Oil volatility effect on stock networking

Liyan Han[1], Qiuna Lv[1], Libo Yin[2*]

1. School of Economics & Management, Beihang University, Beijing, China

2. School of Finance, Central University of Finance and Economics, Beijing, China

[*] the corresponding author, yinlibowsxbb@126.com

Abstract:

In this paper, we innovatively analyze oil volatility effect on oil-related stock networks which are constructed to model stock price comovemnets with change in volatility, which can benefit the performance of a dynamic portfolio. We put forward three network topological indices that are network density, network efficiency and network entropy to quantify and monitor the dynamic evolutions of the daily oil-related stock networks. By testing the linear relationship between oil volatility and network topological indices with in-sample and out-of-sample analyses, we find oil volatility has a stably positive effect on the three network indices. Robustness tests with sub-sample analyses and macro factors also confirm this finding. That is to say, changes in oil volatility can cause positive changes in network density, efficiency and entropy. It further means, in a more stable oil price state, the oil-related stock comovements will weaken, the price link efficiency decreases, and oil-related stocks become more heterogeneous. Besides, asymmetric effect results show that the oil volatility effect can be more significant in high-volatility state, and the Markov-switching model cannot outperform the simple linear model in this study.
Keywords: Oil volatility, stock price comovements, Dynamic conditional correlations, Complex network

1. Introduction

Given that crude oil price is of economic significance in affecting macroeconomic aggregates, the relationship between crude oil volatility and stock market fluctuations has attracted considerable attention from financial investors and policymakers. The important impact of oil volatility on the stock market can be explained in the following three ways. Firstly, uncertain and huge volatility in oil price can leads to huge shocks in production, consumption, and investments, and further the asset prices. Secondly, oil prices can lead to changes of related macroeconomic policy, especially for the developing countries with immature financial policies (You et al., 2017). Then, the financial asset prices can be further affected. Thirdly, crude oil now has been widely used in hedging stock market risk for its high fluidity, which also shows its financial attributes in stock markets. Based on this consideration, researchers provide so much evidence that oil price volatility has profound effect on stock markets returns (Kaul and Seyhun, 1990) and more specifically, stock markets react negatively to higher oil price volatility (Sadorsky, 1999; Elyasiani et al., 2011; Masih et al., 2011; Diaz et al., 2016). Further, Cong et al. (2008) find that the oil volatility shocks have more significant impact on stock returns of mining and petrochemical industry. In recent papers, Raza et al (2016) and Zhu et al. (2017) point out that oil market shocks have a minimal impact on stock returns in the low volatility state and a significant impact in the high volatility state. In that case, stock returns will respond more significantly in volatile oil price period.

However, does individual stocks respond to oil volatility fluctuations homogenously? If not, when will stock prices respond more homogenously under various level of oil volatility? In more concise words to say, does oil volatility influence the stock market correlations? Addressing this question is of great significance for investors to conduct optimal portfolio choices and risk management under various levels of oil price volatility. If oil volatility increase (decrease) can reduce the stock price correlations, investors will gain more potential chances for portfolio diversification in the less-correlated market. As we know, few studies have yet solved this problem. The rare research can be seen in Han et al (2019) who find oil price returns have a significantly negative effect on stock price interactions. This study will be the supplement for the existing researches and the first to investigate the oil volatility effect on stock market interactions.

So far, a strand of literature utilizes network models to investigate stock price interactions. Different types of stock networks are constructed based on the different definitions of nodes and edges. The nodes are usually defined as distinctive stocks, and links are mostly defined with the correlation coefficients between pairs of stock prices, as Mantegna (1999) firstly proposes. Some other authors also use Granger-Causality effects as edges (John et al., 1995). In terms of network configurations, the minimum-cost spanning tree (MST), the planar maximal filtering graph (PMFG) and the winner-take-all approach are proposed by scholars (Bonanno et al., 2001; Tumminello et al., 2005; Chi et al., 2010). The initial researches mainly focus on the construction of static networks. The More recent researches choose to construct dynamic stock network models to explore the time-varying interactions among asset prices. Some use a sliding window to depict the fluctuations of price correlations, which can be seen in Billio et al. (2012), Diebold and Yilmaz (2014) and Castagneto-Gissey et al. (2014). The other literature chooses to use dynamic correlation models, such as the time-varying copula approach (Wen et al., 2012), the dynamic conditional correlation multivariate GARCH (DCC-MV-GARCH) model (Lahrech and Sylwester, 2011; Lyócsa et al., 2012, 2017; Yin et al., 2017) and so on.

Furthermore, another strand of literature concentrates on the influence factors of stock market correlations (networks). Overall, the factors can be divided into three categories. Firstly, some researches find that shocks from the macroeconomy could drive the connectivity of stock markets. For example, Billio et al. (2012) find that before and during financial crises period, the financial systems become much more interrelated in comparison to the tranquil periods, indicating that the network connectedness measures can be an indicator of crisis periods. Lee and Nobi (2018) and Nobi et al (2014) also find during the period of market distress and dislocation, the networks appear to have larger connectivity, which reveals stronger comovements among stock prices. According to Castagneto-Gissey et al. (2014), implementations of crucial market integration and market coupling rules can improve the connectivity degree of related market networks, namely, the price comovements. Secondly, Eom and Park (2017) examine the effects of representative financial factors on the connectivity of the stock networks. The empirical results show that the stock correlations are clearly affected by the common financial factors, such as size factors, market factors, value factor, momentum factors, and so on, and the influence is much greater on central stocks to other stocks. Similar finding can also be seen in Luo and Xie (2012). Thirdly, evidences show that shocks from the crude oil market could also affect the related stock market connectivity. According to Han et al., 2019, exponential decline in oil prices can strengthen the stock market comovements, while increases in oil prices have minimal effect on stock price interactions.

To sum up, the above findings suggest that shocks from macroeconomy, financial markets and oil prices can influence the stock price correlations, and the crude oil volatility effect on stock price interactions can be further studied. Towards this deficiency, this study adds to the literature on the effect of crude oil volatility on the stock markets in three ways. Firstly, the main innovation of our study resides in the investigation of oil volatility effect on oil-related stock market correlations. Previous empirical researches indicate that oil price volatility can influence the stock prices in the oil-related industries more significantly and the effect is more significant in high volatility state. Then it can be assumed that the oil-related stocks may react similarly with common oil volatility and the stock price comovements can be stronger in volatile oil price period. Under this hypothesis, oil price volatility can be an indicator for investors to adjust asset structure and manage risk timely.

Secondly, this study employs the dynamic stock networks to model the time-varying correlations among stock prices, and further the network indicators to quantify the evolutions of correlation degree. In the traditional analyses about influencing factors of stock market comovements, most researchers choose to use the econometrical models to calculate the dynamic correlations among stock prices, and the number of sample stocks is very limited. By employing the network models in this paper, we can study the stock market comovements with much more sample stocks as a whole. Besides, to ensure the substantial information is all retained when constructing networks, we consider using the winner-take-all method to establish edges of the networks (chi et al., 2010).

Thirdly, we determine whether oil price volatility can influence stock networking by examining the directional predictability from oil volatility to the stock network indicators, from both in-sample and out-of-sample perspectives. To check the robustness of the results, we further conduct sub-sample analyses and exclude the disturbance of non-oil factors. Besides, given the fact that information spillover from the crude oil market to the stock market is not structurally stable, we seek to investigate the non-linear property of oil volatility effect on the stock network indices. We therefore further extend our empirical analysis to the asymmetric analyses and Markov regime switching models.

The remainder of this paper is organized as follows. Section 2 presents the data of stocks and crude oil used in our studies. Section 3 introduces the empirical methodologies and network indicators. Section 4 and Section 5 discuss the empirical results about in-sample and out-of-sample forecasts. Section 6 reports the nonlinear checks. Section 7 summarizes the conclusions of our work.

2. Data

2.1 Oil-related stocks

Evidence has shown that oil price volatility has a significant effect on the stocks belonging to the oil-related sectors (Elyasiani er al., 2011). Whether the effect on respective oil-related stock is homogenous needs further study. To solve this problem, we select the oil-related stocks listed on the New York Stock Exchange (NYSE) as sample set, which distribute in the oil & gas production sector, oilfield services sector, oil refining sector and integrated oil sector. The daily closing price data relative to the sample of oil-related stocks is obtained from the Wind database, and spans the period January 4, 2012 to June 13, 2018. With the abandon of stocks with incomplete data, 108 stocks are finally included in the oil-related stock set. The first differences of logarithmic stock prices are computed as stock returns. Each stock return series therefore consists of 1621 observations. Table 1displays the summary statistics for each stock return. As shown in Table 1, the average daily stock returns are all close to zero, ranging from -0.0035 (for CGG) to 0.0011(for ANDV). The skewness and kurtosis measures show that almost all the distributions of the search terms are skewed and leptokurtic, which can be verified by the Jarque–Bera statistics (JB). The Augmented Dickey–Fuller (ADF) stationarity test results for each return are all negative, indicating that all the return series are stationary. The Q statistics show that all the return series are serially auto-correlated. The results of Lagrange-multiplier test for conditional heteroscedasticity reported in the last column show that all the stock returns possess significant ARCH effects which exactly support our choice to use the GARCH-based approach to calculate the dynamic correlation coefficients.

Table 1

Summary statistics of crude oil price volatility

	Mean	Std.Dev	Skewness	Kurtosis	J-B	ADF	Q(20)	ARCH-LM
Brent	0.1078	0.0628	1.7590	4.5858	2263.7	-4.1128	10145.39	795.6038
WTI	0.1183	0.0663	1.8610	4.9525	2600.6	-3.7668	10408.94	838.47

2.2 Oil realized volatility

This paper's objective is to investigate the oil volatility effect on the oil stock networking. Following the literature, this paper utilizes the ex-post measures of variance to model the conditional volatility. The realized volatility, initially employed by Fung and Hsieh (1991), and later is defined as the sum of squared intraday returns computed at short intervals by Andersen and Bollerslev (1998). Therefore, we sum the squared five-minute intraday returns to construct the realized volatility of oil return at the daily frequency. For a specific day *t*, we define the realized variance (RV) as follows:

$$RV_t = \sum_{i=1}^{m} r_{t,i}^2,\ t = 1, 2, \cdots T \tag{1}$$

where m is the number of five-minute intervals in each day, and $r_{t,i}$ denotes the i th five-minute return in the tth day. This ex-post measures of variance is proved to be better than the squared monthly returns (Andersen and Bollerslev, 1997, Andersen et al., 2001,2003) and widely used in the predictive analyses about relationship between stock volatility and macro factors (Christiansen et al., 2012, Paye, 2012).

We collect the high-frequency price data of two oil futures, West Texas Intermediate (WTI) crude oil and Brent oil from Bloomberg database. Fig. 1 depicts the evolution of WTI/Brent oil realized volatility per day over the period of April, 2012-June, 2018. It can be noticed that there is an abrupt increase in the oil volatility during the ex-post period of 2014 and after the period, the oil volatility fluctuates more violently than before. Notably, oil price began to drop from June, 2014 and declined to its historical nadir until January, 2015. Thus, the uncertainty in oil price amplifies after the volatile period.

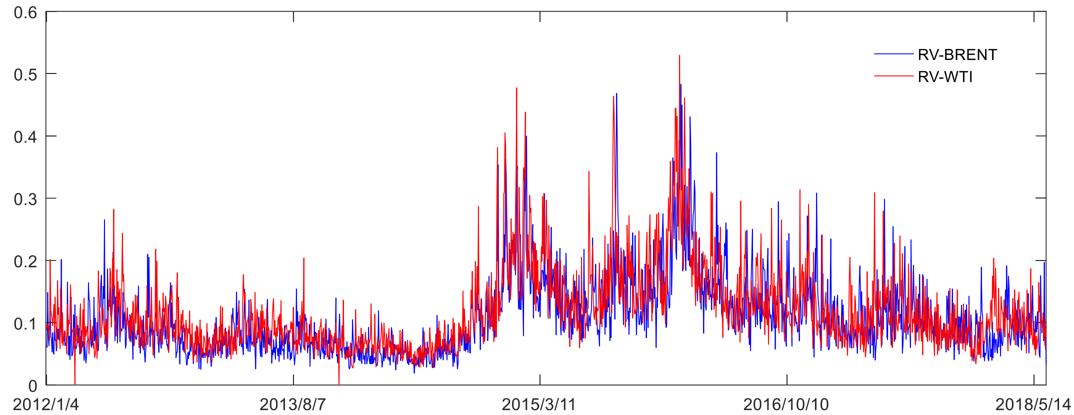

Fig.1. Evolutions of WTI/Brent oil realized volatility

3. Stock networking

A network is usually composed of the elements of nodes and edges. In a stock network, a node will denote an individual stock and a link connecting two nodes denotes that the two stocks present some similarities. To measure the stock similarity, we consider utilizing the cross correlation between stocks, as mainstream researches do (Bonanno, 2010; Chi et al., 2010). Allowing for the time-varying connectedness of networks, researches have moved from the static, unconditional perspective to a dynamic, conditional perspective (Diebold and Yılmaz, 2013). Existing dynamic models are usually constructed over a sliding window (Billio et al., 2012; Diebold and Yılmaz, 2013) or with dynamic conditional correlation method (Lyócsa et al., 2012 and Yin et al., 2017), such as dynamic conditional correlation multivariate GARCH (DCC-MV-GARCH) model (Engle, 2002). As DCC-MVGARCH model is explicit enough to accommodate the object co-movements through time (Mensi et al., 2014), we choose to utilize this model to construct the correlation networks that contain the information about statistical dependencies among the fluctuations of stock prices.

3.1 Dynamic correlation algorithm

Firstly, the dynamic conditional correlation multivariate GARCH (DCC-MV-GARCH) model is used to calculate the dynamic conditional correlation coefficients. Before that, an ARMA model is used to estimate the residuals exerting no autocorrelation for each stock returns series. The specification is as follow:

$$r_t = \alpha + e_t + \sum_{p=1}^{P} \Phi_p r_{t-p} + \sum_{j=1}^{q} \delta_q e_{t-q} \tag{1}$$

The last column in Table 1 indicates that there is significant arch effect in each stock return series. Then, the residual series $e_t = (e_t^1, e_t^2 \cdots e_t^N)$ obtained from the former procedure obeys a multivariate normal distribution:

$$e_t \mid \Omega_{t-1} \sim N(0, H_t) \tag{2}$$

$$H_t = D_t R_t D_t \tag{3}$$

where Ω_{t-1} is the collection of information of the residuals at time *t*; H_t is the conditional variance-covariance matrix of the residuals; $D_t = diag(\sqrt{h_{ii,t}})$ represents the ($N \times N$) diagonal matrix of the conditional standard deviations of the residuals that are modeled by a univariate GARCH(1, 1) process: $h_{ii,t} = \omega_i + \alpha_i e_{i,t-1}^2 + \beta_{iq} h_{i,t-1}$; R_t is the dynamic conditional correlation matrix, which can be calculated as follow:

$$R_t = \left[\rho_t^{ij}\right] = diag(Q_t)^{-1/2} Q_t \ diag(Q_t)^{-1/2} \tag{4}$$

The conditional correlation matrix depends on the standardized residuals ($\varepsilon_{i,t} = e_{i,t} / \sqrt{h_{ii,t}}$), the unconditional variance-covariance matrix of the standard residuals ($\overline{Q}$) and its own lagged term as follows::

$$Q_t = (1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n)\overline{Q} + \sum_{m=1}^{M} \alpha_m (\varepsilon_{t-m} \varepsilon_{t-m}^{'}) + \sum_{n=1}^{N} \beta_n Q_{t-n} \tag{5}$$

Finally, the dynamic conditional correlation coefficient between stock *i* and stock *j* can be given by:

$$\rho_t^{i,j} = \frac{E_{t-1}[\varepsilon_t^i \varepsilon_t^j]}{\sqrt{E_{t-1}[(\varepsilon_t^i)^2]}\sqrt{E_{t-1}[(\varepsilon_t^j)^2]}} \tag{6}$$

Having estimated a 108 × 108 matrix for each day, we get 1621 complete stock networks. Then, edges assigned with weak correlations are removed from the networks by setting a threshold. According to Chi et al (2010), networks generated from different thresholds within a certain criterion range all display scale-free properties. Therefore, we set the lowest bound of high correlation to be 0.5. In this way, if correlation coefficient ρ_t^{ij} is significantly larger than the criterion value, there is an edge connecting the corresponding node *i* and node *j*. Otherwise, the two nodes cannot be connected. With the above procedure, we get 1622 consecutive DCC-Threshold oil-related stock networks.

3.2 Network topological indices

Thus far we have introduced procedure for network constructions. To approach the issue of measuring stock comovements, we need to analyze the mathematical structure of stock networks a little more deeply. We now put forward three topological indicators to work, using them to quantify and monitor the dynamic evolution of interactions among oil-related stocks over the tested period. The network characteristics are described from three dimensions that are network connectivity density, transmission efficiency and stock heterogeneity.

3.2.1 Network connectivity density

Firstly, to intuitively monitor the global connectivity level of the time-varying networks through the tested period, we consider utilizing the index of network density (*D*), which is given by the ratio of the number of existing edges in a network to the maximum possible number of edges if each pair of nodes is connected as follows:

$$D = \frac{2E}{N(N-1)} \tag{7}$$

where *E* denotes the number of links that actually exist and *N* denotes the number of vertices in the network. The indicator is a measure to quantify the overall number of high correlations. The larger the network connectivity density is, the more correlated the stock price fluctuations are. Therefore, this density measurement can be utilized to capture the time-varying interactions of oil-related stock prices.

3.2.2 Price transmission efficiency

Latora and Marchiori (2002) introduce the definition of network efficiency indicator to measure the information exchange efficiency in a system. This definition gives a physical meaning and performs a quantitative analysis for the real world networks.

The information exchange efficiency (e_{ij}) from node *i* to node *j* is defined to be inversely proportional to the shortest distance between node *i* and node *j* (l_{ij}). The formula is given by:

$$e_{ij} = \frac{1}{l_{ij}}, \ \forall i, j \tag{8}$$

Then, the efficiency of a network (*E*) is defined to be the mean value of the information exchange efficiency over all the possible pairs of nodes as follows:

$$E(G) = \frac{1}{N(N-1)} \sum_{i \neq j} e_{ij} \tag{9}$$

In a stock network, nodes are connected according to their high degree of correlations. A stock is more likely to be affected by stocks that are highly correlated with it in term of stock price. Correspondingly, in the dynamic correlation networks, a node is more likely to be affected by its neighborhood. The affection progress is usually by means of price transmission. Thus, the network efficiency indicator measures the price transmission speed in the stock market.

3.2.3 Stock heterogeneity

Except the network properties measuring the network similarity, network entropy (Rashevsky, 1955; Trucco, 1956; Mowshowitz, 1968) is another network indicator to quantify the heterogeneity of a complex network. In a stock network, we can measure the stock market dispersion degree, which may be related with the diversity of firm size, market capitalization, systemic risk contribution or other firm-level factors. Furthermore, by applying this definition to this paper's networks that are constructed based on the correlations of stock returns, we can measure the difference of stock price fluctuations. If stock returns fluctuate differently in the market, there will be more potential chances for portfolio diversification (Narayan et al., 2018).

A commonly used entropy definition in information theory, Shannon entropy (Shannon et al., 1949) has been transformed into diverse frameworks, based on the structural characteristics of a graph. An example can be seen for *SD*-entropy (Cai et al., 2011). Based on the framework of Shannon entropy, this entropy-based measure consider both "node difference" and "edge difference", which can present the network heterogeneity from a more comprehensive perspective (Lv et al., 2018). Therefore, we consider this indicator to estimate stock heterogeneity. The indicator is defined as follows:

$$SDSE = -\sum_{i=1}^{N} I_i \log I_i, \tag{10}$$

$$I_i = \frac{I_i^{'}}{\sum_{i=1}^{N} I_j^{'}} = \frac{(k_i+1)[1-p(k_i)+\Delta]}{\sum_{j=1}^{N}\{(k_i+1)[1-p(k_i)+\Delta]\}}, \quad \Delta \sim O(\frac{1}{N^2}) \tag{11}$$

where N is the number of nodes in a network; $p(k_i)$ is the probability that the degree of node i equals to k_i.

4. In-sample evaluation

This section focuses on evaluating the impact of crude oil volatility on the network indicators from the in-sample perspective. We first examine the linear granger causality relationship between oil volatilities and network indicators. Then, we generate in-sample analyses in an OLS predictive regression framework, where the network indices are regressed on a constant, their own lagged terms and the oil realized volatilities. Finally, robustness tests are conducted by sub-sample analysis and considering macro factors.

4.1 Linear Granger Causality test

Intuitively, shock of oil realized volatility is proved have an effect on stock prices (Kaul and Seyhun., 1990; Zhu et al., 2017), so we deduce that fluctuations in network indicators that monitor the interactions of stock prices may also contain the information about commodity market volatility. Therefore, the oil volatility effect on the stock market interactions can also be analyzed. In this section, we consider Granger Causality test model to have a first basic understanding on the causal relationships between oil price volatility and network indicators.

Table 2

Granger causality tests for network indicators and crude oil volatilities.

	Brent oil volatility	WTI oil volatility
Panel A: *H_0: RV does not Granger cause NI*		
D	6.3186***	6.2116***
E	4.8005***	7.1877***
SDSE	7.1253***	8.8990***
Panel B: *H_0: NI does not Granger cause RV*		
D	13.4368***	11.2967***
E	11.0325***	7.4389***
SDSE	15.3035***	14.2269***

Notes: ***, **,* Denotes statistical significance of the F-test at 0.01, 0.05, 0.1 levels. D denotes the network density, E denotes the network efficiency indicator and SDSE denotes SD-entropy.

Granger causality test is proposed to detect the causal direction between the present values of one variable and the previous value of another variable (Granger, 1969), and the model specification is shown as follows:

$$NI_t = \alpha_{10} + \sum_{i=1}^{p} \alpha_{1i} NI_{t-i} + \sum_{j=1}^{p} \beta_{1j} RV_{t-j} + \varepsilon_{1t} \tag{12}$$

$$RV_t = \alpha_{20} + \sum_{i=1}^{p} \alpha_{2i} NI_{t-i} + \sum_{j=1}^{p} \beta_{2j} RV_{t-j} + \varepsilon_{2t} \tag{13}$$

where *NI* denotes the variable of network indicator, *RV* denotes the oil realized volatility, p is the lag order, α and β are parameters for estimation, ε is an error term. To test whether the Granger causality runs from *RV* to *NI*, the null (H_0) hypothesis is H_0: β_{1j}=0, j=1, 2,$\cdots$, p.

If at least one estimator of β_{1j}s doesn't equal to zero, in other words, H_0 is significantly rejected, then we can conclude that the past oil volatility has a significant linear effect on the present network indicator. It normally implies that oil volatility Granger causes network indicator, and vice versa. The number of lags used in the test is 2, which is chosen on the basis of AIC.

Table 1 reports the F-values for pairwise Granger Causality tests of the relationship between oil volatilities and network indicators. A bidirectional causality running between oil volatility and network indicators can be found for both WTI and Brent oil volatilities. The significant causality running from oil volatilities to all of the network indicators indicates that Brent and WTI oil volatilities both have an impact on the network structure, including network density, efficiency and heterogeneity. Evidences also show that the three network indices Granger causes WTI or Brent oil volatilities at the 1% significance level, implying that network indices can additionally be an efficient tool in the prediction of oil volatilities.

4.2 Networking response to oil volatility

The above estimations verify the oil volatility effect on the oil-related stock networking. However, the sign of the relationship cannot be identified. We seek to utilize a standard OLS regression model in this section. We first consider the following simple OLS prediction models to reveal the marginal predictive power of oil volatility:

$$NI_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i NI_{t-i} + \beta RV_{t-1} + \varepsilon_t \tag{14}$$

By comparison, we utilize the following AR (2) model as benchmark to confirm the predictive content of oil volatility.

$$NI_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i NI_{t-i} + \varepsilon_t \tag{15}$$

To demonstrate the rationality of the model with auto-regressive items, we also consider the simple univariate prediction model as follows:

$$NI_t = \alpha_0 + \beta RV_{t-1} + \varepsilon_t \tag{16}$$

The estimation results for the two regression models together with R^2 statistics are reported in Table 3. The increases in R^2 for the regression model (14) in relation to the benchmark of AR (2) model are also reported. Panel A-C report the estimation results of the regressions on the indicators of network density, network efficiency and network heterogeneity respectively. The results reveal that in the regressions for the three indicators, coefficients on the oil volatilities are all significant at the 10% confidence level, regardless whether WTI or Brent are considered in the regressions. This confirms the significant effect of oil volatility on the stock networking. Then, the coefficient on the oil volatility are all shown to be positive, indicating that an increase in current day's oil volatility will lead to an increase in the next day's indicator of network density, efficiency or heterogeneity. That is to say, volatile oil return will cause stronger interactions among stocks and greater price transmission speed in the oil-related stock market, and the stocks tend to be more homogeneous.

Besides, results for the R^2 statistics show that R^2 values for model (14) are much larger than that of model (16), suggesting a more effective explanation of the model with auto-regressive items. The positive increase in R^2 after adding WTI or Brent oil volatility to the autoregressive model indicates the predictive content of oil volatility, confirming the considerable effect of oil volatility effect on the oil-related stock networking. And comparing the value of ΔR^2 in the regressions, it can be found that WTI oil price volatility provides greater predictive content than Brent oil volatility.

Table 3

Estimation results for network indicators and crude oil volatilities.

Variables	Brent oil volatility		WTI oil volatility	
***Panel A**: Linear regression for network density*				
C	0.0503***	0.2258***	0.0533***	0.2251***
	(12.69)	(1428.26)	(12.83)	(1450.59)
NI_{t-1}	0.7213***		0.7086***	
	(28.83)		(27.79)	
NI_{t-2}	0.0568*		0.0555*	
	(2.28)		(2.24)	
RV_{t-1}	0.0019*	0.0150***	0.0028***	0.0197***

	(2.21)	(11.89)	(3.26)	(17.18)
R^2	0.6064	0.0803	0.6078	0.1543
ΔR^2 (%)	0.1983		0.4296	
***Panel B**: Linear regression for network efficiency indicator*				
C	0.0943***	0.3416***	0.1002***	0.3410***
	(14.12)	(3040.7)	(14.28)	(3083.76)
NI_{t-1}	0.6503***		0.6356***	
	(26.07)		(24.98)	
NI_{t-2}	0.074**		0.0711***	
	(2.97)		(2.87)	
RV_{t-1}	0.0017*	0.0093***	0.0025***	0.0128***
	(2.54)	(10.36)	(3.70)	(15.71)
R^2	0.5179	0.0623	0.5200	0.1324
ΔR^2 (%)	0.3682		0.7752	
***Panel C**: Linear regression for SD-entropy*				
C	1.0502***	4.1839***	1.1442***	4.1828***
	(13.48)	(21429.3)	(13.69)	(22089.46)
NI_{t-1}	0.682***		0.6644***	
	(27.31)		(26.04)	
NI_{t-2}	0.0671**		0.0621**	
	(2.69)		(2.50)	
RV_{t-1}	0.0032**	0.0182***	0.0048***	0.0256***
	(2.82)	(11.69)	(4.15)	(18.34)
R^2	0.5627	0.0779	0.5652	0.1721
ΔR^2 (%)	0.3925		0.8385	

4.3 Robustness check

4.3.1 Sub-sample analysis

In order to investigate whether similar conclusion holds for different situation or period, we will conduct sub-sample analyses in this section. As shown in Fig 1, WTI/Brent oil realized volatilities fluctuated around a relatively low mean level before 2015, while the volatilities trended upward from 2015 and fluctuated around a relatively high mean level. Therefore, we split the sample into two periods: January 2012- December 2014; January 2015- January 2018, namely the stable period and volatile period. Next, we will investigate how stock networks react to shocks in oil price volatility before and after January 2015.

Table 4 summarizes the subsample analyses with model (14). As illustrated in Panel A, Table 4, overall, the three network indicators are significantly influenced by both Brent and WTI oil volatilities during the relatively stable period and the signs on the coefficients appear to be all positive, indicating an increase in the oil volatility has a delayed positive impact on current network indices. Evaluations in Panel B demonstrate the impact of oil volatility on stock networking during the volatile period. The results show that the coefficients on either Brent oil or

WTI oil are all positive, but are not that significant compared with Panel A, indicating that the revealed predictability is stronger over more stable periods. Besides, the positive increases in R^2 indicate that the predictive regressions with oil volatility can perform more accuracy predictions than the benchmark autoregressive model. This also confirms that oil volatility possess strong predictive content in terms of stock networking.

Table 4

Estimation results for the regressions with in sub-sample period

Variables	Network density		Network efficiency		Network heterogeneity	
	Brent	WTI	Brent	WTI	Brent	WTI
Panel A: *Period of January 2012- December 2014*						
C	0.0506***	0.0524***	0.0955***	0.0986***	1.0282***	1.109***
	(8.1)	(8.28)	(9.31)	(9.43)	(8.55)	(8.97)
NI_{t-1}	0.7309***	0.7215***	0.6936***	0.6826***	0.7201***	0.7022***
	(19.4)	(18.8)	(18.49)	(17.82)	(19.22)	(18.34)
NI_{t-2}	0.0449	0.0457	0.0266	0.0284	0.0341	0.0328
	(1.22)	(1.25)	(0.72)	(0.78)	(0.93)	(0.90)
RV_{t-1}	0.0031	0.0040*	0.0035**	0.0040**	0.0047	0.0073***
	(1.31)	(1.80)	(2.03)	(2.44)	(1.62)	(2.65)
ΔR^2 (%)	0.0015	0.0028	0.0046	0.0064	0.0024	0.0064
Panel B: *Period of January 2015- June 2018*						
C	0.0523***	0.0558***	0.0986***	0.1058***	1.094***	1.2141***
	(9.64)	(9.70)	(10.53)	(10.66)	(10.14)	(10.21)
NI_{t-1}	0.7052***	0.6914***	0.6008***	0.5845***	0.6429***	0.6222***
	(20.72)	(19.88)	(17.72)	(16.88)	(18.93)	(17.84)
NI_{t-2}	0.0647*	0.0623*	0.1113***	0.1061***	0.0957***	0.0877***
	(1.91)	(1.84)	(3.28)	(3.13)	(2.83)	(2.58)
RV_{t-1}	0.0009	0.0020**	0.0008	0.0019**	0.0024	0.0041***
	(0.92)	(2.02)	(0.97)	(2.35)	(1.73)	(2.86)
ΔR^2 (%)	0.0007	0.0035	0.0013	0.0070	0.0030	0.0084

4.3.2 Controlling non-oil factors

To examine whether the effect of oil volatility on the network indices can be substituted by the other omitted non-oil variables, we add control variables in the predictive model (14) and benchmark model (15) as follows to perform further robustness tests:

$$NI_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i NI_{t-i} + \beta RV_{t-1} + \theta Cont_{t-1} + \varepsilon_t \tag{16}$$

$$NI_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i NI_{t-i} + \theta Cont_{t-1} + \varepsilon_t \tag{17}$$

where $Cont_{t-1}$ is the vector of non-oil variables. Allowing for the large set of control variables, we use one single non-oil variable in model (16) and (17) as Paye (2012) and Wang et al (2018) do.

In line with Christiansen et al (2012) and Wang et al (2018), we consider 12 macro variables as control in benchmark model. Six variables are related primarily to stock activities including dividend–price ratio (D/P), dividend yield (D/Y), earning–price ratio (E/P), book-to-market ratio (B/M), net issues (NTIS); value-weighted stock index return (VWX). The other set of variables are interest-rate related: Treasury bill rate (TBL), long-term return (LTR), long-term yield (LTY), default yield spread (DFY), default return spread (DFR), inflation rate (INFL). Being of our interest, Table 5 reports the estimators of β in the regressions with incorporation of one single non-oil variable. The coefficient estimates of β are almost significantly positive in all the regressions, regardless of which oil volatility is included in the regression models. These results verify the significant effect of oil volatility effect on the three indices, and prove that oil volatility provides a different predictive content from the non-oil factors, from the in-sample perspective.

Table 5
Coefficient estimates of β in the regressions with non-oil variables being control variables.

Variables	Network density		Network efficiency		Network heterogeneity	
	Brent	WTI	Brent	WTI	Brent	WTI
D/P	0.0986**	0.0766*	0.1039***	0.0902***	0.1227**	0.0912
	(2.59)	(1.99)	(3.36)	(2.79)	(2.21)	(1.59)
D/Y	0.0986**	0.0770**	0.1073***	0.0937***	0.1259**	0.0953*
	(2.64)	(2.04)	(3.52)	(2.95)	(2.31)	(1.70)
E/P	0.1126***	0.0797*	0.1080***	0.0857**	0.1598**	0.1083*
	(2.66)	(1.97)	(3.16)	(2.54)	(2.53)	(1.75)
B/M	0.1089***	0.0833**	0.1072***	0.0909***	0.1508***	0.112**
	(2.97)	(2.27)	(3.57)	(2.93)	(2.78)	(2.02)
NTIS	0.1043**	0.0752*	0.1129***	0.0904***	0.1637**	0.1133*
	(2.52)	(1.88)	(3.32)	(2.66)	(2.6)	(1.81)
TBL	0.1066***	0.0806**	0.1045***	0.0885***	0.1522***	0.1103**
	(2.93)	(2.21)	(3.51)	(2.87)	(2.86)	(2.03)
LTY	0.1015**	0.0711*	0.1129***	0.0903**	0.1749***	0.1247*
	(2.34)	(1.68)	(3.20)	(2.53)	(2.70)	(1.90)
LTR	0.1000***	0.079**	0.1013***	0.0886***	0.1236**	0.0942*
	(2.75)	(2.15)	(3.41)	(2.87)	(2.31)	(1.71)
DFY	0.0839**	0.0588	0.0863***	0.0695**	0.0976*	0.0604
	(2.13)	(1.45)	(2.71)	(2.05)	(1.73)	(1.03)
DFR	0.0984***	0.0772**	0.0989***	0.0844***	0.1243**	0.0938*
	(2.71)	(2.11)	(3.40)	(2.78)	(2.35)	(1.72)
INFL	0.1037***	0.0823**	0.1080***	0.0952***	0.1347**	0.1048*
	(2.83)	(2.23)	(3.67)	(3.1)	(2.51)	(1.89)
VWX	0.0990***	0.0785**	0.0998***	0.0864***	0.1219**	0.0921
	(2.70)	(2.12)	(3.37)	(2.80)	(2.27)	(1.66)
ALL	0.0775	0.0063	0.0588*	0.0187	0.1513	0.0406
	(1.15)	(0.09)	(1.79)	(0.37)	(1.65)	(0.42)

5. Out-of sample analysis

In view of the issue of in-sample excessive fitting (Welch and Goyal, 2008), we are concerned to evaluate the out-of-sample forecasting performance of oil volatility. Therefore, this section conducts out-of-sample predictions without and with macro factors to further confirm the predictability of oil volatility on the stock networking.

5.1 Out-of-sample forecasting performance of oil volatility

In this section, the predictive model (14) is used to generate out-of-sample forecast of the topological indices. All of the out-of-sample predictions are all based on recursive estimation windows. Specifically, we first set Jan 4, 2012 to April 30, 2015 as the initial estimation period containing the first T=800 observations, so that the out-of-sample evaluation period spans from Mar 12, 2015 to Jun7, 2018. Then, the first forecast of network indices on day $T+1$ based on oil volatility is computed as follows:

$$NI_{T+1} = \alpha_T + \sum_{i=1}^{p} \alpha_{i,T} NI_{T+1-i} + \beta_T RV_T \tag{18}$$

where $\alpha_T, \alpha_{i,T}, \beta_T$ are OLS estimates by regressing $\{NI\}_{t=p+1}^{T}$ on a constant, $\{NI\}_{t=j}^{T-p+j-1}$ for $j=1,2,\cdots,p$, and $\{RV\}_{t=p}^{T-1}$. Based on the recursive estimation window, the second forecast is generated as follows:

$$NI_{T+2} = \alpha_{T+1} + \sum_{i=1}^{p} \alpha_{i,T+1} NI_{T+2-i} + \beta_{T+1} RV_{T+1} \tag{19}$$

where the parameter $\alpha_{T+1}, \alpha_{i,T+1}, \beta_{T+1}$ are estimated by regressing $\{NI\}_{t=p+1}^{T+1}$ on a constant, $\{NI\}_{t=j}^{T-p+j}$ for $j=1,2,\cdots,p$, and $\{RV\}_{t=p}^{T}$.

Continuing like this till the end of out-of-sample evaluation period, we can get a series of forecasted network topological indices through the out-of-sample period.

Following Campbell and Thompson (2008), we utilize the out-of-sample R^2 (R_{os}^2) to evaluate the predictive accuracy. The statistic of R_{os}^2 is measured by the percentage reduction of mean squared errors (MSE) of the model we suggest relative to that of the benchmark model. A positive R_{os}^2 means that the suggested predictive regression model performs more accurate prediction than the benchmark model, while a negative R_{os}^2 means the opposite. Besides, we consider using the MSE-F statistic (McCracken, 2007) to test the null hypothesis that the suggested predictive regression model provides equal or larger MSE than the benchmark model against the alternative hypothesis that the predictive model delivers smaller MSE than the benchmark model.

The second row of Table 6 presents the out-of-sample R^2 for predictive model (14) based on the recursive estimation window method, and the MSE-F statistics are shown in the parentheses. As it shows, WTI or Brent oil volatilities both deliver positive out-of-sample R^2 statistics in the regressions on the three indices, ranging from 0.2547% to 0.8938%, indicating that the predictive models with oil volatility perform more accurate predictions than the benchmark autoregressive model. According to F-statistics shown in the parentheses, the MSEs of the predictive model are significantly lower than those of the benchmark model at 1% level.

According to Avramov (2002) and Rapach et al (2010), the model uncertainty can affect the out-of-sample predictive performance of an individual model. In this paper's case, the network topological indices may not be always relevant to the oil volatility. If we still include the irrelevant variable of oil volatility into the predictive model when the current indices are not affected by the past oil volatilities, it may cause over fitting. The in-sample forecasting performance can be improved but the out-of-sample forecasting performance worsens. Following Wang et al (2018), we use a parameter restriction method to improve the out-of-sample forecasting performance. Specifically, we constrain positive sign on the estimated parameter of oil volatility.

The last row of Table 6 presents the out-of-sample forecasting results of the restricted predictive models. We can find the forecasting results of the restricted models are exactly the same with those of the unrestricted models, which signals that the estimated coefficients on WTI or Brent oil volatility are positive all the time, and further oil volatility has a stably positive effect on the network indices.

Table 6

Out-of-sample forecasting results of model (14).

Model	Network density		Network efficiency		Network heterogeneity	
	Brent	WTI	Brent	WTI	Brent	WTI
Without restriction	0.3235***	0.5487***	0.2547***	0.8034***	0.5019***	0.8938***
	(2.66)	(4.52)	(2.09)	(6.63)	(4.13)	(7.39)
With restriction	0.3235***	0.5487***	0.2547***	0.8034***	0.5019***	0.8938***
	(2.66)	(4.52)	(2.09)	(6.63)	(4.13)	(7.39)

5.2 Forecast with macro factors

We now turn to examine whether oil volatility's effect on stock networking can be substituted by any of the macro factors from the out-of-sample perspective. We similarly conduct the out-of-sample forecast based on the recursive estimation window, by adding the non-oil factors in the procedure (18)-(19). The monthly in-sample period spans from January 2012 to April 2015, containing the first T=40 observations, so that the out-of-sample evaluation period spans from Mar, 2015 to Jun, 2018.

Panel A and Panel B of Table 5 report the forecasting results of the unrestricted model and restricted model respectively. Firstly, the results shown in Panel A are exactly the same with that in Pane B, indicating the oil volatility coefficients are stably positive. The positive out-of-sample R^2 statistics shown in the 2th–5th columns suggest that in the regressions on network density or network efficiency index, the incorporation of Brent or WTI oil volatilities significantly promote the forecast precision of the predictive models with non-oil factors. However, in the regressions on the network entropy, benchmark models with non-oil factors of D/P, E/P, DFY, DFR or VWEX outperform the predictive models according to the negative values of R_{os}^2. Therefore, it is easy for the predictive model to significantly outperform the benchmark autoregressive model, in the forecasting of network density or efficiency, but difficult in the regressions on network entropy.

Moreover, we find that the predictability stays the same after imposing restriction on the coefficients of oil volatility, demonstrating the estimated coefficients on oil volatility are positive all the time.

Table 7
Out-of-sample forecasting results for predictive models with macro variables being control variables.

Model	Network density		Network efficiency		Network heterogeneity	
	Brent	WTI	Brent	WTI	Brent	WTI
Panel A: *Without restriction*						
D/P	4.6776**	8.7633***	15.4226***	10.7752***	-6.6294	-1.0439
	(1.67)	(3.27)	(6.2)	(4.11)	(-2.11)	(-0.35)
D/Y	5.411**	10.5965***	19.6914***	13.9924***	2.2116	0.8454
	(1.94)	(4.03)	(8.34)	(5.53)	(0.74)	(0.29)
E/P	7.2387***	9.8215***	12.913***	8.7812***	-4.1487	-0.6064
	(2.65)	(3.7)	(5.04)	(3.27)	(-1.35)	(-0.2)
B/M	12.738***	12.5224***	17.2624***	11.9867***	3.6931*	5.6514**
	(4.96)	(4.87)	(7.09)	(4.63)	(1.3)	(2.04)
NTIS	7.8979***	8.945***	16.5198***	11.0335***	1.9779	3.794*
	(2.92)	(3.34)	(6.73)	(4.22)	(0.69)	(1.34)
TBL	10.4264***	9.263***	15.9394***	9.5436***	3.5525	4.1065*
	(3.96)	(3.47)	(6.45)	(3.59)	(1.25)	(1.46)
LTY	11.7011***	8.725***	17.8065***	11.3426***	8.3154***	7.4859***
	(4.51)	(3.25)	(7.37)	(4.35)	(3.08)	(2.75)
LTR	5.0191**	12.3021***	17.4713***	13.5832***	4.0735	1.7339
	(1.8)	(4.77)	(7.2)	(5.34)	(1.33)	(0.6)
DFY	3.342	2.918	6.4553***	3.0134	-20.7371	-7.928
	(1.10)	(1.02)	(2.35)	(1.06)	(-5.84)	(-2.5)
DFR	2.1061	11.2378***	19.8638***	14.7831***	-1.0332	3.9703*
	(0.73)	(4.3)	(8.43)	(5.9)	(-0.35)	(1.41)
INFL	14.1863***	16.0509***	23.9042***	18.8296***	0.0851	3.078
	(5.62)	(6.5)	(10.68)	(7.89)	(0.03)	(1.08)
VWX	8.4504***	13.5417***	18.6895***	13.2246***	-2.3725	1.9558
	(3.14)	(5.33)	(7.82)	(5.18)	(-0.79)	(0.68)
ALL	-5.6103	14.6433***	1.4122	4.5581	4.2145***	-4.6345
	(-1.75)	(6.86)	(0.47)	(1.44)	(1.45)	(-1.46)
Panel B: *With restriction*						
D/P	4.6776**	8.7633***	15.4226***	10.7752***	-6.6294	-1.0439
	(1.67)	(3.27)	(6.2)	(4.11)	(-2.11)	(-0.35)
D/Y	5.411**	10.5965***	19.6914***	13.9924***	-2.2116	0.8454
	(1.94)	(4.03)	(8.34)	(5.53)	(-0.74)	(0.29)
E/P	7.2387***	9.8215***	12.913***	8.7812***	-4.1487	-0.6064
	(2.65)	(3.7)	(5.04)	(3.27)	(-1.35)	(-0.2)
B/M	12.738***	12.5224***	17.2624***	11.9867***	3.6931*	5.6514**
	(4.96)	(4.87)	(7.09)	(4.63)	(1.3)	(2.04)

NTIS	7.8979***	8.945***	16.5198***	11.0335***	1.9779	3.794*
	(2.92)	(3.34)	(6.73)	(4.22)	(0.69)	(1.34)
TBL	10.4264***	9.263***	15.9394***	9.5436***	3.5525	4.1065*
	(3.96)	(3.47)	(6.45)	(3.59)	(1.25)	(1.46)
LTY	11.7011***	8.725***	17.8065***	11.3426***	8.3154***	7.4859***
	(4.51)	(3.25)	(7.37)	(4.35)	(3.08)	(2.75)
LTR	5.0191**	12.3021***	17.4713***	13.5832***	-4.0735	1.7339
	(1.8)	(4.77)	(7.2)	(5.34)	(-1.33)	(0.6)
DFY	3.342	2.918	6.4553***	3.0134	-20.7371	-7.928
	(1.10)	(1.02)	(2.35)	(1.06)	(-5.84)	(-2.5)
DFR	2.1061	11.2378***	19.8638***	14.7831***	-1.0332	3.9703*
	(0.73)	(4.3)	(8.43)	(5.9)	(-0.35)	(1.41)
INFL	14.1863***	16.0509***	23.9042***	18.8296***	0.0851	3.078
	(5.62)	(6.5)	(10.68)	(7.89)	(0.03)	(1.08)
VWX	8.4504***	13.5417***	18.6895***	13.2246***	-2.3725	1.9558
	(3.14)	(5.33)	(7.82)	(5.18)	(-0.79)	(0.68)
ALL	-5.6103	14.6433***	1.4122	4.5581	4.2145***	-4.6345
	(-1.75)	(6.86)	(0.47)	(1.44)	(1.45)	(-1.46)

6. The nonlinear relationship

We have analyzed the relationships between the network topological indices and oil volatility from the linear perspective. The oil volatility is proved have an effect on the oil-related stock networking from the linear perspective. Studies have indicated that there are nonlinear linkages between the stock market and the oil market (Ajmi et al., 2014; Narayan and Gupta, 2015). Accordingly, it is of interest to further assess whether the relationships between oil volatility and network indices are nonlinear. Therefore, we consider three nonlinear models to determine how indices of oil-related stock networks respond to the nonlinearity of oil volatility.

6.1 Nonlinear Granger Causality test

Given the hypothetical existence of nonlinear relationships between oil volatility and network linkage measurements, we perform the nonlinear Granger causality tests (Baek and Brock, 1992) on their VAR residual series to examine the relationship between oil volatility and network topological indices.

Table 8 presents the *t*-statistics of the nonlinear Granger causality tests applied to the estimated VAR residuals of oil volatility and network topological indices. Following Baek and Brock (1992), the lead lag length is set to be unity; and length scale is set to be 1.5. The lagged length ranges from 1 to 4. As we focus on the oil volatility effect on the stock networking, we mainly look at the results in panel A, where the results for the null hypothesis that oil volatility doesn’t Granger cause network topological indices are reported. There is evidence of unidirectional nonlinear Granger causality running from Brent or WTI oil volatilities to the network indices. And this result holds for every lag length used to carry out the test. None of the *t*-statistics is smaller than 1.5972, seemingly strong evidence of oil volatility effect on oil-related stock networking. As Panel B shows, the null hypothesis that network topological indices don't Granger cause oil volatility is significantly rejected in at least one lag length, suggesting that there is potentially non-linear Granger causality running from stock network indices to oil volatility. That is to say the stock network indices have potential predictive power in regard to oil volatility, which is worthy analyses in the future works.

Table 8
Estimation results for nonlinear Granger Causality test

Lagged	Network density		Network efficiency		Network heterogeneity	
length	Brent	WTI	Brent	WTI	Brent	WTI
Panel A: *H_0: RV does not Granger cause NI*						
1	1.9815**	1.9941**	1.9368**	2.1356**	2.2852**	2.2314**
2	2.5189***	2.0363**	2.5018***	1.5972*	2.8092***	2.4429***
3	2.1428**	2.5776***	2.0427**	2.2517**	2.4019***	3.5677***
4	2.2635**	2.2231**	2.3761***	2.3966***	3.0153***	3.5318***
Panel B: *H_0: NI does not Granger cause RV*						
1	1.5837*	2.2021**	2.168**	1.779**	2.7461***	2.3099**
2	1.0134	3.0522***	2.0233**	3.0414***	2.377***	3.1629***
3	1.4526*	3.0869***	2.5018***	2.7321***	2.4706***	3.4173***
4	1.5539*	3.6728***	1.8745**	3.5399***	2.5431***	3.9994***

6.2 Asymmetric effect

Asymmetric effect is found existing between the oil market and the stock market (Ghosh and Kanjilal, 2016; Salisu and Isah, 2017). For example, Zhu et al. (2017) find that oil-market shocks have a significant impact on stock returns in a high-volatility state and a negligible impact in a low-volatility state. It is possible that the impact of oil volatility on network indicators is asymmetric. Therefore, we also consider investigating the asymmetric linkage between oil volatility and oil-related stock network indices. We examine asymmetric effects by means of volatility decomposition. Specifically, we decompose the daily oil volatility into a component that is higher than the median of realized volatility (RV_{t-1}^{+}) and a component that is lower than the median of realized volatility (RV_{t-1}^{-}). The specification of this model is as follows:

$$NI_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i NI_{t-i} + \beta_1 RV_{t-1}^{+} + \beta_2 RV_{t-1}^{-} + \varepsilon_t \tag{20}$$

Table 9 reports the asymmetric effect analyses. We first focus on the estimated coefficient on the decomposed components of realized volatility in Panel A. We find that the coefficients on RV_{t-1}^{-} are almost insignificant in all of the regressions. The only exception is the regression that reveals significant predictability on network entropy when Brent oil volatility is used in the asymmetric model (20). It indicates that the lower oil volatility has no significant impact on the network indicators. While the coefficients on RV_{t-1}^{+} of WTI oil volatility are all positive and highly significant on at least 10% level, suggesting the oil-related stock network indices show a positive reaction to the higher WTI oil return volatility.

According to the out-of-sample estimation results shown in Panel B, the benchmark model can be significantly beaten by the predictive model in most cases. However, the prediction precision of the asymmetric model is lower than that of the symmetric models (see in Table 6) based on the out-of-sample R^2 reported in the last row. Therefore, it cannot be guaranteed to obtain more accurate predictions if the asymmetry effect is considered in the forecasting models.

The above findings suggest that the oil-related stock market interactions are more likely to be affected by the higher WTI oil volatility, and lower oil volatility will not bring up significant shock to the oil-related stock network linkage. Furthermore, shock of higher oil volatility will strengthen the future oil-related stock interactions and promote the information transmission efficiency and homogenize the oil-related stock market. Therefore, there will be less potential opportunities for portfolio diversification in times of volatile oil price. Besides, the linear symmetric model is good enough to capture the oil volatility effect on the oil-related stock networking.

We additionally observe each stock's price movement in response to the oil volatility fluctuations. During the volatile oil price period, especially the period of June, 2014 to May, 2016, prices of the stocks distributed in the oil & gas production sector, oilfield services sector, oil refining sector and integrated oil sector all show a downward trend. The average stock returns of the four sectors are -0.59, -0.45, -0.41 and -0.29 respectively. According to the above empirical evidences, the stock price comovements strengthen within the increasing oil volatility period, which indicates significant risk exposure in the oil-related stock markets. Therefore, investors can adjust their asset structure and avoid investing the oil-related stocks in the high oil volatility period, especially in the increasing volatility period.

Table 9

Estimation results for asymmetric effect.

Variables	Network density		Network efficiency		Network heterogeneity	
	Brent	WTI	Brent	WTI	Brent	WTI
Panel A: *In-sample estimation results*						
C	0.0508***	0.0537***	0.0949***	0.1010***	1.0563***	1.1486***
	(12.8)	(12.87)	(14.23)	(14.36)	(13.57)	(13.72)
NI_{t-1}	0.7202***	0.7079***	0.6482***	0.6342***	0.6803***	0.6635***
	(28.79)	(27.75)	(26.03)	(24.92)	(27.28)	(25.98)
NI_{t-2}	0.0565**	0.0551**	0.075***	0.0706***	0.0673***	0.0621**
	(2.27)	(2.22)	(3.02)	(2.85)	(2.71)	(2.5)
R_{t-1}^{+}	0.0008*	0.0023**	0.0004**	0.0018**	0.0012**	0.0041***
	(1.75)	(2.20)	(1.88)	(2.24)	(1.89)	(2.99)
R_{t-1}^{-}	-0.0028	0.0005	-0.0039	0.0003	-0.005***	0.0019
	(-1.06)	(0.22)	(-0.44)	(0.16)	(-1.46)	(0.62)
ΔR^2 (%)	0.3305	0.4627	0.8333	0.9302	0.6958	0.8742
Panel B: *Out-of-sample estimation results*						
R_{OOS}^2	-0.3386	0.6169***	0.3756 ***	0.9315***	0.2009**	0.8814***

	(-2.76)	(5.08)	(3.09)	(7.70)	(1.65)	(7.28)

6.3 Markov-switching

The Markov-switching model introduced by Hamilton (1989) has been proven to be another useful econometrics framework in capturing potential nonlinearity or asymmetry relationship of economic factors, especially in accounting for adjustment driven by exogenous events. To further investigate the nonlinear or asymmetric interaction between oil volatility and stock network indices, we use a two-stage Markov regime switching approach, in which only the parameters of oil volatility and residual standard deviation are state-dependent. The model specification is as follows:

$$NI_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i NI_{t-i} + \beta_{s_{t-1}} RV_{t-1} + \varepsilon_{s_t},\ \varepsilon_{s_t} \sim i.i.d\ N(0, \sigma_{s_t}^2), s_t = (0,1). \quad (21)$$

The first two rows in Table 10 report the coefficients on oil volatility in in-sample estimations. In the regressions on the three network indices, the estimated coefficients on Brent or WTI oil volatility are positive in one regime and negative in the other regime for most cases. However, the coefficients are only significant when being positive, which indicate the positive effect is significant and oil volatility has a negatively insignificant effect on the stock network indices in certain regimes.

The last row of Table 10 reports the out-of-sample forecasting results for the regime switching model relative to the benchmark autoregressive model. The R_{OOS}^2 values turn to be negative in all regressions, signaling that the two-stage Markov-switching approach delivers worse forecasts than the benchmark model in all of the regressions regardless which oil volatility is included in the switching model. Compared with the performance of one-regime model (see in Table 6), we conclude that the one-regime linear model can perform better than the two-stage Markov-switching model in investigating the oil volatility effect on stock network indices. The probable reason for this outcome is that Markov-switching model can cause overfitting when the relationships between oil volatility and the indices are rather stable.

Table 10
Estimation results for regime switching model.

Model	Network density		Network efficiency		Network heterogeneity	
	Brent	WTI	Brent	WTI	Brent	WTI
Regime 1	0.0182***	0.0189***	0.0084***	0.0087***	0.0216***	-0.0005
	(5.87)	(5.25)	(3.82)	(3.63)	(5.84)	(-0.71)
Regime 2	-0.0008	-0.0006	0.0004	0.0005*	-0.0007	0.0221***
	(-1.33)	(-1.50)	(1.00)	(1.67)	(-1.17)	(5.26)
R_{OOS}^2	-3.0554	-12.2595	-5.4435	-0.4801	-2.9349	-6.9263
	(-0.30)	(-0.94)	(-0.69)	(1.88)	(0.49)	(-0.22)

7. Conclusion

In this paper, we innovatively analyze whether oil volatility has an effect on oil-related stock networking using daily data for the period January 4, 2012 to June 13, 2018. Following Castagneto-Gissey et al. (2014), we apply network theory to model the comovements of stock prices, and put forward three network topological indices that include network density, network efficiency and network entropy to quantify and monitor the dynamic evolution of oil-related stock networks that are constructed by dynamic conditional correlation multivariate GARCH (DCC-MV-GARCH) model with the threshold method.

We first test the linear relationship between oil volatility and network topological indices by in-sample and out-of-sample analyses. We find oil volatility causes the network indices significantly in term of Granger causality. Furthermore, the oil volatility has a stably positive lagged effect on the three oil-related stock network indices, indicating with increase (decrease) in current oil volatility will cause increase (decrease)in the future network density, efficiency and entropy will. Thus, in a more stable oil price state, the oil-related stock comovements weaken, the price link efficiency decreases, and the oil-related stocks become more heterogeneous. The finding indicates that changes in oil volatility can be a signal for portfolio diversification in oil-related stock markets and decrease in oil volatility can bring more opportunity for investors to construct profitable portfolio and spread risks in oil-related stock markets.

We further examine the robustness of the results by sub-sample analyses and considering extensive alternative benchmark models with macro factors. The results indicate that the relationship has not changed over various periods and the oil volatility effect on the oil-related stock networks has not been affected by the addition of macro factors.

We finally investigate the nonlinear or asymmetric relationship between oil volatility and network topological indices with three non-linear frameworks. Firstly, we find oil volatility also Granger causes the network indices from the non-linear perspective. Secondly, the results of asymmetric effect indicate that oil-volatility shocks have a significant impact on oil-related stock networking in a high-volatility state and a negligible impact in a low-volatility state. Finally, it shows that the simple linear model can perform better than the two-stage Markov-switching model in this study.

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