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# The relationship between regional natural gas markets and crude oil markets from a multi-scale nonlinear Granger causality perspective

Jiang-Bo Geng [a,b], Qiang Ji [b,c,*], Ying Fan [d]

[a] School of Finance, Zhongnan University of Economics and Law, Wuhan 430073, China
[b] Center for Energy and Environmental Policy Research, Institutes of Science and Development, Chinese Academy of Sciences, Beijing 100190, China
[c] Institute of Management Science & Engineering, Nanjing University of Information Science & Technology, Nanjing 210044, China
[d] School of Economics & Management, Beihang University, Beijing 100191, China

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ABSTRACT

This study first decomposes the daily returns of regional gas and crude oil at different time scales, using the ensemble empirical mode decomposition (EEMD) method. It then investigates the causality relationship between each pair of components at the different time scales, by employing the linear and nonlinear Granger causality tests. For the original returns series, this study finds that unidirectional linear Granger causality exists from crude oil markets to North American and European gas markets. However, for nonlinear characteristics, the crude oil and regional gas markets exhibit bidirectional nonlinear Granger causality. On the medium-term time scale, a bidirectional nonlinear spillover effect is found between the markets. The long-term trends for the markets suggest a significant linear relationship; however, no nonlinear spillover effect is found between the crude oil and regional gas markets.



## 1. Introduction

To address climate change and ensure energy supply security, many countries have increased the proportion of natural gas for primary energy consumption. Currently, the global natural gas market is divided into three distinct regional markets: North America, Europe and Asia. For different regional natural gas markets, the level of market development and pricing mechanisms vary. Early on, all regional natural gas markets were primarily based on crude oil prices, which were used as a pricing benchmark. Along with the development of the markets, the pricing mechanism of different regional natural gas markets changed. Currently, the pricing mechanism is based on the market supply and demand in the North American natural gas market, while European and Asian markets are mainly still indexed to crude oil prices. Although pricing mechanisms have changed, the link between natural gas prices and crude oil prices remains strong (Brown and Yücel, 2008). These markets exhibit complex dynamic relationships; in particular, recent increases in global liquefied natural gas trade year-over-year and the appearance of the North American shale gas revolution could change the relationships between regional natural gas markets and the crude oil markets. Analysing the spillover effects between regional natural gas markets and the crude oil markets can reveal the dynamic characteristics of regional markets. This is important information for energy policy makers and energy-related financial institutions to have for the development of appropriate energy policies and to make appropriate decisions to avoid market risks.

The dynamic relationship between natural gas and crude oil prices is very complex. In particular, fluctuations in both crude oil prices and natural gas prices have shown inner multi-scale characteristics; these include, for example, short-term market fluctuations, medium-term fluctuations caused by minor irregular and significant events, and long-term trend (Geng et al., 2016a; Zhang et al., 2008). Therefore, this research analyses the dynamic relationship between crude oil prices and regional natural gas prices from a multi-scale perspective, which is useful for energy policy makers, energy-related financial institutions and investors with various horizons with respect to their strategic investment and risk management decisions. Additionally,

* Corresponding author at: Center for Energy and Environmental Policy Research, Institutes of Science and Development, Chinese Academy of Sciences, China.
*E-mail addresses:* jqwxnjq@163.com, jqwxnjq@casipm.ac.cn (Q. Ji).

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nonlinearity property and structure has been found to exist in crude oil and regional natural gas markets. The existence of these nonlinearities might owe to nonlinear transaction costs, the role of noise traders, and to market microstructure effects, or to an asymmetric adjustment process in the crude oil and regional natural gas markets (Bekiros and Diks, 2008; Chiou-Wei et al., 2008; Silvapulle and Moosa, 1999). The existence of jumps and extreme volatility in the crude oil and regional natural gas prices can also create such nonlinearity (Wilson et al., 1996; Yaya et al., 2015). In addition, regime changes such as some significant changes in economic circumstances, significant economic events, and changes in energy policy can also create structural changes in the pattern of crude oil and regional natural gas prices (Fan and Xu, 2011; Geng et al., 2016a, 2016b; Zhang et al., 2008). Hence, crude oil and regional natural gas markets are expected to exhibit a nonlinear relationship. This study undertakes linear and nonlinear Granger causality tests to analyse the linking mechanisms between these two kinds of markets.

Many studies have indicated that there exists a long-term cointegration relationship between the natural gas and crude oil markets (Hartley et al., 2008). Villar and Joutz (2006) analysed the relationship between Henry Hub and West Texas Intermediate (WTI) prices, and the results showed that the prices exhibited a long cointegration relationship. Asche et al. (2006) found that after the deregulation of the natural gas market in the UK, natural gas prices had a long cointegration relationship with crude oil prices. Panagiotidis and Rutledge (2007) analysed the relationship between UK natural gas prices and Brent crude oil prices from 1996 to 2003, and the results showed that there was a cointegration relationship between the two prices. In this case, the shock that the crude oil market suffered also had an impact on natural gas prices—there was no separation between crude oil and natural gas prices. Ates and Huang (2011) used the recursive cointegration estimation method to analyse the relationship between crude oil and natural gas prices, and the results indicated that there existed a stable long-term equilibrium relationship between prices. Asche et al. (2012) found that the relationship between natural gas and crude oil prices varied in the short term but remained in an equilibrium relationship in the long term. Ramberg and Parsons (2012) suggested that despite natural gas prices having a transient separation from crude oil prices, natural gas and crude oil prices still maintained a long-term cointegration relationship. Brigida (2014) found although natural gas and crude oil prices exhibited a temporary shift in the early 2000s, they had the long-term equilibrium relationship.

The recent North American shale gas revolution may cause natural gas prices to disconnect from crude oil prices. Erdős (2012) found that the US and UK natural gas prices remained in a long-term equilibrium relationship with crude oil prices before 2009; after 2009, the relationship remained unchanged in the UK, while US natural gas prices disconnected from crude oil prices. Loungani and Matsumoto (2012) found that US natural gas prices had separated from crude oil prices, perhaps due to the US shale gas revolution, which caused a sudden increase in natural gas production in the United States, resulting in an oversupply of natural gas. Geng et al. (2016b) analysed the relationship between regional natural gas markets and crude oil markets, and the results showed that North American natural gas prices deviated from crude oil prices while European gas prices remained in a stable, long-term equilibrium relationship with crude oil prices.

The nature of the spillover effect between the natural gas and crude oil markets remains unclear. Some scholars believed there was only a unidirectional effect, from crude oil to natural gas prices. Pindyck (2004) analysed the interrelationship between crude oil and natural gas returns since 1990, and the results showed crude oil price returns had impacted on natural gas price returns but not the other way around. Brown and Yücel (2008) considered the impact of seasonality, weather, natural gas inventory and reduction of natural gas production, among other factors, on natural gas prices. The results showed that crude oil prices played an important role in the determination of natural gas prices when additional factors were considered. Nick and Thoenes (2014) used a structural vector autoregression model to analyse the German natural gas market and found that natural gas prices were primarily affected by crude oil prices in the long term. Ji et al. (2014) found that crude oil price fluctuations had a negative impact on import prices in three regional natural gas markets with a varied degree of response, while the response of natural gas import prices to the increases and decreases in crude oil prices revealed an asymmetric mechanism for the three regional markets, in which the impact of the decrease was relatively stronger. Recently, some scholars have pointed out that in addition to crude oil prices having an impact on natural gas prices, the natural gas market has an impact on the crude oil market. Tonn et al. (2010) found that the price volatility of crude oil and the North American natural gas markets were mutually influenced by each other. Ramirez and Karali (2014) showed that there was a bidirectional volatility spillover effect between crude oil and natural gas markets. Wolfe and Rosenman (2014) also found that the crude oil market and North American natural gas market impacted each other using the price volatility of intraday oil and gas futures contract. Yoncu and Bahramian (2015) showed that there was a bidirectional causality relationship between natural gas and crude oil prices among European regional markets. Lin and Li (2015) used the VEC-MGARCH model to analyse volatility spillover effects between the crude oil market and North American, European and Asian regional natural gas markets, and the results showed that there was a bidirectional volatility spillover effect between the crude oil prices and natural gas prices in the North American and European markets, but this effect did not exist in the Asian market.

The above literature primarily analysed relationships between natural gas and crude oil markets for the original data series, and the conclusions of the existence of a dynamic relationship between the crude oil and natural gas markets are inconsistent. Both market systems are complex with multi-scale characteristics. On different time scales, internal impact mechanisms of the natural gas and crude oil markets are different, which makes the linear and nonlinear Granger causality between the two markets differ at different time scales. This research comprehensively investigates the linear and nonlinear dynamic relationships between daily regional natural gas and crude oil returns from a multi-scale perspective. Generally, this paper makes two main contributions: (1) A multi-scale analysis approach to comprehensively analyse the complex relationship between regional natural gas markets and crude oil markets can identify the internal impact mechanisms of the link between the two kinds of markets at different time scales; (2) A nonlinear Granger causality test is applied to further analyse the contemporaneous causality between regional natural gas and crude oil markets at different time scales.

This paper is organised as follows. Section 2 describes the ensemble empirical mode decomposition (EEMD) method, the linear and nonlinear Granger causality test methods and the data sources. Section 3 presents the empirical results and discussions. Finally, Section 4 presents the conclusions and policy implications of this research.

## 2. Methodology and data sources

This paper uses the EEMD method and linear and nonlinear Granger causality tests to analyse the market relationships. First, natural gas and crude oil market returns are decomposed using the EEMD method. Then, the linear and nonlinear Granger causality relationships between each pair of decomposed components for the natural gas and crude oil market returns are analysed.

### 2.1. EEMD method

The EEMD method is developed by Wu and Huang (2009), based on the empirical mode decomposition proposed by Huang et al. (1998). Compared to the wavelet decomposition and other traditional decomposition methods, the EEMD method has several advantages. Firstly, the EEMD method can deal with nonlinear and non-stationary data effectively (Huang et al., 1998); it is therefore useful in the current context, given that crude oil and regional natural gas price returns have nonlinear characteristics (Geng et al., 2016c; Yu et al., 2015). Secondly, the EEMD method is local, self-adaptive, concretely implicational and highly efficient. It can adaptively decompose an economic time series into simple independent intrinsic mode functions (IMFs) and one residual component, which can be identified as concrete economic implications. Thirdly, the EEMD method is fully posterior meaningful without any a prior basis. However, the wavelet decomposition method demands that a filter base function need to be set prior to decomposition, and it is difficult for some unknown series to set the filter base function before decomposition (Huang et al., 1998; Yu et al., 2008; Zhang et al., 2009). At present, the EEMD method has been used by some scholars to analyse crude oil prices and financial time series, and it can provide a multi-scale framework by which to interpret the formation of crude oil prices and financial time series from a novel perspective, as such, it can help one understand the underlying intrinsic mechanisms of these original data series (Huang et al., 2003; Yu et al., 2008, 2015; Zhang et al., 2008, 2009).

Before decomposing crude oil and regional natural gas price returns, the price returns need to be constructed, by calculating as follows.

$$ROILP_t = \ln(OILP_t/OILP_{t-1}) \tag{1}$$

$$RGASP_t = \ln(GASP_t/GASP_{t-1}) \tag{2}$$

where *ROILP* and *RGASP* denote the crude oil and regional natural gas daily price return, respectively, and *OILP* and *GASP* represent the crude oil and regional natural gas daily price, respectively.

The EEMD method is then used to decompose crude oil and regional natural gas price returns. Specifically, the IMFs and the residual term can be extracted through the following procedure.

(1) Firstly, a white noise series is added to crude oil or regional natural gas price return series $x(t)$, after which the new data series $X(t)$ can be obtained. The white noise series added into the price return series each time should meet the following formula (Wu and Huang, 2009):

$$\varepsilon_n = \frac{\delta}{\sqrt{N}} \tag{3}$$

where $\varepsilon_n$ is the standard deviation of error, $\delta$ is the standard deviation of the added white noise series, and $N$ is the number of ensemble members. In this study, $\delta$ is set to 0.2, and $N$ is set to 100.

(2) All the local maxima and minima of time series $X(t)$ are identified. A cubic spline function is used to fit all the local maxima and local minima of $X(t)$ to generate its upper envelope $u_{\max}(t)$ and lower envelope $u_{\min}(t)$. Then, the mean $v(t)$ can be obtained as follows:

$$v(t) = \frac{[u_{\max}(t) + u_{\min}(t)]}{2} \tag{4}$$

(3) Next, the mean $v(t)$ should be extracted from $X(t)$ and the difference $d(t)$ between $X(t)$ and $v(t)$ can be obtained using the formula:

$$d(t) = X(t) - v(t) \tag{5}$$

(4) The properties of $d(t)$ should be verified. If it satisfies the two restrictions namely, that (a) for the function, the number of zero-crossings and the number of extrema must be equal or differ by more than one, and (b) it is symmetric with respect to a local zero mean. Then, it can be denoted as the $i$th intrinsic mode function (IMF). If it does not, the first step should be repeated $k$ times with different white noise series each time until it does meet these two requirements.

(5) Then, $c_1(t) = d_k(t)$ is obtained as the first IMF. Next, $c_1(t)$ is subtracted from $X(t)$. Moreover, the whole sifting process should continue to be repeated until meeting the following predetermined criteria: either when the component $c_i(t)$ or the residue $r(t)$ becomes so small that it is less than the predetermined value of a substantial consequence, or when the residue $r(t)$ becomes a monotonic function from which no further IMFs can be extracted. Meanwhile, the total extracted number of IMFs is limited to $\log_2 T$, where $T$ is the length of the crude oil or regional natural gas price return series.

The original target time series $x(t)$ can be represented by IMFs and one residual term.

$$x(t) = \sum_{i=1}^{n} c_i(t) + r(t) \tag{6}$$

where $c_i(t)$ represent the IMFs, which are independent and nearly orthogonal to each other. $n$ is the number of IMFs, and $r(t)$ is the one residual term of the original target time series. The decomposed time-series components have different economic implications on different time scales. In particular, the high frequency component is identified as the markets' normal fluctuation, while the low frequency component represents medium-term fluctuations caused by minor irregular and significant events; the residual term, meanwhile, represents the long-term trend of the markets (Zhang et al., 2008).

### 2.2. Granger causality test

#### 2.2.1. Linear Granger causality test

To test the linear causality between crude oil and regional natural gas price returns, the linear Granger causality test is used. First, the Phillips-Perron (PP) unit root test is used to examine whether crude oil and regional natural gas price returns and the decomposed components are stationary (Phillips and Perron, 1988). If all time series are stationary, the vector autoregressive (VAR) model could be used to conduct the linear Granger causality test. In this paper, the bivariate VAR model is constructed as follows:

$$\Delta Y_t = a_1 + \sum_{i=1}^{m} b_{1i}\Delta X_{t-i} + \sum_{j=1}^{m} c_{1j}\Delta Y_{t-j} + \varepsilon_{1t} \tag{7}$$

$$\Delta X_t = a_2 + \sum_{i=1}^{m} b_{2i}\Delta X_{t-i} + \sum_{j=1}^{m} c_{2j}\Delta Y_{t-j} + \varepsilon_{2t} \tag{8}$$

where $a_1$ and $a_2$ are the intercept, $b$ and $c$ represent the estimated coefficients and $m$ represents the optimal lag length of the model, which is determined using the Akaike information criterion (AIC).[1] The null hypothesis in Eq. (7) is that X does not strictly Granger cause $Y$, and $Y$ does not strictly Granger cause $X$ in Eq. (8), represented by $b_{1i}=0$ and $c_{2j}=0 (i=1,2,\ldots,m, j=1,2,\ldots,m)$.

#### 2.2.2. Nonlinear Granger causality test

Considering the linear approach to causality testing has low power detecting certain kinds of nonlinear causal relations, nonlinear models are appealing because they can uncover nonlinear predictive power. Some scholars proposed various nonparametric tests for the Granger non-causality hypothesis. The test by Hiemstra and Jones (1994), which is a modified version of the Baek and Brock (1992) test, is the most frequently used among practitioners in economics and finance. This test can detect the nonlinear Granger-causal relationship between variables by testing whether the past values influence present and future values. However, for this frequently used test, there existed the

[1] The maximum length of lag number is set to 60.

over-rejection problem demonstrated by Diks and Panchenko (2006). Therefore, Diks and Panchenko (2006) developed a new nonlinear Granger causality test that could effectively address these limitations, which was used widely to analyse economic and energy market data (Alzahrani et al., 2014; Bal and Rath, 2015; Gu and Zhang, 2016; Yu et al., 2015). Therefore, this paper utilizes this nonlinear Granger causality test proposed by Diks and Panchenko (2006) to analyse the nonlinear relationship between the regional natural gas and crude oil markets.

Assume that there are two strictly stationary time series datasets, $X_t$ and $Y_t$; if the past and current value of $X$ contains additional information on the future values of $Y$ that is not contained in past and current $Y_t$-values alone, then $X_t$ strictly Granger causes $Y_t$. Let $F_{X,t}$ and $F_{Y,t}$ represent the information sets of the past observations of $X_t$ and $Y_t$ before the time $t+1$, respectively, and let ~ represent the equivalent distribution. When the following conditions are satisfied, the time series $X_t$ is the Granger causality for $Y_t$,

$$(Y_{t+1},\ldots,Y_{t+k})\left|(F_{X,t},F_{Y,t})\sim(Y_{t+1},\ldots,Y_{t+k})\right|F_{X,t} \quad (9)$$

where $k\geq1$ is the forecast boundary and $k=1$ is used to compare the one-step-ahead conditional distribution of $Y_t$ with and without the past and current values of $X_t$. Given the delay vectors $X_t^{Lx}=(X_{t-L_X+1},\ldots,X_t)$ and $Y_t^{Ly}=(Y_{t-L_Y+1},\ldots,Y_t)$, $(L_X,L_Y\geq1)$, the null hypothesis assumes that past observations of $X_t^{Lx}$ contain no additional information about $Y(t+1)$ than those of $Y_t^{L_Y}$.

$$H_0: Y(t+1)\left|\left(X_t^{Lx};Y_t^{Ly}\right)\sim Y(t+1)\right|Y_t^{Ly} \quad (10)$$

For the strictly stationary bivariate time series, Eq. (10) is the invariant distribution of $(Lx+Ly+1)$-dimensional vector $W_t=(X_t^{Lx},Y_t^{Ly},Z_t)$, where $Z_t=Y_{t+1}$. To maintain a compact presentation and discussion, the time subscript should be removed, and the assumption $Lx=Ly=1$ should be set. Then, under the null hypothesis, the conditional distribution of $Z$, given $(X,Y)=(x,y)$, is the same as that of $Z$ given $Y=y$. Thus, Eq. (10) can be restated using the joint distribution density function, as

$$\frac{f_{X,Y,Z}(x,y,z)}{f_Y(y)}=\frac{f_{X,Y}(x,y)}{f_Y(y)}\cdot\frac{f_{Y,Z}(y,z)}{f_Y(y)} \quad (11)$$

According to Eq. (11), $X$ and $Z$ are conditionally independent of $Y=y$ for every fixed value of $y$. Thus, the modified null hypothesis, $H_0$, suggests that the following equation is satisfied.

$$q\equiv E\left[f_{X,Y,Z}(X,Y,Z)f_Y(Y)-f_{X,Y}(X,Y)f_{Y,Z}(Y,Z)\right]=0 \quad (12)$$

making $\hat{f}_w(W_i)$ represent the local density function estimated value of the random vector $W$ at $W_i$ using

$$\hat{f}_w(W_i)=\frac{(2\varepsilon_n)^{-d_W}}{(n-1)}\sum_{j,j\neq i}I_{ij}^W \quad (13)$$

where $I_{ij}^W=I(\|W_i-W_j\|<\varepsilon_n)$, $I(\cdot)$ denotes the indicator function and $\varepsilon_n$ denotes the bandwidth parameter associated with the number of samples for $n$. When a local density function estimated value is given, the following test statistic is constructed.

$$T_n(\varepsilon_n)=\frac{n-1}{n(n-2)}\cdot\sum_i\left(\hat{f}_{X,Y,Z}(X_i,Y_i,Z_i)\hat{f}_Y(Y_i)-\hat{f}_{X,Y}(X_i,Y_i)\hat{f}_{Y,Z}(Y_i,Z_i)\right) \quad (14)$$

For $Lx=Ly=1$, when $\varepsilon_n=Cn^{-\beta}\left(C>0,\frac{1}{4}<\beta<\frac{1}{3}\right)$, the statistic $T_n(\varepsilon_n)$ meets the following conditions:

$$\sqrt{n}\frac{(T_n(\varepsilon_n)-q)}{S_n}\xrightarrow{D}N(0,1) \quad (15)$$

where $\xrightarrow{D}$ represents the convergence in the distribution, and $S_n$ represents an estimated value of the asymptotic variance of $T_n(\cdot)$ as discussed in detail by Diks and Panchenko (2006).[2]

### 2.3. Data sources

For this paper, Henry Hub and national balancing point (NBP) spot daily prices are used as pricing benchmarks for North American and European markets, respectively.[3] The data interval ranges from 2nd January 1997 to 7th January 2016 and the data is extracted from the DataStream database. The unit for the NBP price data for the UK is a pence per therm, and the official exchange rate of the Bank of England is used to translate the unit of the NBP price into US dollars per million Btu. Additionally, WTI and Brent crude oil spot prices are used as the benchmarks for crude oil prices in North America and Europe, respectively (Ji and Fan, 2015, 2016), and are extracted from the US Energy Information Administration website. Fig. 1 shows the trend of the WTI and Henry Hub spot prices and Brent and NBP spot prices from 2nd January 1997 to 7th January 2016. The Henry Hub prices have deviated from the WTI prices since 2009 (Aruga, 2016; Asche et al., 2012; Erdős, 2012; Geng et al., 2016b; Wakamatsu and Aruga, 2013). Fig. 2 shows the WTI and Henry Hub price returns and Brent and NBP price returns from 3rd January 1997 to 7th January 2016.

Table 1 shows descriptive statistics for natural gas and crude oil prices and the corresponding price returns. The ratio of the mean value of the Henry Hub spot prices and NBP spot prices to the average value of crude oil prices is approximately 1/10, which is consistent with the conclusions of previous research (Brown and Yücel, 2008; Huntington, 2007). Referring to the link between crude oil and natural gas prices (Brown and Yücel, 2008; Huntington, 2007), one simple rule of thumb is that natural gas price is one-tenth of crude oil price through fitting the historical data, which can describe well the relationship between natural gas prices and crude oil prices. Meanwhile, if the ratio of natural gas price to crude oil price is still approximately 1/10, shows that the relationship between crude oil and natural gas prices is always stable. If this ratio is different from 1/10, shows that the relationship between crude oil and natural gas prices is broken by external factors. With respect to the price data, the statistics for crude oil and natural gas price returns are at a very small level. The maximum, the absolute value of the minimum and the standard deviation of the Henry Hub and NBP price returns are higher than the ones of the WTI and Brent price returns, which indicates that the price fluctuations in the North American and European natural gas markets are significantly higher than those in the crude oil markets. This is primarily due to natural gas markets being vulnerable to seasonality effects; in particular, the amplitude of market fluctuations is relative larger during the winter. This also indicates that, with respect to the crude oil market, the maturity and stability of North American and European regional natural gas markets are still in ascension.

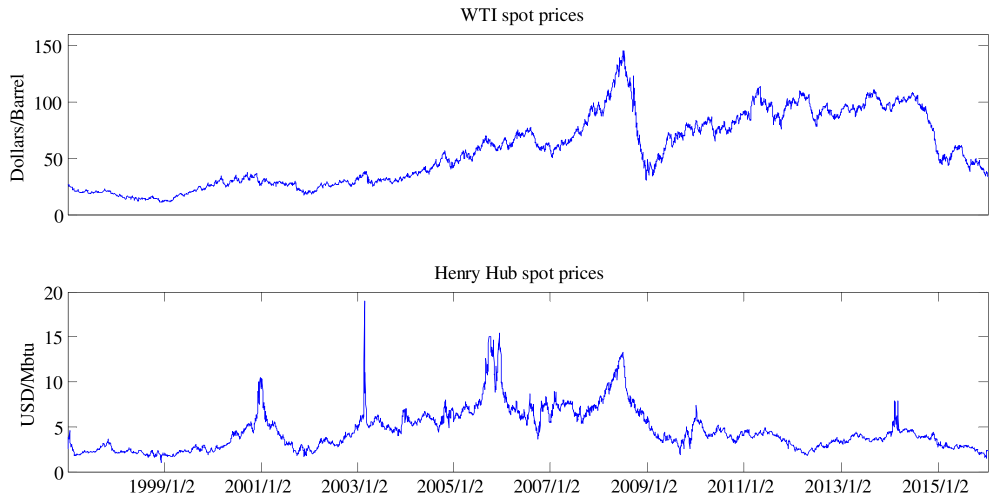
## 3. Empirical study

### 3.1. Multi-scale analysis

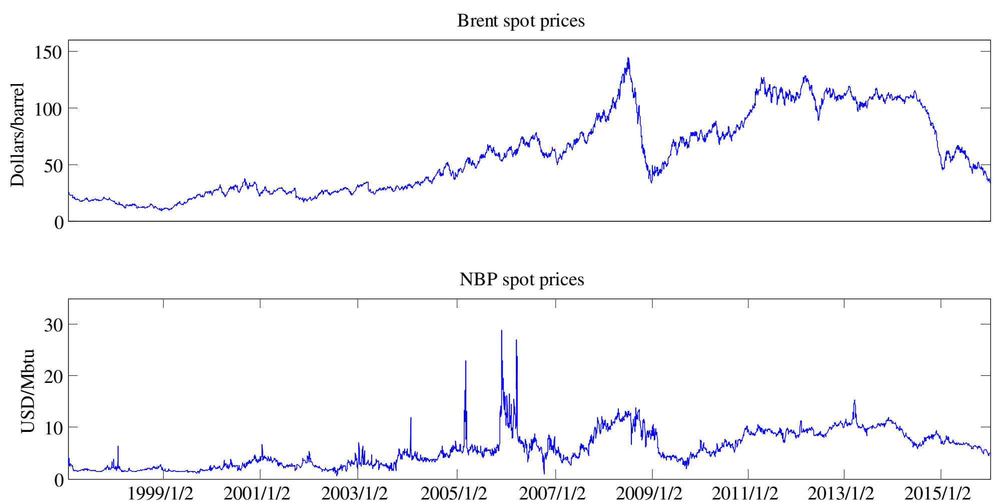
The EEMD method is used to decompose regional natural gas and crude oil price returns, and the results are shown in Figs. 3 and 4. Since the number of IMFs will be restricted to $\log_2 T$, where $T$ is the number of samples, seven IMFs and one residual item are obtained for each of the price returns sequences. All modes are listed in order from

[2] The estimation on the asymptotic variance of $T_n(\cdot)$ was discussed in detail by Diks and Panchenko (2006) in the Appendix A of their paper.

[3] Due to the data on the Asian natural gas daily price was not available and that the price mechanism of natural gas in the Asian market is similar to the one in the European market, the multi-scale linear and nonlinear Granger causality between crude oil and natural gas in the Asia is not analysed.




(a) WTI and Henry Hub daily prices




(b) Brent and NBP daily prices

**Fig. 1.** Crude oil and natural gas daily prices from 2nd January 1997 to 7th January 2016.

high frequency to low frequency. In particular, the multi-scale fluctuations of the decomposition components are determined based on the characteristics of the original returns series, each of which is driven by different internal factors (Huang et al., 1998). To analyse the original returns and the multi-scale decomposition component series, the time-scale duration of each component and the importance of each extracted component to the original returns series are calculated, and the stationarity of the original returns series and the extracted components are measured. These results are shown in Table 2.

Table 2 shows the time scales of various decomposition components. The different internal drivers of different decomposition components for the natural gas and crude oil markets have different economic implications. In particular, IMF1, the average duration of which is 2–4 days, is identified as the markets' normal fluctuation, and it happens at a high frequency. It is mainly caused by a series of factors that have short-term effects, such as bad weather, strikes and depletion of inventory; the duration of these effects tends to be very short. IMFs 2–7, the duration of which spans from one week to one year, are mainly caused by factors that have a medium-term effect. Considering that the time-span duration of IMFs 2–7 is relatively large, for IMFs whose duration is relatively short (i.e., from one week to several months), they contain effects of minor irregular events, and for IMFs whose duration is relatively long (i.e., from several months to one year), they include the effects of some significant events and the effects of energy policy changes. Since natural gas and crude oil are different commodities, the development maturity of each market is distinct, and this causes regional natural gas and crude oil markets to be affected by different factors that bear medium-term effects. In particular, as the world's most important energy resource, crude oil is very important to the economic development and security of energy supplies in many countries. Crude oil markets are also more vulnerable to geopolitical influence from countries that produce crude oil. Regional natural gas markets are mainly influenced by the shock of crude oil prices, hurricanes, the North American shale gas revolution, and other significant events that have medium-term effects. In addition, the global financial crisis of 2008 changed the global economic system, and this has had a significant impact on regional natural gas and crude oil markets alike. Fluctuation of the residual term does not have a significant tendency towards variation, and presents as a smooth curve. The time scale of the residual term is approximately two years, which reflects the long-term trend of the markets. For the regional natural gas markets, the pricing mechanism is primarily based on

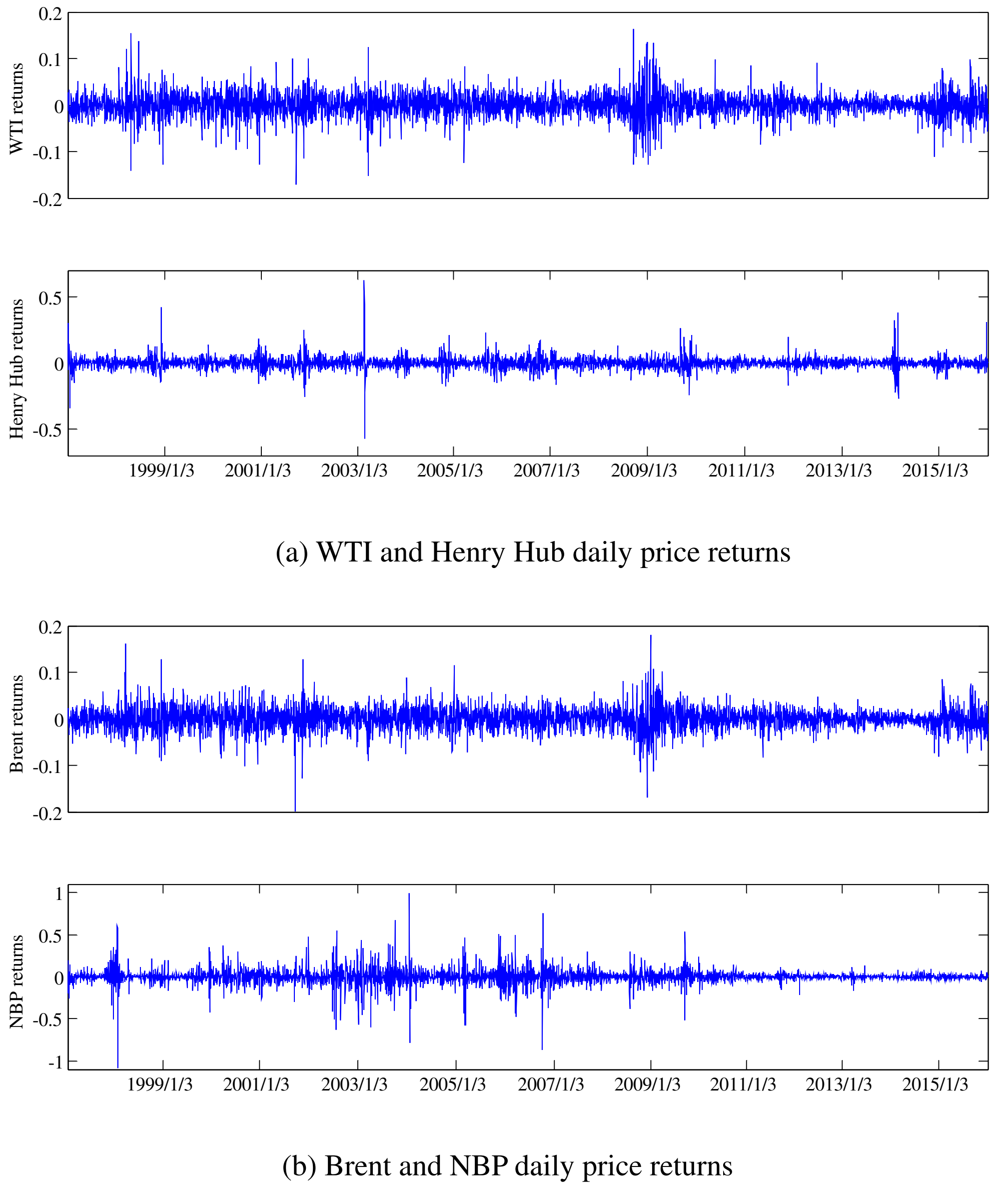



**Fig. 2.** Crude oil and natural gas daily price returns from 3rd January 1997 to 7th January 2016.

crude oil prices, and current long-term trends follow the long-term trends of crude oil markets.

To analyse the importance of each decomposed component, the contributions of each component to the total market fluctuations are measured and calculated; these assessments are based on the proportion of the variance of each component that accounts for the total variances of IMFs and the residual item. Table 2 shows IMF1, which is identified as the markets' normal fluctuation; it accounts for the largest share of overall market fluctuations in both the regional natural gas and crude oil markets. In particular, for the WTI and Henry Hub price return series, the variance of IMF1 accounts for fluctuations in the crude oil market and North American natural gas market at 38.27% and 38.90%, respectively; similarly, for the Brent and NBP price return series, the proportion of IMF1 contributing to crude oil and European natural gas market fluctuations are 35.62% and 39.90%, respectively. The total proportion of the variance of IMFs 2–7, which represent fluctuations caused

**Table 1**
Summary statistics of the prices and returns series for natural gas and crude oil markets.

| | Prices | | | | Returns | | | |
|---|---|---|---|---|---|---|---|---|
| | WTI | Henry Hub | Brent | NBP | WTI | Henry Hub | Brent | NBP |
| Mean | 56.604 | 4.581 | 58.158 | 5.693 | 0.000055 | −0.000017 | 0.000066 | 0.000100 |
| Median | 53.535 | 4.020 | 53.495 | 5.158 | 0.000474 | 0.000000 | 0.000215 | 0.000000 |
| Max | 145.310 | 19.000 | 143.950 | 28.841 | 0.164137 | 0.622735 | 0.181297 | 0.996254 |
| Min | 10.820 | 1.035 | 9.100 | 0.602 | −0.170918 | −0.569533 | −0.198906 | −1.089403 |
| Std. dev. | 31.103 | 2.326 | 35.047 | 3.400 | 0.024782 | 0.043156 | 0.022897 | 0.085577 |

Note: The unit of WTI and Brent prices is dollars per barrel, and the unit of Henry Hub and NBP prices is USD/Mbtu.

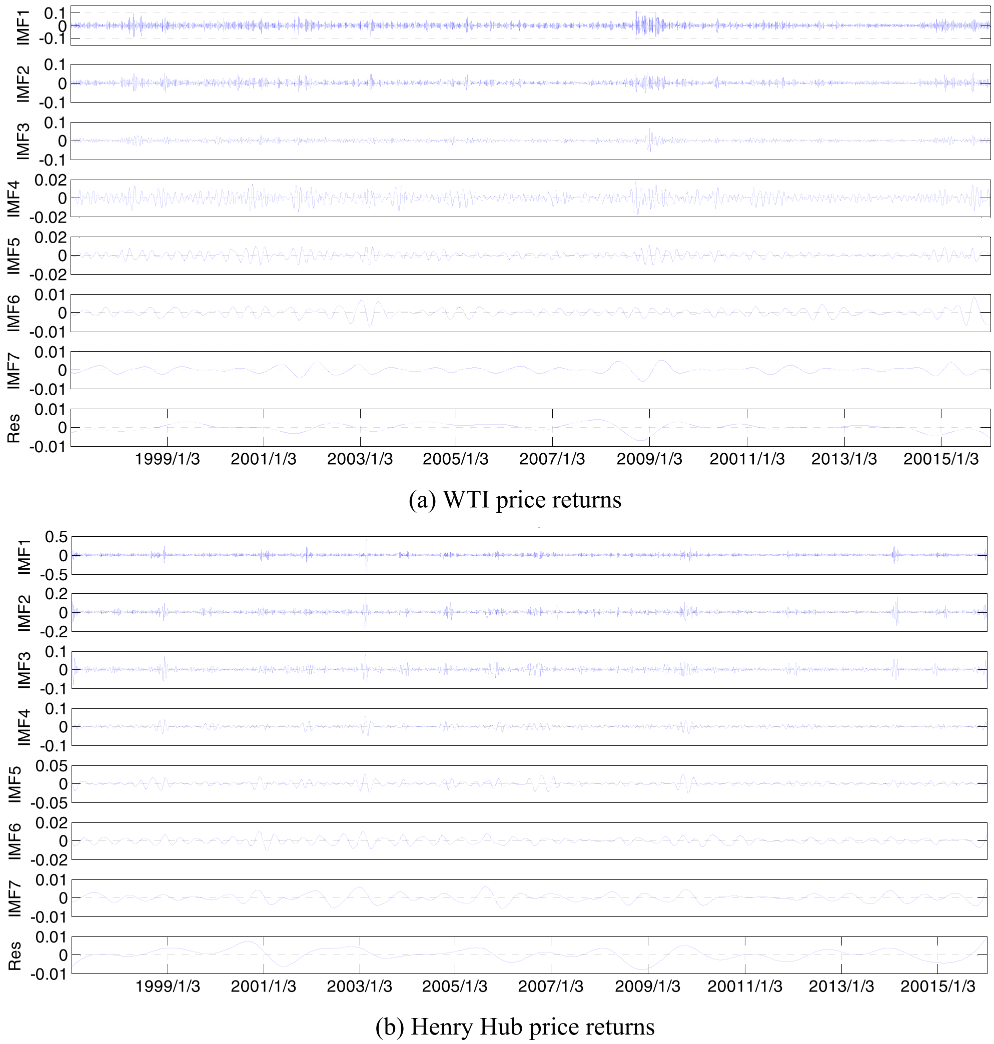



**Fig. 3.** Decomposition results of the WTI and Henry Hub price returns from 3rd January 1997 to 7th January 2016. (Note: The y-axis labels represent the amplitudes of different IMFs and the residual component).

by minor irregular and significant events, is also relatively large, indicating that the shock of minor irregular and significant events can cause large fluctuations in regional natural gas and crude oil markets. The residual terms representing the long-term trends of markets contribute minimally to fluctuations in the markets, which indicate the long-term evolutionary characteristics of each market.

To analyse Granger causality relationships between regional natural gas and crude oil markets from a multi-scale perspective, the extracted components must be stationary. This study uses the PP unit root test to analyse whether the original returns series and decomposed components are stationary; the results of that test are shown in Table 2. The test results indicate that all sequences are stationary, with significance below the 5% confidence level.

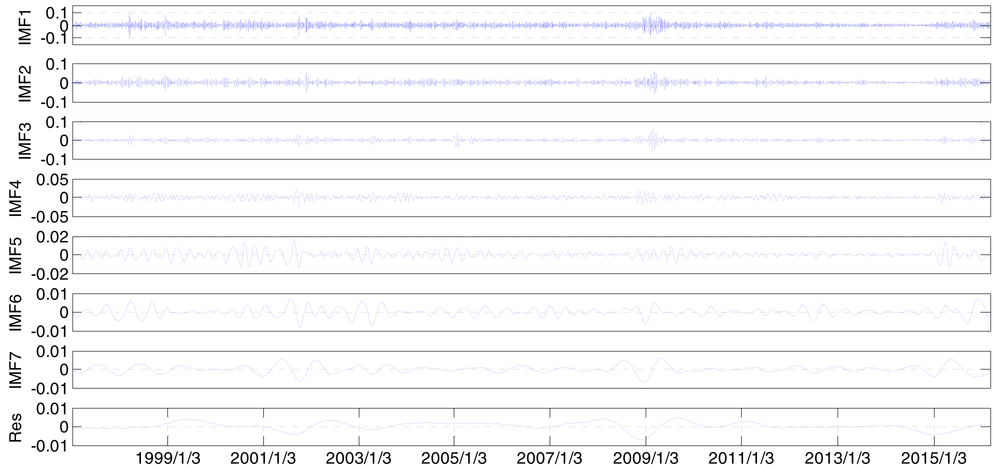
### 3.2. Linear Granger causality analysis between crude oil and natural gas markets

When analysing the linear Granger causality test, the bivariate VAR model for the markets is constructed, and the optimal lag order is determined using the AIC criterion. Table 3 presents the results of the linear Granger causality test between regional natural gas markets and crude oil markets for original data and decomposed series at different scales.

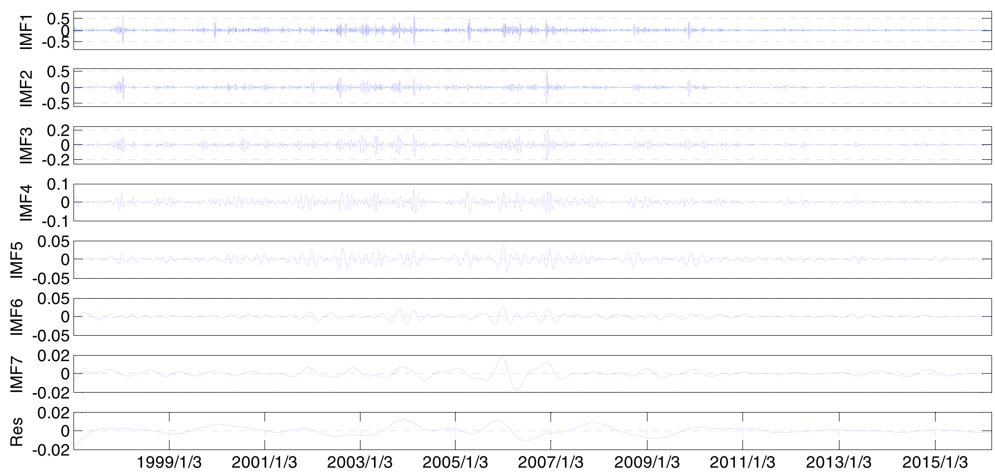
#### 3.2.1. Linear Granger causality between crude oil and North American natural gas markets

For the original returns series, the empirical results show that there exists only a unidirectional linear Granger causality from the crude oil market to the North American natural gas market, and this finding is consistent with those of many previous studies (Brown and Yücel, 2008; Nick and Thoenes, 2014). The early North American natural gas market used crude oil prices as a pricing benchmark, and although the current pricing mechanism of the North American natural gas market is based on market supply and demand, crude oil prices still have a significant impact on natural gas prices in North America.

On a multi-dimensional time scale, the North American natural gas and crude oil markets exhibit different linear Granger causality relationships. For short time scales, the linear Granger noncausality is rejected at the 1% significance level for the IMF1, which indicates that unidirectional linear Granger causality exists from the crude oil market to North American natural gas market. This also indicates that short-term fluctuations of crude oil prices have a linear impact on the short-term fluctuations of the North American natural gas market. For the medium-term time scale, the linear Granger noncausality is rejected at the 5% significance level, supporting the existence of a linear relationship in most cases. According to the multi-scale analysis, the time span of the average duration for IMFs 2–7 of the two markets is from six days




(a) Brent price returns




(b) NBP price returns

**Fig. 4.** Decomposition results of Brent and NBP price returns from 3rd January 1997 to 7th January 2016. (Note: The y-axis labels represent the amplitudes of different IMFs and the residual component).

**Table 2**
Measurements of the original data and extracted modes for returns.

| | Time scale (day) | Mode importance[a] | PP test *Adj. stat.* | Time scale (day) | Mode importance | PP test *Adj. stat.* |
|---|---|---|---|---|---|---|
| | WTI returns | | | Henry Hub returns | | |
| Original | | | −70.80***[b] | | | −64.74*** |
| IMF1 | 2.89 | 38.27% | −167.85*** | 3.01 | 38.90% | −128.40*** |
| IMF2 | 6.18 | 20.45% | −54.86*** | 6.39 | 21.04% | −38.84*** |
| IMF3 | 12.60 | 14.84% | −7.97*** | 12.63 | 13.66% | −6.55*** |
| IMF4 | 24.36 | 8.76% | −7.44*** | 25.13 | 9.76% | −18.80*** |
| IMF5 | 49.23 | 6.30% | −5.79*** | 50.26 | 7.09% | −6.96*** |
| IMF6 | 99.48 | 4.13% | −8.49*** | 108.52 | 3.67% | −8.67*** |
| IMF7 | 198.96 | 3.30% | −6.82*** | 207.61 | 2.44% | −6.88*** |
| Residue | 596.88 | 3.96% | −2.55** | 596.88 | 3.42% | −3.04*** |
| | Brent returns | | | NBP returns | | |
| Original | | | −67.83*** | | | −94.21*** |
| IMF1 | 2.90 | 35.62% | −136.26*** | 2.97 | 39.90% | −133.93*** |
| IMF2 | 6.178 | 19.32% | −31.71*** | 6.42 | 25.89% | −34.58*** |
| IMF3 | 12.90 | 14.71% | −8.27*** | 12.67 | 14.38% | −8.35*** |
| IMF4 | 25.07 | 9.48% | −8.45*** | 24.94 | 7.70% | −6.66*** |
| IMF5 | 53.48 | 7.71% | −5.84*** | 47.65 | 4.37% | −6.34*** |
| IMF6 | 106.96 | 4.78% | −8.72*** | 96.26 | 3.18% | −8.49*** |
| IMF7 | 218.77 | 4.15% | −6.80*** | 209.26 | 2.13% | −7.21*** |
| Residue | 601.63 | 4.24% | −3.09*** | 534.78 | 2.47% | −5.08*** |

[a] Mode importance is calculated based on the proportion of the variance of each component that accounting for the total variances of IMFs and the residual item.
[b] **, *** denote the significance at the 5%, 1% level, respectively.

**Table 3**
Multi-scale linear Granger causality between the crude oil and natural gas returns.

| Time scale | Series | Lag[a] | $H_0$: crude oil does not cause natural gas | | $H_0$: natural gas does not cause crude oil | | Results |
|---|---|---|---|---|---|---|---|
| | | | $\chi^2$ | p-Value | $\chi^2$ | p-Value | |
| *The WTI and Henry Hub returns* | | | | | | | |
| Original level | Original | 6 | 40.80 | 0.000 | 4.22 | 0.647 | WTI ⇒ Henry Hub |
| Short scale | IMF1 | 15 | 33.23 | 0.004 | 20.82 | 0.143 | WTI ⇒ Henry Hub |
| Medium scale | IMF2 | 16 | 14.19 | 0.585 | 14.23 | 0.581 | × |
| | IMF3 | 29 | 33.83 | 0.245 | 42.37 | 0.052 | × |
| | IMF4 | 28 | 58.40 | 0.001 | 84.80 | 0.000 | WTI ⇔ Henry Hub |
| | IMF5 | 41 | 58.75 | 0.036 | 110.60 | 0.000 | WTI ⇔ Henry Hub |
| | IMF6 | 27 | 88.46 | 0.000 | 98.59 | 0.000 | WTI ⇔ Henry Hub |
| | IMF7 | 4 | 97.87 | 0.000 | 221.35 | 0.000 | WTI ⇔ Henry Hub |
| Long scale | Residue | 3 | 1418.06 | 0.000 | 651.66 | 0.000 | WTI ⇔ Henry Hub |
| *The Brent and NBP returns* | | | | | | | |
| Original level | Original | 15 | 26.03 | 0.038 | 13.96 | 0.529 | Brent ⇒ NBP |
| Short scale | IMF1 | 7 | 6.14 | 0.524 | 2.98 | 0.887 | × |
| Medium scale | IMF2 | 17 | 36.73 | 0.004 | 18.94 | 0.332 | Brent ⇒ NBP |
| | IMF3 | 24 | 40.16 | 0.021 | 34.25 | 0.080 | × |
| | IMF4 | 34 | 103.69 | 0.000 | 23.69 | 0.907 | Brent ⇒ NBP |
| | IMF5 | 51 | 202.64 | 0.000 | 40.10 | 0.864 | Brent ⇒ NBP |
| | IMF6 | 24 | 21.16 | 0.629 | 28.78 | 0.228 | × |
| | IMF7 | 22 | 36.92 | 0.024 | 23.33 | 0.383 | Brent ⇒ NBP |
| Long scale | Residue | 3 | 142.01 | 0.000 | 231.11 | 0.000 | Brent ⇔ NBP |

[a] The lag number is determined based on the AIC criterion.

to 220 days, primarily due to the effects of minor irregular and significant events. The linear Granger causality test result is not significant for IMF2 and IMF3 for the North American natural gas and crude oil markets, but there is a bidirectional linear Granger causality for IMFs 4–7 of the two markets. There are two main reasons for these results. First, IMFs 4–7 are formed due to the impact of factors having a medium-term effect, such as the shock impact of significant events or structural changes in energy policies, which could structurally change the entire energy system, resulting in similar market changes that increase the spillover effects between the crude oil and natural gas markets. Second, since the duration of the fluctuation sequences is long, the shock impact of these factors on the markets is difficult to eliminate in the short term, and these effects can spillover from one market to the other. Meanwhile, these results may stem from the fact that the second and third time scales contain the effects of minor irregular events, the duration of which is relatively short. Therefore, the shock impact of these minor irregular events on the markets is relatively easy to be eliminated in the short term, and then these effects cannot spillover from one market to the other. In summary, on a medium-term time scale, there exists significant bidirectional linear Granger causality between the North American natural gas market and the crude oil market. For long-term trends, a mutually affecting relationship is found between the two residual terms of the market returns. This is further evidence that long-term trends of returns for the North American natural gas market and crude oil market tend to be similar.

For the original returns series, there exists only a unidirectional linear Granger causality from the crude oil market to the North American natural gas market. However, a bidirectional linear Granger causality exists between IMFs 4–7 and long-term trends between the two markets. This is revealed during the multi-scale analysis, in which IMF1 representing the short-term fluctuation has the largest influence on both the natural gas and crude oil markets; the contributions of IMFs 4–7 and the trend term are comparatively smaller. Thus, the market relationship of the main decomposed component (IMF1) determines the market relationship of the original returns series.

#### *3.2.2. Linear Granger causality between crude oil and European natural gas markets*

For the original returns series, the empirical results show that a unidirectional linear Granger causality exists from the crude oil market to the European natural gas market. This is because the pricing benchmark of the European natural gas market has been always indexed to the crude oil prices.

On a multi-dimensional time scale, European markets exhibit different linear causalities. For the short-term scale, there is no linear Granger causality for IMF1 between the European natural gas market and the crude oil market. For the medium-term time scale, the linear Granger noncausality is rejected at the 5% significance level, which indicates that there is a unidirectional linear Granger causality for IMF2, IMFs 4–5 and IMF7 of the two markets, from the crude oil market to the European natural gas market. This is mainly due to the impact of minor irregular and significant events on the crude oil market, such as structural changes in energy policies that lead to European natural gas market fluctuations. Unlike the bidirectional linear Granger causality existing between the North American markets at the mid-term time scale, a linear Granger causality from the European natural gas market to crude oil market at this scale does not exist. For long-term trends, the residual terms of the market returns mutually affect each other. This is further evidence that long-term trends for European natural gas and crude oil market returns fluctuate in a similar manner.

### *3.3. Nonlinear Granger causality analysis between crude oil and natural gas markets*

The residuals series is obtained using the VAR model to filter the data, and the nonlinear Granger causality test is used to analyse the nonlinear Granger causality relationship between the residuals series for the original returns series and multi-scale components of regional natural gas markets and the crude oil markets. According to Diks and Panchenko (2006), the lag is set to $Lx = Ly = 1, 2, \ldots, 6$, the bandwidth parameter $C$ is set to 8, the theoretical optimal rate $\beta$ is set to 2/7 and the optimal bandwidth $\varepsilon_n$, based on the sample size, is set to 1.

#### *3.3.1. Nonlinear Granger causality between crude oil and North American natural gas markets*

The nonlinear Granger test results for the North American markets are shown in Table 4. In each Panel in Table 4, two null hypothesis tests are estimated to investigate the nonlinear Granger causality from WTI to HH or from HH to WTI at different scales with changing $Lx = Ly$ from 1 to 6. For the original returns series, it is found that Granger noncausality is rejected at the 5% significance level in the North American markets, indicating the existence of bidirectional nonlinear

**Table 4**
Multi-scale nonlinear Granger causality between WTI and Henry Hub returns.

| $Lx = Ly$ | $H_0$: WTI does not cause HH | $H_0$: HH does not cause WTI | $H_0$: WTI does not cause HH | $H_0$: HH does not cause WTI |
|---|---|---|---|---|
| | *Tn* | *Tn* | *Tn* | *Tn* |
| | Panel A: Original data | | Panel F: IMF5 | |
| 1 | 3.590***[a] | 2.919*** | 3.494*** | 3.968*** |
| 2 | 3.054*** | 3.578*** | 3.252*** | 3.643*** |
| 3 | 2.488*** | 2.837*** | 2.761*** | 3.222*** |
| 4 | 2.767*** | 2.507*** | 1.936** | 2.262** |
| 5 | 2.440*** | 2.361*** | 1.864** | 1.730** |
| 6 | 2.398*** | 2.153** | 1.561* | 1.920** |
| | Panel B: IMF1 | | Panel G: IMF6 | |
| 1 | 2.383*** | 2.570*** | 3.971*** | 2.775*** |
| 2 | 2.226*** | 2.655*** | 3.350*** | 3.296*** |
| 3 | 2.306** | 2.405*** | 3.063*** | 3.246*** |
| 4 | 2.220** | 2.184** | 2.757*** | 3.173*** |
| 5 | 2.125** | 1.843** | 2.036** | 2.343*** |
| 6 | 2.083** | 1.694** | 1.119 | 2.182** |
| | Panel C: IMF2 | | Panel H: IMF7 | |
| 1 | 0.261 | 1.483* | 1.955** | 2.805*** |
| 2 | 0.675 | 1.609* | 1.844** | 2.831*** |
| 3 | 0.583 | 1.198 | 1.740** | 2.551*** |
| 4 | 0.808 | 0.781 | 1.955** | 2.056** |
| 5 | 0.995 | 0.762 | 1.915** | 2.137** |
| 6 | 1.098 | 0.461 | 2.126** | 2.052** |
| | Panel D: IMF3 | | Panel I: Residue | |
| 1 | 3.095*** | 2.115** | 0.734 | 0.006 |
| 2 | 3.187*** | 2.136** | 0.804 | 0.084 |
| 3 | 3.383*** | 2.500*** | 0.845 | 0.179 |
| 4 | 3.491*** | 2.146** | 0.904 | 0.296 |
| 5 | 3.558*** | 1.716** | 0.965 | 0.434 |
| 6 | 3.558*** | 1.444* | 1.130 | 0.661 |
| | Panel E: IMF4 | | | |
| 1 | 3.783*** | 4.039*** | | |
| 2 | 3.409*** | 3.500*** | | |
| 3 | 2.507*** | 2.631*** | | |
| 4 | 2.370*** | 2.644*** | | |
| 5 | 2.401*** | 2.670*** | | |
| 6 | 2.037** | 2.311** | | |

[a] *, ** or *** denote the significance at the 10%, 5% or 1% levels, respectively.

Granger causality between the North American natural gas and crude oil markets. This differs from the unidirectional linear Granger relationship existing from the crude oil market to the North American natural gas market.

For the short-term time scale, the nonlinear Granger noncausality is rejected at the 5% significance level for IMF1 between the North American natural gas market and the crude oil market, indicating that a bidirectional nonlinear Granger causality exists between the two markets and that the short-term fluctuations in crude oil and natural gas markets have a nonlinear mutual impact on each other. This is different from the linear Granger causality test result that only short-term fluctuations in crude oil market are found to have an impact on short-term fluctuations in the North American natural gas market. The reason for this may be that there is a strong substitute relationship between natural gas and crude oil, as a certain proportion of industrial sectors and electric power generators in U.S. have the ability to switch between gas and products refined from crude oil, as a production input; in this way, they can use whichever energy source is less expensive at any given time. Drastic short-term fluctuations caused by the release of inventory announcements and seasonal demand changes can be transmitted mutually between the North American natural gas market and the crude oil market. Inventory announcement information in the natural gas and crude oil markets is very important to market and trading participants, who usually pay more attention to fundamental market information. Inventory not only speaks to the market's supply and demand conditions, but it also reflects the pressures of changing market fundamentals on natural gas and crude oil prices in the short term (Bu, 2014; Chiou-Wei et al., 2014; Linn and Zhu, 2004). The release of inventory information on natural gas shortages implies anticipated increases in natural gas prices, and some facilities that can use either of these two energy sources may then choose to use crude oil. Similarly, the release of information on a natural gas glut would attract those firms that can use either fuel, as they would expect a drop in natural gas prices. Meanwhile, the effect of inventory information regarding either crude oil shortages or gluts has an impact on natural gas prices. Therefore, information found in released inventory announcements regarding crude oil or natural gas prices can mutually make the other market fluctuate in the short term.

For the medium-term time scale, the results suggest that Granger noncausality is rejected at the 5% significance level, supporting the existence of a nonlinear relationship between the two markets in most cases (i.e., except for IMF2). Most nonlinear Granger causality test results are consistent with the linear Granger causality test results. However, there is still some difference between linear and nonlinear test results. For example, nonlinear bidirectional Granger causality between the two markets can be statistically proven for IMF3 at the 5% significance level, while linear bidirectional Granger causality between these two markets cannot be discovered for the pair of IMF3. The possible reason is that the factors driving medium-term time scale fluctuations tend to be some irregular events and changes to energy policy, and induce nonlinear characteristics of the medium-term modes of the two market returns. Therefore, the nonlinear Granger causality test can effectively capture the nonlinear information for IMFs.

For the long-term trends, the nonlinear Granger causality test results indicate the absence of nonlinear Granger causality between the residual terms of the two market returns; this is unlike the case with the linear test results, which indicate the existence of bidirectional linear Granger causality for long-term trends between the North American natural gas market and the crude oil market. This may be due to the characteristics of linear causality and the low complexity of long-term trends in these markets. No mutual nonlinear structural influence exists between long-term trends in North America, and the liaison mechanism between the long-term trends of the two markets follows a simple linear relationship rather than a complex nonlinear relationship.

### *3.3.2. Nonlinear Granger causality between crude oil and European natural gas markets*

The nonlinear Granger causality test results for the European markets are shown in Table 5. Similar to Table 4, nonlinear Granger causality tests at two different directions (from Brent to NBP and from NBP to Brent) are estimated at different scales. For the original returns series, the test results indicate that the Granger noncausality is rejected at the 1% significance level between the European natural gas market and the crude oil market. This indicates that bidirectional nonlinear Granger causality exists between the European markets; this finding is markedly different from the conclusion that only a unidirectional linear Granger relationship exists from the crude oil market to the European natural gas market.

For the short-term time scale, the Granger noncausality is rejected at the 1% significance level for IMF1 of the European markets, indicating that bidirectional nonlinear Granger causality exists. This indicates that the short-term fluctuations of crude oil prices and the short-term fluctuations of the European natural gas market have mutual nonlinear effects; these findings differ from the linear Granger causality test results, which indicate the absence of mutual spillover effects between the crude oil market and the European natural gas market on a short-term time scale. The reason for this may be that the release of inventory announcements and seasonal demand changes lead to short-term drastic fluctuations in market prices, which makes structural short-term fluctuations mutually responsive between the European markets.

For the medium-term time scale, the nonlinear Granger noncausality is rejected at the 5% significance level, which suggests the existence of a nonlinear link between the two markets in most cases,

**Table 5**
Multi-scale nonlinear Granger causality between Brent and NBP returns.

| $Lx = Ly$ | $H_0$: Brent does not cause NBP | $H_0$: NBP does not cause Brent | $H_0$: Brent does not cause NBP | $H_0$: NBP does not cause Brent |
|---|---|---|---|---|
| | *Tn* | *Tn* | *Tn* | *Tn* |
| | Panel A: Original data | | Panel F: IMF5 | |
| 1 | 3.635***[a] | 4.606*** | 5.108*** | 4.353*** |
| 2 | 4.526*** | 5.185*** | 5.444*** | 4.893*** |
| 3 | 4.503*** | 4.895*** | 6.115*** | 5.484*** |
| 4 | 4.606*** | 4.565*** | 6.275*** | 5.744*** |
| 5 | 4.071*** | 4.526*** | 6.062*** | 5.777*** |
| 6 | 4.001*** | 4.151*** | 5.925*** | 5.454*** |
| | Panel B: IMF1 | | Panel G: IMF6 | |
| 1 | 4.497*** | 4.486*** | 3.132*** | 3.659*** |
| 2 | 4.762*** | 4.815*** | 3.991*** | 3.688*** |
| 3 | 4.836*** | 4.592*** | 3.428*** | 3.516*** |
| 4 | 5.268*** | 4.584*** | 3.639*** | 3.406*** |
| 5 | 5.196*** | 4.296*** | 3.609*** | 3.452*** |
| 6 | 5.113*** | 4.096*** | 3.464*** | 3.227*** |
| | Panel C: IMF2 | | Panel H: IMF7 | |
| 1 | 3.315*** | 2.467*** | 2.101** | −1.883 |
| 2 | 3.196*** | 2.783*** | 2.901*** | −2.118 |
| 3 | 3.626*** | 3.004*** | 3.153*** | −2.325 |
| 4 | 3.889*** | 3.343*** | 3.304*** | −2.372 |
| 5 | 4.180*** | 3.626*** | 3.324*** | −2.485 |
| 6 | 4.180*** | 3.908*** | 3.249*** | −2.180 |
| | Panel D: IMF3 | | Panel I: Residue | |
| 1 | 2.628*** | 1.728*** | −1.182 | 0.298 |
| 2 | 3.246*** | 2.145** | −1.128 | 0.311 |
| 3 | 4.572*** | 2.508*** | −0.648 | −0.067 |
| 4 | 4.542*** | 2.778*** | −0.550 | −0.274 |
| 5 | 5.041*** | 3.207*** | −0.331 | −0.383 |
| 6 | 5.115*** | 3.378*** | 0.006 | −0.536 |
| | Panel E: IMF4 | | | |
| 1 | 3.776*** | 4.050*** | | |
| 2 | 4.703*** | 4.203*** | | |
| 3 | 5.583*** | 4.120*** | | |
| 4 | 5.360*** | 3.997*** | | |
| 5 | 6.033*** | 3.866*** | | |
| 6 | 5.757*** | 3.643*** | | |

[a] ** or *** denote significance at the 5% or 1% levels, respectively.

**Table 6**
Multi-scale nonlinear Granger causality between WTI and Henry Hub returns after GARCH filtering.

| $Lx = Ly$ | $H_0$: WTI does not cause HH | $H_0$: HH does not cause WTI | $H_0$: WTI does not cause HH | $H_0$: HH does not cause WTI |
|---|---|---|---|---|
| | *Tn* | *Tn* | *Tn* | *Tn* |
| | Panel A: Original data | | Panel F: IMF5 | |
| 1 | 3.873***[a] | 2.394*** | 1.229 | 3.447*** |
| 2 | 3.391*** | 3.328*** | 1.940** | 3.050*** |
| 3 | 3.045*** | 2.948*** | 2.177** | 2.522*** |
| 4 | 3.186*** | 2.648*** | 2.002** | 2.093** |
| 5 | 2.868*** | 2.218** | 1.546* | 1.882** |
| 6 | 2.580*** | 2.122** | 1.342* | 1.724** |
| | Panel B: IMF1 | | Panel G: IMF6 | |
| 1 | 1.936** | 1.736** | 1.954** | 0.694 |
| 2 | 2.003** | 1.900** | 1.756** | −0.314 |
| 3 | 2.407*** | 1.847** | 1.647** | 0.187 |
| 4 | 2.290** | 1.815** | 1.671** | 0.425 |
| 5 | 2.333*** | 1.411* | 1.591** | 0.582 |
| 6 | 2.177** | 1.382* | 1.535* | 0.880 |
| | Panel C: IMF2 | | Panel H: IMF7 | |
| 1 | 1.787** | 2.265** | −0.915 | 1.737** |
| 2 | 1.387* | 1.997** | −0.801 | 1.704** |
| 3 | 1.437* | 1.320* | −0.681 | 1.635* |
| 4 | 1.567* | 1.004 | −0.609 | 1.654** |
| 5 | 1.735** | 0.695 | −0.468 | 1.609* |
| 6 | 1.978** | 0.596 | −0.450 | 1.607* |
| | Panel D: IMF3 | | Panel I: Residue | |
| 1 | 2.140** | 2.198** | 3.559*** | 1.282* |
| 2 | 1.973** | 1.407* | 3.542*** | 1.351* |
| 3 | 1.262 | 0.727 | 3.497*** | 1.378* |
| 4 | 1.408* | 0.625 | 3.463*** | 1.515 |
| 5 | 1.747** | 0.610 | 3.415*** | 1.723** |
| 6 | 2.009** | 0.630 | 3.370*** | 1.918** |
| | Panel E: IMF4 | | | |
| 1 | 3.808*** | 3.516*** | | |
| 2 | 3.497*** | 3.053*** | | |
| 3 | 3.000*** | 2.184** | | |
| 4 | 2.547*** | 1.498* | | |
| 5 | 2.489*** | 1.225 | | |
| 6 | 2.656*** | 1.027 | | |

[a] *, ** or *** denote the significance at the 10%, 5% or 1% levels, respectively.

except for IMF7. Unlike the linear Granger test results which only discovered the linear unidirectional Granger causality running from the Brent market to European gas market in most cases with the exception for IMF3 and IMF6, most of the nonlinear results show that bidirectional nonlinear spillover effects exist between the European markets. This is because the factors driving these medium-term time scale changes are primarily minor irregular and significant events and changes in energy policy which may lead to structural changes. Due to these structural changes, the decomposition modes of the two market returns on the medium-term time scale show obvious nonlinear features. In this case, the traditional linear Granger causality test cannot effectively capture nonlinear information.

As for the long-term trends, the nonlinear Granger causality test results indicate that no nonlinear Granger causality exists between the two residual terms of the market returns; these results differ from the linear test results, which indicate bidirectional linear Granger causality for long-term trends. The main reason for this may be that the long-term trends in the European markets are linear, and from a long-term time scale perspective, there are no nonlinear spillover effects between the markets.

### 3.4. Robustness tests

Due to that crude oil and regional natural gas markets might have a time-varying volatility, the GARCH effect should be considered when nonlinear Granger causality tests are conducted (Reboredo, 2014). To make our results more robust, regional natural gas and crude oil price series are filtered using a GARCH model for capturing the GARCH effect. During the nonlinear Granger causality test, the residuals are obtained using the GARCH model to filter the data. The nonlinear Granger causality test is used to analyse the contributions of the GARCH effect on the spillover effects between the North American markets. The nonlinear Granger causality test results for the GARCH (1, 1) filtered data for the North American natural gas and crude oil markets are shown in Table 6.

Based on the results displayed in Table 6, the statistical significance of the nonlinear results does not become significant weaker after the GARCH model filtration. This indicates that the GARCH effect has little contribution to the spillover effects between the North American natural gas market and crude oil market on the short- and medium-term time scales. The significance of the relationship between the residuals of the two markets is enhanced after the GARCH model filtration, possibly because the simple linear characteristic of long-term trends does not contain significant volatility. When analysing the nonlinear relationship between the long-terms trends of both markets, the GARCH model is not sufficient for model identification.

The GARCH effect should be also considered when analysing the nonlinear Granger causality relationship between the European markets. Table 7 shows the results of the nonlinear Granger causality test for the GARCH (1, 1) filtered data from the European natural gas and crude oil markets. By comparing the results of Tables 5 and 7, it is easy to find that the statistical significance of the nonlinear results for the GARCH model filtration is not weakened. This indicates that the GARCH effect

**Table 7**
Multi-scale nonlinear Granger causality between Brent and NBP returns after GARCH filtering.

| $Lx = Ly$ | $H_0$: Brent does not cause NBP | $H_0$: NBP does not cause Brent | $H_0$: Brent does not cause NBP | $H_0$: NBP does not cause Brent |
|---|---|---|---|---|
| | *Tn* | *Tn* | *Tn* | *Tn* |
| | Panel A: Original data | | Panel F: IMF5 | |
| 1 | 4.035***[a] | 4.909*** | 2.283** | 1.916** |
| 2 | 4.257*** | 5.312*** | 2.494*** | 2.073** |
| 3 | 4.443*** | 4.941*** | 3.172*** | 2.248** |
| 4 | 4.372*** | 4.522*** | 3.479*** | 2.439*** |
| 5 | 3.903*** | 4.505*** | 3.690*** | 2.414*** |
| 6 | 3.936*** | 4.217*** | 3.686*** | 2.518*** |
| | Panel B: IMF1 | | Panel G: IMF6 | |
| 1 | 3.920*** | 5.048*** | 1.280 | 1.278 |
| 2 | 4.533*** | 4.987*** | 1.475* | 1.178 |
| 3 | 4.627*** | 4.652*** | 1.684** | 1.174 |
| 4 | 4.765*** | 4.803*** | 1.873** | 1.227 |
| 5 | 4.945*** | 4.472*** | 2.319** | 1.274 |
| 6 | 5.250*** | 4.336*** | 2.552*** | 1.413* |
| | Panel C: IMF2 | | Panel H: IMF7 | |
| 1 | 2.839*** | 3.267*** | 1.472* | 0.447 |
| 2 | 2.726*** | 2.850*** | 1.471** | 0.506 |
| 3 | 2.889*** | 2.600*** | 1.502* | 0.549 |
| 4 | 3.088*** | 2.463*** | 1.527* | 0.604 |
| 5 | 3.538*** | 2.373*** | 1.533* | 0.660 |
| 6 | 3.604*** | 2.584*** | 1.621* | 0.700 |
| | Panel D: IMF3 | | Panel I: Residue | |
| 1 | 2.597*** | 2.058** | −0.062 | 0.305 |
| 2 | 3.428*** | 2.775*** | −0.054 | 0.315 |
| 3 | 3.549*** | 3.095*** | −0.068 | 0.341 |
| 4 | 3.417*** | 2.863*** | −0.071 | 0.326 |
| 5 | 3.300*** | 2.561*** | −0.067 | 0.310 |
| 6 | 3.320*** | 2.286** | −0.041 | 0.320 |
| | Panel E: IMF4 | | | |
| 1 | 3.659*** | 2.665*** | | |
| 2 | 3.955*** | 2.221** | | |
| 3 | 4.066*** | 1.878** | | |
| 4 | 3.770*** | 1.877** | | |
| 5 | 3.523*** | 2.095** | | |
| 6 | 3.314*** | 2.270** | | |

[a] *, ** or *** denote the significance at the 10%, 5% or 1% levels, respectively.

has also little contribution to the spillover effects between the European markets on the short-, medium-or long-term time scales.

## 4. Conclusions and policy implications

Using the EEMD and multi-scale analysis, this study systematically analyses the linear and nonlinear Granger causality relationships between regional natural gas markets and crude oil markets. For original returns series, only a unidirectional linear causality was found to exist from the crude oil markets to the North American and European natural gas markets; however, the crude oil and regional natural gas markets exhibit bidirectional nonlinear causality. On the short-term time scale, unidirectional linear causality is found from the crude oil market to the North American natural gas market, while no linear spillover effects are found to exist between the crude oil market and the European natural gas market; however, bidirectional nonlinear causality is found to exist between the crude oil and regional natural gas markets. On the medium-term time scale, bidirectional linear spillover effects are found to exist between the crude oil market and the North American natural gas market, while only a unidirectional linear causality exists from the crude oil market to the European natural gas market; however, a strong and mutual nonlinear spillover effect is found between the crude oil and regional natural gas markets. On the long-term time scale, only a significant bidirectional linear causality exists between the crude oil and regional natural gas markets. These findings indicate that the proposed analytical framework provides a new perspective for analysing spillover effects between regional natural gas and crude oil markets.

The above findings can help energy policy makers and market investors comprehensively understand the horizon-specific information on dependence and nonlinear causality between regional natural gas markets and the crude oil markets, which have implications for them investing and making hedging strategies with different horizons in these markets. For energy policy makers, since there exist bidirectional nonlinear spillover effects between the North American and European natural gas market and crude oil markets for the original returns series. They need to focus on the potential shock caused by the price uncertainty of the both of the two kinds of markets, at the same time, they need to pay attention to the risk spillover between regional natural gas markets and crude oil markets as result of the above potential shock. Furthermore, on short- and medium-term time scales, the markets have bidirectional nonlinear spillover effects, which confirm that the markets' normal fluctuation in the regional gas market and the shock impact on regional natural gas markets caused by other minor irregular and significant events and energy policy changes all have an impact on the crude oil markets. This type of market information can help energy policy makers better manage market spillover and mitigate risks. For investors creating market portfolios and conducting risk management, natural gas or crude oil can be used to design appropriate hedging strategies. Taking into account the price behaviour relationship in the short-, medium- and long-term scale, when regional natural gas prices or crude oil prices are predicted, relevant additional information from the other market should be a key consideration.

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## Appendix A. Supplementary data

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