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To cite this article: Yue-Jun Zhang & Shu-Hui Li (2019): The impact of investor sentiment on crude oil market risks: evidence from the wavelet approach, Quantitative Finance, DOI: 10.1080/14697688.2019.1581368

To link to this article: https://doi.org/10.1080/14697688.2019.1581368

Published online: 22 Mar 2019.
The impact of investor sentiment on crude oil market risks: evidence from the wavelet approach

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(Received 2 September 2018; accepted 1 February 2019; published online 22 March 2019)

Investor sentiment has become an important factor affecting oil price volatility and extreme risk. Therefore, we utilise a VaR-GARCH model to detect the extreme risk of the crude oil market during 2007–2017, and then explore the causality between investor sentiment and extreme risk in the crude oil market, and their lead-lag and co-movement relationships in the time-frequency domain. The empirical results show that: firstly, investor sentiment leads downside risk but lags the upside risk in the crude oil market; secondly, in the time domain, there is a co-movement between investor sentiment and extreme risk in the crude oil market, in particular, investor sentiment may Granger cause extreme risk in the crude oil market at the 1% significance level but not vice versa; thirdly, in the frequency domain, weak coherence can be found in high-frequency bands but increases in low-frequency bands during the whole sample period, which indicates that the impact of investor sentiment on extreme risk in the crude oil market will last for a long time, although the affected period tends to decrease.

Keywords: Investor sentiment; Extreme risk; Crude oil market; Wavelet

1. Introduction

With the development of economic globalisation and financial liberalisation, price fluctuations in the crude oil market have become increasingly intense, and have further increased the revenue risk of market participants (Zhang and Wei 2011). As a result, extreme risk in the crude oil market has had a significant impact on the stable development of many national economies. For example, Katircioglu et al. (2015) report a statistically significant negative impact of the crude oil price on GDP, CPI and unemployment in OECD countries in the long term. Reboredo and Ugolini (2016) analyse the effect of crude oil market risk on different stock returns for three developed economies (USA, UK, and European Monetary Union) and five BRICs countries. They find that the upside spillover effect of extreme rises in crude oil prices on stock returns is larger than the downside spillover effect.

As a matter of fact, the crude oil market is a typical complex system; the extreme risk of the crude oil market results from a combination of a series of uncertain factors, including fundamental factors such as supply, demand and inventory, and non-fundamental factors such as speculative transactions and the US dollar exchange rate (Zhang et al. 2008, Ratti et al. 2016, Miao et al. 2017, Yao et al. 2017). These driving factors will be reflected by the changes in investor sentiment in the crude oil market, thus impacting the volatility of crude oil returns and risks.

In recent years, investor sentiment has received widespread attention in financial markets (Benhabiba et al. 2016). Lee et al. (2002), for example, confirm that change in investor sentiment is a systemic risk which is ultimately priced; in the stock market, if investors are optimistic over a certain period, this tends to raise stock prices and brings better returns, which is called the Bandwagon effect (Brown and Cliff 2005). Sayim and Rahman (2015) examine the effects of institutional and individual investor sentiment on the returns and volatility of the Istanbul Stock Market (ISM). Their results show that institutional investor sentiment has a greater impact than individual investor sentiment. In particular, they show that American investor sentiment is systematic and cannot be diversified. Hence, it is necessary to include investor sentiment into international asset pricing models; however, as for how to measure investor sentiment, different researchers use diverse proxy variables which overall can be divided into two categories: direct indices and indirect indices. A direct index refers to direct data obtained by directly investigating

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investors’ views on the current market situation and their expectations for the future. In the United States, there are mainly two institutions producing indices reflecting these expectations; one is the University of Michigan Consumer Confidence Index (UMCCCI) and the other is the Conference Board Consumer Confidence Index (CBCCI). The indirect index refers to objective data indirectly reflecting investor sentiment extracted from financial market data as proxy variables for an investor sentiment. The literature now covers the use of the indirect index in empirical research, but the measurement methods used vary. For example, Verma and Soydemir (2006) decompose investor sentiment into two parts: the rational and irrational components, which can be captured by 12 sets of data such as inflation rate, currency fluctuation and AAII. Then the investor sentiment index is linearly combined therefrom. Baker and Wurgler (2006, 2007) construct an investor sentiment index according to the turnover rate, closed-end fund discount rate, IPO first-day yield, and other proxy variables, and they confirm the ability of investor sentiment in predicting stock returns. Based on the possibility of the highest price and the lowest price being the closing price, He (2012) and He and Casey (2015) utilise a binomial probability distribution model to construct an investor sentiment index, which is confirmed to offer excellent predictions of crude oil price.

Nevertheless, the methods for constructing an investor sentiment index have no unified standard for the selection of proxy variables. Hence the basis for the selection by scholars varies, and thus their empirical results are usually not the same, because of which the robustness of the methods is difficult to ensure. On the other hand, collecting the data for an investor sentiment index based on direct observation of bullish and bearish tendencies is difficult, and it is also difficult to verify the validity and authenticity of the direct data. He (2012) and He and Casey (2015) construct an emotional endurance index and assume that all information will eventually be absorbed in closing prices. Therefore, the net effect of investor sentiment is reflected in closing prices, which means that the impact of time-varying emotions can be captured through daily closing prices. In view of this, this paper follows He (2012) in constructing an investor sentiment index for the crude oil market.

It should be noted that after 2011 the spread between WTI and Brent prices has widened, so we also aim to investigate the relationship between investor sentiment and extreme risk in both the WTI and Brent crude oil markets. Specifically, we utilise the wavelet method for it can add more knowledge of the investors. The wavelet method can show the variation of the periodic component of a time series, which probably is locally stationary and inhomogeneous, allowing us to describe the local behaviour of market participants (Vacha and Barunik 2012). For example, the hedgers are concerned with long-term equilibrium, while the speculators tend to focus on short-term trading. The traditional correlation coefficient uses a single value to describe the correlation of two time series, while wavelet consistency can provide a matrix to show accurate correlation at each time and frequency point. This advantage makes it useful for observing the shift of coherency between investor sentiment and extreme risk in crude oil market. As for the oil industry specifically, some interesting relationships may exist at different frequencies: oil prices may act like a supply shock at high and medium frequencies, thus affecting industrial production. In the longer run (lower frequencies), it is industrial production, through the demand effect, that affects oil prices (Conraria and Soares 2011). Therefore, it is important to identify the differences in the coherence between investor sentiment and extreme risk in crude oil market both over time and across frequency.

The main contribution of this paper is as follows: on the one hand, a great deal of literature has focused on verifying the impact of investor sentiment on crude oil returns, but this paper constructs an investor sentiment index for crude oil markets in recent years, based on the theoretical framework proposed by He (2012). Meanwhile, it also empirically analyses the causal relationship between investor sentiment and extreme risk in the crude oil market, and further analyses the direction and intensity of co-movement in the crude oil market in different time-frequency domains via the wavelet method. Based on wavelet theory, this paper studies the effects of the degree of investor sentiment on extreme risk in crude oil markets. In addition, our research results can provide useful references for regulators in shaping operational rules for crude oil markets, so that they can introduce regulatory policies to guide investor investment behaviour in time. At the same time, they are useful for investors to understand the influence mechanism of investor sentiment on extreme risk in crude oil markets and to predict the complex changes in crude oil prices.

The remainder of this paper is organised as follows: Section 2 provides a literature review, Section 3 presents the methodology, its empirical application is covered in Section 4, and Section 5 concludes.

2. Literature review

Since price acts as an exogenous driver to economic fundamentals, a great number of studies have investigated the macroeconomic effects of oil price shocks. For instance, Hamilton (2011) proves that the relation between GDP growth and crude oil prices is not linear. Afterwards, Hamilton (2009) finds that the price run-up of 2007–08 was caused by strong demand confronting stagnating world production, while previous oil price shocks were primarily caused by physical disruptions of supply. Consequently, the effects of different types of oil shock may have some differences (Kilian 2009). For example, Kilian and Park (2009) show that unanticipated changes in the crude oil prices, driven by demand and supply shocks, explain about 20% of the long-run changes in the US returns. Also, Lorusso and Pieroni (2018) show that unanticipated booms in oil demand have different effects than unexpected oil supply disruptions on the UK economy. As for the information in the frequency domain, Lorusso and Pieroni (2018) find that although increases in aggregate and oil market-specific demand do not depress the UK economy in the short run, shortfalls in crude oil supply cause an immediate fall in GDP growth.

In recent times, international crude oil trade has steadily expanded and its market risk has exerted a strong impact on the GDP of numerous countries (Benhmad 2013, Gbatu et al.)
The impact of investor sentiment on crude oil market risks

2017, Karaki 2017). Therefore, it is important to predict crude oil market changes accurately; however, crude oil market forecasts are not always precise. For example, the EIA estimated that crude oil prices were expected to be around $28 per barrel in 2010 while the actual average crude oil price on the New York Stock Exchange was $79.61 per barrel in 2010. What is worse, just before the sharp fall in crude oil prices in mid-2014, EIA raised its WTI forecast for 2014 to nearly $96 per barrel.† In addition, the boom in financial markets has prompted more speculators to enter the market, leading to enlarging the volatility and risk in crude oil markets (Coleman 2012, Zhang et al. 2019); however, it is sometimes difficult to explain this volatility from traditional economic view such as supply and demand situation. Therefore, behavioural finance classifies investors’ expectations, which cannot be explained by fundamental information, as investor sentiment, which has become a vital indicator in the subsequent study. De Long et al. (1990) propose a noise trader model (DSSW), which has significant influence in related fields. It indicates that in the environment of limited arbitrage, if investor sentiment influences others, arbitrage cannot eliminate the erroneous pricing caused by irrational behaviour and investor sentiment. Hence, sentiment becomes a systemic risk affecting the equilibrium price of financial assets. On the other hand, the significance of the DSSW model is also that it involves the impact of investor sentiment on the earnings and volatility (Liston 2016, Guo et al. 2017). Baker and Wurgler (2006) define investor sentiment based on investor belief in the future cash flow and investment risk of assets. They also propose the following proxy variables: closed-end fund discount, stock turnover rate of New York Stock Exchange, IPO quantity, the average return on the first day of listing, equity financing, dividend maturity ratio, etc. Then they resort to principal component analysis to construct the BW index of investor sentiment by these proxy variables suggested by Huang et al. (2015a). Moreover, others widely used proxies of investor sentiment include the Economic Policy Uncertainty Index (Baker et al. 2016), the Financial Stress Index published by the Federal Reserve Bank of St. Louis, the volatility index, and the Oil Volatility Index. Furthermore, based on the widely used Search Volume Index (Power and Turvey 2010, Huang et al. 2016). As a result, GARCH class models cannot meet our needs in this regard. In addition, variance is used to measure the scale of risk in GARCH class models, but fluctuation is two-directional and variance is not considered to distinguish between negative and positive volatilities. In particular, after the outbreak of financial crisis, two-directional risk spillover significantly increases and positive (negative) shifts in the strict sense cannot be called extreme risk to the long (short) position. Thereby the corresponding results are far from sufficient. On the other hand, the information in the frequency domain cannot be ignored since returns on assets are in part determined by investor decision-making in different time-frames, ranging from a few minutes (short-term decision-making) to several years (long-term decision-making).

Based on the above discussion, we employ the wavelet method to analyse the relationship between investor sentiment and the extreme risk in crude oil market: the wavelet method offers significant advantages over decomposing the time series into time-frequency domain components and extracting the characteristics of time series implicit in various frequency domains (Lee 2004, Ghosh et al. 2011, Chakrabarty et al. 2015, Zheng 2015, Huang et al. 2015b).

Based on the wavelet analysis, the statement that one market has a leading role in another market does not mean that there is a specific causality between them (Brown 1999). Hence, we firstly use the Granger causality test method to verify whether investor sentiment is a crucial predictor of extreme risk, or not. Then we measure the value-at-risk (VaR) during the sample period via the VaR-GARCH model to study the extreme risk in crude oil market. Finally, via the wavelet analysis, we investigate the impact of investor sentiment on extreme risk in crude oil market as well as undertaking a robustness test on the empirical results.

3. Methods

3.1. Investor sentiment measurement

It is generally believed that the impact of all investor sentiment on crude oil market will ultimately be reflected in the

prices of crude oil, and the net effect of investor sentiment would be captured by the closing prices of crude oil, which has been used to construct an investor sentiment index (Parsons 2010, He 2012, He and Casey 2015). The essence of this process is to measure the strength of both bullish and bearish investors through the possibility of the highest and lowest prices eventually becoming closing prices, as shown in equation (1):

\[ P_t \times H_t + (1 - P_t) \times L_t = C_t \]  

where \( P_t \) refers to the possibility that the highest price in crude oil market becomes the closing price, and the value ranges within \([0,1]\), and \((1 - P_t)\) represents the possibility that the lowest price becomes the closing price. When \( P_t > 0.5 \), it indicates that a majority of investors hold positive attitude; when \( P_t = 0.5 \), it indicates the strength of bullish and bearish investors is flat; and when \( P_t < 0.5 \), we can say that a majority of investors hold negative attitude.

Then, investor sentiment can be further expressed as

\[ SE_t = P_t - 0.5 \]  

where positive (negative) \( SE \) means bullish (bearish) attitude. This index has advantage in effectively measuring investor reactions to all news, which will be reflected in the closing prices and significantly affect the changes of crude oil market returns (Savor 2012).

### 3.2. VaR-GARCH model

The data of crude oil returns often have a fat tail and conditional heteroscedasticity characteristics (Hou and Suardi 2012), because of which a GARCH class model is often used to fit the data. Furthermore, GARCH (1,1) model is generally sufficient to simulate the variance dynamics of financial time series (Bollerslev et al. 1992, Arvanitis and Louka 2017), and the model structure is as shown in equations (3) and (4):

Variance equation:

\[ \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \quad \alpha_1 > 0, \beta_1 < 0, (\alpha_1 + \beta_1) < 1 \]  

Mean equation:

\[ Y_t = \beta X_t + u_t, u_t \sim N(0, \sigma_t^2) \]  

Since the variance obtained by the GARCH model only reflects the risk level in general and we cannot model the extreme risk, hence we introduce the VaR, which can compute the maximum loss that investors (or producers) may suffer under the confidence level determined in advance within a certain period (Cabedo and Moya 2003, Fan et al. 2008); however, considering the obvious fat tail phenomenon in the crude oil returns series, this paper assumes that the standard residual follows the generalised error distribution, and obtains the conditional mean \( \mu_t \), and conditional variance \( \sigma_t \) of crude oil returns at time \( t \) by the GARCH model, and then further obtains VaR when oil returns rise and fall (i.e. upside, and downside, risks, respectively), as shown in equations (5) and (6), respectively:

\[ \text{VaR}^+ = \mu_t + Z_\alpha \sigma_t \]  
\[ \text{VaR}^- = \mu_t - Z_\alpha \sigma_t \]

where \( Z_\alpha \) is the left quantile followed by the standard residual in the GARCH model, i.e. \( F(Z_\alpha) = \alpha \).

### 3.3. Wavelet approach

#### 3.3.1. The wavelet.

Because the wavelet approach enable to transform the time domain series into time-frequency domain data (Joo and Kim 2015), the wavelet theory is introduced to study the dynamic relationship between investor sentiment and extreme risk in crude oil market from different time-frequency domains (Büssow 2007, Rua and Nunes 2009). The selection of mother wavelet is much important when wavelet transform is applied to an investor sentiment series and extreme risk data in crude oil market. Here, a Morlet wavelet is singled out as the mother wavelet, as its non-orthogonality can be used for continuous and discrete variables, and the imaginary part of complex number can reveal amplitude and phase information.

The Morlet wavelet is specified as

\[ \psi(t) = \pi^{-1/4}e^{\omega_0^2t^2}e^{-\frac{1}{2}t^2} \]  

where \( \omega_0 \) is the central frequency.

Following the Heisenberg principle of uncertainty, there is some uncertainty between the time and frequency in the Morlet wavelet. The central frequency of the Morlet wavelet \( \omega_0 = 6 \) is a fair selection, as it adequately balances the time and frequency localisations (Grinsted et al. 2004).

#### 3.3.2. Continuous wavelet transforms.

Continuous wavelet transforms (CWT) are applied when we extract information in crude oil market from the frequency domain, as CWT can provide a time-frequency domain window that changes with frequency so as to effectively overcome the disadvantage that the window size does not change with frequency (Percival and Walden 2000). In addition, CWT preserves energy in a series when analysing investor sentiment and extreme risk in crude oil market.

We set time series \( x(t) \in L^2(R) \), and the function \( \psi_{ab}(t) \) is a continuous wavelet generated by the basic wavelet \( \psi(t) \) that depends on parameters \( a \) and \( b \) as follows:

\[ \psi_{ab}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t - b}{a}\right) \]

where \( a, b \in R, a \neq 0 \), and \( a \) and \( b \) are the scale factor and place factor of the wavelet function, respectively (\( a \) determines how the wavelet is dilated, while \( b \) determines the precise position of the wavelet); in brief, \( a \) and \( b \) determine the position of the wavelet time-frequency window in the frequency, and time, domains, respectively. When \( a \) is smaller (larger), the wavelet is compressed more (less), and
the information in higher (lower) frequency bands can be detected.

The continuous wavelet transform \( W_s(a,b) \) is shown as

\[
W_s(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \psi \left( \frac{t-b}{a} \right) dt
\]  

(9)

After replacing \( x(t) \) in equation (9) with investor sentiment and extreme risk series in two benchmark crude oil markets, respectively, we can obtain the wavelet coefficient matrix of \( a \times b \) for all the three series. The value of \( W_s(a,b) \) refers to the variance (local energy) at row \( a \) and column \( b \) of examined series.

The wavelet coefficients and Parseval are respectively shown as

\[
x(t) = \frac{1}{C_\psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} W_s(a,b) \psi_{ab}(t) \frac{1}{a^2} \, da \, db
\]  

(10)

\[
||x||^2 = \frac{1}{C_\psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} |W_s(a,b)|^2 \frac{1}{a^2} \, da \, db
\]  

(11)

where the squared absolute value of wavelet coefficients is summed in equation (11) to get the total energy of the examined series. It can be seen from equations (8) to (10) that both investor sentiment and extreme risk series in the two crude oil markets can be finally reconstructed by the wavelet coefficients (see equation (10)), and the wavelet function must meet the condition as follows:

\[
C_\psi = \int_{-\infty}^{+\infty} \frac{|\psi(w)|^2}{|w|} \, dw < \infty
\]  

(12)

where \( \psi(w) \) is the Fourier transform of wavelet (more detail can be found in Percival and Walden (2000)).

3.3.3. Wavelet coherence. To observe whether, or not, there is co-movement between investor sentiment and extreme risk in crude oil market, we adopt the cross wavelet transform and wavelet coherence approaches to detect their covariance. The cross wavelet transform can find out the areas where the two examined time series have high common energy, which indicates local covariance, while wavelet coherence indicates the correlation of this cross transform in the time-frequency domain. The difference between the two approaches is that the wavelet coherence can be normalised by the power spectrum of these two examined time series. The cross-wavelet spectrum and wavelet coherence are shown as equations (13) and (14), respectively:

\[
W_{xy}(a,b) = W_x(a,b)\overline{W_y(a,b)}
\]  

(13)

\[
R^2(a,b) = \frac{|S(b^{-1}W_x(a,b))|^2}{S(b^{-1}W_x(a,b))^2 S(b^{-1}W_y(a,b))^2} \]  

(14)

where \( S \) refers to a smoothing process over time as well as scale between the time and frequency domain; \( W_x(a,b) \) and \( \overline{W_y(a,b)} \) are the wavelet transform of extreme risk in crude oil market and the wavelet transform of complex conjugate of investor sentiment, respectively; if the value of \( W_{xy}(a,b) \) is larger, the two time series have a higher common energy area and the two examined series are significantly correlated.

We can measure the co-movement between investor sentiment and extreme risk in time and frequency domains, respectively, by using the wavelet squared coherence, i.e. the wavelet coherence coefficient \( R^2(a,b) \), which remains between 0 and 1. If the value is higher, the co-movement is stronger and the value increases as the synergy between the two series increases. Therefore, by observing the profile (i.e. significant area) measured above, we can identify those areas where investor sentiment moves together with extreme risk series of crude oil market in the time and frequency domains, thereby specifically evaluating the variational characteristics of their co-movement in the time and frequency domain. The Monte Carlo method is used to test the significance of the wavelet coherent spectrum (Hastings 1970).

3.3.4. Phase difference. Considering that the wavelet coherence coefficient is a squared value, it cannot differentiate between positive and negative correlations. For this reason, following Torrence and Compo (1998), we obtain the investor sentiment \( y(t) \) by calculating the phase-difference in the wavelet transform series, which indicates the lead-lag information between the two series, and the phase-difference can be defined as

\[
\phi_{xy}(a,b) = \tan^{-1} \left( \frac{\Im[S(b^{-1}W_x(a,b))]}{\Re[S(b^{-1}W_x(a,b))]} \right)
\]  

(15)

where \( \Im \) is an imaginary operator and \( \Re \) refers to a real part operator. Hence, we refer to a two-dimensional plot that displays the results of the wavelet coherence difference. The phase-difference value of zero indicates that investor sentiment and extreme risk series in crude oil market and investor sentiment move together in the specified time and frequency domain, and the value of \( \pi \) or \(-\pi\) indicates that the two series are in the same, or a reverse, relationship; if the value remains within \([0, \pi/2] \cup [\pi, 3\pi/2]\), it indicates that the change of extreme risk series \( z(t) \) in crude oil market leads the investor sentiment series \( y(t) \); and if the value remains within \([\pi/2, \pi] \cup [3\pi/2, 2\pi]\), it indicates that investor sentiment \( y(t) \) stays in a leading position. The wavelet toolbox we use in this paper is developed by Grinsted et al. (2004).

4. Data description and empirical results

4.1. Data description

We use the data of both WTI and Brent crude oil spot prices to analyse the relationship between investor sentiment and extreme risk in different time and frequency domains. Daily price data for the two benchmark crude oils are derived from EIA and the sample time interval is 01/03/2007–12/31/2017, since this period contains significant crude oil price fluctuations like the sharp rise due to global aggregate demand and financial crisis, as well as the sensational geopolitical events (Lorusso and Pieroni 2018). The returns of WTI and Brent
are written as \( r_t = 100 \times (\ln(p_t) - \ln(p_{t-1})) \), and 2767 observations are obtained, respectively. The daily price series to construct the investor sentiment is PHLX|OSX, drawn from the Datastream database, which is a price return index of 15 oil service companies. The index has the potential to track the strength of crude oil market such as oil production and oil prices (He and Casey 2015). Then we construct our investor sentiment index \( SE \) according to equations (1) and (2).

Table 1 reports summary statistics on crude oil returns and investor sentiment. We can find that, firstly, skewness is positive for the two crude oil return series while it is negative for investor sentiment. Secondly, both crude oil returns exhibit obvious fat tails in their distribution. Thirdly, the J-B test results show that at the 1% significance level, both crude oil return and investor sentiment significantly reject the normality of the unconditional distribution. Finally, ADF and PP unit root test results show that the three time series are stationary at the 1% significance level.

### 4.2. Empirical results and discussions

#### 4.2.1. The extreme risks of crude oil returns.

According to the method in Section 3.2, we calculate the VaR of crude oil returns series. Figure 1 depicts the calculation results, and their descriptive statistics are shown in Table 2. Under the null hypothesis that VaR is fully estimated, the statistic LR follows the chi-squared distribution with one degree of freedom, and the critical value is 3.84 at the 5% significance level. As \( LR < 3.84 \) can be seen in the last column of Table 2, the VaR is supposed to be fully estimated. In addition, we find that there is obvious volatility clustering phenomenon in several periods, and there are short-term downside falls especially during 07/2008–01/2010 and 08/2014–10/2016, respectively. The short-term downside risks in 2008 were mainly due to changes in global financial and economic conditions that triggered global demand changes (Kilian 2009), while the short-term downside risks in 2014 may result from changes in the supply side, mainly because the Saudi-based OPEC countries wanted to increase production and squeezed at low-priced crude oil so as to minimise the market share of other oil producing countries and US shale oil. For another, there were short-term upside rises in crude oil prices around 05/2010, 02/2011, and 07/2012, while crude oil prices fell sharply in both 05/2011 and 12/2014.

#### 4.2.2. The results of Granger causality test.

According to the minimum AIC and SIC values of the VAR model, we select the optimal lag length, and detect the causality relationship between investor sentiment and extreme risk in Brent and WTI markets, respectively. Results are listed in Table 3. We can find that, at the 5% significance level, investor sentiment may Granger cause extreme risk in both upside and downside directions in crude oil market, but changes of extreme risk may not significantly lead to a shift in investor sentiment. Therefore, during the sample period, we can say that investor sentiment is an important driving force of extreme risk in crude oil market; in other words, investor sentiment has a strong ability to predict the changes of extreme risk in crude oil markets; however, the results are not consistent with Deeney et al. (2015) and Qadan and Nama (2018), who conclude that the effect between investor sentiment and crude oil market risk is mutual. In our opinions, the extreme risks in crude oil market have little significant effect on investor sentiment, because in addition to crude oil positions, investors may also have numerous other asset positions. According to the Target Weights of the Bloomberg L.P. Commodity Index in 2017, investment accounts in crude oil were merely about 15% of all commodity investment.†. As a result, crude oil price movements do not necessarily play a dominant role in predicting the complex changes of investor sentiment.

On the contrary, investor sentiment is an important driver of extreme risk changes in crude oil market. Investors’ instantaneous feedback to crude oil market’s frequent subtle changes

![Figure 1. Crude oil market returns and VaRs (%).](https://www.eia.gov/finance/markets/crudeoil/financial_markets.php)
is proved to be significant, so that investors’ continuously adjusting their investment strategy would also make crude oil market risks have different variation characteristics. Generally, the extreme risk in crude oil market is proportional to excessive speculative behaviour (Zhang 2013, Gogolin and Kearney 2016, Shanker 2017). Consequently, crude oil prices are controlled by the financial market system and major Anglo-American oil companies, which account for the significant impact of investor sentiment on extreme risk in crude oil market.

4.2.3. The evolution of volatility in the time-frequency domain. We draw the wavelet power spectrum to show the continuous power spectrum for investor sentiment and extreme risk series in Figure 2. The horizontal axis represents time while the vertical axis represents frequency which is converted to time units (day). The wavelet power spectrum depicts variance in each of time and frequency. Besides, the thin black line in Figure 2 indicates the cone of influence (COI), which is shown in a lighter shade. As its edge is below the COI and wavelet power is affected by discontinuity, it is hard to explain (Hastings 1970). Significant areas of variance lie within the thick black contour, which designates the 5% significance level against red noise. Meanwhile, the significance values are generated by the Monte Carlo approach. The main results are as follows.

Firstly, the significant areas of variance which, against red noise, indicate high volatility during these periods: in Figure 2(a) through (d), overall, the whole significant areas of variance are in the time before 12/2010 (i.e. 01/2007–12/2012) with a period longer than 128 days, although these are early affected by the edge effect. The significant area of variance in the low-frequency (long-term) bands may indicate that crude oil market is suffering from long-term turbulence, thereby it suggests recent structural problems (Dewandaru et al. 2017): this can be attributed to the long-term impact of the US sub-prime crisis on the global economy during this period. Previous literature has specifically argued about this. For instance, based on a class of kernel-based test statistics, Du and He (2015) argue that bidirectional positive risk spillover in the stock and crude oil markets increases during the financial crisis. Similarly, the chaos tests by Lahmiri (2017) suggest that the behaviour of crude oil price volatility turned to be irregular and unpredictable after the financial crisis of 2008, and this effect persists in a period after the financial crisis. However, within a period of less than 16 days, the volatility of investor sentiment appears much more intense and the extreme risk of two crude oil markets only showed a dense high significant area of variance in 2008 and 2015. Hence it means that excessive investor sentiment during the crisis may lead to short-term fluctuations in crude oil returns, and further increases the volatility and the possibility of extreme risks.

Secondly, in general, the significant areas of covariance between investor sentiment and extreme risk series in crude oil markets are shown in Figure 3. In 2007–2011 (in low frequency) and 2014–2016 (in medium-low frequency), the significant area of covariance was very similar to that as shown in Figure 2, especially in the sub-figures for downside risk in the WTI market. This may indicate that the volatility spillover effect between investor sentiment and extreme risk in crude oil market is more significant in the time domain where the volatility clustering is more obvious. In addition, Figure 4 shows the correlation and phase-difference between investor sentiment and extreme risk in crude oil market. As the phase-difference during the crisis is greater than that in the stable period, it indicates a strong correlation, and also indicates that investor sentiment has a direct impact on the occurrence of extreme risk in crude oil market. Andriosopoulos et al. (2017) produce very similar results, and find that there are significant contagion, and volatility spillover, effects between the time series of financial market data when volatility changes significantly during the financial crisis.

Thirdly, it is difficult to return investor sentiment to stability in the short term once it has started to fluctuate severely. In Figure 2(e), the significant areas of variance in investor sentiment, between 10/2008 and 08/2013, are statistically significant, early influenced by the edge effects, gathering in the low-frequency bands as well as lasting up to five years: this result is consistent with Yang et al. (2017), who find

<table>
<thead>
<tr>
<th>Table 2. Estimation results of VaR.</th>
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<tr>
<td><strong>Mean</strong></td>
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<tr>
<td>WTI Upside risk</td>
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<td>WTI Downside risk</td>
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<td>Brent Upside risk</td>
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<td>Brent Downside risk</td>
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<th>Table 3. Granger causality test results.</th>
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<tr>
<td><strong>Null hypothesis</strong></td>
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<td>SE does not Granger cause Brent upside risk</td>
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<tr>
<td>Brent upside risk does not Granger cause SE</td>
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<td>SE does not Granger cause Brent downside risk</td>
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<td>SE does not Granger cause WTI downside risk</td>
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<td>WTI downside risk does not Granger cause SE</td>
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that the persistence of investor sentiment is closely related to the focus of investors. For example, when in a rising market, investors pay more attention to optimistic reports, while ignore the reports containing negative signals; in contrast, in declining markets, investors are more vulnerable to pessimistic reports, while positive reports do not have significant impact. Thus, once a deviation of prices occurs, it means that a continuous unidirectional deviation will occur in the long term. On the other hand, a high degree of optimism can lead to investor’s over-confidence in their ability when assess an investment. This can account for policymakers’ overestimating the probability of success and underestimating the risk of investment decision-making. Hence, the risk from investment decision-making is accumulated, promoting the occurrence of extreme risk (Kuhnen and Knutson 2011, Bassi et al. 2013).

4.2.4. The lead-lag and co-movement analysis relating to extreme risk. To study the lead-lag and co-movement relationship between investor sentiment and extreme risk in crude oil market, we calculate their local wavelet covariance at specific time and frequency in Figure 3, using the cross-wavelet transforms. Then we can analyse the coherence and wavelet phase difference between them from Figure 3. The phase arrows provide information on the relative phase of investor sentiment with the extreme risk series (upside risk series and downside risk series) in crude oil markets, respectively. Right (left) arrows indicate in-phase (reverse phase) and up (down) arrows indicate that investor sentiment lags (leads) extreme risk in crude oil market. Following Grinsted et al. (2004) to measure the wavelet phase-difference at a specific frequency, we calculate the results and plot Figure 3. The phase-differences in each frequency domain are shown in

Figure 2. Wavelet power spectrum.
The impact of investor sentiment on crude oil market risks

Figure 3. Cross wavelet transforms.

Figure 4. Wavelet coherence.
two types of technological innovations, a dramatical break occurred in 2008 and 2010, and the application of hydraulic fracturing (or fracking), enabled the US to grow the US oil production industry; and shale oil production has dramatically the production of abundant shale oil resources and horizontal drilling and hydraulic fracturing (or fracking), enabled the US to grow the US oil production industry; and shale oil production has gained a large share of the overall WTI production; besides, the WTI-Brent price spread has risen. As a result, the US oil industry has been facing a major change (Chen and Huang 2015).

Secondly, comparing Figure 3(a) with (c) as well as comparing Figure 3(b) with (d), we find that investor sentiment has significant leading and co-movement effect on the downside risk of crude oil markets, but lags significantly behind the upside risk, as shown in Figure 3(b) and 3(d), the majority of arrows in the significant areas point to the right and up. In contrast, most arrows in the significant areas of covariance point to a downside risk in Figure 3(a) and (c), indicating that investor sentiment plays a leading role in the downside risk in crude oil market. Further combining with the results of causality test in Table 3, investor sentiment Granger causes extreme risk in crude oil market, then we can say that investor sentiment may lead to the occurrence of downside risk in crude oil market. The results are consistent with a variety of previous studies: Qadan and Nama (2018) suggest that investor sentiments drive greater changes in oil returns and volatility. Besides, in Table 4, it can be found that the phase of investor sentiment and downside risk of crude oil market decreases when the period increases, suggesting that downside risk is more sensitive to the shifts of investor sentiment. From 12/2015 to 12/2016, Figure 3(a) and 3(c) have significant areas of covariance in the high-frequency bands with a period of about 32 days, indicating the accumulation of downside risk in crude oil market in the short term. The phases of WTI and Brent markets in this period are 130.6610 and 115.3045, respectively (Table 4), and the two phases mean that investor sentiment stays in a leading position. Together with the results in Table 3, it can be found that investor sentiment significantly Granger causes extreme risk in crude oil market. Hence, it indicates that investor sentiment makes a significantly direct contribution to the downside risk in crude oil market during this period. Besides, it confirms that excessive investor sentiment may lead to increasing volatility in crude oil returns and short-term shocks as well as increased likelihood of extreme risk.

On the other hand, when we combine the position of OPEC’s insistence on not cutting production in late 2014, particularly driven by Saudi Arabia’s rulers, it can be found that investors in crude oil market predict ample supply and weak demand in the future. Hence it is believed that such news leads rising bearish sentiment that has triggered decrease in long position, so that crude oil prices plunged from high levels. For instance, Brent crude oil prices fell from $133 per barrel to less than $27 per barrel in 07/2014–01/2016.† As Yao et al. (2017) argue, sentiment index changes drive changes in oil earnings and oil price volatility, thus volatility in investor sentiment can have significant impact on crude oil market.

Analysing the upside risk of crude oil market in the time domain, we can find that during the crisis, many other events all exert significant influence on investor sentiment, such as the collapse of real estate bubble in 2008, the supply trend of OPEC’s limited production in 2010–2012, geopolitical events such as the US and Russian elections, the war in Libya, the oil embargo in Iran, and so on. Not all events have the same direction of impact, and thus lead to higher volatility of investor sentiment during such a period (Huang et al. 2017, Pan et al. 2017, Zhang and Wang 2019). In other words, it directly results in the oil price deviating significantly from the fundamentals and further leads to the occurrence of extreme risk. For example, as the Libyan war began in February 2011, investors expected a tight supply and changes in spot oil deliveries due to a lack of elasticity in the supply of oil, and the bullish mood in crude oil market pushed oil prices to increase (on the whole). As shown in Figure 1, on 22 February, 2011, WTI returns rose to 8.6%, although on 18 February oil returns fell to −0.02%.

4.2.5. The frequency analysis relating to extreme risk. In the frequency domain, the main results related to extreme risk can be reduced to three aspects: firstly, the influence of investor sentiment on extreme risk will last for a long time, with a period exceeding 128 days in general. As shown in Figure 5, the correlation between investor sentiment and extreme risk in crude oil market is up to 0.8 in the long term, and in Figure 4, there are rarely any apparent significant areas in the high-frequency (short-term) bands, in brief, investor sentiment causes extreme risk in crude oil market in the long term, which is different from the finding of Deeney

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† https://money.usnews.com/investing/articles/2016-03-01/why-is-investor-sentiment-so-bad.
et al. (2015). According to the empirical evidence from the dynamic overlapping generation model by Benhabib et al. (2016), in the rational-expectations framework, investor sentiment impinges constantly on extreme risk, and even small scales of emotional volatility would be magnified so resulting in strong and continuous volatility in the real economy.

As Yao et al. (2017) argue, investors have become more frightened after the financial crisis. In addition, Ding et al. (2017) confirm that the impact of an innovation in investor sentiment shifting from stock market to crude oil market lasts about eight months via impulse response empirical evidence in 2005–2015. Consequently, it can explain the phenomenon whereby there is significant coherence in the low-frequency bands in Figure 4. Combined with the above statement that investor sentiment, once fluctuating, is difficult to return to a stable state, we can draw the conclusion that long-term volatility in investor sentiment continues to accumulate in the closing price of crude oil. Moreover, this phenomenon promotes crude oil prices continuing to rise or fall and directly accounting for the occurrence of extreme risk.

Secondly, during 01/2014 to 12/2015, there is a significant area of covariance in the medium term in Figure 3 (with a period of about 128 days). The phase arrows in Figure 3 almost all point straight upwards or downwards, indicating that investor sentiment is weakly correlated to extreme risk in crude oil market in the medium term. As can be seen from Table 4, the phase of this period is close to 90°, indicating that there is almost no correlation. While most of the sub-figures in Figure 4 show that, around 12/2015, the arrows in significant areas of high coherence were disordered, indicating staggered leading, and even reversed, phase action. Put another way, there is no significant lead-lag relationship between investor sentiment and the extreme risk in crude oil market at low- and medium-frequency bands during this period. As a matter of fact, the recession in crude oil market during this period is mainly due to geopolitical events in oil-exporting regions (such as the direct rivalry between OPEC, particularly Saudi Arabia and the Gulf States, and north American shale oilproducers). In addition, from a more fundamental perspective, during this period, developing countries led by China and India grew rapidly, and their huge growth in energy consumption substantially affected the global economy. It is therefore difficult for investors to reach a consensus on crude oil market expectations, and the correlation between the two variables is
respectively. The results are shown in Table 5. We can find oil market with investor sentiment in each frequency domain, further, we can explore the dynamic relation medium term (32–128 days), and long term (256–512 days) three frequency domain ranges: the short term (2–32 days), domain, so as to analyse the robustness of the results from reconstructed series of all the three series in each frequency domain, test results.

Secondly, as shown from Table 5, in all the frequency domain ranges, the effect of investor sentiment on upside (downside) risk is negative (positive) because the coefficients are almost negative (positive), at the 5% significance level, in accordance with the relevant result in Section 4.2 and the causality test results.

Thirdly, we find that investor sentiment and extreme risk in crude oil market exhibit strong auto-regression, that is, they are greatly influenced by their respective early fluctuations. As can be seen from Table 5, the absolute value of the first-order lag term coefficient of major series in each frequency domain is greater than 0.9. In particular, the absolute value of the first-order lag term coefficient of major series in each frequency domain ranges, the effect of investor sentiment on upside risk is negative (positive) because the coefficients are almost negative (positive), at the 5% significance level, in accordance with the relevant result in Section 4.2 and the causality test results.

4.3. The robustness analysis

The continuous wavelet transform has been widely used in the study of dynamic coherence of time series in the time-frequency domain (Torrence and Compo 1998, Grinsted et al. 2004, Dewandaru et al. 2017, Pal and Mitra 2017, Reboredo et al. 2017). In this sub-section, we use the discrete wavelet f8 to test the robustness of the results above (Percival 1995, Gallegati 2012).

Firstly, the f8 wavelet decomposition is used to obtain the reconstructed series of all the three series in each frequency domain, so as to analyse the robustness of the results from three frequency domain ranges: the short term (2–32 days), medium term (32–128 days), and long term (256–512 days) periods. Furthermore, we can explore the dynamic relationship between investor sentiment and extreme risk in crude oil market with investor sentiment in each frequency domain, respectively. The results are shown in Table 5. We can find that, in the long term, the absolute value of the coefficient between investor sentiment and lagged extreme risk in crude oil market is less than 0.0003, which is almost close to zero; in other words, extreme risk has less impact on investor sentiment in crude oil market in the long term. This indicates that the influence of investor sentiment on extreme risk in crude oil market mainly proceeds in a long-term manner, in accordance with the relevant result in Section 4.2 and the causality test results.

Note: oil (−1) refers to the column of crude oil extreme risk first-order lag sequence. BU: Brent upside risk, BD: Brent downside risk, WU: WTI upside risk, WD: WTI downside risk. *, ** and ***: statistically significant at the 10%, 5% and 1% levels, respectively.

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<th>Table 5. The result of discrete wavelet.</th>
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<tr>
<td>Brent upside risk &amp; SE</td>
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<td>BU</td>
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<tr>
<td>Panel A: short-term (up to 32 days)</td>
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<tr>
<td>C</td>
</tr>
<tr>
<td>oil (−1)</td>
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<tr>
<td>oil (−2)</td>
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<td>SE (−1)</td>
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<td>SE (−2)</td>
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<td>$R^2$</td>
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<tr>
<td>Panel B: middle-term (32-128 days)</td>
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<tr>
<td>C</td>
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<tr>
<td>oil (−1)</td>
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<tr>
<td>oil (−2)</td>
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<tr>
<td>SE (−1)</td>
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<tr>
<td>SE (−2)</td>
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<tr>
<td>$R^2$</td>
</tr>
<tr>
<td>Panel C: long-term (over128 days)</td>
</tr>
<tr>
<td>C</td>
</tr>
<tr>
<td>oil (−1)</td>
</tr>
<tr>
<td>SE (−1)</td>
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<td>$R^2$</td>
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Firstly, the fk8 wavelet decomposition is used to obtain the reconstructed series of all the three series in each frequency domain, so as to analyse the robustness of the results from three frequency domain ranges: the short term (2–32 days), medium term (32–128 days), and long term (256–512 days) periods. Furthermore, we can explore the dynamic relationship between investor sentiment and extreme risk in crude oil market with investor sentiment in each frequency domain, respectively. The results are shown in Table 5. We can find that, in the long term, the absolute value of the coefficient between investor sentiment and lagged extreme risk in crude oil market is less than 0.0003, which is almost close to zero; in other words, extreme risk has less impact on investor sentiment in crude oil market in the long term. This indicates that the influence of investor sentiment on extreme risk in crude oil market mainly proceeds in a long-term manner, in accordance with the relevant result in Section 4.2 and the causality test results.

Secondly, as shown from Table 5, in all the frequency domain ranges, the effect of investor sentiment on upside (downside) risk is negative (positive) because the coefficients are almost negative (positive), at the 5% significance level, in accordance with the relevant result in Section 4.2.4.

Thirdly, we find that investor sentiment and extreme risk in crude oil market exhibit strong auto-regression, that is, they are greatly influenced by their respective early fluctuations. As can be seen from Table 5, the absolute value of the first-order lag term coefficient of major series in each frequency domain is greater than 0.9. In particular, the absolute value of the first-order lag term coefficient of extreme risk series in crude oil market in the medium term is greater than 1.9, indicating that once affected by other factors such as geopolitical events, this effect will endure, and, as a result, investor sentiment is unlikely to recover to its initial state, which confirms the previous result.

Finally, considering the period of 2000–2007 witnessed a sharp rise in oil price, we also detect the observations during this time period for the robustness of the results above using the wavelet coherence approach.† We can find from the figure of Wavelet power spectrum that, during 2000–2007, the significant areas of variance are over a period of 256 days and disordered in the time domain (Makin et al. 2014, Baumeister and Kilian 2016).

Finally, before August 2014 (01/2007–08/2014), the significant areas of high coherence in Figure 4 were generally found in the low-frequency bands (with a period longer than 256 days), but after 2014, the periods decreased to less than 256 days. In other words, the period of investor sentiment affecting extreme risk decreases. Although in the short term, investor sentiment may lead to an increase in oil price volatility, in the long term, oil price risk can be mitigated by hedging and can occur through a variety of mechanisms (Nikitopoulos et al. 2017). Therefore, it can be concluded that, post–2015 (2015–2017), the period of investor sentiment affecting extreme risk in crude oil markets begins to decrease.

† Detailed results can be obtained upon request.
within the period of 64 days. The long-term volatility over 256 days can be attributed to structural problems (Kilian and Park 2009), while the majority of significant areas, which are almost within the period of 64 days, confirms the result in Section 4.2.3 that excessive investor sentiment may lead to short-term volatility in oil returns and further increase extreme risks in crude oil market. Meanwhile, we can also find from the figure of wavelet coherence that in the significant areas of sentiment and two downside risks, the main arrows point to down and right, which confirms that investor sentiment has leading and co-movement effect on downside risk of crude oil markets as mentioned in Section 4.2.4. In addition, the significant areas of high coherence are mainly about the period of 128 days, which means that the influence of investor sentiment on extreme risk may last a long period and confirms the result in Section 4.2.5 although the examined time period is different. Overall, the central results still hold during the time period of 2000-2007.

5. Conclusions and future work

In recent years, investor sentiment has played an important role in the volatility of extreme risk, significantly affecting the stability of crude oil markets. Therefore, we investigate the impact of investor sentiment on extreme risk in the crude oil market based on a wavelet approach. Some key conclusions may be drawn as follows.

In the time domain, there is a significant causal relationship and co-movement between investor sentiment and extreme risk in the crude oil market in the long term. Investor sentiment leads to downside risk in the crude oil market, and investor sentiment may Granger cause extreme risk in crude oil market at the 1% significance level, but not vice versa. Hence, when investor sentiment volatility is significant, it has a direct role in promoting the occurrence of extreme risk, especially during the financial crisis period. In addition, the volatility spillover effect between investor sentiment and downside risk in the crude oil market is more obvious in the time domain where volatility clustering is more apparent. Meanwhile, it is difficult for investor sentiment to return to its original level once it starts to fluctuate. Therefore, investor sentiment is an important driver of extreme risk in crude oil markets.

In the frequency domain, the significant areas show weak correlation with the correlation increasing in the low-frequency bands, and the significant areas of coherence between investor sentiment and extreme risk in the crude oil market mainly have a long-term (longer than 128 days) effect. In other words, the impact of investor sentiment on extreme risk in the crude oil markets has a long duration, but the impact period tends to decrease.

The above conclusions have important implications for both investors and market regulators. On the one hand, investor sentiment can be used as an important predictor of crude oil prices. Therefore, no matter whether institutional investors or individual investors, they should understand crude oil market sentiment and its connotations and elucidate the relationship between investor sentiment and extreme risk in crude oil markets. As a result, they would be conducive to preventing the extreme evolution of market sentiment, promoting better decision-making among investors, reducing investment risk, and improving investment returns in the crude oil market. Specifically, investors in the crude oil market should be able to make profits by taking into sufficient consideration the impact of investor sentiment.

On the other hand, when faced with unilateral market decline, market regulators should take effective measures as soon as possible, such as fiscal and taxation policies, so as to stabilise market sentiment, reduce the probability of extreme risk, avoid the trend that volatility of investor sentiment continues to suppress development in the crude oil market. Specifically, regulators and policy makers can resist extreme risk as well as stabilising the operation of the crude oil market by tracing the dynamic impact of investor sentiment in the market.

Of course, there remains much work to be done on investor sentiment in crude oil markets in the future. This paper focuses on the effect of investor sentiment on the extreme risk in crude oil spot markets. In the future, we can continue to explore whether the financial derivatives market will be affected by investor sentiment in the crude oil market and study the oil asset pricing mechanisms in a new big-data environment. In addition, we can also examine how to model the dynamic changes in oil prices and investor sentiment so as to realise prediction and early-warning of oil price risk, and eventually to provide more support for predicting financial market dynamics.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the National Natural Science Foundation of China under Grant [nos. 71273028, 71322103, and 71774051], the National Program for Support of Top-notch Young Professionals of China under Grant [no. W02070325], the Changjiang Scholars Program of the Ministry of Education of China under Grant [no. Q2016154], and the Hunan Youth Talent Program.

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