Energy Economics 95 (2021) 105140

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

The role of news sentiment in oil futures returns and volatility forecasting: Data-decomposition based deep learning approach

Yuze Li [a,b], Shangrong Jiang [c], Xuerong Li [a,*], Shouyang Wang [a,c]

[a] Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing 100190, China
[b] School of Mathematical Sciences, University of Chinese Academy of Sciences, Beijing 100049, China
[c] School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100049, China

ARTICLE INFO

Article history:
Received 6 July 2020
Received in revised form 28 November 2020
Accepted 20 January 2021
Available online 29 January 2021

Keywords:
News sentiment
Returns and volatility forecasting
Variational mode decomposition
Deep learning

ABSTRACT

In this paper, we extract the qualitative information from crude oil news headlines, and develop a novel VMD-BiLSTM model with investor sentiment indicator for crude oil forecasting. First, we construct a sentiment score considering cumulative effect from contextual data of oil news texts. Then, we adopt an event-based method and GARCH model to investigate the impact of news sentiment on returns and volatility. A non-recursive signal decomposition method, namely variational mode decomposition (VMD), is applied to decompose the historical crude oil return and volatility data into various intrinsic modes. After that, a bidirectional long short-term memory neural networks (BiLSTM) is introduced as the deep learning prediction model that integrates both the qualitative and quantitative model inputs. Our empirical results indicate that the shock of news sentiment significantly causes the fluctuation of oil futures prices, and news sentiment has an asymmetric impact on the volatility of oil futures. The incorporation of sentiment score is always helpful for improving the forecasting performances in all benchmark scenarios. Specifically, our proposed data-decomposition based deep learning model is more effective than several econometric and machine learning models.

1. Introduction

It is universally acknowledged that the crude oil futures market is a typical risk aggregation market that attracts worldwide attentions: The oil future price movements are identified to be more likely exposed to global political events and receive simultaneous shocks from other financial asset markets (Leduc and Sill, 2004; Considine and Larson, 2001). On the other hand, the prices of global financial assets also receive positive feedbacks from oil future price movements and disturbances (Hamilton and Wu, 2014; Teterin et al., 2016). For crude oil safety management and assets allocation strategy concerns, the precise prediction for oil future market returns and risks is able to provide useful guideline for policy makers and investors. However, the nonlinearity property of oil future market price is formulated by different types of factors, such as supply and demand relationship (Kilian, 2009), international events (Zhao et al., 2016) and investor sentiment (Qadan and Nama, 2018), which makes it a tough task in oil returns and volatilities prediction for the complex structures of oil price.

An abundant amount of studies is devoted to predict the oil returns and volatilities utilizing the historical time-series data of oil market and economic related influencing factors. For example, Fan et al. (2008) use historical observations of WTI and Brent crude oil time-series data to predict the future oil prices based on genetic algorithm. (Shin et al., 2013) introduce semi-supervised learning approach to investigate the impact factors that affect the oil price movements, including OPEC and SAUDI oil production, USD exchange rates and Producer price index etc. However, some underlying factors, such as investor sentiment, may act as potential causes of oil price changes and fluctuations (Du et al., 2016; Qadan and Nama, 2018), which is hard to assess and calculate in empirical works due to non-quantization characteristic of market sentiment and reaction.

Scholars have attempted to find out appropriate proxies for the investor concerns and sentiments of financial market. For example, Baker and Wurgler (2007) utilize a combination of financial indices to quantify the investor sentiment in stock market, including stock trading volume, mutual fund flows and IPO volume etc. Smales (2017) introduces CBOE Volatility Index (VIX) as a measure of investor fears and investigates the relationship between VIX and stock returns. Kostopoulos et al. (2020) apply Google search volumes as a proxy for trading intensities of individual investors in German. However, the previous measurements of investor sentiments show less effectiveness in providing untapped information for assets returns and volatilities prediction due to the following weakness (Li et al., 2019). First, official indices and statistics, such as transaction volume, are identified to provide less unexplored information about investor attentions, which is mainly due to its less consistency with the individual traders (Deng et al., 2012).

* Corresponding author at: Academy of Mathematics and Systems Science, Chinese Academy of Sciences, 55th Zhongguancun East Road, Beijing, China.
E-mail address: lixuerong@amss.ac.cn (X. Li).

https://doi.org/10.1016/j.eneco.2021.105140
0140-9883/

Second, the intensity and volume data of search engine contain too much investors-irrelevant noise (Limnios and You, 2018). As a result, the sentiment indicators calculated by search indices may show less effectiveness and confidence level in financial assets prediction.

Natural Language Processing (NLP) techniques and big available dataset provide a novel framework for investor sentiment indicator constructions. By crawling the news headlines from hubs and websites for energy news, news dataset of crude oil can be tokenized. Utilizing the headline documents, daily investor sentiments are scored generated based on vector space models (Salton et al., 1975). Finally, returns and volatilities of crude oil are predicted by incorporating the daily polarity score of market sentiment. Sentiment index based on news headlines has the following advantages: First, news headlines reflect key information of investor attention, which can be measured and obtained efficiently through NLP techniques. Second, sentiment index calculated by news headline contains less noise and irrelevant information, which is helpful to improve the reliability of indicator construction (Nassirtoussi et al., 2015). In this paper, we formally investigate the impact of news sentiment on oil futures returns and volatility by an event-based method and GARCH model estimations. Overall, the daily investor sentiment of crude oil is computed by NLP technique in this paper and act as a novel predictor for crude oil future returns and volatilities.

Several types of forecasting methods have been applied to oil future returns and volatility prediction by previous works, such as econometric models (Klein and Walther, 2016) and machine learning approaches (Yu et al., 2008; Tang et al., 2015; Yu et al., 2017). However, the econometric or machine learning typed predictors achieve inferior forecasting performance in comparison with the newly introduced deep learning approach (Mallqui and Fernandes, 2018). Utilizing the artificial neural networks consisting of multiple hidden layers, deep learning model shows superior time-series data predictability over its counterparts (LeCun et al., 2015). In recent years, deep learning has been applied broadly in crude oil time-series data prediction. For example, Zhao et al. (2017) apply a novel stacked denoising autoencoders (SDAE) for crude oil forecasting based on a large dataset of exogenous influencing parameters. Luo et al. (2019) employ a novel convolutional neural networks (CNN) model to improve the short-term prediction performance for crude oil market.

Since crude oil market returns and volatilities are non-stationary time-series data and consistent with complex influencing factors, the prediction accuracies of the proposed models may suffer due to the high volatilities. In recent studies, a novel ensemble forecasting method, namely "Decomposition and Ensemble", has been developed to handle the task of irregular and non-stationary time-series data prediction (Bergmeir et al., 2016; Risse, 2019). This method decomposes the original time-series data into several stationary cycles, which can be estimated by forecasting models individually and finally integrated to generate the forecasting output. Among all the decomposition approaches, empirical mode decomposition (EMD) typed method is the predominant approach utilized in current empirical works (Wen et al., 2017; Santhosh et al., 2019). However, the prediction error term may accumulate during the combination process of individual decomposed data forecasting, which is considered to reduce the prediction accuracies (Tang et al., 2015). In addition, EMD typed models may also give rise to the mode-mixing problem, which may probably produce the oscillations with similar scales in single decomposed factors (Colominas et al., 2014).

Based on the above studies, this paper develops a novel VMD-BiLSTM model with investor sentiment indicator for crude oil forecasting. First, we extract the qualitative information from crude oil news headlines and conduct sentiment analysis on the contextual data, which provides effective and unexplored information for deep learning forecasting. Moreover, we adopt an event-based method and GARCH model to investigate the impact of news sentiment on returns and volatility. Second, a non-recursive signal decomposition method, namely variational mode decomposition (VMD), is applied to decompose the historical crude oil return and volatility data into various intrinsic modes. Compared to the predominant decomposition approach EMD, VMD is tested to avoid the mode-mixing problem effectively (Dragomiretskiy and Zosso, 2014). Third, a bidirectional long short-term memory neural networks (BiLSTM) is introduced as the deep learning prediction model that integrates both the qualitative and quantitative model inputs. The proposed BiLSTM model can extract a two-way sequential relationship in the time series data.

According to our empirical results, we find the shock of news sentiment significantly causes the fluctuation of oil futures prices. Specifically, oil futures prices react positively around positive news shocks, and present relatively weak decline surrounding negative news shocks. According to the estimations of GARCH models, we find that news sentiment has an asymmetric impact on the volatility of oil futures. As for oil return and volatility forecasting, the incorporation of news index is always helpful for improving the forecasting performances in all benchmark scenarios. Specifically, our proposed data-decomposition based deep learning model is more effective than several econometric and machine learning models.

The major contributions of this paper may lie in that, to the best of our knowledge, this is the first paper to incorporate the sentiment index of oil market based on NLP technique for oil future returns and volatilities prediction, which serves as an initial attempt to improve the forecasting results utilizing the hidden and effective information of irrational behaviors in the crude oil market. Furthermore, we empirically confirm the effectiveness of our proposed hybrid deep learning models for oil return and volatility forecasting. Our proposed model outperforms several benchmark econometrics, machine learning models, deep learning models and hybrid learning models. The methodology and empirical results presented by our study shed new light on risk controls of oil-related assets based on large-scale online datasets and data-driven approaches.

The rest of this paper is arranged as follows: Section 2 presents the research framework, news text analysis methods and forecasting models; Section 3 tests the impact of news sentiment on oil returns and volatility based on an event-based method and the estimation of GARCH models; Section 4 presents the empirical results of oil returns and volatility forecasting, including several robustness tests. Finally, the concluding remarks and future directions are concluded in Section 5.

2. Methodology

2.1. Research framework

The forecasting approach proposed in this study aims to utilize qualitative information extracted from financial news headlines and quantitative information extracted from market time series data to improve the return and volatility forecasting accuracy in the crude oil futures market. The framework of our proposed approach is shown in Fig. 1. Specifically, there are five major steps, namely data collection, data preprocessing, sentiment analysis, data decomposition, as well as returns and volatility forecasting. These steps are explained in detail in Sections 2.2–2.5.

2.2. Data collection and preprocessing

For this study, we collected two different datasets separately: crude oil futures price data and news headlines. In terms of the crude oil price dataset, the Brent (LCO) crude oil daily futures contract closing prices are retrieved from Investing.com, for the time period from January 4, 2010 to September 17, 2019. In terms of the news headlines dataset, all the available news data related to "Crude oil" from oilprice.com, which is one of the largest hubs for energy news in the world with

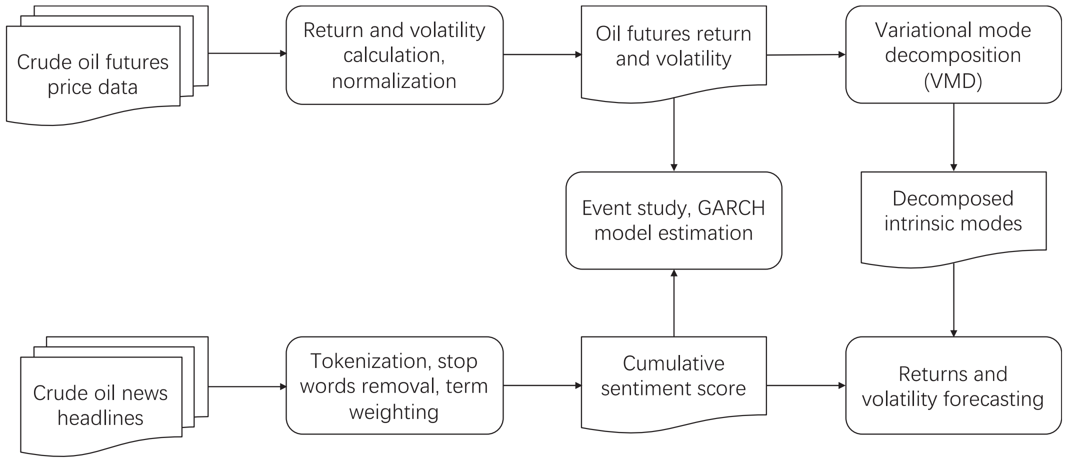

Fig. 1. Framework of the proposed approach.

over 100,000 daily visitors, for the same time period as the crude oil news headline data. Instead of using full news articles in the analysis, we use news headlines due to several advantages: first, news headlines can provide a sufficient summary of the key news information; second, news headlines contain much less repetition and fewer irrelevant words than the news article itself (Nassirtoussi et al., 2015).

We first preprocess the raw news headlines dataset using tokenization to convert all headlines into lower cases, and to remove stop words and punctuations. Stop words are the most common words in a language, such as "the", "a", "on", "all" and "is". Since stop words, along with punctuations, do not carry important information related to the text, they are removed during preprocessing.

After removing stop words and punctuations, the "bag-of-words" approach is then employed to transform new texts into vectors. In this approach, each document (news headline) is represented by a vector, and each word within the document represents an element in the vector. The length of each vector is determined by the number of distinct words in the corresponding news headline in the dataset. In this study, we also use a commonly used weighting technique, namely Term Frequency-Inverse Document Frequency (TF-IDF), in the vectorization process to evaluate the importance of a word to a specific document in a collection of documents. The importance of the word increases proportionally with the number of times it appears in the document, but decreases with the number of documents that contain the word in the collection. Specifically, the TF-IDF score of word x in a document is calculated as follows in Eq. (1):

$$\mathrm{TF-IDF} = \mathrm{TF}^*\mathrm{IDF} \tag{1}$$

where

$$\mathrm{TF} = \frac{\textit{Frequency of term x in a document}}{\textit{Total number of terms in the document}}$$

$$\mathrm{IDF} = \log_e\left(\frac{\textit{Total number of documents}}{\textit{Frequency of documents containing term x}}\right)$$

In terms of the crude oil price data, we select the daily returns of the Brent crude oil futures contracts as well as the 7-day volatility as the prediction targets. The daily logarithmic returns (r_t) and the 7-day volatility (v_t) are derived from the raw daily closing prices as follows in Eq. (2) and (3), respectively:

$$r_t = \ln p_t - \ln p_{t-1} \tag{2}$$

$$v_t = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(r_t - \bar{r}_t)^2} \tag{3}$$

where r_t denotes the daily logarithmic returns of the asset. n represents the number of days used to calculate the volatility (7 in this study). $\bar{r}_t$ represents the n day mean return of the asset. v_t is the 7-day volatility of the asset.

In order to eliminate the differences in variable dimension and increase model forecasting reliability, we normalize the data in the range of [0,1] as shown below in Eq. (4):

$$\hat{x_t} = \frac{x_t - \min x_t}{\max x_t - \min x_t} \tag{4}$$

where x_t denotes the true value of the time series at time t. $\max x_t$ and $\min x_t$ are the maximum and the minimum true value of the time series, respectively.

2.3. Sentiment analysis

In this study, we employ the *Sentimentr* package in R to calculate the sentiment of each processed news headline. The *Sentimentr* package returns the polarity score in the range of [−1.0, 1.0] for each document. The news is considered as positive news if its polarity score is above zero, otherwise, it is considered as negative news. In general, the more negative the polarity score, the more negative the news; the more positive the polarity score, the more positive the news.

As pointed by previous studies, news often has a rather continuous effect on the investor's sentiment in the actual futures market (Akhtar et al., 2013). That is to say, the public sentiment on a specific day is shaped by the combination of news on the day and that in previous few days. However, the more recent news is more influential than the old news. Considering this situation, we formulate a cumulative sentiment score (CSS) following Kiritchenko et al. (2014) and Chowdhury et al. (2014). In this study, we assume any piece of news will have a significant impact on the investor sentiment for seven days, and that its impact exponentially declines each day after its release, which is consistent with the actual situation of news impact (Huang et al., 2014). Therefore, the cumulative sentiment score on day t is the sum of sentiment value on day t and sentiment value of previous six days, as shown in Eq. (5):

$$CSS_t = \sum_{i=1}^{6} e^{-\frac{i}{7}} SV_{t-i} + SV_t \tag{5}$$

where SS_t is the *cumulative sentiment score* on day t. $e^{-\frac{i}{7}}SV_{t-i}$ represents the exponentially-adjusted sentiment value of day $t-i$. SV_t denotes the sentiment value of day t.

2.4. Data decomposition

According to previous literature, decomposing the original time series data into sub-series modes with different economic implications can help the neural networks capture its tendency and cyclicity (Wang et al., 2014). In this study, we employ variational mode decomposition (VMD) in the data decomposition process for the daily returns and 7-day volatility time series of Brent crude oil. In general, VMD is a non-recursive optimization technique that decomposes the original input signal $f(t)$ into a series of discrete and stationary intrinsic modes u_k through Wiener filtering and Hilbert transform (Liu et al., 2016). The optimization procedure is as follows (Zhang et al., 2017):

Step 1: Calculate the Hilbert transform of each mode u_k and transform into respective uni-sided frequency spectrum.

Step 2: Alter the frequency spectrum of each mode u_k to narrow frequency baseband

Step 3: Conduct the H^1 Gaussian smoothness on the demodulated signal to obtain the bandwidth of each mode u_k.

The optimal solution is obtained using the alternative direction method of multipliers (ADMM) (Hestenes, 1969) and the original input signal $f(t)$ is decomposed into K intrinsic modes.

2.5. Deep learning forecasting model: BiLSTM

Bidirectional recurrent neural networks (BiRNN) structure is first proposed by Schuster and Paliwal (1997), which can utilize both forward and backward information in the data. Compared with the traditional unidirectional neural networks structure, it is able to extract information from both past and future, thus improving the prediction accuracy. In this study, we modify the original BiRNN to replace the RNN cells with long short-term memory (LSTM) cells since it can effectively learn long-range dependencies (Zhang et al., 2018). The bidirectional long short-term memory (BiLSTM) network structure contains two hidden layers that run in opposite directions and concatenate them to the same output layer so the neural network can extract bidirectional sequential relationships that exist in the time series data. Its structure is shown in Fig. 2.

In this study, we aim to forecast the daily returns and 7-day volatility of Brent crude oil futures by utilizing hybrid information inputs. The detailed forecasting process is outlined as follows:

Step 1: Calculate the daily cumulative sentiment score using the extracted news headlines related to crude oil price.

Step 2: Decompose the target variable (i.e., the daily logarithmic returns and 7-day volatility) into different intrinsic modes using VMD.

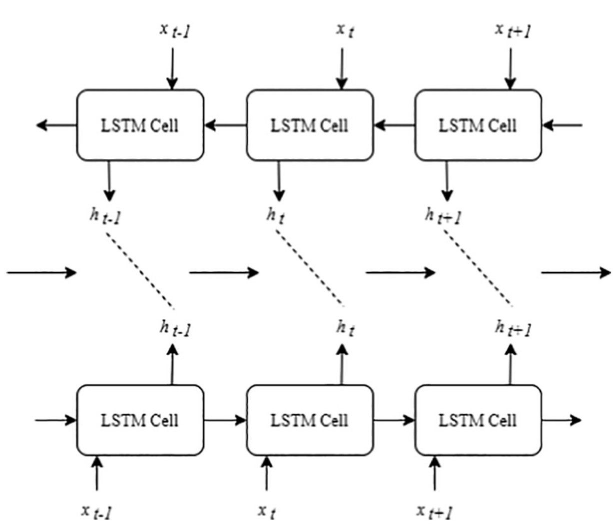

Fig. 2. BiLSTM neural networks structure.

Step 3: Construct the forecasting input dataset by combining the daily cumulative sentiment score and the decomposed intrinsic modes.

Step 4: Organize the input dataset into a sliding window group with length of 7 days from time $t-6$ to time t.

Step 5: Import the input dataset into the BiLSTM neural networks to predict the daily returns and 7-day volatility at time $t+1$.

Our BiLSTM prediction model consists of five layers: an input layer, a forward hidden layer, a backward hidden layer, an output layer and a fully-connected layer. The dimensions of the input layers, hidden layers and the output layer are all set to the same dimension as the input dataset. The fully-connected layer consists of one node that corresponds to the dimension of the final prediction value. The input dataset is first imported into the BiLSTM model through the first four layers, then it passes through the fully-connected layer to generate the daily logarithmic returns and 7-day volatility predictions at time $t+1$. In this study, the input window length is set to 7 days, which is recommended as the optimal input length for short-term forecasting in previous literature (Zhu et al., 2019). The model utilizes the Adam optimizer with the learning rate set to 0.01. Within the LSTM cells, the *tanh* function is selected as the activation function.

2.6. Senti-GARCH model and asymmetry Senti-GARCH model

In this study, we attempt to examine the response of oil futures market to the news sentiment of the market information that had just arrived, and compare the volatility forecasting performance of deep learning models and GARCH models. Therefore, we propose the following Senti-GARCH (p, q, m) model, including *cumulative sentiment score* CSS_t in the conditional variance equations:

$$r_t = \alpha_0 + \sum_{j=1}^{J} \alpha_j r_{t-j} + \varepsilon_t, \varepsilon_t \sim (0, \sigma_t^2) \tag{6}$$

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{p} \beta_{\sigma,i} \sigma_{t-i} + \sum_{j=1}^{q} \beta_{\varepsilon,j} \varepsilon_{t-j} + \sum_{k=0}^{m} \gamma_k CSS_{t-k} \tag{7}$$

where r_t is the daily returns on oil futures contracts; σ_t^2 is conditional variance of oil futures returns. To capture the effect of news sentiment on conditional volatility, we added $\sum_{k=0}^{m} \gamma_k CSS_{t-k}$ to the variance equations.

As indicated by Roache and Rossi (2010), given the asymmetrical nature of commodity markets, it would be reasonable to explore the effect of negative and positive news on futures volatility. Verma (2012) and Bahloul and Bouri (2016) indicate that rational arbitrageurs and irrational investors hold opposite beliefs, so that when irrational investors are optimistic, there is upward pressure on prices, which is hard for rational investors to overcome. In contrast, in the case of pessimism, it is easier for rational investors to trade against the irrational investors and counterbalance the short-term deviation from fundamental prices caused by the irrational traders. To test whether the asymmetric effect of optimism and pessimism exists for oil futures volatility, we added the dummy variables d_t and (1 - d_t), which capture the positive and negative news respectively to the variance equations of the Senti-GARCH (p, q, m) model (where $d_t = 1$ if the news sentiment is positive, and 0 otherwise). The asymmetry Senti-GARCH (p, q) model identifies the possibility that volatility may react differently to positive and negative news. The following model was estimated:

$$r_t = \alpha_0 + \sum_{j=1}^{J} \alpha_j r_{t-j} + \varepsilon_t, \varepsilon_t \sim (0, \sigma_t^2) \tag{8}$$

$$\sigma_t^2 = \beta_0 + \sum_{i=1}^{p} \beta_{\sigma,i} \sigma_{t-i} + \sum_{j=1}^{q} \beta_{\varepsilon,j} \varepsilon_{t-j} + \gamma^{+} d_t CSS_t + \gamma^{-} (1-d_t) CSS_t \tag{9}$$

where γ^{+} and γ^{-} are the coefficients that are checked to evaluate the asymmetric impact of news sentiment on conditional volatility.

3. The impact of news sentiment on oil futures returns and volatility

In this section, we investigate the impact of news sentiment on oil futures returns and volatility by an event study method and the estimation of Senti-GARCH models.

3.1. Event study

We employ event studies as described in MacKinlay (1997) and used in Tetlock et al. (2008). We define a day in which the *cumulative sentiment score* CSS_t is higher than q quantile of the total sample of CSS_t as a positive news shock. Analogously, a day in which CSS_t is lower than 1-q quantile of the total sample of CSS_t as a negative news shock.

We first aggregate the number of positive news shocks for each month, as well as the number of negative news shocks, and compare them with the evolution of oil future prices. According to Fig. 3, the period in which the oil futures prices are increasing is basically in accordance with the period in which the number of positive news shocks is increasing. Similarly, when the number of negative news shocks is increasing, the oil futures prices are decreasing accordingly. These results suggest that news sentiment presents correlation with the trend of oil futures prices.

Next, we analyze the return dynamics around the news shock events by computing the cumulative return from 10 days before up to 10 days after the event for all events of the same type. Specifically, we use a threshold quantile q of 80% on the set of 2538 trading days and select 385 positive news shock and negative news shock events. This results in 386 positive and negative news shock event cumulative return paths. From these paths, we simulate the average cumulative return and 95% bootstrapped confidence intervals as described in Davidson and Mackinnon, (2004) for each time in the event window. Simple plots of the average cumulative returns and the confidence intervals for each event type and for each time in the event window present the differences between the event types.

Fig. 4 presents the average cumulative return paths of oil futures prices around news shock events for each event type. The return evolution is clearly different for the two event types. For positive news shocks, the returns show strong increase which is significantly different from zero prior to and after the event day. Whereas the return path of negative news shocks shows slight decline prior the event day, and is only significantly different from zero before 4 days after the event day. Generally, the oil futures prices react positively around positive news shocks, and present relatively weak decline surrounding negative news shocks.

We further undertake more event studies which have the same setup as the event study in Fig. 5, but for threshold levels q of 50, 70 and 90%. Clearly, the discriminating power increases for a higher threshold. These results demonstrate that different levels of news sentiment have different effects on oil prices. Generally, the more intense the news sentiment, the greater the impact on oil futures prices.

3.2. Estimations of GARCH models

In this study, we further investigate the effect of news sentiment on the volatility of oil futures by examining the estimations of Senti-GARCH models proposed in Section 2.5. Table 1 presents the estimations of GARCH models with and without dummy variables on sample period, from January 4, 2010 to September 17, 2019. The lag order of mean and variance equations are selected based on Akaike information criterion.

According to the estimation results in Table 1, news sentiment is significantly related to oil futures volatility at the 5% level of significance. The significant lag order of news sentiment is 2, which suggest that the effect duration of news sentiment on volatility is about 2 days.

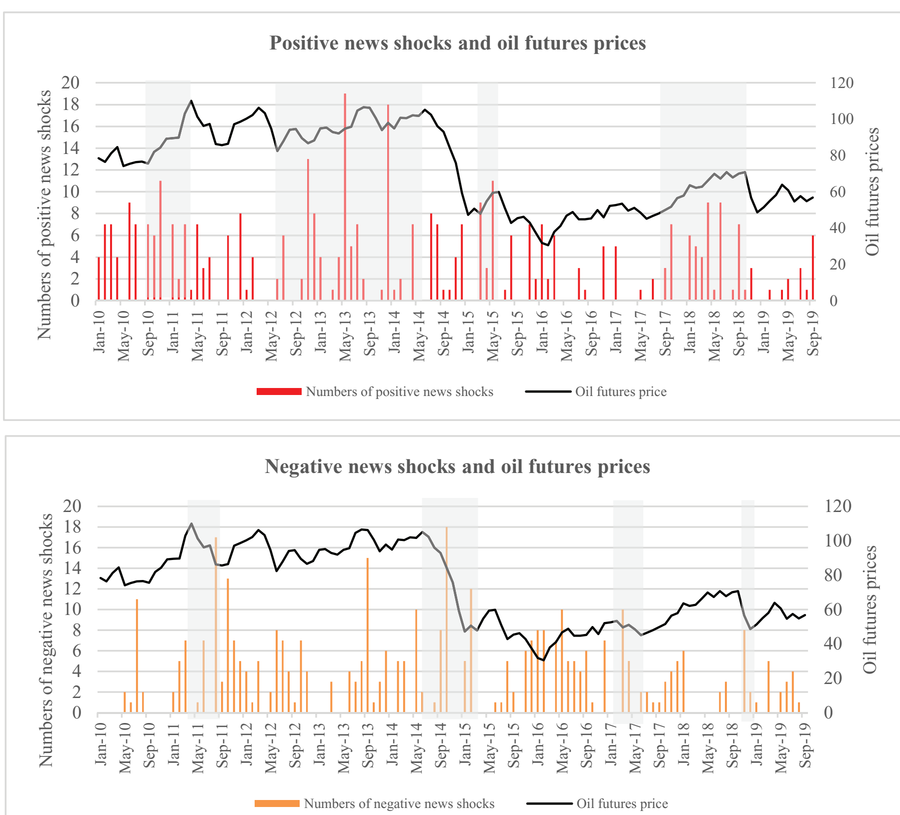

Fig. 3. Positive and negative news shocks compared with oil futures prices.

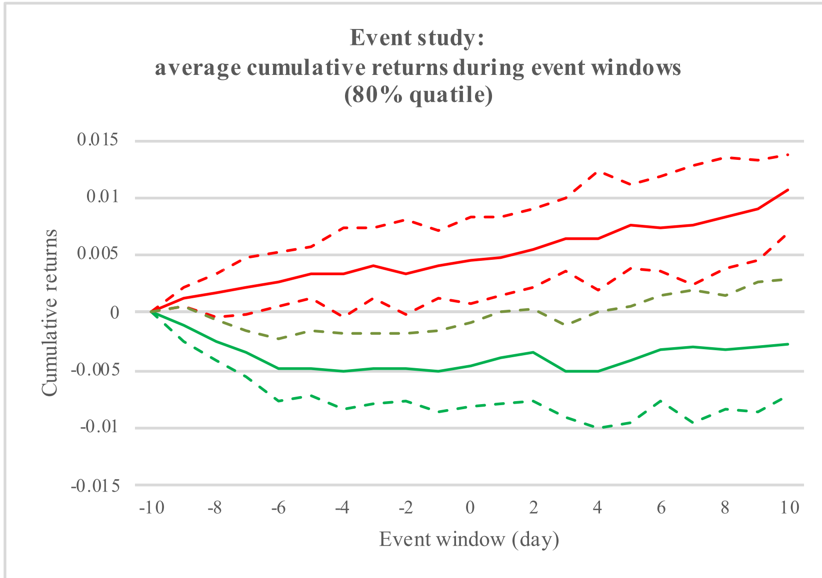

Fig. 4. The average cumulative return paths of oil futures prices around news shock events. Red line and green line represent the average cumulative return paths of positive and negative news shocks, respectively. Red dotted lines and green dotted lines represent 95% bootstrapped confidence intervals.

Specifically, news sentiment is positively related to volatility on 1-day lag, and negatively related to volatility on 2-day lag. This suggest that positive (negative) news is possibly increase (decrease) volatility in short period, and decrease (increase) volatility in longer period. The possible behavioral explanation of this result is that, positive news conveys optimistic sentiment to investors, and it is hard for rational investors to diminish the difference between the market price and its fundamental value, given the upward pressure on prices caused by irrational traders. This, in turn, results in an increase in price volatility. While for longer period, the rational traders will dominate the market in moving asset prices in the direction of their fundamental value, and hence, minimizing volatility.

As for asymmetry effects of news sentiment, we find that both positive and negative news is significantly related to oil futures volatility at the 5% or 1% level of significance. Specifically, positive news is negatively related to volatility, while negative news is positively related to volatility. This result shows that news sentiment has an asymmetric impact on the volatility of oil futures. Investors tend to react differently to positive news and negative news.

4. Oil futures returns and volatility forecasting

4.1. Data, descriptive statistics and evaluation metrics

In this study, we first obtained two datasets as our raw data: a crude oil futures price dataset and news headlines dataset. Both of the datasets are sampled from the period of January 4, 2010 to September 17, 2019. The crude oil futures price, the raw dataset is preprocessed to derive the

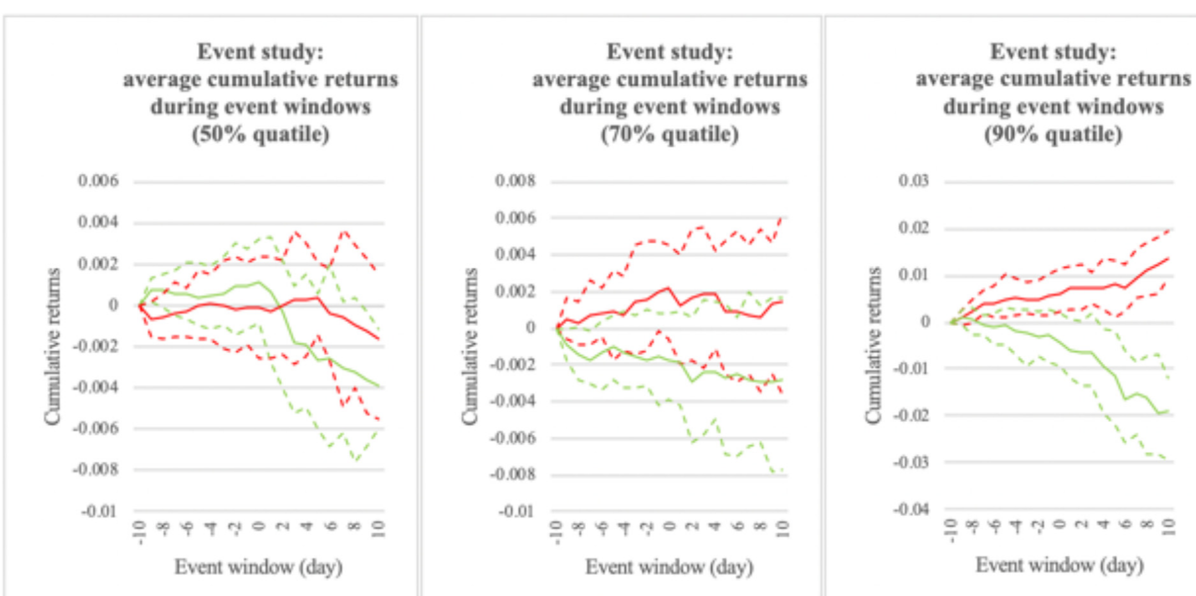

Fig. 5. The average cumulative return paths of oil futures prices around news shock events with threshold levels q of 50, 70 and 90%. Red line and green line represent the average cumulative return paths of positive and negative news shocks, respectively. Red dotted lines and green dotted lines represent 95% bootstrapped confidence intervals.

Table 1
the estimations of Senti-GARCH model and asymmetry Senti-GARCH model.

Parameter	Senti-GARCH model	Asymmetry Senti-GARCH model
	Coefficient (Standard error)	Coefficient (Standard error)
α_1	−0.0383* (0.0224)	−0.0360 (0.0222)
$\beta_{\sigma,1}$	0.1116*** (0.0212)	0.1042*** (0.0154)
$\beta_{\sigma,2}$	−0.0810*** (0.0196)	/
$\beta_{\varepsilon,1}$	1.3708*** (0.2117)	0.6665*** (0.1547)
$\beta_{\varepsilon,2}$	−0.4044** (0.1976)	−0.1676 (0.1865)
$\beta_{\varepsilon,3}$	/	0.3853*** (0.0869)
γ_0	0.0012** (0.0005)	/
γ_1	−0.0011** (0.0005)	/
γ_+		−0.0005** (0.0002)
γ_-		0.0011*** (0.0004)
Adjusted R-squared	0.2719	0.2661

Note: ***, ** and * denotes the statistical significance level of 10%, 5% and 1%.

daily logarithmic returns, as well as the 7-day volatility, which are used as prediction target variables. On the other hand, the sentiment score of each news headline is calculated, and aggregated by day to construct the 7-day cumulative sentiment score as part of the model inputs.

Our dataset consists of 2541 trading day observations. Therefore, we partition the dataset into two sets: a training set and a testing set with a split ratio of 9:1, which means the preceding 90% of the data are used to train the prediction model and the rest 10% are used to evaluate the model. Overall, our training set consists of 2286 observations, and the testing set contains 255 observations from September 24, 2018 to September 17, 2019. To ensure that our prediction model is robust and not overfitted to the training data, we employ a rolling forecast process where the rolling window is set to 60 days, after which the model generated a one-step-ahead prediction based on data from 7 trading days. As illustrated in Fig. 6, there are a total of 4 rolling testing periods: period 1 is from September 24, 2018 to December 13, 2018; period 2 is from December 14, 2018 to March 11, 2019; period 3 is from March 12, 2019 to June 3, 2019; period 4 is from June 4, 2019 to September 17, 2019.

The common descriptive statistics for the two target variables: daily logarithmic return and the 7-day volatility, as well as the constructed cumulative sentiment score are displayed in Table 1. As can be observed from Table 2, the high kurtosis value exhibited for all three time series

Table 2
Descriptive statistics.

	Count	Mean	Std. Dev.	Skewness	Kurtosis	ADF Test
Return	2548	-0.00007	0.0190	0.1121	6.7745	−53.66 ***
Volatility	2548	0.0166	0.0091	1.5165	6.4076	−8.73 ***
Sentiment	2548	-0.1247	0.5958	-0.2898	7.4651	−9.57 ***

Note: *** denotes the statistical significance level of 1%.

data suggest that they are all non-normally distributed. In addition, the augmented Dickey-Fuller test (ADF) results for all three time-series are statistically significant under the 1% significance level, which means they are all stationary.

To assess the accuracy of the forecasting models, we adopted the Mean Square Error (MSE) as the loss function of BiLSTM model in this study, which is calculated as follows:

$$MSE = \frac{1}{N}\sum_{t=1}^{N}\left(\widehat{x}_t - x_t\right)^2 \tag{10}$$

We select the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) as the evaluation measures for return forecasting. Meanwhile, Heteroscedasticity Adjusted Mean Squared Error (HMSE) and Heteroscedasticity Adjusted Mean Absolute Error (HMAE) are selected as the evaluation measures for volatility forecasting. They are calculated as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(\widehat{x}_t - x_t\right)^2} \tag{11}$$

$$MAE = \frac{1}{N}\sum_{t=1}^{N}\left|\widehat{x}_t - x_t\right| \tag{12}$$

$$HMSE = \frac{1}{N}\sum_{t=1}^{N}\left(1 - \frac{x_t}{\widehat{x}_t}\right)^2 \tag{13}$$

$$HMAE = \frac{1}{N}\sum_{t=1}^{N}\left|1 - \frac{x_t}{\widehat{x}_t}\right| \tag{14}$$

where $\widehat{x}_t$ and x_t, $(t = 1, 2, \ldots, N)$ is the predicted value and the actual value at time t, and N represents the total number of data points in the testing set. In general, the lower the error values (RMSE, MAE,

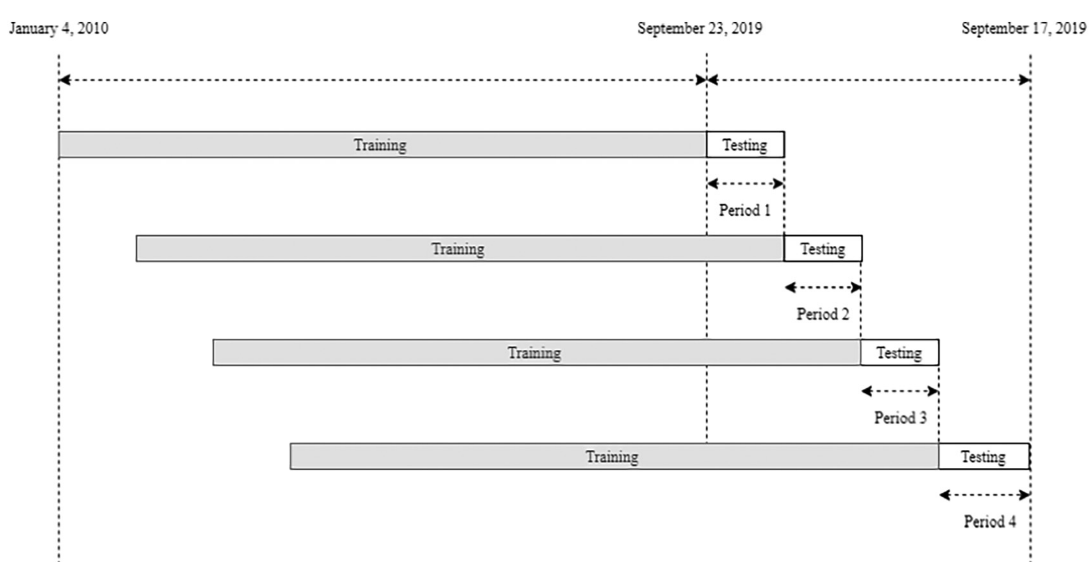

Fig. 6. Rolling Forecasting Process.

HMAE and HMSE) and the higher the directional accuracy, the better the forecasting model performance.

4.2. Prediction results

The daily logarithmic return and 7-day volatility for crude oil futures are decomposed into 11 intrinsic modes respectively as shown in Fig. 7. The 11 intrinsic modes are labeled from M1 to M11, where M1 represents the mode with the lowest frequency and M11 represents the mode with the highest frequency. It can be observed that the decomposed intrinsic modes all exhibit different periodicity. For both the daily logarithmic return and 7-day volatility, the M1 reflects the relative long-term trend of the time series, where M2-M11 reflects the relative short-term fluctuations in the market.

In order to evaluate the prediction performance of the proposed approach, we first construct benchmark models using various state-of-the-art forecasting techniques to conduct both horizontal performance comparisons. For horizontal performance comparison, we construct several benchmark models, which utilize the same decomposition and sentiment input features as the proposed approach, through econometric-based approach, traditional machine learning approach and deep learning approach. The benchmark models include autoregressive integrated moving average (ARIMA) model, linear regression (LR) model, support vector regression (SVR) model and uni-directional long short-term memory (LSTM) model. For volatility forecasting, we also compare the forecasting performance of our proposed approach with the GARCH models proposed in this study and the hybrid ANN-GARCH model. To ensure consistency of comparisons, all benchmarks utilizes the same training window as the proposed model. Tables 3 and 4 present the horizontal forecasting performance comparisons for the daily logarithmic returns, respectively.

Looking at the horizontal daily logarithmic return performance comparisons between the proposed approach and other benchmark forecasting approaches as shown in Table 3, it is clear that proposed approach is able to significantly outperform the other four benchmark forecasting models in terms of RMSE and MAE across all four testing intervals. The proposed approach obtained an average RMSE and MAE of 0.0151 and 0.0101, respectively. In comparison to the best performing

Table 3
Horizontal return comparisons.

	RMSE			
	Period 1	Period 2	Period 3	Period 4
Proposed	0.0159	0.0123	0.0089	0.0215
LSTM	0.0776	0.0652	0.0792	0.0794
SVR	0.0988	0.1041	0.0678	0.1201
LR	0.1008	0.1041	0.0676	0.1213
ARIMA	0.0959	0.1124	0.0554	0.1085
	MAE			
	Period 1	Period 2	Period 3	Period 4
Proposed	0.0121	0.0091	0.0068	0.012
LSTM	0.0554	0.0521	0.0601	0.0598
SVR	0.0692	0.0765	0.0469	0.0808
LR	0.0706	0.0754	0.0468	0.0812
ARIMA	0.0703	0.0837	0.0421	0.0841

benchmark model, the proposed approach is able to reduce the average RMSE and MAE by 80.08% and 82.25%, respectively, which indicates that our proposed approach is able to significantly improve the prediction fitting performance. Thus, it shows that our proposed approach is able to effectively improve the market trend predictive ability of the model.

Examining the horizontal 7-day volatility performance comparisons between the proposed approach and other benchmark forecasting approaches as shown in Table 4, a similar pattern can be observed: The proposed approach is able to achieve the smallest HMSE and HMAE, which demonstrates that our proposed approach is able to consistently improve the prediction accuracy across various market conditions. As a result, the proposed approach is not only more precise in terms of mathematical calculations, but also more practical in real-world applications.

To further analyze the effects of decomposed intrinsic modes and the extracted news headlines sentiment on the prediction performance of the model, we conduct vertical prediction performance comparison where we compare the performance of the proposed model and benchmark models with different inputs, namely the decomposition input and the single sentiment input. The decomposition input only uses the decomposed intrinsic modes as input to predict the target variables.

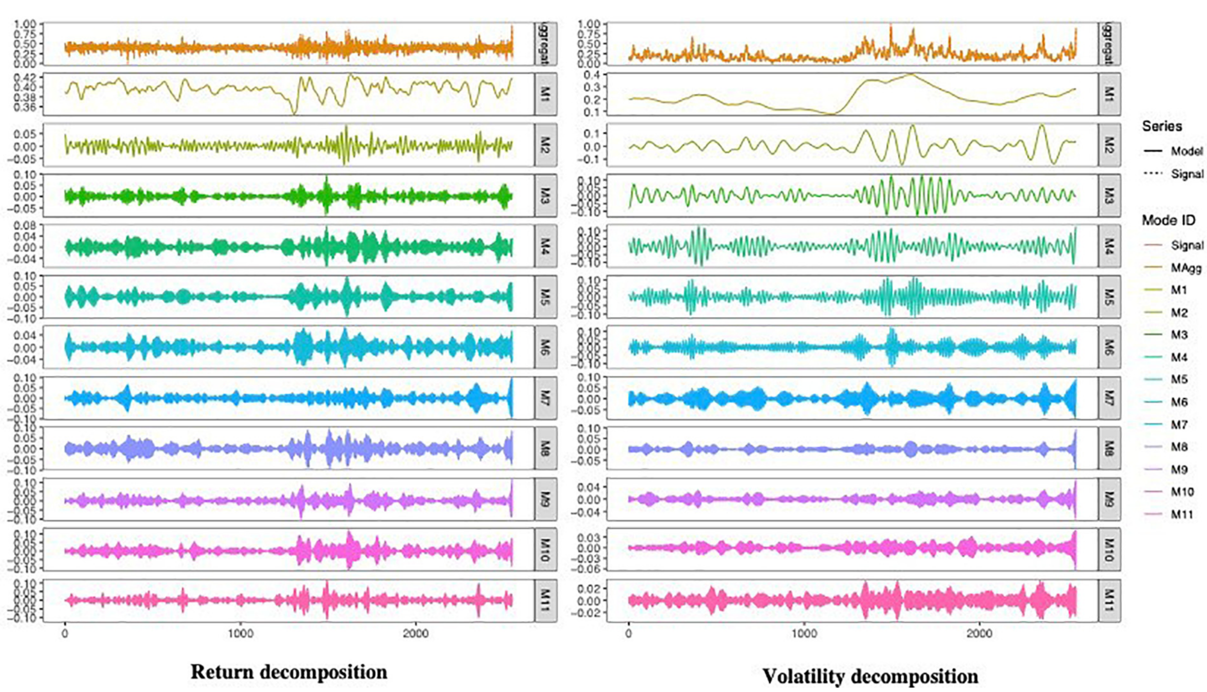

Fig. 7. VMD decomposition results.

Table 4
Horizontal volatility comparisons.

	HMSE			
	Period 1	Period 2	Period 3	Period 4
Proposed	0.0033	0.0023	0.0058	0.0065
LSTM	0.0607	0.1227	0.0928	0.0775
SVR	0.0656	0.2151	0.1285	0.1098
LR	0.0768	0.2278	0.1329	0.1143
ARIMA	0.0532	0.0915	0.0822	0.0643
ANN-GARCH	0.0705	0.0713	0.0919	0.0832
Senti-GARCH	0.0931	0.0903	0.1361	0.0939
Asymmetry Senti-GARCH	0.0911	0.0906	0.1360	0.0950
Benchmark GARCH	0.0928	0.0896	0.1354	0.0934
	HMAE			
	Period 1	Period 2	Period 3	Period 4
Proposed	0.0428	0.0372	0.0499	0.0584
LSTM	0.1467	0.1925	0.1791	0.1671
SVR	0.1677	0.2640	0.2809	0.2126
LR	0.1907	0.1453	0.2864	0.2839
ARIMA	0.1295	0.1841	0.1690	0.1503
ANN-GARCH	0.2029	0.2641	0.2767	0.2374
Senti-GARCH	0.9648	0.9499	0.9166	0.9692
Asymmetry Senti-GARCH	0.9547	0.9520	0.9189	0.9746
Benchmark GARCH	0.9634	0.9466	0.9127	0.9665

The single sentiment input integrates both the decomposed intrinsic modes and the daily sentiment score to form its input dataset. However, instead of using the 7-day cumulative sentiment score, it uses the single daily sentiment score without considering the aggregated effects of previous news headlines. Tables 5 and 6 show the vertical prediction performance comparisons for the daily logarithmic return and 7-day volatility, respectively.

Looking at the daily logarithmic return prediction performance in Table 5, we can see that when different inputs are incorporated, the performance of all models displayed similar fitting performances and trend predictive abilities. Taking the proposed BiLSTM deep learning approach as an example, the decomposition input that uses only the intrinsic modes achieved the worst performance out of all three input techniques, obtaining an average RMSE and MAE of 0.0172 and 0.0126, respectively. In comparison, when the daily sentiment scores feature extracted from the financial news headlines are included in the single sentiment input, the prediction performance of the model experienced an observable increase across all evaluation criteria: the average RMSE and MAE decreased by 3.98% and 1.95%, respectively. This improvement may be due to that by incorporating the calculated sentiment value as part of the model input, the model is able to capture the possible market reactions to the news headlines, which cannot be fully reflected in the decomposed intrinsic modes. Further, when the cumulative effects of previous news headlines are considered in the inputs for the proposed model, the improvement is more significant: the proposed model is able to decrease the RMSE and MAE value by 12.81% and 19.88%, respectively.

Table 5
Vertical return comparison.

	RMSE				
	BiLSTM	LSTM	SVR	LR	ARIMA
Decomposition	0.0168	0.8139	0.1096	0.1083	0.0975
Single Sentiment	0.0162	0.8256	0.1088	0.1152	0.0966
Sentiment + Decomposition	**0.0146**	0.0753	0.0977	0.0984	0.0931
	MAE				
	BiLSTM	LSTM	SVR	LR	ARIMA
Decomposition	0.0123	0.0599	0.0704	0.0703	0.0715
Single Sentiment	0.0121	0.0607	0.0698	0.0692	0.0728
Sentiment + Decomposition	**0.0104**	0.0568	0.0683	0.0685	0.0701

Table 6
Vertical volatility comparison.

	HMSE				
	BiLSTM	LSTM	SVR	LR	ARIMA
Decomposition	0.0061	0.0907	0.1305	0.1407	0.0787
Single Sentiment	0.0051	0.0896	0.1308	0.1416	0.0743
Sentiment + Decomposition	**0.0045**	0.0884	0.1297	0.1379	0.0728
	HMAE				
	BiLSTM	LSTM	SVR	LR	ARIMA
Decomposition	0.0551	0.1786	0.2534	0.2519	0.1594
Single Sentiment	0.0513	0.1754	0.2586	0.2461	0.1635
Sentiment + Decomposition	**0.0471**	0.1713	0.2313	0.2265	0.1582

Examining the 7-day volatility prediction results in Table 6, we can observe a similar pattern: The incorporation of the sentiment feature extracted from the news headlines is able to provide more useful information to the model and increase the fitting performance across all models. However, this improvement is much more significant when the cumulative impact of news headlines on the market sentiment is taken into consideration in the proposed approach. In comparison to the worst-performing benchmark model, our proposed model is able to enhance the HMSE and HMAE by 9.72% and 8.94%, respectively. Therefore, this improvement in performance demonstrated that the market sentiment is not only affected by the current news headlines, it is also impacted by the aggregated effects of previous news headlines. Therefore, by incorporating the cumulative sentiment scores as part of the input, our proposed approach is able to depict the changes in the crude oil market more realistically. As a result, our proposed approach is able to enhance the prediction performance in forecasting the daily returns and volatility of the crude oil market.

4.3. Statistical significance test

To further verify the superiority of our proposed approach, we conduct the Diebold-Mariano test (Chen et al., 2014; Ng et al., 2014) between the proposed approach and all the benchmark models for both the daily logarithmic return and 7-day volatility forecasts during the testing period. The results tabulated in Table 7 indicate that the performance of the proposed approach is significantly better than all the models for both return and volatility forecasting during the testing period. Specifically, the outperformance is significant under the 1% significance level for the Single Sentiment model, LSTM model, SVR model, LR model, ARIMA model, hybrid ANN-GARCH model and all GARCH models; for the Decomposition model, the outperformance is significant under the 10% significance level.

Table 7
Diebold-Mariano Test

	Proposed	
	Return	Volatility
Decomposition	−1.67 *	−1.78 *
Single Sentiment	−3.60 ***	−1.99 **
LSTM	−6.02 ***	−2.96 ***
SVR	−5.59 ***	−17.63 ***
LR	−5.62 ***	−18.09 ***
ARIMA	−6.04 ***	−2.74 ***
ANN-GARCH	/	−9.31 ***
Senti-GARCH	/	−12.19 ***
Asymmetry Senti-GARCH	/	−12.16 ***
Benchmark GARCH	/	−12.18 ***

Note: ***, **, * respectively denotes the statistical significance level of 1%, 5% and 10%. The elements in this table indicate Diebold-Mariano statistics.

5. Conclusion

In this study, we propose a novel VMD-BiLSTM model incorporating investor sentiment indicator for crude oil forecasting. Specifically, we collection dataset of crude oil news headlines and conduct sentiment analysis on the contextual data, which provides effective and unexplored information for deep learning forecasting. We empirically investigate the impact of news sentiment on returns and volatility based on event study and GARCH model. As for return and volatility forecasting, variational mode decomposition (VMD) is applied to decompose the historical crude oil return and volatility data into various intrinsic modes. After that, a bidirectional long short-term memory neural networks (BiLSTM) is introduced as the deep learning prediction model that integrates both the qualitative and quantitative model inputs.

Our empirical results indicate that news sentiment significantly causes the fluctuation of oil futures prices, and serves as an effective predictor for oil returns and volatility. Specifically, oil futures prices significantly react around news shocks, regardless of positive or negative shocks. Moreover, we find that news sentiment has an asymmetric impact on the volatility of oil futures. According to forecasting comparisons, the data-decomposition based deep learning model integrating sentiment score always performs better than several econometric and machine learning models.

Our study presents an early attempt to integrating online text data into oil return and volatility forecasting. In future research, more sources of online data could be utilized for forecasting, such as user-generated contexts (UGC) from social media, or oil-related firms' disclosure. Furthermore, other NLP techniques could be adopted for text analysis of oil market news, such as topic identification and event extraction. Our study indicates the viability of application of deep learning model in return and volatility forecasting. More deep learning models are also promising to further improving the forecasting performances of oil return and volatility.

Funding

This work was supported by the National Natural Science Foundation of China (grant number 71901205).

Declarations of Competing Interest

None.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105140.

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