Jurnal Ekonomi Malaysia 55(3) 2021 1 - 21
http://dx.doi.org/10.17576/JEM-2021-5503-01

The Impact of News Sentiment on the Stock Market Fluctuation: The Case of Selected Energy Sector

(Impak Sentimen Berita terhadap Turun Naik Pasaran Saham: Kes Sektor Tenaga Terpilih)

Ling Wu
University of Malaya

Siew Hock Ow
University of Malaya

ABSTRACT

This paper examines the impact of the sentiments of OPEC news on stock market prices of public listed oil and gas companies in Bursa Malaysia. We used data of stock market prices from randomly selected oil and gas companies for the period of 2012 to 2017. For the methodology, we first established a supervised machine learning algorithm-based news classifier to classify the OPEC news following its sentiments. We developed a financial news sentiment classifier by combining machine learning algorithms and lexicon-based labelling methods. We then applied the event study method to investigate how stock market prices react to OPEC news' sentiment. The results showed a negative correlation between OPEC news sentiment and stock market prices of oil and gas companies during the event window based on each OPEC news release date. The results further showed that the stock market prices do not react to OPEC news sentiment on event day. These findings should provide some guides to stock investors on the movement of the selected stock market prices of energy sector companies during the event window period.

Keywords: OPEC; news sentiment; oil and gas industry; Bursa Malaysia; machine learning; event study
JEL: C88, G14

ABSTRAK

Kertas ini mengkaji kesan sentimen berita OPEC ke atas harga pasaran saham syarikat minyak dan gas yang tersenarai awam di Bursa Malaysia. Data harga pasaran saham syarikat minyak dan gas yang dipilih secara rawak untuk tempoh masa 2012 hingga 2017 digunakan dalam kajian ini. Dalam proses tersebut, sebuah mesin pengkelasan berita diselia berasaskan algoritma telah dihasilkan untuk tujuan mengklasifikasikan berita OPEC mengikut sentimen syarikat. Pengklasifikasi sentimen berita kewangan dibina dengan menggabungkan algoritma pembelajaran mesin dan kaedah pelabelan berdasarkan leksikon. Selain itu, kaedah kajian peristiwa juga digunakan untuk mengkaji tindak balas harga pasaran saham terhadap sentimen berita OPEC. Dapatan kajian mendapati korelasi negatif di antara sentiment berita OPEC dan harga pasaran saham syarikat minyak dan gas tersenarai awam di Bursa Malaysia. Keputusan selanjutnya menujukkan harga pasaran saham syarikat minyak dan tersenarai awam di Bursa Malaysia tidak bertindak balas kepada sentimen berita OPEC pada hari acara (hari keluaran berita). Penemuan ini memberikan satu gambaran yang jelas kepada pelabur saham tentang pergerakan harga pasaran saham bagi keenam-enam buah syarikat Malaysia dalam sektor tenaga dalam tempoh tetingkap peristiwa.

Kata kunci: OPEC; sentimen berita; industri minyak dan gas; Bursa Malaysia; pembelajaran mesin; kajian acara

Received 27 November 2019; Revised 02 July 2021; Accepted 15 August 2021; Available online 30 August 2021

INTRODUCTION

In the mid-long term, the movement of oil price has exerted an impact on the fluctuation of stock prices globally (Yu-Ling Hsiao et al. 2019). Compared with other commodities, petroleum has a significant influence on the world economy, especially when it comes to triggering economic recessions (Xiao et al. 2019). Therefore, the announcement of oil-related news can influence the stock market at large, which will affect the stock returns of market participants (Narayan & Narayan 2017). The Organization of the Petroleum Exporting Countries (OPEC) is known as an economic organization established by a group of Petro-states in 1960, to regulate and formulate policies on petroleum production and prices for its member countries. To date, OPEC has a total of 14 member countries holding a proven reservation of over 80 percent of global oil and accounting for 44 percent of global oil production (Ahmad 2016). It is widely acknowledged that oil supply and demand are known as the two most fundamental factors for oil prices. To address these issues, OPEC hold annual conferences among its members to make decisions on oil prices as well as oil productions. The announcements made through OPEC conferences are of vital importance to the global oil market (Razek & Michieka 2019). On this fact the OPEC exerts great influence on global oil prices, and its news announcements draws increasing attention from market participants as well as the research community. Understanding the pattern of fluctuation caused by OPEC news sentiments can provide crucial information to assist share market investors to make better investment decisions. By analyzing the news announcements released by OPEC, investors concerned with the crude oil markets may receive pivotal information on the market. (Al Rousan et al. 2018).

The efficient market theory (efficient market hypothesis) defines that the market is efficient when it has a great number of rational profit-maximizers actively involved. Since each player can access the information freely, the prices thus should reflect all known information (Fama 1970). A large number of studies, covering various aspects, have been conducted to test the efficient market theory. Some studies analyzed the market's reaction on the first few days following certain specific announcements. They established that financial assets quickly react to new information, which thus confirms the efficiency of the capital market (Khoj & Akeel 2020). It is a popular economic theory in the research field concerning impact of news sentiments on the stock market.

However, research is limited on fluctuation of stock prices for Malaysian public listed companies in the energy sector (Oil & gas), following impact of OPEC news announcements. This study is thus justified as Malaysia is not only a non-OPEC member but also a major oil-exporting country in South East Asia. The purpose of this paper is to investigate the impact of sentiments arising from OPEC news announcements on stock market prices of public listed oil & gas companies in Bursa Malaysia. The study will formulate an innovative sentiment classifier and apply event study methods to analyze the fluctuation of stock market prices. Our dataset comprises OPEC announcements released on the OPEC official website from June 2012 to December 2017.

The commonly-used techniques used for news sentiment analysis can be divided into two main categories – unsupervised lexicon-based approach and supervised machine learning-based approach. In the former approach, a dictionary of sentiment words is commonly used to count those sentiment or emotional words in the articles (Moreno-Marcos et al. 2018). In the latter, the articles' sentiment is analyzed by a machine learning algorithm which is trained by manually or automatically labelling news data (Yadav et al. 2019). By combining the lexicon-based and machine learning approaches, classifiers have the potential to improve the performance of sentiment classification (Song et al. 2020). In this research, a supervised machine learning algorithm-based classifier is used to analyze the OPEC news' sentiment. The lexicon-based approach is applied in labelling the training data. Specifically, we applied the Loughran and McDonald's Financial Sentiment Dictionaries (Loughran & Mcdonald 2011) which contain sentiment words from the finance domain. Furthermore, to investigate the impact imposed by a certain event on stock market prices, the method of an event study is also applied in this investigation.

The research will make contributions in the following two areas: 1) By combining Loughran-McDonald Master Dictionary with Stochastic Gradient Descent machine learning algorithm, an innovative financial news sentiment classifier with relatively higher accuracy (70%) is formulated to analyze the sentiment of OPEC news announcements. 2) The results of the study potentially provide valuable information to investors to assist them in making a more informed investment decision based on these sentiments.

The rest of this paper is organized as follows: Section 2 presents the related literature. Section 3 focuses on the introduction of the data employed in this research. Section 4 describes the methodology used. The data implementation and estimation of the classifier are presented in Section 5. Section 6 contains research results. Finally, the study conclusion is given in Section 7.

LITERATURE

Past empirical studies used the efficient market hypothesis in examining news impact on the capital market. Studies conducted by Engelberg et al. (2011) and Wisniewski et al. (2013) suggest that investors' sentiment is deeply influenced by news, which in turn, affects the price of the stock market. Their study applied the information efficiency of the efficient market hypothesis. Similarly, Uhl (2014) studied the impact of Reuters news' sentiment on Dow Jones industrial stock index and volume. He confirmed the impact of Reuters' sentiment on the stock market and noted that negative sentiments exerted greater impact. His study demonstrated that the market adjusts its prices based on newly released information. Further, Sorto et al (2017), studied 30 days of news on five companies traded in the Dow Jones Industrial Average (DJIA) and compared the ensuing news sentiment with the financial market data of selected companies. Their results demonstrated the information efficiency and unpredictability of the market, thus maintaining the efficient market hypothesis.

Shantha Gowri and Ram (2019) examined news impact on individual's investment decisions, and concluded that the stock market reacts to all kinds of news such as macroeconomic, company and political. But the investment decision of individuals can be irrational due to its heuristic nature including biases attributed to differences in the researcher's personal background, cognitive inefficiency and mental frame. They also established that the efficient market hypothesis does not comply when cognitive informational inefficiency of investors cause their reaction or overreaction and under reaction. Bagh (2020) studied the exchange rate of the PKR/USD currency during the late nineties to early 2000. His result demonstrated that news sentiment has significant impact on exchange rates. He also observed that Pakistan's foreign exchange market was moving toward efficiency when the data was being collected.

In the last few decades, a number of studies have been conducted on OPEC news' impact on certain markets. The Hyndman (2008) study on OPEC announcements from August 1986 to September 2002 concludes that the announcements do affect the oil prices and stock returns in the global oil industry. Analysis on some cases in his study suggests that the fluctuation of abnormal returns affected by OPEC announcements can be ±5%. A study was conducted by Demirer and Kutan (2010), on the US Strategic Petroleum Reserve (SPR) and OPEC's announcements released between 1983 to 2008 on the spot and future oil prices. The results indicate that following the announcement, an abnormal return of the related markets witnessed apparent fluctuations. Conversely, the announcements from SPR did not show any influence on the abnormal returns. A similar study was conducted by Schmidbauer and Rösch (2012), on OPEC's production decisions from January 1986 to September 2009 and the WTI (West Texas Intermediate) daily oil prices. Their findings indicate strong evidence of OPEC's news effects on volatility which appear to be not significant when it comes to the decisions to increase production, but the impact was however shown highly pronounced in the case of decisions to cut or maintain the production level. Nevertheless, a study conducted by Mensi et al (2014) on the volatility of oil market prices and the price of crude oil based on OPEC announcements released between May 1987 to December 2012 demonstrated that the OPEC announcements on "cut" and "maintain" decisions on oil production have a great impact on the returns and volatility of crude oil markets. However, Loutia et al (2015), investigated the effect of OPEC production decisions (increase, cut, maintain) on both WTI and Brent crude oil prices between March 1991 and February 2015. Their findings suggest that the OPEC announcements vary across periods (pre- or post-announcement), production decisions and oil prices. Narayan and Gupta (2015) carried out an extensive study by employing monthly oil price data for over one century (1859-2013). The results indicate that oil price is regarded as an important variable for the prediction of stock returns and there is apparent evidence of nonlinear predictability. Similarly, the study by Croese (2015) on OPEC news announcements' impact on European oil firm's stock return suggests comparable findings. Furthermore, recent research which analyzed OPEC news data from 2003 to 2014 indicates that negative news produce positive effects on the stock market returns of US energy companies (Gupta & Banerjee, 2018).

The approaches mentioned in the literature regarding news impact on the stock market are different in three aspects: i) Feature processing (a process to generate information which can be analyzed based on the given data); ii) machine learning algorithm which is used to classify the text based on the output of feature processing; and iii) data set from a certain field which consists of two parts; the news textual data and the corresponding data on the reaction of the stock market (Chatzis et al., 2018). Detailed methods applied in this research can be found in the 'Methods' section of this paper.

In a nutshell, the validity of efficient market theory to different studies may vary and even if these seek for the truth behind the efficient market theory, no final conclusion was derived (Ali et al., 2018). In addition, although these past studies have established the impact of OPEC news on various markets, studies on how stock market prices, of Malaysian oil & gas companies, react to OPEC news sentiment is still substantially limited.

DATA

Historical statistical data related to stock market prices employed in this research were sourced from proven reliable dataset for financial research - namely, the website of Yahoo Finance (The historical stock prices data is retrieved from https://finance.yahoo.com/lookup). Also, simple random sampling was used to generate the suitable dataset. This sampling method not only has the highest generalizability but also gives the least bias (Qiu et al. 2020). The selection of sample size followed Sorto et al. (2017) who predicted the fluctuation of financial markets based on news sentiment, and Azman Firdaus (2016) who studied environmental reports from Malaysian oil & gas companies from the aspect of linguistic. A total of six companies were randomly selected from 28 oil & gas companies listed on the Main Market Board of Bursa Malaysia for a study on the fluctuation of their stock market prices under the impact of OPEC news sentiments. With the fact that some of the data were related to historical stock market prices that can only be traced back to 2012, this study thus spanned six years' data (2012 to 2017). Table 1 illustrates details of the selected companies for the study.

TABLE 1: The list of stock market prices companies dataset

NO	Name of Company	Stock Code	Sector	Established Year
1	Petron Malaysia Refining & Marketing Berhad	3042	Energy	1893
2	HengYuan Refining Company Berhad	4324	Energy	1960
3	Bumi Armada Berhad	5210	Energy	1995
4	Hibiscus Petroleum Berhad	5199	Energy	2007
5	Sumatec Resources Berhad	1201	Energy	1979
6	Sapura Energy Berhad	5218	Energy	2012

In addition, two textual data sets were employed in this study. The first was sourced from the official press release column on the OPEC official website. The OPEC news textual data set comprised a total of 116 news articles that were published on the 'Press Release' column of the official website (https://www.opec.org/opec_web/en/press_room/28.htm), from 2012 to 2017. The dataset was established to provide a relevant source of OPEC news for the analysis of the news-based sentiments.

The other textual data set was from a Wall Street Journal news articles data set (Chen 2017), which was established through compiling news articles released in the 'Markets' column on the news website (https://www.wsj.com/news/markets) spanning 2017-06-07 to 2017-07-26. It contained a total of 2,062 financial news articles, which were adapted for further processing into training data for machine learning algorithms. This data set was used to provide sufficient words for the training as related to financial news sentiment.

METHODS

This research contains two parts: 1) textual data processing and classification which uses lexicon-based labeling and Machine learning algorithms, and 2) stock markets statistical data analysis using event study methods.

LEXICON-BASED LABELLING

The sentiments of one word may vary following the different background of the text (Arif et al. 2018). For instance, in the general dictionary, the word 'climb' has neutral sentiment, but it has positive sentiment in financial articles (Mikolov et al. 2013). Thus, Loughran and McDonald's Financial Sentiment Dictionaries (Loughran & Mcdonald 2011), which is specifically built for the analysis on the sentiment of financial news, is employed in labelling the financial news texts. In this approach, each word in the sentence is analyzed by comparing it to the existed sentiment words in the dictionary, whether it's positive, negative or neutral. The sentences' sentiment is estimated by the difference in counts between the positive words and negative words.

Since the lexicon-based sentiment analysis approach determines the sentiment of the text by detecting those sentiment lexicon words in the text (Khoo & Johnkhan 2018)Multi-perspective Question Answering (MPQA. In this research, the lexicon-based sentiment analysis is applied to label the training textual data for the machine learning classifiers. The Loughran and McDonald's Financial Sentiment Dictionaries is used for preprocessing the textual data for two reasons: 1) The textual data needs to be labelled with its sentiments so it can be further processed and applied to train the machine learning classifiers. 2) Comparing to manually labelling, using lexicon-based labelling is much more efficient. 3) The lexicon resource from financial domain can enhance the accuracy of machine learning classifiers for this research.

MACHINE LEARNING ALGORITHMS

Machine learning algorithms, to make computers learn from experience, is one of the most rapidly developing techniques which settles in the intersection research field of statistics and computer science (Bonaccorso 2018). It has developed a deep diversity due to its aim to solve a variety of problems and to cover a wide variety of different kinds of data (Ayyadevara 2018).

There are mainly three categories of machine learning algorithms, supervised machine learning algorithms, unsupervised machine learning algorithms and reinforcement learning algorithms. In supervised machine learning algorithms, each instance in the dataset is labelled with known classifications. Otherwise, without those labels, it's called unsupervised machine learning (Bonaccorso 2018). By applying unsupervised learning, researchers aim to find out the unknown but useful classes of items (Alloghani et al. 2020). On the contrary, supervised machine learning, aims to train the learner with known features and labels. There is also another kind of machine learning algorithm called reinforcement learning. Reinforcement learning algorithms' training data is provided by the external trainer. Its training data is a scalar reinforcement signal which constantly returns the measure of the system's performance. Therefore, the learner can discover which action has the best result by trying each action in turn (Sutton & Barto 2018).

This research applied the supervised machine learning algorithms to build the classifier for the OPEC news texts. Supervised machine learning algorithms involve analyzing the labelled data and generally form the predictions by learned features.

EVENT STUDY METHOD

There are mainly two kinds of information that may lead to the fluctuation in stock market prices—the information that is released by a company, such as a dividend announcement or personnel change announcement, and the information that is likely to impose an impact on the stock market prices, such as big flaw reported found in the product and influential news from third parties (Akita et al. 2016). To investigate whether OPEC news sentiments have an impact on the selected energy sector (oil & gas) companies share market prices, the event study method is applied in this research. This method was initially introduced in 1969 (Fama et al. 1969). And it is a technique of statistical analysis which aims to estimate the reaction of the stock market to certain events, such as important personnel announcement of the company, mergers, dividend announcements and so on (Sorescu et al. 2017).

For event study, there are two crucial parameters, event window and estimate period. The former decides on how many days share market prices data should be analyzed based on the event date. Proper event window can not only include the impact of analyzed events but also avoid the influence of other irrelevant events. Therefore, a suitable event window should ensure a reliable result of the analysis. When it comes to studying impact of certain event on share market prices, the event window will vary based on the difference inherent in those events (Nisar & Yeung 2018).

The choice of event window in fact may differ among different studies, and there are no formal rules in choosing it. This research adopts event window length of 5 trading days, before and after the event day, from a related research titled "Do OPEC announcements influence oil prices?" (Loutia et al. 2015). The same event window is also applied in related studies conducted by Horan et al (2004) and Bina and Vo (2007). In this research therefore, the event window includes 5 trading days after and 5 trading days before the event date, and an event window of 11days including the even day.

In addition, the estimated period decides on how many days the share market price data should be included to calculate the expected return. The estimated period should exclude the event window so that the expected return is not affected by the event. Similar to the event window, there is no exact procedure for estimating the best period. Since the stock market prices in the energy sector (oil & gas) companies may greatly fluctuate, the estimated period cannot be too long, otherwise, it does not reflect the influence of OPEC news announcements. On the other hand, if the estimation period is too short, there would not be enough observations for an adequate estimation of the model (Yu & Huarng 2020).

Since the estimation period of 30 days is a common choice in the literature, this study will also adopt the same 30 trading days prior to the starting day of the event window for the estimation period (Philipp & Andre 2016). The expected return is the mean of daily return over the estimation period (Chen & Hwang 2019). Figure 1 illustrates how the event method is applied in the study.

RESEARCH DESIGN

Based on the generated data sets and chosen techniques applied in this research, the research design is shown as Figure 2.

DATA ANALYSIS

Textual data and historical stock market data are analyzed separately. According to the accuracy score of the machine learning classifier and the regression analysis of OPEC announcement sentiments, and the fluctuation of selected oil & gas companies' stock market prices, findings of the research can be generated.

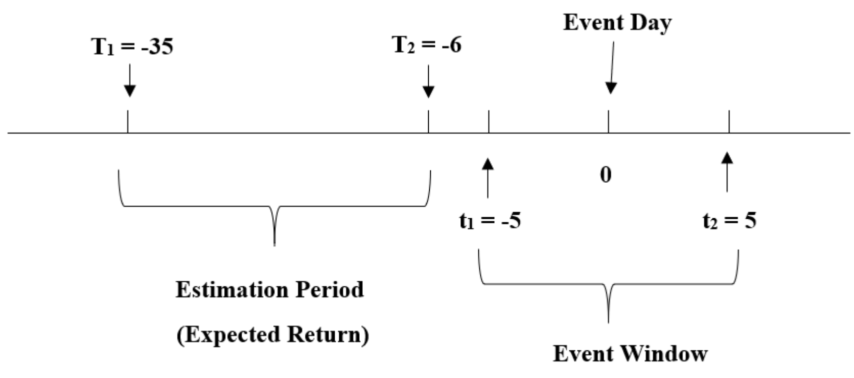

FIGURE 1. Event study methods used in this research

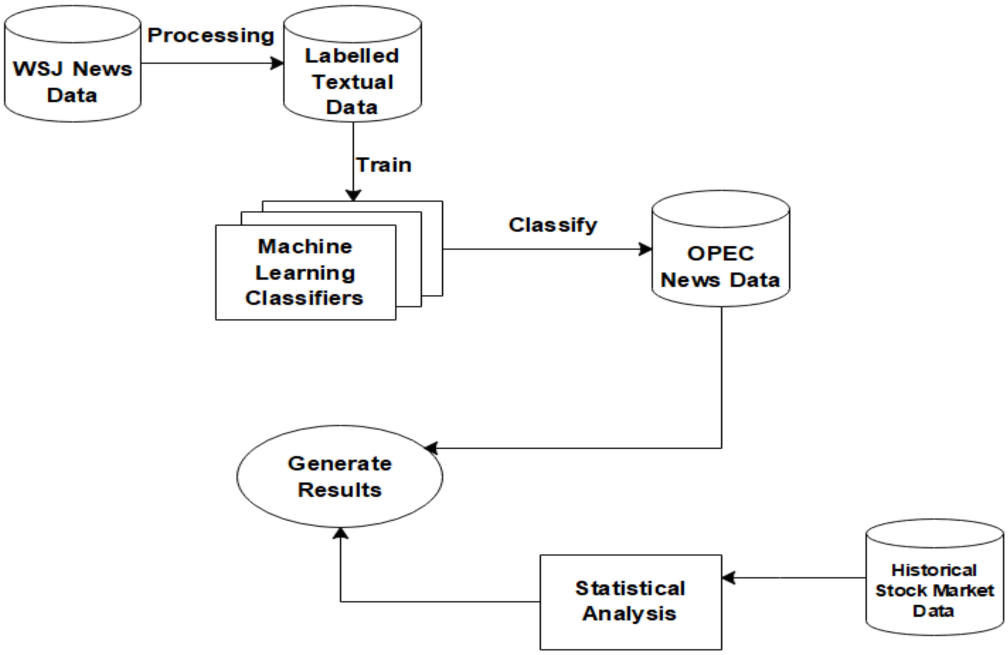

FIGURE 2. Research design

PREPARATION OF TRAINING DATA

In this study machine learning classifiers were developed to classify the OPEC news. The textual data sourced from the Wall Street Journal news was initially processed for the purpose of raining the classifiers of machine learning. In the data set a total of 2,062 financial news articles were available and these were broken down into 37,452 sentences. Once each sentence was tokenized, the Loughran and McDonald Financial Sentiment Dictionaries (Loughran & Mcdonald 2011) was applied to analyze the sentiment of the sentence.

Each word in the sentence was compared with those in the said dictionaries (Loughran & Mcdonald 2011). The calculation of sentiment for the whole sentence was then carried out according to the number of positive and negative word, using the evaluation method named relative proportional difference (Will et al. 2011). The calculation formula of this method is as follows.

$$S = (P-N) / (P+N) \quad (1)$$

In this formula, S refers to the sentiment score of the sentence, P denotes the number of positive word and N represents the number of negative words. The result in S ranges from -1 to 1. If S=0, it indicates that the sentiment of the sentence is neutral. If S > 0, it means that the sentiment of the sentence is positive. Otherwise, the sentiment is negative.

Based on the results obtained from lexicon-based sentiment analysis mentioned above, these sentences are further labeled with ‘-1’, ‘1’ and ‘0’ to represent its sentiment whether it’s ‘negative’, ‘positive’ or ‘neutral’. It is proven that imbalanced data can lead to different prediction confidence of the different classes in the target domain (Krawczyk 2016). To balance the training data, the study then randomly chooses the same number of sentences in each category of sentiment from the total 37,452 labelled sentences. We employ a total of 12,000 sentences which consists of 4,000 sentences for each kind of sentiment, to train the machine learning classifiers.

After labelling every sentence with its sentiment, from the financial news articles on Wall Street Journal, the methods of bag-of-words representation, stop words removal and TF-IDF feature processing are then adopted. This serves to weigh the value of sentiment words for the whole data set and transfer the textual data to numerical data based on its weight. After experiencing the procedures of feature processing, the financial news textual data of the Wall Street Journal is then processed as a proper training data set for the algorithms of machine learning.

TEST OF MACHINE LEARNING ALGORITHMS

To find out which supervised machine learning algorithm-based classifier shows better performance, multiple supervised machine learning algorithms-based classifiers are tested separately. Table 2 shows the classification report obtained from the differently tested classifiers.

Each classifier’s accuracy score is shown in Figure 3.

CLASSIFICATION OF OPEC NEWS

Based on performance results of different supervised machine learning algorithms mentioned above, it was

TABLE 2. Classification report of tested supervised machine learning classifiers

Classifier	Sentiment (S)	Precision	Recall	F1-Score	Support
Stochastic Gradient Descent Classifier	-1	0.71	0.72	0.71	803
	0	0.61	0.63	0.62	792
	1	0.79	0.75	0.77	806
Gaussian Naïve Bayes Classifier	-1	0.55	0.50	0.52	815
	0	0.43	0.52	0.47	780
	1	0.56	0.51	0.53	806
Multinomial Naïve Bayes Classifier	-1	0.68	0.75	0.72	815
	0	0.65	0.42	0.51	780
	1	0.67	0.83	0.74	806
Complement Naïve Bayes Classifier	-1	0.61	0.71	0.66	803
	0	0.58	0.34	0.43	792
	1	0.62	0.78	0.69	806
Bernoulli Naïve Bayes Classifier	-1	0.74	0.25	0.37	803
	0	0.38	0.87	0.53	792
	1	0.67	0.27	0.39	806
Support Vector Classifier	-1	0.73	0.61	0.67	803
	0	0.53	0.71	0.61	792
	1	0.80	0.68	0.74	806
Random Forest Classifier	-1	0.71	0.38	0.50	803
	0	0.43	0.79	0.56	792
	1	0.78	0.52	0.62	806

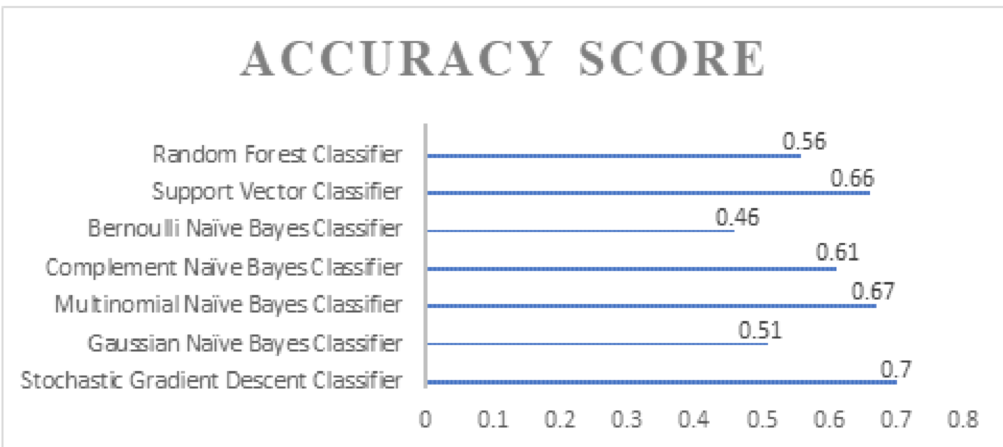

FIGURE 3. Accuracy score of each classifier

shown that Stochastic Gradient Descent Classifier (SGDC) outperforms other tested supervised machine learning algorithms. In consequence, the SGDC machine learning classifier was adopted in this study to classify the sentiments of OPEC news announcements. The machine analyzed each sentence in every OPEC news article, followed by tagging '-1' which stands for negative, '0' for neutral and '-1' represents negative. As mentioned earlier in section 4.1, the sentiment in the article was calculated by the evaluating method of relative proportional difference. The formula *(1)* is applied here as well. For calculating the sentiment of the article, P refers to the number of positive sentences in the article and N denotes the number of negative sentences. As such, the result obtained for each article may range from -1 to 1.

Table 3 shows the sentiment results obtained from OPEC news announcement from 2012 to 2017.

TABLE 3. Sentiment score obtained from the OPEC news announcements collected

Event Day	Sentiment	Event Day	Sentiment	Event Day	Sentiment	Event Day	Sentiment	Event Day	Sentiment	Event Day	Sentiment
2012-06-14	-0.5	2014-10-02	-0.75	2016-09-09	-0.14	2016-12-15	-0.25	2017-04-24	-0.2	2017-09-05	-0.25
2012-06-28	0.33	2014-11-27	-0.67	2016-09-26	1.00	2016-12-16	-0.25	2017-04-27	0.09	2017-09-06	0.00
2012-07-16	-0.20	2015-02-05	-0.33	2016-09-28	-0.33	2017-01-08	-0.50	2017-04-28	-0.20	2017-09-14	0.20
2012-09-25	0.00	2015-06-04	0.33	2016-10-14	-0.57	2017-01-11	-0.56	2017-05-22	0.00	2017-09-15	-0.33
2012-09-27	-0.42	2015-06-05	-0.08	2016-10-18	-0.43	2017-01-14	-0.41	2017-05-24	-0.50	2017-09-22	0.56
2012-10-04	0.43	2015-06-24	-0.40	2016-10-19	-0.33	2017-01-17	-0.23	2017-05-25	-0.42	2017-09-28	-1.00
2012-12-12	0.17	2015-07-30	-0.60	2016-10-24	0.33	2017-01-22	-0.22	2017-05-31	0.14	2017-09-29	-0.60
2013-03-21	0.20	2015-09-01	-0.33	2016-10-26	-0.65	2017-02-07	-0.14	2017-06-01	-0.75	2017-10-10	0.43
2013-05-31	-0.25	2015-09-08	-0.60	2016-10-29	0.60	2017-02-08	0.00	2017-06-09	0.50	2017-10-21	0.43
2013-07-29	-0.20	2015-12-04	-0.67	2016-11-02	-1.00	2017-02-14	-0.40	2017-06-13	-0.78	2017-10-24	0.20
2013-10-24	-0.33	2015-12-18	0.33	2016-11-05	0.00	2017-02-15	0.17	2017-06-22	0.20	2017-11-07	0.25
2013-11-08	0.33	2016-03-21	0.00	2016-11-07	-0.45	2017-02-21	0.00	2017-06-26	-0.20	2017-11-30	-0.27
2013-11-11	0.11	2016-06-02	-0.23	2016-11-08	0.40	2017-02-24	-0.67	2017-07-18	-0.20	2017-12-01	-0.05
2013-12-04	-0.17	2016-06-22	-0.40	2016-11-17	0.20	2017-03-06	0.00	2017-07-23	-1.00	2017-12-13	0.43
2014-03-31	0.50	2016-06-30	-0.60	2016-11-19	-0.14	2017-03-10	0.22	2017-07-24	0.11	2017-12-20	0.40
2014-04-30	0.33	2016-08-01	-0.50	2016-11-21	-0.43	2017-03-11	-0.40	2017-07-29	-0.52	2017-12-21	-0.33
2014-06-11	-0.56	2016-08-04	0.25	2016-11-30	-0.29	2017-03-16	0.14	2017-08-02	-0.56		
2014-06-24	-0.10	2016-08-08	0.33	2016-12-10	-0.33	2017-03-26	-0.30	2017-08-08	-0.60		
2014-07-18	-0.27	2016-09-05	-0.80	2016-12-13	-0.09	2017-04-04	0.54	2017-08-14	-0.72		
2014-09-16	0.60	2016-09-06	-0.75	2016-12-14	-0.27	2017-04-11	0.60	2017-08-24	-0.14		

FLUCTUATION OF STOCK MARKET PRICES

Cumulative Abnormal Return (CAR) is employed in this study as the index to indicate the fluctuation of market prices related to the selected companies' stock during the time of the event window based on each event day (news release day). CAR is also known as a key index to gauge the OPEC news' influence on the stock market prices of selected companies and how the influence occurs. The formula for calculating CAR is as follows:

$$\text{CAR}= \sum_{t}^{T}\text{AR} \tag{2}$$

In the formula, AR represents abnormal return, while t refers to the starting day of analysis and T the closing day. Thus, CAR requires the abnormal return for its calculation.

The abnormal return can be calculated as follows:

$$\text{AR} = \text{R} - \text{ER} \tag{3}$$

In the formula, R refers to Daily Return and ER denotes Expected Return.

Accordingly, daily return and expected return are required to be calculated for obtaining an abnormal return.

The formula for calculating daily return is as follows:

$$\text{R} = (\text{R}_2\text{-R}_1)/\text{R}_1 \tag{4}$$

R_2 refers to the closing price during the day of the analysis, and R_1 indicates the closing price of the previous day.

And, the formula for the calculation of the Expected Return (ER) is listed as follows:

$$\text{ER} = \overline{\text{R}} \tag{5}$$

$\overline{\text{R}}$ refers to the mean daily return over the estimation period (Guidi et al. 2006).

In the study the 30 trading days before the starting day of the event window are adopted as the period for estimation, and the event window is established as the period of 5 trading days before and after the event day.

The results of cumulative abnormal return of the selected companies which is calculated based on the event window of each event date, as well as the average cumulative abnormal return of each event for all those six selected companies, are shown in Appendix A. Table 4 shows part of the results.

Furthermore, to study whether stock market prices of selected oil & gas companies are influenced by OPEC news announcement on the event day, this research also analyzes abnormal return from those companies and the average of abnormal return from six companies on each event day. Table 5 shows part of the results.

Full results of the analyzed companies' event day fluctuation are provided in Appendix B.

IMPACT OF OPEC ANNOUNCEMENTS

To study the relationship between OPEC news sentiments and the fluctuation of stock market prices from selected companies, the method of further statistical analysis is highly preferred. In this research, regression analysis is adopted to analyze the relationship between the two variables.

Regression analysis is known as statistical modelling containing a set of statistical processes for the estimation of the relationships among the variables analyzed. Because it can provide a conceptually simple method for the investigation over functional relationships among variables, regression analysis has already turned out to be one of the most widely adopted statistical analysis tools for the analysis of multifactor data. In regression analysis, the standard approach

TABLE 4. CAR and Average CAR of selected companies on each event day

Event Day	1201 CAR	3042 CAR	4324 CAR	5199 CAR	5210 CAR	5218 CAR	Average CAR
2012-06-14	0.017878	0.000696	0.004354	0.007515	0.004741	-0.00479	0.275%
2012-06-28	-0.15662	-0.00093	0.002489	0.006285	-0.00346	-0.00522	-0.149%
2012-07-16	-0.0047	-0.00015	-0.00156	0.00969	0.003104	0.006867	0.103%
2012-09-25	-0.16933	0.005061	0.003416	0.003455	0.00213	0.001936	-0.101%
2012-09-27	-0.0772	0.005612	0.001347	0.002548	0.001517	0.003484	0.160%
2012-10-04	0.013434	0.003167	0.001649	0.005682	0.000719	0.005488	-0.163%
2012-12-12	0.059761	-0.00347	-0.00428	0.00145	0.00067	0.007555	-0.089%
2013-03-21	-0.10686	-0.0005	-0.00367	0.005092	-0.00088	-0.00317	-0.107%
2013-05-31	0.066684	-0.00896	-0.00043	-0.00159	-0.0062	-0.00433	0.149%
2013-07-29	0.024748	-0.00068	-0.0001	-0.00224	0.001968	-0.00444	0.109%
2013-10-24	-0.11317	-0.00084	-0.00355	-0.01668	0.000178	0.000377	0.117%
2013-11-08	-0.04396	0.000248	0.001392	-0.0077	-0.00515	0.001574	-0.158%
2013-11-11	-0.07808	0.000459	0.003281	-0.0077	-0.0004	0.003566	-0.069%

CAR: Cumulative Abnormal Return

TABLE 5. Event day abnormal return of selected companies

Event Day	1201 EDAR	3042 EDAR	4324 EDAR	5199 EDAR	5210 EDAR	5218 EDAR	Average EDAR
2012-06-14	1.014115	-0.002058	0.0316229	0.0012462	-0.007664	-0.018635	0.197%
2012-06-28	-0.21078	-0.005426	0.0017668	0.0319448	-0.005772	-0.012212	-0.972%
2012-07-16	-0.1612	-0.005625	0.0105064	0.0248138	0.0005568	-0.00535	0.753%
2012-09-25	-0.20382	0.002744	0.0312452	-0.017429	-0.001305	-0.00773	-0.775%
2012-09-27	-0.18949	-0.00492	-0.009986	0.0209979	0.0012233	-0.007424	-0.174%
2012-10-04	1.017044	0.005091	0.025657	-0.015447	0.0142035	0.009876	0.777%
2012-12-12	-0.12049	-0.008937	-8.67E-05	0.0014296	-0.003164	0.034529	-0.065%
2013-03-21	-0.19008	0.007456	-0.016063	0.0013382	0.0073135	0.008564	0.646%
2013-05-31	-0.11176	-0.010244	-0.002264	-0.001031	-0.018517	0.086473	0.442%
2013-07-29	-0.64702	-0.018046	-0.005414	0.0007907	0.001837	0.000526	-1.088%
2013-10-24	-0.18625	-0.016155	-0.007501	-0.008892	-0.000298	-0.010341	0.089%
2013-11-08	0.084088	-4.92E-05	0.0018752	-0.021337	-0.010405	0.042241	-0.027%
2013-11-11	-0.02125	0.000162	0.0079629	0.0045972	-0.002588	-0.003016	-0.657%

EDAR: Event Day Abnormal Return

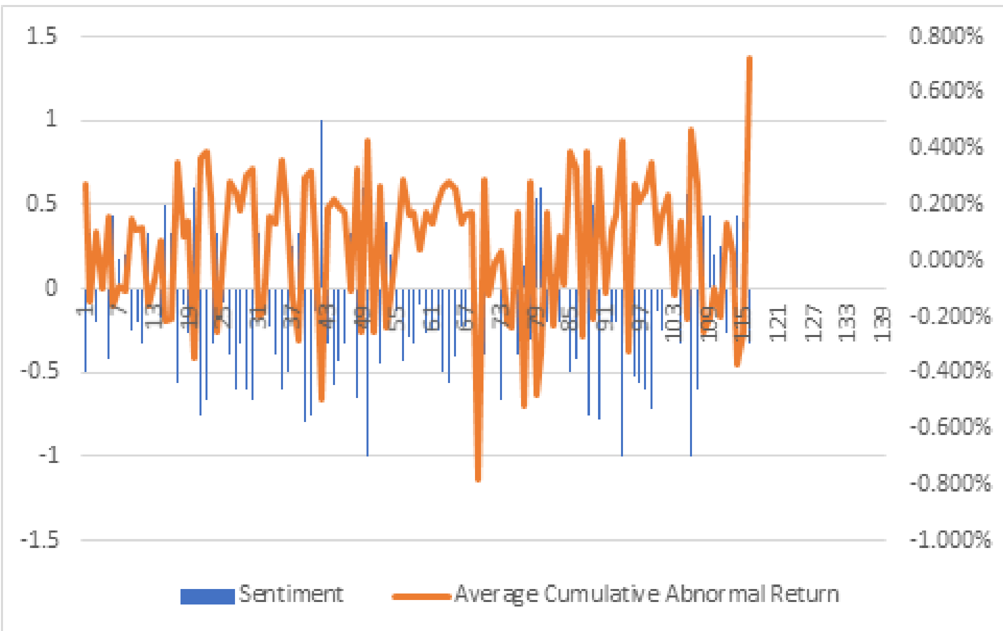

FIGURE 4. Relationship between OPEC news sentiment and ACAR

is regarded as taking data, fitting a model, and then evaluating the fit by using t statistic, F score, and R^2 (Samprit & Hadi 2015).

Before the analysis of the datasets using regression analysis, a diagram was initially generated which shows the overall trending of OPEC news sentiment and fluctuation of stock market prices for selected oil & gas companies. Figure 4 listed shows the relationship between OPEC news sentiments and Average Cumulative Abnormal Return (ACAR) of stock market prices from the selected companies which were observed during the event window according to each event date of the news release.

Figure 4 shows a trend—OPEC news sentiment and ACAR, that is a negative correlation between them. To obtain more detailed statistics on the relationship between OPEC news sentiment and average cumulative abnormal return from the selected companies, the regression analysis was conducted as shown in Table 6 below. The results illustrates the regression analysis on OPEC news sentiments and average cumulative abnormal return from selected companies occurring at the event window.

TABLE 6. The results of regression analysis 1 - Regression Statistics

Regression Statistics	
Multiple R	0.867534064
R Square	0.752615351
Adjusted R Square	0.750445311
Standard Error	0.001266982
Observations	116

It is quite evident there is a strong correlation between the two variables with more than 75 percent of the data fitting into the regression line. Table 7 also listed the results of the analysis of variance (ANOVA).

In Table 8 the p-value for regression is less than 0.05, and t value -2, indicating strong evidence against the null hypothesis (Samprit & Hadi, 2015). A significant linear relationship thus exists between the two variables. The relationship between OPEC news sentiments and ACAR of the selected companies can be expressed as follows:

$$\text{ACAR} = -0.00026291 - 0.00539395 * Sentiment \quad (6)$$

Figure 5 shows the fit along the plot of the sentiment line. The figure further proves the linear relationship between OPEC news sentiment and ACAR of the companies.

The study also examined data on the abnormal return for each selected company following release date of the OPEC news, and the relationship between OPEC news sentiment and these returns on event day. The results may indicate the influence of OPEC news sentiment on stock market prices of the oil & gas companies on the event day.

Figure 6 compares the OPEC news sentiment with average abnormal return (fluctuation) from the selected companies on event day.

There is no significant statistical relationship between OPEC news sentiment and the fluctuation of stock market prices on the event day. The relationship was further examined through regression analysis. The results are listed below.

The R square value is 0.0013584, which is close to 0, indicating non-significant correlation between the

TABLE 7. The results of regression analysis 1 – ANOVA (Part I)

	df	SS	MS	F	*Significance F*
Regression	1	0.000556732	0.000557	346.8208	2.26607E-36
Residual	114	0.000182998	1.61E-06		
Total	115	0.000739729			

TABLE 8. The results of regression analysis 1 – ANOVA (Part II)

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.00026291	0.00012569	-2.09169	0.038687	-0.000511897	-1.39E-05
Sentiment	-0.00539395	0.000289637	-18.6231	2.27E-36	-0.005967719	-0.00482

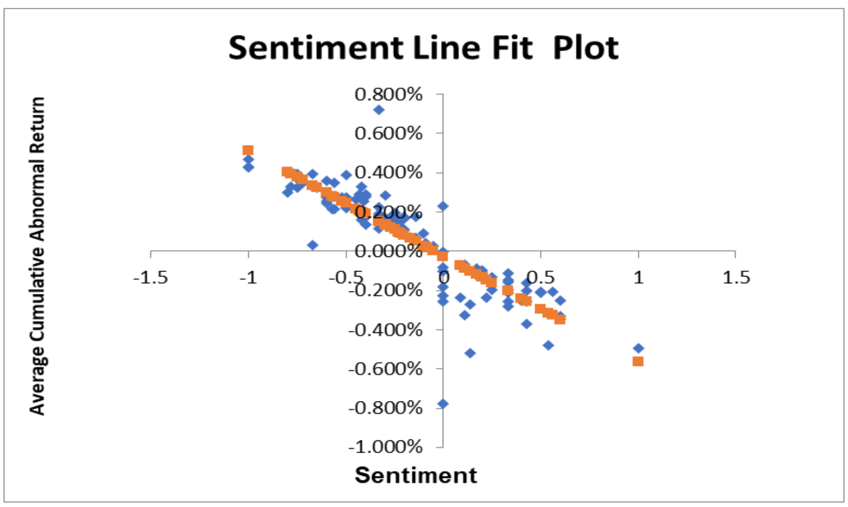

FIGURE 5. Fit plot of sentiment line (ACAR)

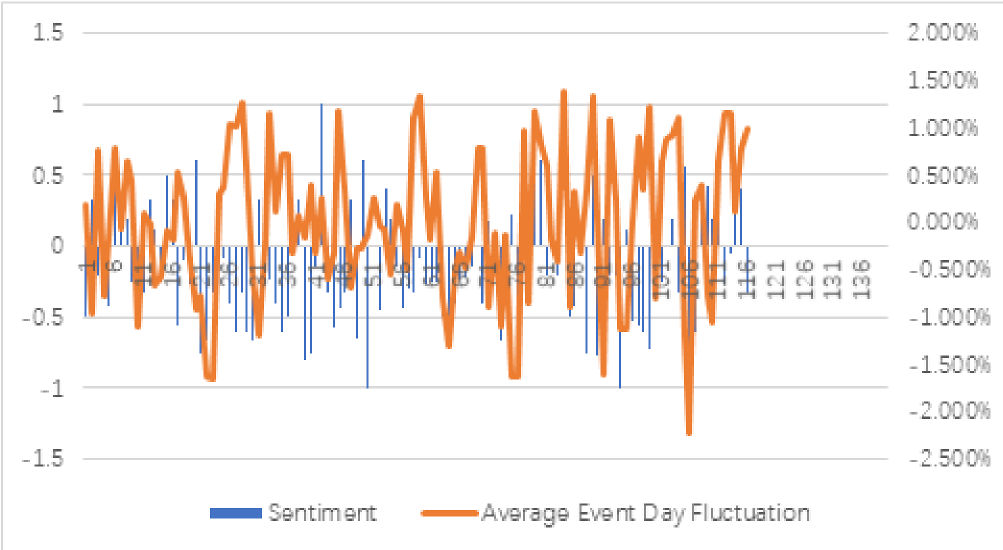

FIGURE 6. Relationship between OPEC news sentiment and AEDF

two variables. Table 10 and Table 11 show the ANOVA results.

The results further confirm the non-significant relationships between the two variables on the event date. Both F and P values are greater than 0.05.

Figure 7 shows the sentiment line fit plot between daily fluctuations and news sentiment based on abnormal returns from the companies studied. Figure 7 further proved the non-significant statistical relationship between OPEC news sentiment and the fluctuation of stock market prices from companies on the event day.

TABLE 9. The results obtained from regression analysis 2 – Regression Statistics

Regression Statistics	
Multiple R	0.0368571
R Square	0.0013584
Adjusted R Square	-0.007402
Standard Error	0.0080873
Observations	116

TABLE 10. The results obtained from regression analysis 2 – ANOVA (Part I)

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	1.01424E-05	1.01E-05	0.155073	0.69446918
Residual	114	0.007456054	6.54E-05		
Total	115	0.007466196			

TABLE 11. The results obtained from regression analysis 2 – ANOVA (Part II)

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.0001397	0.000802295	0.174109	0.862089	-0.00144965	0.001729
Sentiment	0.000728	0.001848783	0.393793	0.694469	-0.00293439	0.0043905

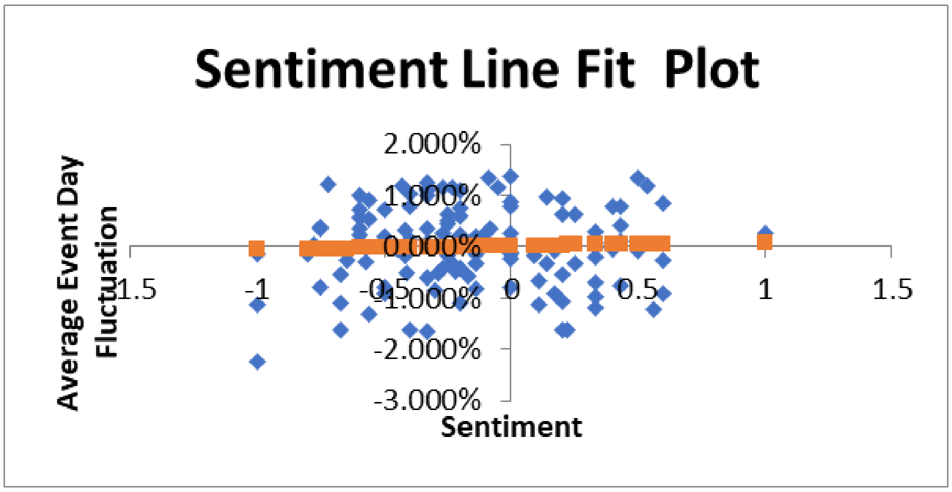

FIGURE 7. Sentiment Line Fit Plot (AEDF)

CONCLUSION

In summary, this study established that there is a negative correlation between OPEC news sentiment and average cumulative abnormal return during the event window in selected companies in the energy sector (oil & gas), based on OPEC news release date. However, there is no significant statistical relationship between OPEC news sentiment and the abnormal return of the selected oil & gas companies, on the event day. The findings provide useful guidelines to stakeholders who invest in those six selected energy sector companies. By investing near the OPEC news release day they thus make a better informed investment decision.

This paper contributes to the existing literature on the OPEC role in the global oil markets and oil & gas companies' stock market returns through the lenses of Malaysia. We developed a financial news sentiment classifier by combining machine learning algorithms and lexicon-based labelling methods. We also used event study methods to examine the impact of OPEC announcements. The machine learning classifier proposed in our study not only can be employed to analyze the sentiment of OPEC effectively but also accurately applied to arrive at a good score by combining with the lexicon-based labelling. Once the sentiment of OPEC announcements is accurately analyzed, this study has achieved its objectives, namely to elucidate the relationship between the sentiment of OPEC announcements and stock market fluctuation in public listed Malaysian oil & gas companies.

Future works can focus on creating a machine learning classifier with improved performance. This can be done in two ways. Firstly, despite the Loughran and McDonald Financial Sentiment Dictionaries updating their word list ever since they were first introduced in 2011, they were still unable to cover all the sentiment words in the financial text. Through building a better lexicon dictionary in the financial domain, the accuracy of lexicon analysis in the financial news text can be improved. Consequently, the accuracy of the machine learning algorithm-based classifier can also be improved through using better training data as processed by an improved lexicon dictionary. Secondly, the machine learning algorithm-based classifier can be improved by applying better parameters. This should require further study in the mathematic domain. By improving the algorithm itself, the performance of the machine learning algorithm-based classifier can also be enhanced.

REFERENCES

Ahmad, P. R. 2016. Political tension in OPEC. *Pro Publico Bono-Magyar Közigazgatás* 2: 118–137.

Akita, R., Yoshihara, A., Matsubara, T. & Uehara, K. 2016. Deep learning for stock prediction using numerical and textual information. *In 2016 IEEE/ACIS 15th International Conference on Computer and Information Science (ICIS)*: 1–6.

Al Rousan, S., Sbia, R. & Tas, B. K. O. 2018. A dynamic network analysis of the world oil market: Analysis of OPEC and non-OPEC members. *Energy Economics* 75: 28–41.

Ali, S., Shahzad, S. J. H., Raza, N. & Al-Yahyaee, K. H. 2018. Stock market efficiency: A comparative analysis of Islamic and conventional stock markets. *Physica A: Statistical Mechanics and Its Applications* 503: 139–153.

Alloghani, M., Al-Jumeily, D., Mustafina, J., Hussian, A. & Aljaaf, A. . 2020. A systematic review on supervised and unsupervised machine learning algorithms for data science. In *Supervised and Unsupervised Learning for Data Science*: 3–21. Springer.

Arif, M. H., Li, J., Iqbal, M. & Liu, K. 2018. Sentiment analysis and spam detection in short informal text using learning classifier systems. *Soft Computing* 22(21): 7281–7291.

Ayyadevara, V. 2018. *Pro Machine Learning Algorithms*. Apress: Berkeley,CA,USA.

Azman Firdaus, A. N. F. 2016. *Interdiscursive Analysis Of Corporate Environmental Reports of Oil and Gas Companies in Malaysia*. University of Malaya.

Bagh, T. 2020. News Sentiments Intricacy: Does News Sentiments Impact Forex Market: An Event Study Approach in Perspective of Pakistan. *Journal of Global Economics* 8(4): 1–5.
Bina, C. & Vo, M. 2007. OPEC in the epoch of globalization: An event study of global oil prices. *Global Economy Journal* 7(1).
Bonaccorso, G. 2018. *Machine Learning Algorithms:Popular algorithms for data science and machine learning.* (2nd ed.). Packt Publishing Ltd.
Chatzis, S. P., Siakoulis, V., Petropoulos, A., Stavroulakis, E. & Vlachogiannakis, N. 2018. Forecasting stock market crisis events using deep and statistical machine learning techniques. *Expert Systems with Applications* 112: 353–371.
Chen, J. L. (Alex), & Hwang, H. (David). 2019. Business cycle, expected return and momentum payoffs. *Finance Research Letters* 29(February): 83–89.
Chen, L. 2017. News-Processed-Dataset. Retrieved from https://figshare.com/articles/News-Processed-Dataset/5296357
Croese, M. & Westerman, W. 2015. OPEC's influence on European oil stock returns. *Energy Technology and Valuation Issues*: 57–80.
Demirer, R. & Kutan, A. M. 2010. The behavior of crude oil spot and futures prices around OPEC and SPR announcements: An event study perspective. *Energy Economics* 32(6): 1467–1476.
Engelberg, J. E. & Parsons, C. A. 2011. The causal impact of media in financial markets. *The Journal of Finance* 66(1): 67–97.
Fama, E. F. 1970. Efficient Capital Markets: A Review of Theory and Empirical work. *The Journal of Finance* 25(2): 383–417.
Fama, E. F., Fisher, L., Jensen, M. C. & Roll, R. 1969. The adjustment of stock prices to new information. *International Ecnomic Review* 10(1): 1–21.
Guidi, M. G. D., Russell, A. & Tarbert, H. 2006. The effect of OPEC policy decisions on oil and stock prices. *OPEC Review* 30(1): 1–18.
Gupta, K. & Banerjee, R. 2018. Does OPEC news sentiment influence stock returns of energy firms in the United States? *Energy Economics* 77: 34–45.
Horan, S. M., Peterson, J. H., Mahar, J., Horan, S. M., Peterson, J. H. & Mahar, J. 2004. Implied volatility of oil futures options surrounding OPEC meetings. *The Energy Journal* 25(3): 103–125.
Hyndman, K. 2008. Disagreement in bargaining: An empirical analysis of OPEC. *International Journal of Industrial Organization* 26(3): 811–828.
Khoj, H. & Akeel, H. 2020. Testing Weak-Form Market Efficiency: The Case of Saudi Arabia. *Asian Economic and Financial Review* 10(6): 644–653.
Khoo, C. S. G. & Johnkhan, S. B. 2018. Lexicon-based sentiment analysis: Comparative evaluation of six sentiment lexicons. *Journal of Information Science* 44(4): 491–511.
Krawczyk, B. 2016. Learning from imbalanced data: open challenges and future directions. *Progress in Artificial Intelligence* 5(4): 221–232.
Loughran, T. I. M. & Mcdonald, B. 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance* 66(1): 35–65.
Loutia, A., Mellios, C. & Andriosopoulos, K. 2015. Do OPEC announcements influence oil prices? *Energy Pol* 90: 262–272.
Mensi, W., Hammoudeh, S. & Yoon, S. M. 2014. How do OPEC news and structural breaks impact returns and volatility in crude oil markets? Further evidence from a long memory process. *Energy Economics* 42: 343–354.
Mikolov, T., Corrado, G., Chen, K. & Dean, J. 2013. Efficient estimation of word representations in vector space. *ArXiv Preprint ArXiv:*1301.3781: 1–12.
Moreno-Marcos, P. M., Alario-Hoyos, C., Munoz-Merino, P. J., Estevez-Ayres, I. & Kloos, C. D. 2018. Sentiment analysis in MOOCs: A case study. *IEEE Global Engineering Education Conference, EDUCON*: 1489–1496.
Narayan, P. K. & Gupta, R. 2015. Has oil price predicted stock returns for over a century? *Energy Economics* 48: 18–23.
Narayan, S. & Narayan, P. K. 2017. Are oil price news headlines statistically and economically significant for investors? *Journal of Behavioral Finance* 18(3): 258–270.
Nisar, T. M. & Yeung, M. 2018. Twitter as a tool for forecasting stock market movements: A short-window event study. *Journal of Finance and Data Science* 4(2): 101–119.
Philipp, L. & Andre, K. S. 2016. Information processing in freight and freight forward markets: an event study on OPEC announcements. *Diskussionspapier*: 172.
Qiu, J., Wang, B. & Zhou, C. 2020. Forecasting stock prices with long-short term memory neural network based on attention mechanism. *PLoS ONE* 15(1): 1–15.
Razek, N. H. A. & Michieka, N. M. 2019. OPEC and non-OPEC production, global demand, and the financialization of oil. *Research in International Business and Finance* 50(May): 201–225.
Samprit, C. & Hadi, A. 2015. *Regression analysis by example*. John Wiley & Sons.
Schmidbauer, H. & Rösch, A. 2012. OPEC news announcements: Effects on oil price expectation and volatility. *Energy Economics* 34(5): 1656–1663.
Shantha Gowri, B. & Ram, V. S. 2019. Influence of news on rational decision making by financial market investors. *Investment Management and Financial Innovations* 16(3): 142–156.
Song, C., Wang, X. K., Cheng, P. -F., Wang, J. -Q. & Li, L. 2020. SACPC: A framework based on probabilistic linguistic terms for short text sentiment analysis. *Knowledge-Based Systems* 194: 105572.
Sorescu, A., Warren, N. L. & Ertekin, L. 2017. Event study methodology in the marketing literature: an overview. *Journal of the Academy of Marketing Science* 45(2): 186–207.
Sorto, M., Aasheim, C., Wimmer, H. & Wimmer, H. 2017. Feeling The Stock Market: A Study in the Prediction of Financial Markets Based on News Sentiment. Proceedings of the Southern Association for Information Systems Conference, 24 -25 March. St. Simons Island, GA, USA, 1-8.
Sutton, R. S. & Barto, A. G. 2018. *Reinforcement learning: An introduction*. MIT Press.
Uhl, M. W. 2014. Reuters Sentiment and Stock Returns. *Journal of Behavioral Finance* 15(4): 287–298.
Will, L., Benoit, K., Slava, M. & Laver, M. 2011. Scaling policy preferences from coded political texts. *Legislative Studies Quarterly* 36(1): 123–155.

Wisniewski, T. P. & Lambe, B. 2013. The role of media in the credit crunch: The case of the banking sector. *Journal of Ecnomic Behavior and Organization* 85(1): 163–175.

Xiao, J., Hu, C., Ouyang, G. & Wen, F. 2019. Impacts of oil implied volatility shocks on stock implied volatility in China: Empirical evidence from a quantile regression approach. *Energy Economics* 80: 297–309.

Yadav, R., Kumar, A. V. & Kumar, A. 2019. News based supervised sentiment analysis for prediction of futures buying behaviour. *IIMB Management Review*.

Yu-Ling Hsiao, Lin, W., Wei, X., Yan, G., Li, S. & Sheng, N. 2019. The impact of international oil prices on the stock price fluctuations of China's renewable energy enterprises. *Energies* 12(4630): 1–17.

Yu, T. H. K. & Huarng, K. H. 2020. A new event study method to forecast stock returns: The case of Facebook. *Journal of Business Research* 115(June): 317–321.

Ling Wu*
Department of Software Engineering
Faculty of Computer Science & Information Technology
University of Malaya
50603 Kuala Lumpur
MALAYSIA.
E-mail: wuling@siswa.um.edu.my

Siew Hock Ow
Department of Software Engineering
Faculty of Computer Science & Information Technology
University of Malaya
50603 Kuala Lumpur
MALAYSIA.
E-mail: show@um.edu.my

* Corresponding author

APPENDIX A. CAR and Average CAR of selected companies on each event day

Event Date	1201 CAR	3042 CAR	4324 CAR	5199 CAR	5210 CAR	5218 CAR	Average CAR
2012-06-14	0.017878	0.000696	0.004354	0.007515	0.004741	-0.00479	0.275%
2012-06-28	-0.15662	-0.00093	0.002489	0.006285	-0.00346	-0.00522	-0.149%
2012-07-16	-0.0047	-0.00015	-0.00156	0.00969	0.003104	0.006867	0.103%
2012-09-25	-0.16933	0.005061	0.003416	0.003455	0.00213	0.001936	-0.101%
2012-09-27	-0.0772	0.005612	0.001347	0.002548	0.001517	0.003484	0.160%
2012-10-04	0.013434	0.003167	0.001649	0.005682	0.000719	0.005488	-0.163%
2012-12-12	0.059761	-0.00347	-0.00428	0.00145	0.00067	0.007555	-0.089%
2013-03-21	-0.10686	-0.0005	-0.00367	0.005092	-0.00088	-0.00317	-0.107%
2013-05-31	0.066684	-0.00896	-0.00043	-0.00159	-0.0062	-0.00433	0.149%
2013-07-29	0.024748	-0.00068	-0.0001	-0.00224	0.001968	-0.00444	0.109%
2013-10-24	-0.11317	-0.00084	-0.00355	-0.01668	0.000178	0.000377	0.117%
2013-11-08	-0.04396	0.000248	0.001392	-0.0077	-0.00515	0.001574	-0.158%
2013-11-11	-0.07808	0.000459	0.003281	-0.0077	-0.0004	0.003566	-0.069%
2013-12-04	0.003706	0.000342	0.002247	0.016507	-0.00286	0.003676	0.069%
2014-03-31	-0.00364	0.001158	-0.00141	-0.00141	0.004962	0.010471	-0.214%
2014-04-30	0.00313	0.001505	0.000733	0.007446	-0.00076	-0.00177	-0.211%
2014-06-11	0.002771	-0.00972	1.61E-05	0.006066	0.00453	0.00693	0.348%
2014-06-24	0.017716	-0.00731	-0.00105	0.006126	-0.00037	0.004041	0.089%
2014-07-18	0.016524	0.00342	-0.00322	0.00187	0.007025	-0.00414	0.144%
2014-09-16	-0.01125	-0.00158	-0.00496	-0.00301	0.015471	-0.02804	-0.344%
2014-10-02	-0.01236	0.001063	0.002992	0.002461	-0.01277	-0.01005	0.369%
2014-11-27	-0.01271	-0.00796	0.001157	0.005933	-0.016	-0.01101	0.392%
2015-02-05	-0.00527	-0.00035	0.00486	0.000849	-0.0064	-0.00394	0.226%
2015-06-04	-0.00227	-0.00275	0.001735	0.009274	-0.00501	-0.00266	-0.255%
2015-06-05	-0.00227	-0.00122	0.000247	0.008258	-0.00603	-0.0037	0.031%
2015-06-24	0.004333	-0.00252	-0.00065	0.003934	0.008058	0.005597	0.279%
2015-07-30	-0.0085	0.007309	0.001643	0.00608	-0.00306	0.000992	0.245%
2015-09-01	0.020796	-0.00136	0.00115	-0.00123	0.003898	0.018048	0.178%
2015-09-08	0.022415	0.001679	0.004682	0.001951	0.012716	0.01774	0.301%
2015-12-04	-0.00904	0.022478	0.005041	0.026234	-0.01533	-0.01389	0.327%
2015-12-18	0.002058	0.005385	0.010402	0.022554	0.000154	0.003946	-0.199%
2016-03-21	-0.00062	0.007902	0.015104	-0.02132	0.00401	-0.01703	-0.181%
2016-06-02	-0.00054	0.005799	0.001301	0.011421	0.006907	0.010145	0.158%
2016-06-22	-0.00104	0.005824	-0.00056	-0.00288	0.004659	0.001533	0.134%
2016-06-30	0.004924	0.004537	0.000639	-0.0004	0.008956	0.004958	0.361%
2016-08-01	0.00582	0.002985	0.000982	-0.00585	-0.0015	0.006969	0.221%
2016-08-04	-0.01507	0.010567	0.001196	-0.00775	-0.0029	0.001086	-0.132%
2016-08-08	0.001007	0.01515	0.00123	-0.0023	0.001858	0.008449	-0.282%
2016-09-05	-0.00519	-0.00565	-0.00025	-0.00846	0.012375	-0.00517	0.300%
2016-09-06	-0.00857	-0.00589	-0.00129	-0.00782	0.009902	-0.00692	0.323%
2016-09-09	-0.00872	-0.00528	-0.00044	0.005505	-0.00945	-0.00311	0.066%
2016-09-26	-0.00305	-0.0028	0.001249	0.001474	-0.00838	0.000872	-0.493%
2016-09-28	-0.00091	-0.00186	0.000402	-0.0018	-0.00703	0.004162	0.190%
2016-10-14	0.014638	0.00684	-0.00011	0.028373	-0.00078	-0.00131	0.217%

cont.

cont.

2016-10-18	-6.2E-05	0.001486	0.000615	0.046613	-0.0027	-0.00167	0.195%
2016-10-19	-6.2E-05	-0.00101	0.000291	0.020263	-0.00538	-0.00583	0.172%
2016-10-24	-0.01521	-0.00168	0.000214	0.012695	-0.01231	-0.00087	-0.111%
2016-10-26	-0.03191	-0.00477	-0.0003	0.015108	0.003575	-0.00632	0.326%
2016-10-29	0.007629	0.035339	0.020334	0.049399	0.010225	-0.00817	-0.253%
2016-11-02	-0.02612	-0.00276	-0.0016	-0.02181	-0.0015	-0.00832	0.428%
2016-11-05	-0.00254	-0.00576	-0.00029	-0.02168	-0.00552	-0.01391	-0.254%
2016-11-07	-0.00254	-0.00576	-0.00029	-0.02168	-0.00552	-0.01391	0.266%
2016-11-08	0.005291	-0.00259	0.001017	-0.02214	-0.00705	-0.01348	-0.239%
2016-11-17	0.022626	1.43E-06	0.001172	-0.0217	-0.01565	0.000229	-0.131%
2016-11-19	0.014109	-0.00049	-0.00207	-0.0119	-0.01897	0.001125	0.067%
2016-11-21	0.014109	-0.00049	-0.00207	-0.0119	-0.01897	0.001125	0.290%
2016-11-30	-0.00999	-0.0063	-0.02977	0.00185	-0.01243	0.00596	0.166%
2016-12-10	0.021935	-0.00099	-0.01654	0.015432	0.016308	0.008055	0.176%
2016-12-13	0.021935	-0.00099	-0.01654	0.015432	0.016308	0.008055	0.042%
2016-12-14	0.025654	-0.00079	-0.01186	0.018369	0.01556	0.010988	0.176%
2016-12-15	0.023694	-0.00169	0.000775	0.016762	0.014956	0.008688	0.134%
2016-12-16	0.019534	-0.00106	0.002139	0.019336	0.013466	0.010079	0.197%
2017-01-08	-0.01291	0.000371	0.030583	-0.00447	0.002453	-0.00177	0.259%
2017-01-11	-0.03127	0.002807	0.033946	-0.00399	-0.00559	-0.00606	0.279%
2017-01-14	-0.03163	0.002064	0.019352	-0.00778	-0.00534	-0.00993	0.257%
2017-01-17	-0.03853	0.006234	0.009164	-0.01747	-0.0071	-0.00845	0.135%
2017-01-22	-0.02024	0.007943	0.01435	-0.02296	-0.00806	-0.00389	0.162%
2017-02-07	-0.00045	0.011701	0.007946	-0.00126	0.008344	0.005039	0.176%
2017-02-08	-0.00579	0.010741	0.004046	0.000619	0.005104	0.003844	-0.780%
2017-02-14	-0.01869	-0.00307	-0.00663	-0.01542	0.019848	0.004551	0.290%
2017-02-15	-0.02878	-0.0031	-0.00672	-0.01644	0.021553	8.05E-05	-0.123%
2017-02-21	-0.03713	0.047491	0.049192	-0.03285	0.003037	-0.00851	-0.003%
2017-02-24	-0.00934	0.014748	0.006372	-0.01699	0.003411	-0.00078	0.033%
2017-03-06	-0.01034	-0.01945	0.004042	-0.02087	-0.01199	-0.00552	-0.225%
2017-03-10	-0.0087	-0.01964	-0.01919	-0.01797	-0.0038	-0.00695	-0.235%
2017-03-11	-0.00632	-0.01979	-0.01965	-0.01503	-0.00415	-0.00946	0.176%
2017-03-16	0.008244	-0.01801	-0.01645	-0.01402	-0.00302	-0.01359	-0.519%
2017-03-26	0.002164	-0.00377	-0.0106	0.013021	-0.00498	-0.00495	0.284%
2017-04-04	0.004483	0.001294	0.00749	0.027446	0.005431	0.01073	-0.480%
2017-04-11	0.006669	-0.00964	0.000111	0.002844	0.005137	0.005709	-0.330%
2017-04-24	-0.00644	0.008901	0.000428	0.001141	-0.00105	0.000592	0.173%
2017-04-27	-0.00672	0.00459	-0.00492	-0.00164	0.000941	-0.00475	-0.235%
2017-04-28	0.000274	0.01117	-0.00531	-0.00015	0.000959	-0.00296	0.089%
2017-05-22	0.006207	-0.01561	0.017224	-0.00347	-0.00356	-0.00279	-0.082%
2017-05-24	-0.01034	-0.01495	0.004926	0.00845	-0.00249	-0.00785	0.387%
2017-05-25	-0.01127	-0.01259	0.009052	0.0108	0.001068	-0.00451	0.330%
2017-05-31	0.016847	0.060591	0.092551	0.029248	0.022477	-0.00684	-0.270%
2017-06-01	-0.00053	-0.01352	0.001727	0.005875	-0.00182	-0.00294	0.391%
2017-06-09	-0.0027	-0.01319	-0.01974	-0.01279	-0.00144	0.00558	-0.205%

cont.

cont.

2017-06-13	0.007653	-0.01418	-0.0189	-0.01123	-0.00264	-0.00776	0.328%
2017-06-22	0.015135	-0.01722	-0.02382	-0.00766	-5.5E-05	-0.01444	-0.118%
2017-06-26	-0.00358	-0.00966	-0.01558	0.002105	0.001553	-0.00529	0.111%
2017-07-18	-0.00506	0.009327	0.010092	0.002722	-0.00238	0.000774	0.163%
2017-07-23	-0.00515	0.010973	0.029847	0.004789	-0.00388	-0.00367	0.430%
2017-07-24	-0.00515	0.010973	0.029847	0.004789	-0.00388	-0.00367	-0.324%
2017-07-29	-0.00798	0.013618	0.0353	0.003635	-0.00201	-0.0016	0.273%
2017-08-02	0.01241	0.005866	0.024854	0.014403	0.002564	0.002842	0.214%
2017-08-08	0.003269	-0.00537	-0.01602	0.009174	0.00302	0.000988	0.254%
2017-08-14	0.01123	-0.01479	-0.00833	0.00869	0.006239	8.32E-06	0.348%
2017-08-24	0.006129	-0.00723	-0.01084	-0.00662	0.003912	-0.00274	0.067%
2017-09-05	0.001145	0.016997	0.005642	0.00323	-0.00111	0.012313	0.165%
2017-09-06	0.001145	0.01251	0.003627	0.00491	-0.00046	0.01005	0.232%
2017-09-14	0.021204	0.004918	-0.00409	0.036973	0.000253	0.013017	-0.125%
2017-09-15	0.021204	0.003704	-0.00558	0.035126	-0.00144	0.004986	0.141%
2017-09-22	0.01159	0.00068	-0.00094	0.036371	-0.00328	-0.0018	-0.209%
2017-09-28	-0.01296	0.002822	0.00367	-0.01139	-0.00671	-0.01342	0.469%
2017-09-29	-0.02227	0.002891	0.000542	-0.00053	-0.00777	-0.01209	0.276%
2017-10-10	-0.00952	0.003089	0.003031	0.002542	0.000608	0.001574	-0.258%
2017-10-21	-0.00082	-0.00718	-0.00421	-0.02284	0.001264	0.005173	-0.201%
2017-10-24	-0.00082	-0.00385	-0.00124	-0.02472	0.001891	0.003771	-0.099%
2017-11-07	0.017938	0.002222	0.019262	-0.01155	0.007733	-0.00673	-0.198%
2017-11-30	0.003215	0.00109	-0.00191	-0.00158	-0.00397	-0.0279	0.136%
2017-12-01	-0.00588	-0.00179	-0.00271	0.000573	-0.0082	-0.0388	0.026%
2017-12-13	-0.01298	0.012403	0.013253	0.00718	-0.0045	-0.04685	-0.371%
2017-12-20	-0.00056	0.004301	0.018724	0.002203	0.001917	0.011223	-0.251%
2017-12-21	0.015202	0.007214	0.021001	0.000526	0.0033	0.009911	0.723%

APPENDIX B. Event Day Abnormal Return of Selected Companies

Event Date	1201 EDAR	3042 EDAR	4324 EDAR	5199 EDAR	5210 EDAR	5218 EDAR	Average EDAR
2012-06-14	1.014115	-0.002058	0.0316229	0.0012462	-0.007664	-0.018635	0.197%
2012-06-28	-0.21078	-0.005426	0.0017668	0.0319448	-0.005772	-0.012212	-0.972%
2012-07-16	-0.1612	-0.005625	0.0105064	0.0248138	0.0005568	-0.00535	0.753%
2012-09-25	-0.20382	0.002744	0.0312452	-0.017429	-0.001305	-0.00773	-0.775%
2012-09-27	-0.18949	-0.00492	-0.009986	0.0209979	0.0012233	-0.007424	-0.174%
2012-10-04	1.017044	0.005091	0.025657	-0.015447	0.0142035	0.009876	0.777%
2012-12-12	-0.12049	-0.008937	-8.67E-05	0.0014296	-0.003164	0.034529	-0.065%
2013-03-21	-0.19008	0.007456	-0.016063	0.0013382	0.0073135	0.008564	0.646%
2013-05-31	-0.11176	-0.010244	-0.002264	-0.001031	-0.018517	0.086473	0.442%
2013-07-29	-0.64702	-0.018046	-0.005414	0.0007907	0.001837	0.000526	-1.088%
2013-10-24	-0.18625	-0.016155	-0.007501	-0.008892	-0.000298	-0.010341	0.089%
2013-11-08	0.084088	-4.92E-05	0.0018752	-0.021337	-0.010405	0.042241	-0.027%
2013-11-11	-0.02125	0.000162	0.0079629	0.0045972	-0.002588	-0.003016	-0.657%
2013-12-04	0.006453	0.007221	0.0069379	-0.004831	0.0042619	-0.005216	-0.559%
2014-03-31	-0.01634	0.000771	-0.002578	-0.007756	0.0193259	0.004478	-0.086%

cont.

cont.

2014-04-30	0.004405	0.002312	0.0011833	0.0011866	-0.000537	-0.004736	-0.188%
2014-06-11	0.000893	-0.002814	0.0003222	0.0095675	-0.008064	0.034435	0.540%
2014-06-24	0.128316	-0.010496	0.0003238	0.0094792	0.0008738	-0.001695	0.256%
2014-07-18	0.005783	0.00625	-0.0079	-0.005326	-0.002445	-0.009096	-0.403%
2014-09-16	-0.02946	0.000322	0.0046202	0.0078953	-0.02431	-0.001508	-0.908%
2014-10-02	0.001835	0.011599	0.0086135	0.0086008	-0.023228	-0.027916	-0.783%
2014-11-27	-0.04452	-0.010906	0.0014429	0.0102636	-0.04955	-0.036282	-1.630%
2015-02-05	-0.05028	0.026597	-0.013806	-0.008894	-0.038094	-0.023923	-1.656%
2015-06-04	0.002107	-0.006312	-0.000146	0.1072304	0.0026234	-0.017843	0.296%
2015-06-05	-0.02289	-0.049947	-0.052355	0.0232729	-0.013094	-0.006869	0.364%
2015-06-24	0.080803	-0.002239	-0.002063	0.0075871	0.020046	0.008346	1.037%
2015-07-30	0.001332	-0.001324	-0.000169	-0.002221	0.0212118	0.032325	1.014%
2015-09-01	0.011368	-0.021571	0.0060867	-0.006051	-0.009733	0.05166	1.262%
2015-09-08	0.088181	0.000632	-0.002819	-0.004289	0.0069671	0.033175	0.583%
2015-12-04	0.004079	0.031915	-0.006562	0.1293083	-0.013852	-0.010905	-0.542%
2015-12-18	0.004479	-0.023732	0.0046812	-0.015821	-0.021847	-0.030406	-1.200%
2016-03-21	-0.00062	0.014382	0.0166574	-0.011079	0.0062615	-0.016989	-0.230%
2016-06-02	0.003233	-0.008135	0.0201293	-0.021226	0.0228108	0.022545	1.159%
2016-06-22	0.052641	0.011543	0.0032159	0.0272106	0.0386753	-0.004298	0.127%
2016-06-30	-0.04334	0.012005	0.000284	-0.000542	0.0247192	0.017059	0.717%
2016-08-01	0.004276	-0.006504	0.0104457	-0.001484	-0.000392	0.006226	0.726%
2016-08-04	-0.0025	0.001594	-0.006537	-0.003278	-0.002419	0.008189	-0.320%
2016-08-08	0.000528	0.041281	0.0002821	-0.002491	0.0042651	-0.000255	0.081%
2016-09-05	-0.00091	-0.008592	0.0030128	-0.004206	0.005442	0.016092	-0.154%
2016-09-06	0.000495	0.011919	0.003146	-0.001289	-0.004321	0.004484	0.385%
2016-09-09	0.000846	-0.010457	0.003121	-0.022007	-0.012374	0.003581	-0.320%
2016-09-26	0.060226	-0.004203	0.0009452	-0.026802	-0.006629	-0.022448	0.261%
2016-09-28	0.003254	-0.004584	-0.00316	-0.002038	-0.005247	-0.016043	-0.590%
2016-10-14	0.008288	0.010913	-0.00012	-0.019835	-0.002146	-0.013504	-0.309%
2016-10-18	0.067117	-0.001946	0.0035945	-0.020668	0.0038812	-0.005122	1.174%
2016-10-19	0.004617	0.02312	-7.81E-06	-0.027931	0.0176016	-0.008058	0.339%
2016-10-24	0.004617	-0.018578	0.0002115	0.1683041	-0.014303	-0.006419	-0.682%
2016-10-26	0.002828	-0.022724	-6.4E-06	0.0071364	0.0022298	-0.008608	-0.261%
2016-10-29	0.084284	-0.01835	0.0002107	0.0069153	0.0165663	-0.001996	-0.262%
2016-11-02	-0.08042	-0.010105	-0.003383	-0.048211	-0.004678	-0.006614	-0.138%
2016-11-05	0.011343	-0.003915	-0.003274	0.0348384	0.0089653	-0.00158	0.267%
2016-11-07	0.011343	-0.003915	-0.003274	0.0348384	0.0089653	-0.00158	-0.046%
2016-11-08	0.008565	-0.001362	0.0001036	-0.016584	0.0151236	0.011192	-0.059%
2016-11-17	0.01202	-0.003933	0.0005415	-0.070692	-0.030375	-0.006221	-0.538%
2016-11-19	0.011768	0.001333	0.0069407	0.082834	0.0030376	0.009272	0.186%
2016-11-21	0.011768	0.001333	0.0069407	0.082834	0.0030376	0.009272	-0.079%
2016-11-30	0.095933	-0.002537	-0.003094	-0.005547	-0.021856	0.025817	-0.505%
2016-12-10	0.111192	-0.005781	0.0215899	0.0253843	0.0417325	0.040528	1.111%
2016-12-13	0.111192	-0.005781	0.0215899	0.0253843	0.0417325	0.040528	1.327%
2016-12-14	0.014222	0.010745	0.0099591	0.0760224	0.0152083	-0.01616	0.263%

cont.

cont.

2016-12-15	0.012261	-0.011181	0.0059491	0.0430245	-0.009391	0.001943	-0.177%
2016-12-16	-0.08198	0.007446	0.0144779	-0.013259	0.0153357	0.015037	0.522%
2017-01-08	0.045427	-0.011546	0.0868888	0.0776123	0.0014396	-0.009864	-0.802%
2017-01-11	-0.07562	-0.011504	0.0047275	0.0234743	-0.009949	-0.028871	-1.302%
2017-01-14	-0.14189	0.009816	-0.017423	-0.097222	-0.018735	-0.024049	-0.499%
2017-01-17	0.052684	0.015094	0.0082066	0.0579329	0.0030903	0.000146	-0.312%
2017-01-22	-0.01575	0.017386	-0.00078	-0.009313	-0.038016	-0.005586	-0.489%
2017-02-07	-0.0135	0.035348	0.0330739	-0.020266	0.0075415	-0.029778	-0.149%
2017-02-08	-0.12461	0.0042	0.0308902	-0.028607	-0.01742	0.01928	0.778%
2017-02-14	-0.01461	0.02531	-0.010445	-0.030646	0.0145233	0.018763	0.776%
2017-02-15	-0.01935	-0.007894	-0.014309	-0.040619	-0.022195	-0.008664	-0.897%
2017-02-21	-0.07024	-0.055544	0.0215682	0.0090715	0.0027841	-0.004173	-0.118%
2017-02-24	-0.06315	0.006467	-0.036376	0.0008183	-0.035932	0.010898	-1.091%
2017-03-06	-0.06613	-0.012712	-0.010598	0.0079506	-0.019808	0.006669	-0.126%
2017-03-10	0.067923	-0.039992	-0.043194	-0.058326	-0.012845	-0.052407	-1.628%
2017-03-11	-0.06779	-0.027987	-0.026709	-0.04662	-0.026607	0.005256	-1.628%
2017-03-16	0.000939	-0.001643	0.0002622	0.0106862	0.0233655	0.037944	0.977%
2017-03-26	0.000919	-0.01599	-0.009066	-0.030435	-0.032999	-0.008952	-0.845%
2017-04-04	0.003184	-0.004898	0.0020224	-0.012452	0.0107339	0.068925	1.183%
2017-04-11	0.00537	-0.022511	-0.00851	0.0034053	2.323E-05	0.029315	0.841%
2017-04-24	-0.00125	-0.001362	-0.000807	0.0019794	-0.009505	0.004282	0.593%
2017-04-27	-0.06776	-0.002569	-0.012017	-0.009074	-0.007807	-0.009237	-0.182%
2017-04-28	0.070337	0.027537	-0.00805	-0.009884	-0.007873	0.004102	-0.411%
2017-05-22	0.080549	-0.013303	0.0315373	0.033242	0.0057952	0.019975	1.383%
2017-05-24	0.001062	-0.001952	8.442E-05	-0.033301	-0.007935	0.003016	-0.899%
2017-05-25	0.001221	-0.011633	0.0824571	-0.010072	0.0055591	0.00374	0.335%
2017-05-31	-0.07829	-0.032903	-0.062612	0.1341881	0.0476086	-0.05332	-0.325%
2017-06-01	0.005775	0.027194	0.0514412	0.0126463	-0.00614	0.018126	0.350%
2017-06-09	0.003498	-0.011343	-0.031945	-0.024487	0.0134242	0.041248	1.332%
2017-06-13	0.006276	-0.005424	-0.010179	-0.002039	0.0002636	0.00712	0.060%
2017-06-22	0.006182	-0.040705	-0.059848	-0.014513	-0.013372	-0.024094	-1.611%
2017-06-26	0.003311	-0.003527	-0.016966	-0.011893	-0.019689	0.002797	1.093%
2017-07-18	0.001554	0.026526	0.0113134	-0.022633	0.0019522	0.005169	0.241%
2017-07-23	0.001465	-0.010736	0.0189674	-0.007515	0.0011033	-0.003855	-1.130%
2017-07-24	0.001465	-0.010736	0.0189674	-0.007515	0.0011033	-0.003855	-1.130%
2017-07-29	-0.00136	0.015884	0.139932	0.0035667	0.0090175	-0.002166	0.036%
2017-08-02	0.001667	0.021327	0.0523676	0.0032486	0.0103885	0.012916	0.897%
2017-08-08	0.101616	-0.047645	-0.025278	0.1107161	0.0096027	0.012509	0.348%
2017-08-14	0.001313	-0.015099	-0.042925	0.0229508	0.0304359	0.014832	1.233%
2017-08-24	-0.09571	0.000174	-0.007748	0.0097465	-0.004932	-0.003153	-0.807%
2017-09-05	0.001145	0.032586	0.0110566	-0.024927	-0.000544	0.024739	0.646%
2017-09-06	0.001145	0.024561	0.0097557	0.047252	0.000123	0.046013	0.873%
2017-09-14	0.001751	0.006515	-0.005498	-0.012644	0.0119936	0.015152	0.934%
2017-09-15	0.101751	-0.014026	-0.008359	0.0313859	0.0181117	0.051228	1.102%
2017-09-22	-0.00098	-0.002091	-0.001248	-0.003494	-0.002183	-0.000649	-1.215%

cont.

cont.

2017-09-28	0.083569	0.002982	0.0011442	-0.021872	-0.01672	-0.077988	-2.232%
2017-09-29	-0.09114	-0.005291	0.0004159	-0.013117	0.0040027	0.016701	0.235%
2017-10-10	-0.00195	0.004668	0.0027193	0.030375	0.0075795	0.000239	0.405%
2017-10-21	-0.10183	0.025418	0.005761	-0.028537	0.0006061	-0.009066	-0.771%
2017-10-24	-0.00183	-0.023411	-0.016419	-0.071754	0.0076484	-0.023402	-1.058%
2017-11-07	-0.0019	0.00457	0.0155067	-0.00432	-0.005928	0.021093	0.639%
2017-11-30	-0.0988	-0.030258	-0.026153	-0.023004	0.0112041	0.009607	1.143%
2017-12-01	0.001195	-0.00286	-0.00833	-0.002197	-0.002948	0.002029	1.143%
2017-12-13	-0.10591	0.015153	0.0366855	0.0151083	-0.008888	-0.004985	0.116%
2017-12-20	-0.00258	0.024698	0.0181719	-0.005002	0.0131458	0.000557	0.781%
2017-12-21	0.004091	-0.003773	-0.023083	0.0084504	0.0008139	0.014642	0.999%