boost the oil price.
(4) In the 26th OPEC+ Ministerial Meeting (held on 2 March 2022), OPEC+ decided to increase the monthly overall production by 0.4 million barrels per day (mb/d) for April 2022. Accordingly, our OPEC+ policy index has experienced a notable nadir during this period.
(5) In the 33rd OPEC+ Ministerial Meeting (held on 5 October 2022), OPEC+ decided to decrease the overall production by 2 mb/d, leading to a significant peak of our proposed OPEC+ policy index and an expected positive impact on the oil price.

Second, the positive mean value (0.3602) of the OPEC+ policy index we constructed suggests that in recent years, OPEC+ countries have been inclined to adopt a series of production-cut policies to stimulate the oil price. This policy tendency can be seen as a response to the demand decline caused by the pandemic, with OPEC+ countries implementing proactive production policies, such as production cuts, to stabilize the oil price and maintain global economic stability.

5.2. Relationship between the proposed OPEC+ policy index and the crude oil price

To further explore the dependency relationship between crude oil price and our proposed OPEC+ policy index, two pendentive correlation test techniques, namely the co-integration test and the Granger causality tests (with linear and nonlinear versions) are employed. The corresponding relationship results are reported in Table 4, respectively.

Table 4
Relationship between our proposed OPEC+ policy index and the crude oil price.

Panel A: Co-integration test		
Hypothesized No. of CE(s)	Trace Statistic	Prob.
None	88.1428	0.0000
At most 1	25.8785	0.0000

Panel B: Linear Granger causality test			
H_0: The OPEC+ policy index does not Granger cause oil price		H_0: Oil price does not Granger cause the OPEC+ policy index	
F-Statistic	Prob.	F-Stats	Prob.
3.1544	0.0146	1.2112	0.3061

Panel C: Nonlinear Granger causality test		
$Lx = Ly$	H_0: The OPEC+ policy index does not Granger cause oil price	H_0: Oil price does not Granger cause the OPEC+ policy index
	T_n	T_n
1	1.4355*	1.4587*
2	1.7613**	1.2258
3	2.1668**	1.8628**
4	2.6522***	2.6834***

Regarding the co-integration test, the trace test indicates the null hypothesis of none cointegration equations is rejected at the 5% significance level, providing evidence of a long-term relationship between the crude oil price and the OPEC+ policy index.

As for the linear Granger causality test, the results support a unidirectional causality flowing from the OPEC+ policy to the oil price at the 5% significance level. While the causality in the reverse direction (flowing from the crude oil price to the OPEC+ policy index) is not significant. This result implies that the OPEC+ policy index may have a direct and linear impact on the crude oil price and hold the potential to forecast its forthcoming movements. For example, if OPEC+ decides to increase production, this decision can lead to a linear increase in the global oil supply, which tends to put downward pressure on the crude oil price due to oversupply.

As for the nonlinear Granger causality test, the results support a bidirectional causality at the 10% level for most cases (except for the case $Lx = Ly = 2$, where the oil price does not Granger cause the OPEC+ policy index). The findings demonstrate that the OPEC+ policy may exert a nonlinear impact on the crude oil price since decisions made by OPEC+ are not always uniform or predictable. While linear relationships might capture the basic cause-and-effect relationship (e.g., production cuts leading to price increases), OPEC+ can implement policies in a nuanced and flexible manner, which may result in non-linear effects. In addition, regarding whether the oil price can Granger-cause OPE + policies, we arrived at different conclusions in linear and nonlinear tests: the linear test results did not indicate that the oil price Granger-cause OPEC+ policies, whereas the non-linear test results indeed confirmed this association. This result indicates that the oil price can influence changes in OPEC+ policies because OPEC+ has consistently aimed to maintain and stabilize the oil price. When the oil price experiences significant declines, OPEC+ implements policies such as production cuts to stimulate the oil price, and this stimulating mechanism is characterized by complexity and nonlinearity.

Comparing our conclusions with existing Granger causality test results, our findings are both consistent with previous research and reveal novel discoveries. Specifically, our linear findings corroborate some of the findings of Kaufman et al. [74] and Derbali et al. [45], both of whom established that OPEC behavior can Granger cause fluctuations in oil prices, but not vice versa. However, our nonlinear Granger causality analysis yields contrasting results from the aforementioned studies that employed linear methods. Notably, we uncover new evidence indicating that changes in oil prices also Granger cause shifts in OPEC+ behavior, and this effect tends to be nonlinear. In summary, the results of both correlation tests consistently demonstrate a strong association between the proposed OPEC+ policy index and the crude oil price. The findings provide empirical evidence to support the value of our proposed OPEC+ policy index as a tool for predicting the crude oil price. In particular, the nonlinear and nonlinear causal results provide useful implications for using both linear models and nonlinear models for oil price forecasting.

5.3. Forecasting results

The proposed OPEC+ policy index is finally applied to forecast the WTI crude oil futures price. According to the linear and nonlinear association, eight representative models are employed for forecasting, including both linear types (i.e., LR and ARIMAX) and nonlinear types (i.e., SVR, BPNN, ELM, BiGRU, RF, and XGBoost). Parameters for these forecasting techniques are presented in the Appendix. The sample series was partitioned into two distinct sets: a training dataset encompassing the initial 80% of the sample period and a testing dataset comprising the remaining 20%. The lag order is selected as 4 (weeks) which is selected by estimating a VAR model. The effectiveness of the proposed framework was assessed using multi-step ahead predictions, considering various time horizons ranging from 1 to 4 weeks, which provides a comprehensive assessment of its robustness.

Accordingly, the point-by-point forecasting errors with (and without) our proposed OPEC+ policy index are illustrated in Fig. 5. It is obvious that there are two special phases (demarcated by dashed lines) within the testing period, during which the forecasting errors notably exceed those observed at other times. The first phase is characterized by a precipitous decline in the oil price attributable to the Omicron pandemic, while the subsequent phase is distinguished by a rapid escalation in the oil price prompted by the outbreak of the

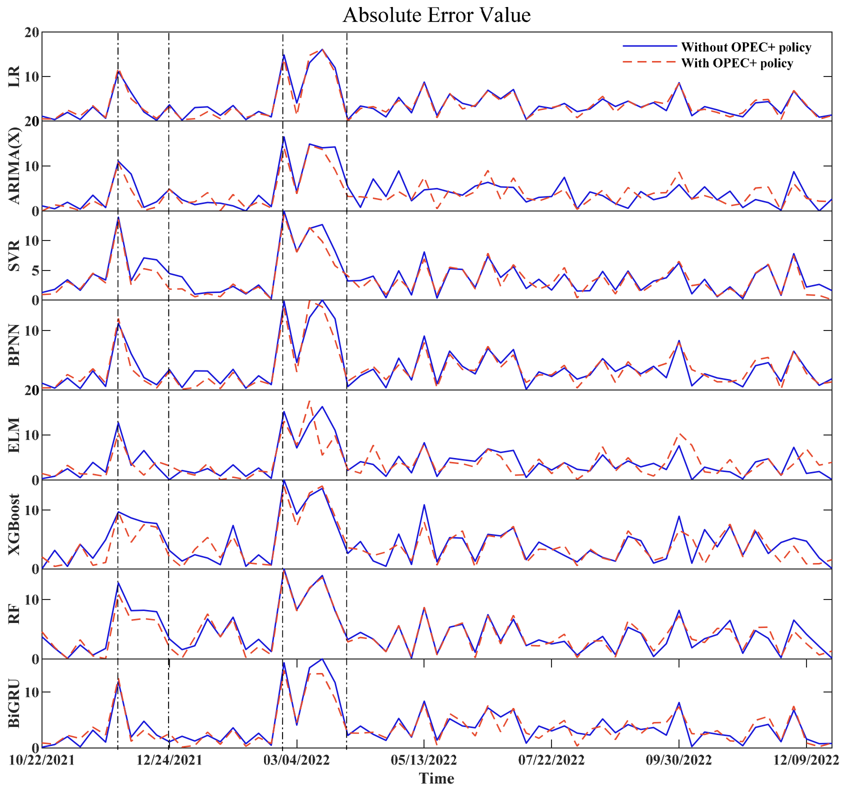

Fig. 5. The out-of-sample point-by-point errors for one-step-ahead predictions.

Table 5
1-step-ahead forecasting results with and without our proposed weekly OPEC+ policy index.

	Without the OPEC+ policy index			With the OPEC+ policy index		
	MAE	RMSE	TU	MAE	RMSE	TU
LR	3.8237	5.1865	0.0282	3.6707	5.1198	0.0278
ARIMA(X)	4.0815	5.5030	0.0298	3.7574	5.0032	0.0271
SVR	3.9497	5.1313	0.0278	3.5712	4.7443	0.0257
BPNN	3.7153	5.0741	0.0276	3.5483	4.8914	0.0265
ELM	3.8348	5.2337	0.0284	3.7325	5.0148	0.0273
BiGRU	3.7652	5.1828	0.0281	3.6468	4.8981	0.0265
RF	4.2684	5.4720	0.0297	4.1007	5.2937	0.0288
XGboost	4.3497	5.5649	0.0303	3.9912	5.1658	0.0281

Table 6
2-step-ahead forecasting results with and without our proposed weekly OPEC+ policy index.

	Without the OPEC+ policy index			With the OPEC+ policy index		
	MAE	RMSE	TU	MAE	RMSE	TU
LR	5.1278	6.4679	0.0353	4.9048	6.3796	0.0347
ARIMA(X)	5.7469	7.4461	0.0403	4.9765	6.3364	0.0344
SVR	5.1656	6.5084	0.0352	4.6182	6.0503	0.0327
BPNN	5.1438	6.4532	0.0352	4.8456	6.2533	0.0340
ELM	5.1032	6.5977	0.0359	4.5335	5.9360	0.0324
BiGRU	5.2798	6.7535	0.0367	4.7882	6.2790	0.0341
RF	5.2043	6.5475	0.0357	4.9582	6.3044	0.0344
XGboost	5.5846	7.0877	0.0386	4.9476	6.3787	0.0347

Table 7
3-step-ahead forecasting results with and without our proposed weekly OPEC+ policy index.

	Without the OPEC+ policy index			With the OPEC+ policy index		
	MAE	RMSE	TU	MAE	RMSE	TU
LR	6.1683	7.3595	0.0401	5.9277	7.3013	0.0396
ARIMA(X)	6.8994	8.9706	0.0486	6.0349	7.3750	0.0400
SVR	5.9037	7.3848	0.0399	5.6717	7.0449	0.0381
BPNN	6.1574	7.3690	0.0401	5.8526	7.2181	0.0391
ELM	6.3907	7.8687	0.0425	5.6259	7.1306	0.0387
BiGRU	6.5636	7.7929	0.0423	5.8096	7.1547	0.0388
RF	6.3079	7.5502	0.0412	6.0729	7.1892	0.0391
XGboost	7.0238	8.4150	0.0458	5.6410	6.9415	0.0378

Table 8
4-step-ahead forecasting results with and without our proposed weekly OPEC+ policy index.

	Without the OPEC+ policy index			With the OPEC+ policy index		
	MAE	RMSE	TU	MAE	RMSE	TU
LR	7.2139	8.8674	0.0481	7.2950	8.8748	0.0479
ARIMA(X)	8.6690	10.8267	0.0586	7.6996	9.2666	0.0502
SVR	7.0630	8.9264	0.0480	7.1854	8.7677	0.0474
BPNN	7.1948	8.8770	0.0481	7.2717	8.8402	0.0477
ELM	8.0307	9.8934	0.0531	7.0794	8.9656	0.0484
BiGRU	7.9519	9.4526	0.0510	7.0901	8.7724	0.0475
RF	7.0819	8.6773	0.0472	6.9867	8.3688	0.0453
XGboost	8.2188	9.8976	0.0537	7.9100	9.1866	0.0492

Table 9
The MCS test in 1-step-ahead forecasting.

Loss function	AE				MSE			
Methods	TMAX		TR		TMAX		TR	
OPEC+ policy	Without	With	Without	With	Without	With	Without	With
LR	0.1168	**1.0000**	0.1131	**1.0000**	0.4467	1.0000	0.4548	1.0000
ARIMA(X)	0.1851	**1.0000**	0.1819	**1.0000**	0.1019	**1.0000**	0.1008	**1.0000**
SVR	0.0043	**1.0000**	0.0053	**1.0000**	0.0146	**1.0000**	0.0149	**1.0000**
BPNN	0.2290	**1.0000**	0.2280	**1.0000**	0.2758	1.0000	0.2724	1.0000
ELM	0.7466	1.0000	0.7431	1.0000	0.5953	1.0000	0.5897	1.0000
BiGRU	0.4355	1.0000	0.4340	1.0000	0.2199	**1.0000**	0.2166	**1.0000**
RF	0.2088	**1.0000**	0.1958	**1.0000**	0.1752	**1.0000**	0.1722	**1.0000**
XGboost	0.0727	**1.0000**	0.0683	**1.0000**	0.0237	**1.0000**	0.0227	**1.0000**

Russia-Ukraine conflict. Surprisingly, models incorporating our proposed OPEC+ policy index consistently exhibit lower errors in these critical phases, indicative of the effective response of OPEC+ policies to extreme oil price volatilities. Particularly, during the two identified phases, OPEC+ convened 6 ministerial meetings (i.e., the 23rd-28th sessions), in which the effect of the Omicron pandemic and the Russia-Ukraine conflict were addressed. The observed decrease in forecasting errors in models integrating the OPEC+ policy index underscores its instrumental role in enhancing the robustness of the forecasting framework during periods of exceptional market dynamics.

Furthermore, the final prediction results under multi-step prediction are illustrated in Tables 5–8 Based on the results, two crucial findings can be deduced. First, it is obvious that our proposed OPEC+ policy index is an optimal predictor for the crude oil price. In particular, all eight representative forecasting techniques that incorporate our proposed OPEC+ policy index exhibit superior performance compared to those that do not, as indicated by lower values of MAE, RMSE, and TU. Additionally, the robustness of the OPEC+ policy index in predicting the crude oil price is evident across different forecasting horizons, particularly for horizons ranging from 1 to 3 (i.e., within three weeks). However, in the case of a 4-step ahead prediction, it appears that the predictive capability of our proposed OPEC+ policy index for the oil price has somewhat decreased. This result is consistent with [75], which suggests that public information may be absorbed into prices over time, leading to a decreasing predictive power of news as the prediction horizon extends. While in most instances, the predictive models incorporating the OPEC+ policy index still exhibit lower errors compared to those without the index, there are exceptions, such as LR, SVR (in terms of MAE), and BPNN (in terms of MAE).

Second, the choice of optimal forecasting technique is contingent upon the inclusion of the OPEC+ policy index as well as variations in the forecasting horizons. Specifically, for models without the OPEC+ policy index, BPNN outperforms other models in the 1-step-ahead, SVR demonstrates superior performance in the 2-step-ahead and 3-step-ahead forecasting, and RF demonstrates the best

Table 10
The MCS test in 2-step-ahead forecasting.

Loss function	AE				MSE			
Methods	TMAX		TR		TMAX		TR	
OPEC+ policy	Without	With	Without	With	Without	With	Without	With
LR	0.1731	**1.0000**	0.1776	**1.0000**	0.5415	1.0000	0.5352	1.0000
ARIMA(X)	0.1438	**1.0000**	0.1443	**1.0000**	0.0928	**1.0000**	0.0879	**1.0000**
SVR	0.0077	**1.0000**	0.0071	**1.0000**	0.0096	**1.0000**	0.0089	**1.0000**
BPNN	0.0761	**1.0000**	0.0757	**1.0000**	0.2170	**1.0000**	0.2156	**1.0000**
ELM	0.0964	**1.0000**	0.0983	**1.0000**	0.0665	**1.0000**	0.0672	**1.0000**
BiGRU	0.0970	**1.0000**	0.0952	**1.0000**	0.0962	**1.0000**	0.0948	**1.0000**
RF	0.2791	1.0000	0.2736	1.0000	0.2732	1.0000	0.2766	1.0000
XGboost	0.1572	**1.0000**	0.1572	**1.0000**	0.1079	**1.0000**	0.1061	**1.0000**

Table 11
The MCS test in 3-step-ahead forecasting.

Loss function	AE				MSE			
Methods	TMAX		TR		TMAX		TR	
OPEC+ policy	Without	With	Without	With	Without	With	Without	With
LR	0.1413	**1.0000**	0.1110	**1.0000**	0.6399	1.0000	0.6403	1.0000
ARIMA(X)	0.2383	**1.0000**	0.2486	**1.0000**	0.0700	**1.0000**	0.0645	**1.0000**
SVR	0.3394	1.0000	0.3576	1.0000	0.1149	**1.0000**	0.1128	**1.0000**
BPNN	0.0619	**1.0000**	0.0341	**1.0000**	0.2399	**1.0000**	0.2427	**1.0000**
ELM	0.0416	**1.0000**	0.0382	**1.0000**	0.0452	**1.0000**	0.0454	**1.0000**
BiGRU	0.1412	**1.0000**	0.1100	**1.0000**	0.1512	**1.0000**	0.1533	**1.0000**
RF	0.2917	1.0000	0.4357	1.0000	0.1304	**1.0000**	0.1313	**1.0000**
XGboost	0.0166	**1.0000**	0.0226	**1.0000**	0.0089	**1.0000**	0.0080	**1.0000**

Table 12
The MCS test in 4-step-ahead forecasting.

Loss function	AE				MSE			
Methods	TMAX		TR		TMAX		TR	
OPEC+ policy	Without	With	Without	With	Without	With	Without	With
LR	1.0000	0.7266	1.0000	0.7302	1.0000	0.9713	1.0000	0.9752
ARIMA(X)	0.2913	1.0000	0.2912	1.0000	0.1074	**1.0000**	0.1083	**1.0000**
SVR	1.0000	0.8057	1.0000	0.8065	0.6780	1.0000	0.6787	1.0000
BPNN	1.0000	0.7413	1.0000	0.7473	0.8686	1.0000	0.8708	1.0000
ELM	0.0752	**1.0000**	0.0718	**1.0000**	0.0534	**1.0000**	0.0568	**1.0000**
BiGRU	0.1269	**1.0000**	0.1245	**1.0000**	0.0961	**1.0000**	0.0974	**1.0000**
RF	0.7379	1.0000	0.7381	1.0000	0.3115	1.0000	0.3086	1.0000
XGboost	0.5788	1.0000	0.5783	1.0000	0.2801	1.0000	0.2769	1.0000

performance in the 4-step-ahead forecasting. For models with the OPEC+ policy index, BPNN, ELM, XGboost, and RF exhibit superior performance in 1-step-ahead, 2-step-ahead, 3-step-ahead, and 4-step-ahead forecasting (as measured by RMSE), respectively. Interestingly, we find these optimal models are all machine learning models. This result aligns with the majority of existing oil price prediction literature (Li et al., 2024; Xu et al., 2023), as machine learning models are better at capturing the non-linear and complex data features of oil prices compared to linear regression. The underlying reason may be that machine learning models have advantages in capturing the nonlinear patterns and irregularities hidden within the impact of OPEC+ policies on oil price series.

The MCS test is further conducted to examine the statistical significance of models incorporating the proposed OPEC+ policy index in comparison to models without the index. Tables 9–12 depict the p-values based on different loss functions (i.e., absolute error (AE) and mean squared error (MSE)) and test methods (TMAX and TR) for 1-4-step-ahead predictions. For 1-3-step-ahead predictions, the p-values of models with the proposed OPEC+ policy index remain 1 all the time, and in most of the cases without the index, the p-values are smaller than the significant level of 0.25 (as bolded). This result provides evidence that models incorporating the proposed OPEC+ policy index outperform models without the index in a statistically significant manner. However, for the 4-step-ahead prediction, on the one hand, not all models incorporating the OPEC+ policy index own p-values of 1, as observed in cases such as LR, SVR, and BPNN; on the other hand, only a few models (i.e., ARIMA, ELM and BiGRU) reject the null hypothesis at the 0.25 significance level. These empirical results indicate that the predictive effectiveness of our proposed OPEC+ policy index is significant only within three-week forecast horizons.

Table 13
1-step-ahead forecasting results with and without our proposed daily OPEC+ policy index.

	Without the OPEC+ policy index			With the OPEC+ policy index		
	MAE	RMSE	TU	MAE	RMSE	TU
LR	2.3480	3.1482	0.0171	2.3399	3.1428	0.0170
ARIMA(X)	2.3895	3.2121	0.0174	2.1919	2.9726	0.0161
SVR	2.1424	2.9045	0.0157	2.1711	2.9357	0.0159
BPNN	2.2151	2.9638	0.0161	2.1170	2.8800	0.0156
ELM	2.3354	3.3811	0.0183	2.2450	3.0744	0.0167
BiGRU	2.2220	2.9811	0.0162	2.1856	2.9725	0.0161
RF	2.2451	2.9506	0.0160	2.1366	2.8191	0.0153
XGboost	2.2382	2.9138	0.0158	2.1756	2.8602	0.0155

Table 14
2-step-ahead forecasting results with and without our proposed daily OPEC+ policy index.

	Without the OPEC+ policy index			With the OPEC+ policy index		
	MAE	RMSE	TU	MAE	RMSE	TU
LR	3.1981	4.2621	0.0231	3.1882	4.2581	0.0231
ARIMA(X)	3.2947	4.3555	0.0236	3.1180	4.1768	0.0226
SVR	3.0647	4.1071	0.0222	3.0793	4.1193	0.0223
BPNN	3.0909	4.1405	0.0224	3.0818	4.1311	0.0223
ELM	3.3922	4.9348	0.0267	3.1273	4.1674	0.0226
BiGRU	3.0919	4.1327	0.0224	3.0412	4.1298	0.0223
RF	3.1966	4.1618	0.0226	3.1334	4.0715	0.0221
XGboost	3.1406	4.1154	0.0223	3.1368	4.1012	0.0222

Table 15
3-step-ahead forecasting results with and without our proposed daily OPEC+ policy index.

	Without the OPEC+ policy index			With the OPEC+ policy index		
	MAE	RMSE	TU	MAE	RMSE	TU
LR	3.7882	5.0251	0.0272	3.7861	5.0279	0.0273
ARIMA(X)	3.9003	5.1307	0.0278	3.7208	4.9303	0.0267
SVR	3.7412	4.9347	0.0267	3.7280	4.9310	0.0267
BPNN	3.7760	4.9629	0.0269	3.7529	4.9538	0.0268
ELM	4.1225	5.8644	0.0318	3.6979	4.8881	0.0265
BiGRU	3.6899	4.8903	0.0265	3.6765	4.8880	0.0264
RF	3.8193	4.9711	0.0270	3.8156	4.9652	0.0269
XGboost	3.8236	4.9775	0.0269	3.7810	4.9667	0.0269

Table 16
4-step-ahead forecasting results with and without our proposed daily OPEC+ policy index.

	Without the OPEC+ policy index			With the OPEC+ policy index		
	MAE	RMSE	TU	MAE	RMSE	TU
LR	4.1581	5.6225	0.0305	4.1418	5.6066	0.0304
ARIMA(X)	4.2668	5.7244	0.0310	4.0557	5.4256	0.0294
SVR	4.1615	5.6258	0.0305	4.0994	5.5529	0.0301
BPNN	4.1353	5.6089	0.0304	4.1040	5.5395	0.0300
ELM	4.5766	6.2845	0.0340	4.1412	5.6080	0.0304
BiGRU	4.0530	5.4663	0.0297	4.0437	5.4479	0.0295
RF	4.1090	5.4399	0.0295	4.1392	5.4897	0.0298
XGboost	4.1770	5.5542	0.0300	4.1812	5.5476	0.0301

6. Further applications

6.1. Further applications of daily OPEC+ policy index

The empirical findings have effectively validated the efficacy of our constructed weekly OPEC+ policy index in forecasting the crude oil price. These results hold promise for supporting strategic planning and policy formulation in medium-term horizons. However, within the crude oil market, daily predictions hold equal significance, particularly for short-term trading and risk

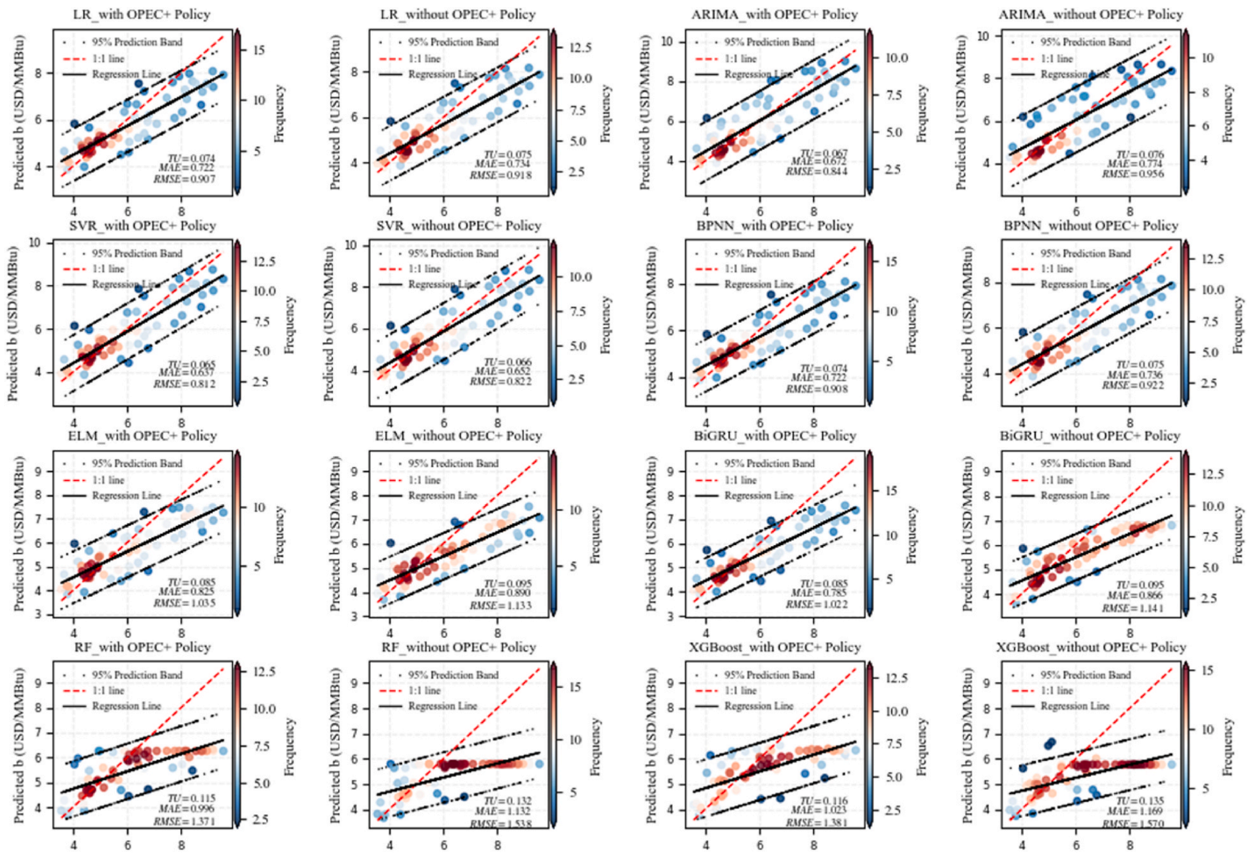

Fig. 6. Density scatter plots of observed against predicted gas futures price in 1-step-ahead forecast.

management strategies. Consequently, we have devoted to developing a daily OPEC+ policy index and subsequently testing its predictive capabilities for daily crude oil prices.

The construction of the daily OPEC+ policy index follows a methodology similar to that of the weekly index. Within the same time periodicity (2017–2022), daily data boasts a larger sample size (1516 points) compared to weekly data, thereby furnishing additional evidence to enhance the robustness of our research framework. Predictive performances of the linear OPEC+ index on the crude oil price are illustrated in Tables 13–16, corresponding to forecasting horizons 1–4 days, respectively.

The results reveal that the constructed daily OPEC+ policy index continues to exhibit forecasting efficacy on oil prices, even though the predictive performance is not as good as that of the weekly index. Specifically, except for certain models and specific forecasting steps (i.e., SVR at steps 1 and 2, LR at step 3, and RF and XGBoost at step 4), the inclusion of the OPEC+ policy index enhances the predictive accuracy compared to models without the index. This finding further validates the robustness of our forecasting framework and indicators.

6.2. *Further applications to the natural gas market*

For a considerable period, fuel switching between natural gas and crude oil has historically been a crucial factor influencing their pricing trends. As demonstrated by Vücel and Guo [76], the crude oil price is closely correlated with the natural gas price, with the crude oil price being shaped by world oil market conditions, and U.S. natural gas price adjusting to the oil price. The empirical study above has thoroughly validated the predictive capability of our proposed OPEC+ policy index for the crude oil price. In this section, we will delve deeper into the predictive ability of the OPEC+ policy index for the natural gas price. Using the Henry Hub natural gas futures price as the forecast target, the forecast results are shown in Figs. 6–9.

On the one hand, our constructed OPEC+ policy index demonstrates a commendable ability to predict natural gas futures prices. We found that in almost all models and at all horizons, the prediction errors (i.e., MAE, RMSE, and TU) embedded with the OPEC+ policy index are smaller than those without the index. This predictive performance reflects the direct or indirect impact of policy changes in OPEC+ countries on the natural gas market. On the other hand, SVR shows the best forecasting performance for natural gas among all prediction models, particularly when integrated with the OPEC+ index. It consistently achieves the minimum prediction error across all horizons. This result can be attributed to the inherent capability of SVR in capturing non-linear relationships between OPEC+ dynamics and gas prices [77]. Additionally, SVR exhibits strong robustness in predicting data with outliers and noise, such as

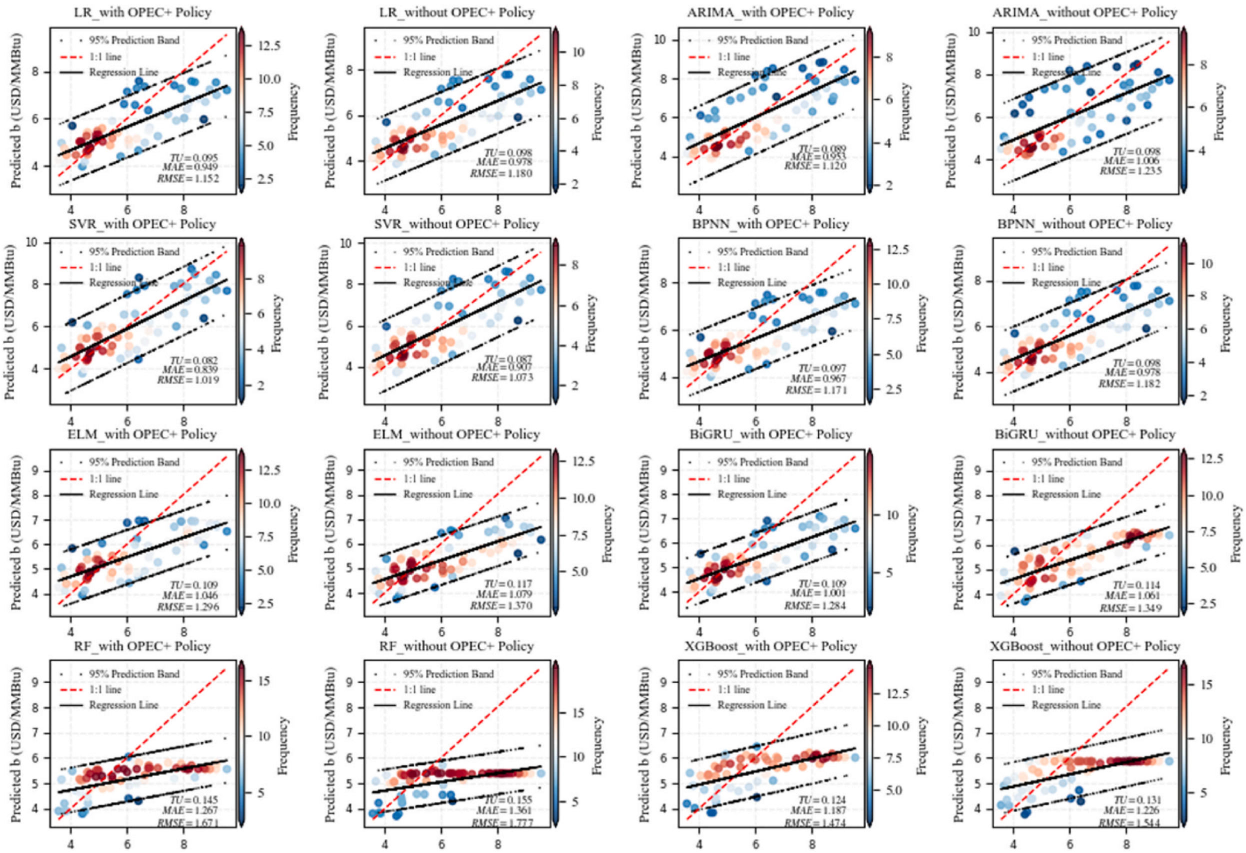

Fig. 7. Density scatter plots of observed against predicted gas futures price in 2-step-ahead forecast.

natural gas prices [24,63,78]. However, when the index is not considered, SVR only demonstrates optimal predictive performance at horizons 1–3. In the absence of the index at the four-step horizon, BPNN emerges as the model with the most effective predictive performance. In summary, the successful application of the OPEC+ policy index in forecasting the gas futures price provides powerful support for the effectiveness of the index.

7. Concluding remarks

By harnessing the power of text mining, this research aims to construct a groundbreaking news-based OPEC+ policy index and evaluate its predictive capacity with respect to the crude oil price. By crawling and mining news headlines associated with OPEC+ decisions, we establish an innovative index that provides deeper insights into the complexities inherent in OPEC+ policies and their potential repercussions on the oil price. Moreover, this study investigates the relationship between the WTI crude oil futures price and the proposed OPEC+ policy index. Finally, the applications of this index in the realms of crude oil price forecasting as well as natural gas forecasting are explored, thereby demonstrating its efficacy and relevance in practical forecasting scenarios. Main conclusions of this paper can be summarized as follows:

(1) Our proposed OPEC+ policy index exhibits a high degree of alignment with the production change decisions made by OPEC+ and demonstrates notable peaks and troughs that correspond to the occurrence of OPEC+ Ministerial Meetings.
(2) The co-integration test confirms a long-term relationship between crude oil price and the proposed OPEC+ policy index, while the Granger causality test demonstrates a significant unidirectional linear causality running from the OPEC+ policy index to crude oil price and a bidirectional nonlinear causality, indicating the index's powerful predictive ability for the future oil price.
(3) Our proposed OPEC+ policy index consistently outperforms alternative models in predicting the WTI crude oil price across different forecasting horizons (i.e., 1–4 weeks), and the predictive ability is more significant within 3 weeks. During periods of high forecasting errors caused by the Omicron variant and the Russia-Ukraine conflict, models incorporating the OPEC+ policy index achieve superior forecasting performance.
(4) Our proposed OPEC+ policy index also has a predictive effect on the natural gas futures price and daily crude oil price, indicating its robustness and effectiveness as a predictor for the energy system.

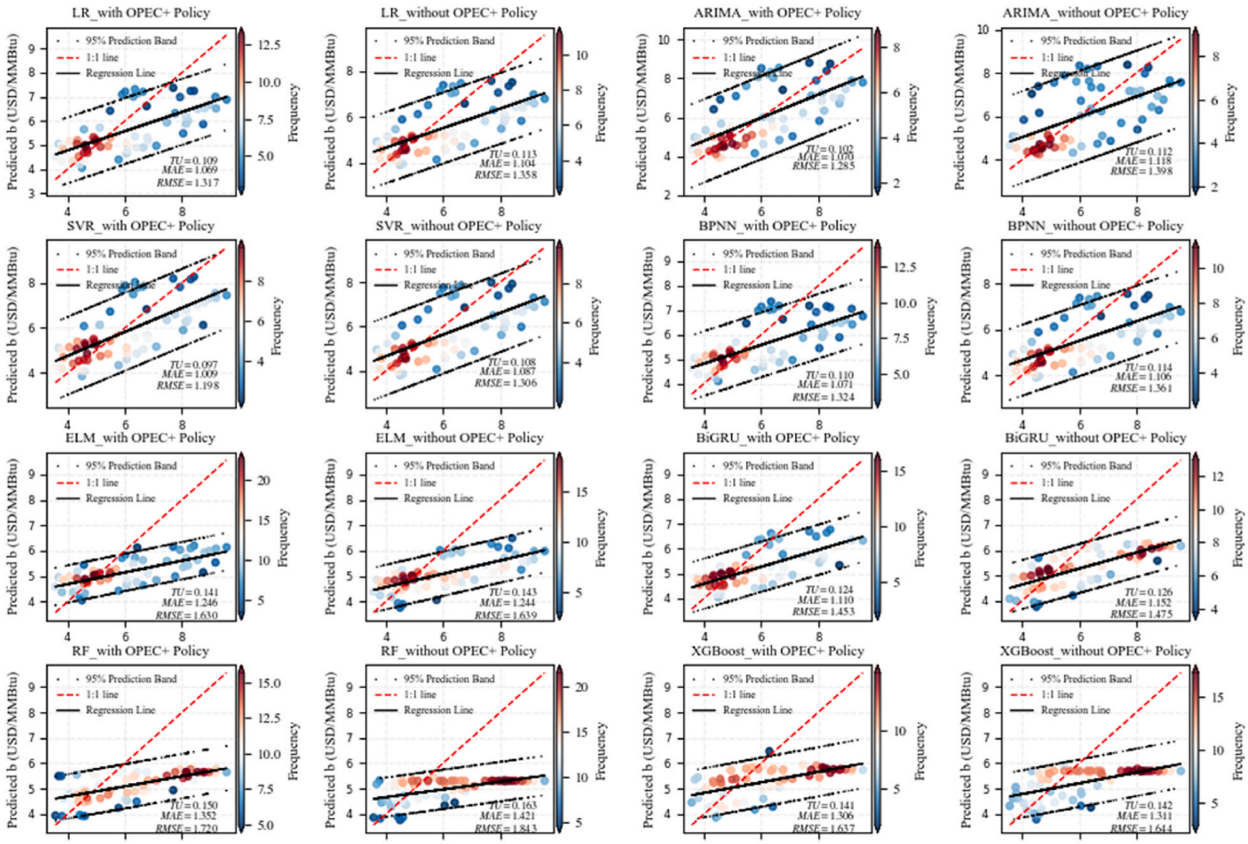

Fig. 8. Density scatter plots of observed against predicted gas futures price in 3-step-ahead forecast.

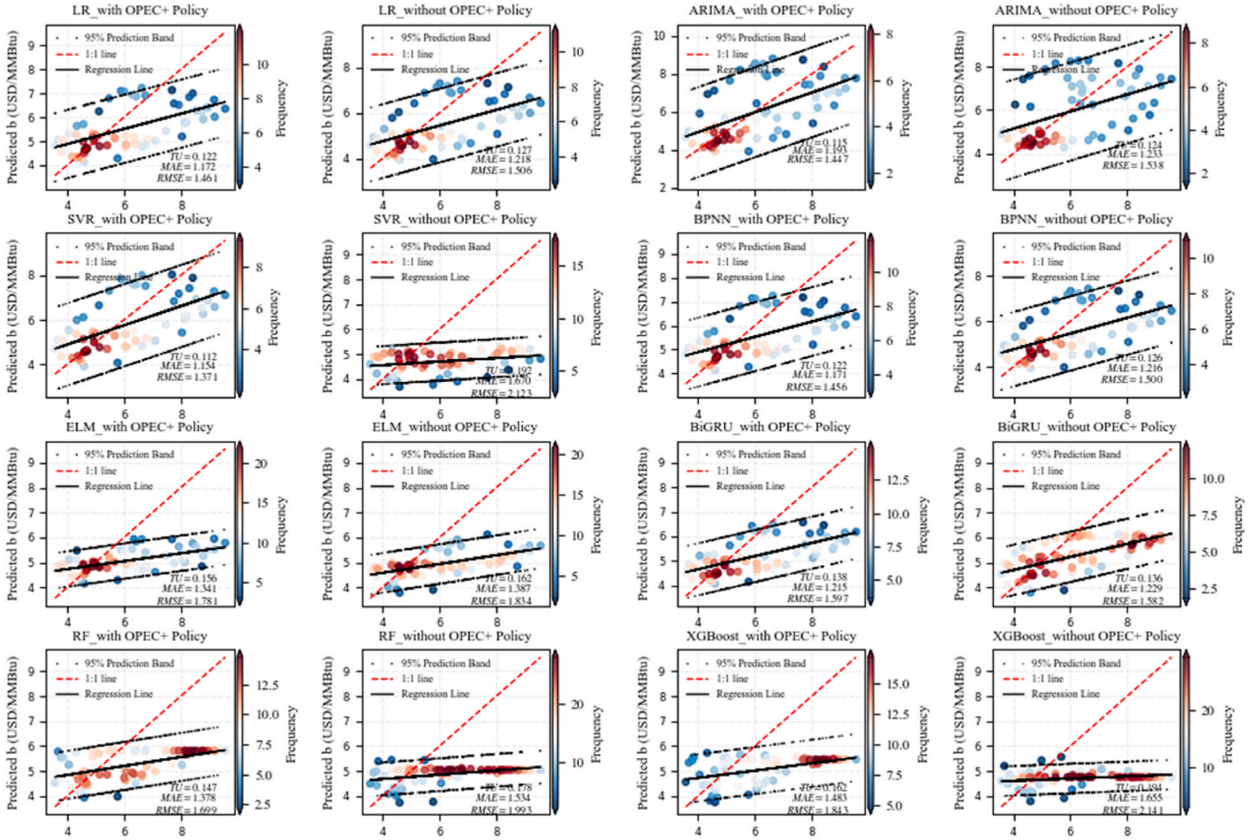

Fig. 9. Density scatter plots of observed against predicted gas futures price in 4-step-ahead forecast.

The findings of this research hold significant policy implications. For example, the development of the news-based OPEC+ policy index through text mining techniques offers policymakers and market participants a valuable tool for understanding and analyzing the behavior of OPEC+ decisions. Investigating the potential impact of OPEC+ decisions on the oil price, facilitated by the news-based OPEC+ policy index, can inform decision-making processes for investment strategies, market forecasting, and policy formulation. By incorporating the proposed index into forecasting models, policymakers and industry stakeholders can make more informed decisions and adapt their strategies to the dynamic nature of the crude oil market.

It is important to acknowledge that there are potential avenues for future research and extensions to this study. For instance, incorporating data decomposition methods such as wavelet analysis or empirical mode decomposition models may enhance the robustness and accuracy of the proposed OPEC+ policy index in predicting the crude oil price.

Data availability statement

Data will be made available on request.

CRediT authorship contribution statement

Jingjing Li: Writing – original draft, Methodology, Conceptualization. **Zhanjiang Hong:** Writing – original draft, Software. **Lean Yu:** Writing – review & editing, Supervision, Conceptualization. **Chengyuan Zhang:** Validation, Formal analysis. **Jiqin Ren:** Supervision.

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.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (No. 72101167, No. 72201201) and the Youth Academic Innovation Team Project of Capital University of Economics and Business (No. QNTD202103).

Appendix

Table A1
Hyperparameters of the forecasting models in weekly oil price forecasting.

Models	Parameters with OPEC + Policy Index	Parameters without OPEC + Policy Index
LR	Fit with intercept	Fit with intercept
ARIMAX	Parameters are selected by minimizing the AIC criterion	Parameters are selected by minimizing the AIC criterion
SVR	$C = 1$, epsilon = 0.01, RBF kernel (*gamma* is decided by grid search method)	$C = 1$, epsilon = 0.01, RBF kernel (*gamma* is decided by grid search method)
BPNN	Layer = 3, Num_neurons_h1, h2, h3 = 8, 6, 1 Epochs = 400	Layer = 3, Num_neurons_h1, h2, h3 = 8, 4, 1 Epochs = 500
ELM	Num_hidden = 12, $C = 1$	Num_hidden = 12, $C = 1$
BiGRU	Num_hidden = 8, Epochs = 300, Lr = 0.1	Num_hidden = 16, Epochs = 1000, Lr = 0.1
RF	N_estimators = 60, Min_samples_leaf = 3, Max_depth = 5	N_estimators = 50, Min_samples_leaf = 5, Max_depth = 5
XGBoost	N_estimators = 50, Min_child_weight = 3, Lr = 0.5, Max_depth = 5, Reg_lambda = 2	N_estimators = 50, Min_child_weight = 3, Lr = 0.5, Max_depth = 5, Reg_lambda = 2

Table A2
Hyperparameters of the forecasting models in natural gas price forecasting.

Models	Parameters with OPEC+ Policy Index	Parameters without OPEC+ Policy Index
LR	Fit with intercept	Fit with intercept
ARIMAX	Parameters are selected by minimizing the AIC criterion	Parameters are selected by minimizing the AIC criterion
SVR	$C = 100$, epsilon = 0.01, RBF kernel (*gamma* is decided by grid search method)	$C = 100$, epsilon = 0.01, RBF kernel (*gamma* is decided by grid search method)
BPNN	Layer = 3, Num_neurons_h1, h2, h3 = 8, 4, 1 Epochs = 100	Layer = 3, Num_neurons_h1, h2, h3 = 8, 4, 1 Epochs = 100
ELM	Num_hidden = 12, $C = 1$	Num_hidden = 6, $C = 1$
BiGRU	Num_hidden = 6, Epochs = 200, Lr = 0.01	Num_hidden = 6, Epochs = 200, Lr = 0.01
RF	N_estimators = 10, Min_samples_leaf = 3, Max_depth = 10	N_estimators = 10, Min_samples_leaf = 5, Max_depth = 10
XGBoost	N_estimators = 40, Min_child_weight = 3, Lr = 0.1, Max_depth = 6, Reg_lambda = 1	N_estimators = 40, Min_child_weight = 3, Lr = 0.1, Max_depth = 6, Reg_lambda = 1

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