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Research article

Spillover effects between oil and natural gas prices: Evidence from emerging and developed markets

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Abstract: In this paper, we highlight and empirically analyze the spillover effect of oil and natural gas prices between emerging and developed countries over the period from December 2001 to Jun 2017. A Granger causality test and the DY spillover index are used to investigate the connectedness in energy markets of the USA, Europe, and China. Our main findings are that oil and natural gas markets have significant Granger causality. Furthermore, the emerging markets play an important influencing role on many developed markets both in returns and volatility spillover systems. The spillover index between different markets has clear time-varying characteristics and a strong correlation with specific events. These results can have good applicability in practice.

Keywords: spillover effect; DY index; granger causality test; oil; natural gas; emerging countries; developed countries

JEL codes: E02, O13, Q43

1. Introduction

Enhanced correlation of crude oil and natural gas market during the global financial crisis has spurred renewed interests of policymakers and academics. This study aims to investigate the transmission mechanism between oil and natural gas market across different regions. Two main purposes present in our research. On the one hand, we study whether the price of one market can be transmitted to another market. In general, past findings indicate evidence of a stable long-run relationship between the two prices as well as an asymmetric pass-through of oil prices to natural gas prices (Atil et al., 2014; Apergis and Vouzavalis, 2018; Sun et al., 2019). When the price of crude oil increases, customers will choose to buy natural gas instead of oil products, thus increasing the demand for natural gas. According to EIA's 2002 manufacturing energy consumption survey (MECS), about 18 percent of natural gas usage can be converted into petroleum products. On the other hand, the United States, Europe, and China are selected as the major regions for an analysis of developed markets and emerging markets. The reasons for we choose these three different regions reflect the following three aspects. First, China and the United States are two most important consumers of crude oil in the world. One-third of the world's incremental oil demand was consumed by China between 1995 and 2004, and China's consumption is expected to grow nearly threefold over the next 20 years[1]. Second, natural gas consumption in the United States and Europe is about 40% of total global natural gas consumption[2]. Third, the sharp increase in crude oil and natural gas prices and their volatility are closely linked with consumption and production expenditures in energy-exporting and energy-importing countries. Understanding this transmission mechanism is of paramount importance for economic and energy policy making, optimal hedging, and portfolio risk management.

Crude oil and natural gas are substitutes for consumption, and supplements for production and competitors (e.g., Wolfe and Rosenman, 2014; Apergis and Vouzavalis, 2018). In the long run, these fuel prices should form an equilibrium level, leading to the close substitution of oil and natural gas (Erdős, 2012). Oil and natural gas have become one of the main fuels of production in modern life, and they are widely used in many sectors. Because prices are in equilibrium, when the price of one fuel increases, people should buy the other fuel. The research done by Aloui et al. (2014) shows that the crude oil and natural gas are generally complementary or substitutable through the relationship with the residual fuel oil. Moreover, oil and natural gas are complementary and competitors to electricity production. Both fuels have been economic resources for operators to compete. So, when the price of crude oil rises, it may increase the demand for natural gas, leading to the competition between oil and natural gas. Past findings indicate a stable long-run relationship between the prices of oil and gas as well as a directional influence from oil prices to natural gas prices (Atil et al., 2014). Above all, oil and gas markets are closely linked, depending on each other, and competitive.

Numerous evidence confirmed that a significant spillover existed within the oil and natural gas prices between different regions. Cross-markets connectedness in energy markets is caused by its similar function in daily life and industrial production. The estimation of the VECM resulted in identifying evidence of a stable relationship between natural gas and crude oil prices (Caporin and Fontini, 2017). Atil et al. (2014) based on nonlinear autoregressive distributed lags model, showed that natural gas prices are changing significantly with oil prices, and natural gas can serve as a substitute for crude oil in consumption or production of other energy sources. Ewing, Malik and Ozfidan (2002) examined the transmission of volatility spillover between the oil and natural gas markets using daily returns data. Aloui et al. (2014) investigated the extreme covariance and dependence between the crude oil and natural gas markets, finding a significant spillover effect between crude oil and natural gas. In addition, there is a significant spillover effect across oil and gas markets in different regions. Lin and Li (2015) considered the regional segmentation of natural gas

[1] See the US Energy Information Administration website.

[2] See the 2018 CNPC Economics & Technology Research Institute working paper.

markets and their different pricing mechanism and showed that fluctuations in crude oil can spill into natural gas markets in both North America and Europe. Erdős (2012) showed that Asian natural gas prices are linked to oil, so the Asian premium for crude oil has a spillover effect on natural gas prices. A large number of literature has proved that oil and gas prices have spillover effects between different regions.

There are very limited studies on the spillover effects across oil and natural gas prices between emerging and developed markets. Before the global financial crisis, there is a bi-directional volatility spillover effect between two markets, whereas after the crisis, there is an unidirectional volatility spillover effect from the Chinese financial market to other financial markets (Ke et al., 2010; Majdoub and Sassi, 2017; Li et al., 2018). In the early stage, many studies mainly focused on the spillover among developed countries, indicating that fluctuations of one developed country could be transmitted to other developed markets. Gupta and Wohar (2018) studied the effects of oil price volatility on economic performance in a multi-country context, including the seventeen main industrialized OECD countries. Antonakakis and Vergos (2013) discovered the spillover effect among European countries (France, Italy, Greece and Spain, etc.). In recent years, with the opening of the economy and the development of emerging markets, interests in whether there is a spillover effect between emerging and developed markets arise. Wang and Firth (2004) proposed that the volatility spillover has been bi-directional between China's markets and the developed markets. There are significant volatility spillovers in China to other developed markets (Zhou and Zhang, 2012). There is a distinct possibility of a dynamic relationship between emerging and developed markets (Singh et al., 2010). We conclude that it is not just developed markets that can affect emerging markets. Emerging markets are also influencing developed markets.

Combined with the above, the contribution of our paper to the literature is threefold. First, using the Granger causality test to prove the significant connection and interact between oil and natural gas. Second, we prove that not only the developed market can affect the emerging market, but also the price fluctuations of the emerging market can affect the developed market. This result has not been previously documented and is helpful in further research on energy markets. Considering the regional segmentation and different pricing mechanism of natural gas, we study the returns and volatility spillovers in the United States, Europe, and China. Third, the study concludes that spillovers between emerging and developed markets are strongly correlated with specific events.

The remainder of the paper is organized as follows: In section 2, we present the data and primarily tests for the oil and natural gas series. Section 3 describes the main methodology. The empirical results are provided in Section 4. Section 5 concludes the article.

2. Data and preprocessing

2.1. Data source and description

Energy price data of the sample in this study can be obtained directly. The empirical research uses monthly prices of crude oil and natural gas from the USA, Europe, and China. The crude oil price WTI in the USA, Brent in Europe, and the natural gas price Henry hub in the US (USAG) are obtained from the USA Energy Information Administration. Bloomberg provides the crude oil price Daqing in China. Natural gas prices are proxied by the Russian natural gas border price in Germany (EURG) from the International Monetary Fund. As the earliest crude oil price Daqing in China is from December 2001, and the final natural gas price in Germany is in June 2017. Thus, the sample period is from December 2001 to June 2017. The reason for using monthly data is that only monthly data of natural gas prices are available in Europe. And monthly data have sufficient frequency to analyze the spillover effects across markets over time (Lin and Li, 2015).

All the price series are converted to returns by taking log differences. Considering the volatility, we closely follow Ji et al. (2018): The quarterly volatility of the data is calculated using the variance of monthly returns within the same quarter. Table 1 reports summary statistics of both returns and volatility for both the oil and natural gas markets. Panel A of Table 1 shows that the means of all the returns are positive during our sample period, reflecting generally rising prices. The WTI, Brent, and Daqing have a maximum mean of 0.005, which is followed by an EURG return of 0.002. The return of the USAG has the minimum mean, with a value of 0.001, but it also has the largest standard deviation, 0.129. The standard deviation of Daqing is higher than other oil prices. The most returns series are negatively skewed except for the USAG. All returns series display excess kurtosis. The Jarquee Bera test rejects the null hypothesis, indicating that none of the returns follows normal distribution. In Panel B of Table 1, the order of the mean for volatility is roughly similar to the standard deviation of the returns. In addition, the volatility series do not follow normal distribution either.

Table 1. Summary statistics of oil and natural gas returns and volatility.

	Mean	Max.	Min.	Std. D.	Skew.	Kurt.	J-B	Obs.
Panel A: Returns								
WTI	0.005	0.214	−0.332	0.089	−0.836	4.606	41.633***	186
Brent	0.005	0.196	−0.311	0.091	−0.912	4.395	40.869***	186
Daqing	0.005	0.241	−0.553	0.108	−0.936	6.236	108.336***	186
USAG	0.001	0.380	−0.407	0.129	0.252	3.769	6.555**	186
EURG	0.002	0.196	−0.288	0.068	−0.678	7.119	145.718***	186
Panel B: Volatility								
WTI	0.004	0.024	0.000	0.004	2.381	9.880	180.878***	62
Brent	0.004	0.036	0.000	0.006	3.094	14.213	423.741***	62
Daqing	0.006	0.030	0.000	0.007	2.106	7.512	98.442***	62
USAG	0.010	0.065	0.000	0.014	2.155	7.318	96.164***	62
EURG	0.003	0.028	0.000	0.005	3.323	16.273	569.218***	62

Figure 1 shows some consistent trends and fluctuation in the evolution of prices. During the period of 2007–2009, they all have experienced great increases and sharp decreases, which is resulted from the economic bubbles and the global financial crisis in 2008. Then, with the recovery of the economy, the trends of the oil and natural gas prices become more different since 2010.

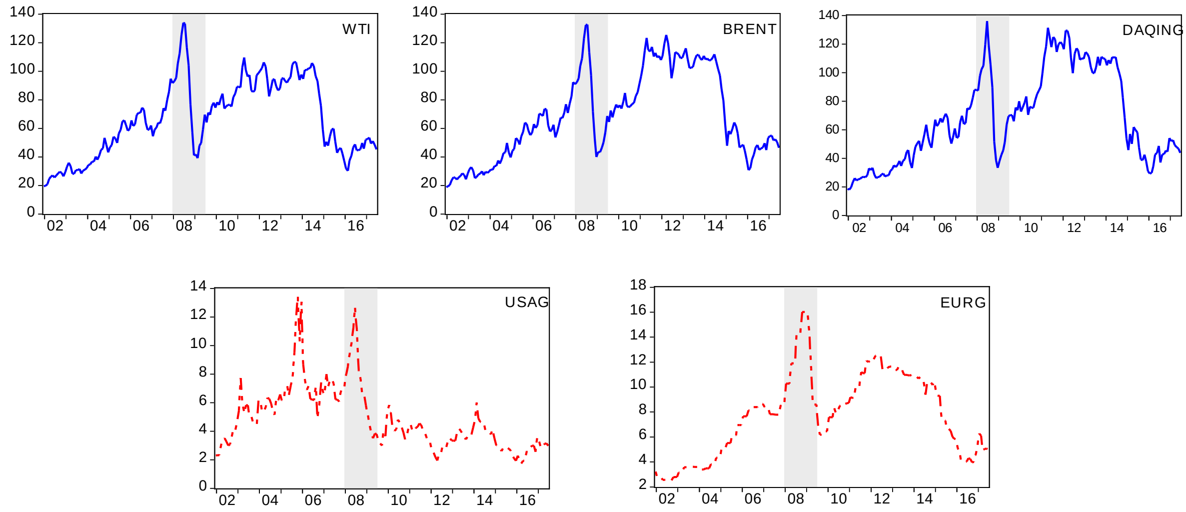

Figure 1. Monthly oil and natural gas prices.

2.2. Primary tests

The quantitative inspection starts from the ADF test of data series. At present, it is generally believed that a necessary antecedent work for regression analysis of time series is to check the stationarity of data and whether there is a cointegration relationship between related variables. We tested the stationarity of five variables in the price of crude oil and natural gas. It is found that none of the five groups of data is stationary sequence. Therefore, the difference sequence is performed for the five groups of data, and the results show that the original data is stable after the first-order difference. It means that all the five variables are integrated into first-order (see Table 2).

Table 2. Stationarity test result.

		ADF test statistic	P-value
WTI		−0.759	0.386
Brent		−0.722	0.403
Daqing		−0.743	0.393
USAG		−0.994	0.286
EURG		−0.871	0.337
WTI (1st-diff)		−8.920	0.000
Brent (1st-diff)		−9.006	0.000
Daqing (1st-diff)		−10.192	0.000
USAG (1st-diff)		−14.401	0.000
EURG (1st-diff)		−4.940	0.000
ε_t		−5.025	0.000
	1% level	−2.577	
Test critical value	5% level	−1.943	
	10% level	−1.616	

Although the five groups of data are not stationary sequences, they are stable after the first-order difference. If there is a cointegration relationship between the five groups of data, an Engle-Granger causal test can be carried on. To determine whether the data groups have cointegration relationship, we need to carry out OLS regression tests on the five groups of variables, as shown in Equation 1.

$$WTI = \alpha + \beta \cdot Brent + \theta \cdot Daqing + \gamma \cdot USAG + \lambda \cdot EURG + \varepsilon_t \quad (1)$$

First, the OLS regression is performed on the cointegration equation, and then the stationarity of the residuals of the equations is tested. Carrying out the ADF test for Equation 1, the test results (see Table 2) show that the residuals are a stationary sequence. So, the five groups of data have a cointegration relationship.

An important inference shown in Table 3 is that oil and natural gas markets have significant Granger causality. Under the condition that five groups of data have been proved to have a cointegration relationship, the Granger causality test can be conducted. The lag order is 1–3 of the Granger cause test. The test results are shown in Table 3. There are three main findings: (1) Daqing is the Granger cause of WTI and Brent. The volatility of commodity price in emerging markets probably leads to the volatility of commodity price in developed markets. Due to the immaturity of the emerging market pricing mechanism, the commodity prices in emerging markets are more affected to external uncertainties than those in developed markets. Fernández et al. (2018) found that fluctuations in commodity prices are an important driver of business cycles in small emerging market economies (EMEs); (2) the USAG Granger causes the EURG. This result indicates the integration of regional markets in continental Europe and North America. Siliverstovs et al. (2005) showed that the price of natural gas in Europe changed proportionally with time, so it was highly integrated with the north American natural gas market. The fluctuations of natural gas price can interact among developed countries; (3) the bi-directional causality between the crude oil and the natural gas indicates that there is a certain relationship between the price of natural gas and that of oil. Wolfe and Rosenman (2014) thought that production of natural gas may increase as a co-product of oil or may decrease as a result of higher-cost productive resources. While the net effect of an increase in oil prices on the natural gas supply may be ambiguous, the effect on the natural gas demand is clear, resulting in a positive relation between oil and natural gas prices.

Table 3. Pairwise Granger causality tests.

	Null Hypothesis:	Obs.	F-Statistic	Prob.
Oil market	Brent does not Granger Cause WTI	184	1.829	0.144
	WTI does not Granger Cause Brent		0.549	0.649
	Daqing does not Granger Cause WTI	184	10.519	0.000
	WTI does not Granger Cause Daqing		1.739	0.161
	Daqing does not Granger Cause Brent	184	16.280	0.000
	Brent does not Granger Cause Daqing		1.917	0.129
Gas market	EURG does not Granger Cause USAG	184	1.992	0.117
	USAG does not Granger Cause EURG		5.137	0.002
Between oil and gas market	USAG does not Granger Cause WTI	184	0.421	0.738
	WTI does not Granger Cause USAG		1.482	0.221
	EURG does not Granger Cause WTI	184	2.330	0.076
	WTI does not Granger Cause EURG		29.630	0.000
	USAG does not Granger Cause Brent	184	0.490	0.690
	Brent does not Granger Cause USAG		1.343	0.262
	EURG does not Granger Cause Brent	184	2.843	0.039
	Brent does not Granger Cause EURG		20.507	0.000
	USAG does not Granger Cause Daqing	184	0.523	0.667
	Daqing does not Granger Cause USAG		1.099	0.351
	EURG does not Granger Cause Daqing	184	0.218	0.884
	Daqing does not Granger Cause EURG		14.9048	0.000

3. Methodology

The following content aims at briefly presenting the construction of the spillover index and its derivatives. It follows the settings presented in the DY spillover index (Diebold and Yilmaz, 2012). Let x_t be a covariance stationary variable of dimension N that obeys a Vector Autoregressive model:

$$x_t = \sum_{i=1}^{P} \Phi_i x_{t-i} + \varepsilon_t \tag{2}$$

where ε_t is an independent and identically distributed vector of size N that follows a Gaussian distribution with a zero mean and a variance matrix denoted Σ. Its moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the $N \times N$ coefficient matrices A_i obey the equation:

$$A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p} \tag{3}$$

with A_0 an $N \times N$ identity matrix and $A_i = 0$ for $i < 0$. Such a representation is usually used to perform and impulse response analysis or a forecasting variance decomposition. In both cases, they aim at understanding how the estimated system is working: How shocks ε_t spread from the i^{th} element of the system to others in a sequential manner. The variance decomposition allows us to assess the fraction of the H-step-ahead error variance in forecasting x_i that is due to shocks to x_j, $j \neq i$, for each i.

The covariance matrix of ε_t is usually none diagonal. Diebold and Yilmaz proposed to use the generalized VAR framework that produces variance decomposition that are invariant to ordering, hereafter KPPS (Koop et al., 1996; Pesaran and Shin, 1998; Diebold and Yilmaz, 2012).

We simply follow Diebold and Yilmaz and use the presentation of their methodology. Denoting the generalized H-step-ahead forecast error variance decompositions by $\theta_{ij}(H)$, for $H = 1, 2, \cdots$, we have

$$\theta_{ij}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_j\right)} \tag{4}$$

Note that unlike the ones obtained through Cholesky factorization, generalized H-step-ahead forecast error variance decomposition does not have to sum to one, and in general they do not follow: $\sum_{j=1}^{N} \theta_{ij}(H) \neq 1$.

To normalize the variance decomposition obtained from the generalized approach, we sum all (own and spillover of shocks) contributions to an energy markets forecast error. When we divide each source of energy markets shock by the total of energy markets contributions, we obtain the relative contributions to each market by itself and other markets:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)} \tag{5}$$

Now, by construction $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$.

Total spillovers: Using the contributions from the generalized variance decomposition approach, we can construct a total spillover index:

$$TS(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100 \tag{6}$$

Directional spillover: We only consider directional spillovers now. We measure directional spillover transmitted by market i to all other markets j as

$$DS_{i \to}(H) = \frac{\sum_{j=1, j \neq i}^{N} \tilde{\theta}_{ji}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}(H)} \times 100 \tag{7}$$

Net spillovers: Finally, we obtain the net spillovers transmitted from market i to all other markets as

$$NS_i(H) = DS_{i\rightarrow}(H) - DS_{i\leftarrow}(H) \tag{8}$$

Net spillovers are simply the difference between gross energy market shocks transmitted to and gross energy market shocks received from all other markets.

Net pairwise spillover: The net volatility spillover in Equation 10 provides summary information about how much each market contributes to the volatility in other markets in net terms. It is also of interest to examine the net pairwise volatility spillovers, which we define as

$$\begin{aligned} NPS_{ij}(H) &= \left(\frac{\tilde{\theta}_{ji}(H)}{\sum_{i,k=1}^{N} \tilde{\theta}_{ik}(H)} - \frac{\tilde{\theta}_{ij}(H)}{\sum_{j,k=1}^{N} \tilde{\theta}_{jk}(H)} \right) \cdot 100 \\ &= \left(\frac{\tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H)}{N} \right) \cdot 100 \end{aligned} \tag{9}$$

The net pairwise volatility spillover between market i and j is simply the difference between the gross volatility shocks transmitted from market i to market j and those transmitted from j to i.

4. Empirical results

4.1. Results on the returns system

The spillover effects of oil and natural gas returns are calculated following Diebold and Yilmaz (2012). Using these returns series, we then estimate the VAR model presented in Equation 2, selecting the lag using the Schwarz Criterion (1 lag here). From these estimations, we compute the given spillover as in Equation 7. A 24-month ahead forecasting horizon (H) for variance decomposition is used to construct the spillover table. All of these results are presented in Table 4.

Table 4. Full-sample spillover connectedness for original returns.

	WTI	Brent	Daqing	USAG	EURG	From
WTI	34.961	24.830	29.472	3.291	7.446	13.008
Brent	13.981	46.049	32.715	3.174	4.082	10.790
Daqing	17.583	24.067	46.026	5.203	7.122	10.795
USAG	28.517	26.121	10.088	31.777	3.498	13.645
EURG	17.086	30.332	24.408	4.813	23.361	15.328
To	15.433	21.070	19.337	3.296	4.429	TSI = 63.565
NS	2.426	10.280	8.542	−10.349	−10.898	

Table 4 illustrates the static returns spillover relationship between oil and natural markets. It reports the connectedness matrix with pairwise contribution and the sum of “From” and “To” measures for each variable. The diagonal elements in the matrix show self-contributions. And the total spillover index appears in the lower right corner is 63.565%. In each market, the proportion of self-contribution is generally the largest. The Brent has the largest self-explanatory power, with 46.049% due to its own variations, and the next is Daqing (46.026%) which is very close to the Brent. The self-explanatory power of the WTI and the USAG is 34.961% and 31.777% respectively. The EURG has the lowest self-explanatory power, which is 23.361%. Moreover, we can see the “From” column that the directional spillover from others to the EURG is relatively the largest at 15.328%, followed by the USAG and the WTI at 13.645% and 13.008% respectively. From the “To” row, we can also see that the directional spillovers to others from the Brent is the largest at 21.07%, followed by Daqing (19.337%) and the WTI (15.433%). Specifically, 10.795% of the Daqing spillover variation, which is the greatest contribution, is made by the crude oil of the Brent (24.067%). The next is the crude oil of the WTI (17.583%), followed by the natural gas of the EURG (7.122%) and the USAG (5.203%).

This shows that emerging markets are increasingly influencing many developed markets. A mechanism of interdependence volatility spillovers has been found to exist between China’s markets and the developed markets of the USA (Wang and Wang, 2010). Zhang and Wang (2014) found that returns and volatility spillovers between China and world oil markets are bi-directional and the influence of China’s oil market on the world oil market has intensified in recent years.

Figure 2 describes the directional spillover connectedness network. In this figure, each circle represents a node, and the five nodes represent crude oil and natural gas markets in three regions. The arrow indicates a positive pairwise connection from the start node to the end node. To understand the figure more intuitively, we use thicker arrows for the edges with higher connectedness values, and thinner arrows for the edges with lower connectedness values. For example, the WTI has a high influence on the USAG, and the Brent also has a great influence on the EURG. These two arrows are the thickest. The USAG has a little influence on the EURG, so this arrow is the thinnest. Moreover, the size of the nodes represents the degree of outward connection. For example, the Daqing crude oil has the greatest number of outward arrows as a net contributor to the other four nodes, so the size of the node of the Daqing crude oil is the largest. the EURG has the highest number of inward arrows as a net receiver from the other four nodes, thus it has the smallest size of node.

In general, crude oil and natural gas returns can interact and influence each other in three regions. The crude oil of Daqing has the largest influence on the other four markets. This shows that the emerging market has significant spillover effects to other developed markets. And the crude oil of the Brent also has a lot of effects, especially for the natural gas market. It indicates that the fluctuation of the crude oil price can spill to the natural gas market.

The dynamic evolution of returns spillover overtime is more sufficient in revealing the dynamic interact and influence between oil and natural markets. We performed a rolling estimation of oil and natural gas returns spillovers using a 36-month rolling window (a time equivalent to 3 year) in order to analyze such potential time variation. From these estimations, we also compute the given spillover as in Equation 8 with a 36-month rolling window. The dynamic total spillover index for original returns is presented in Figure 3.

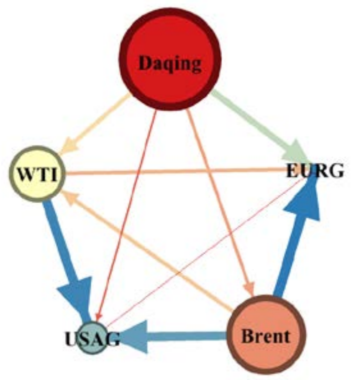

Figure 2. Full-sample directional spillover connectedness network for original returns.

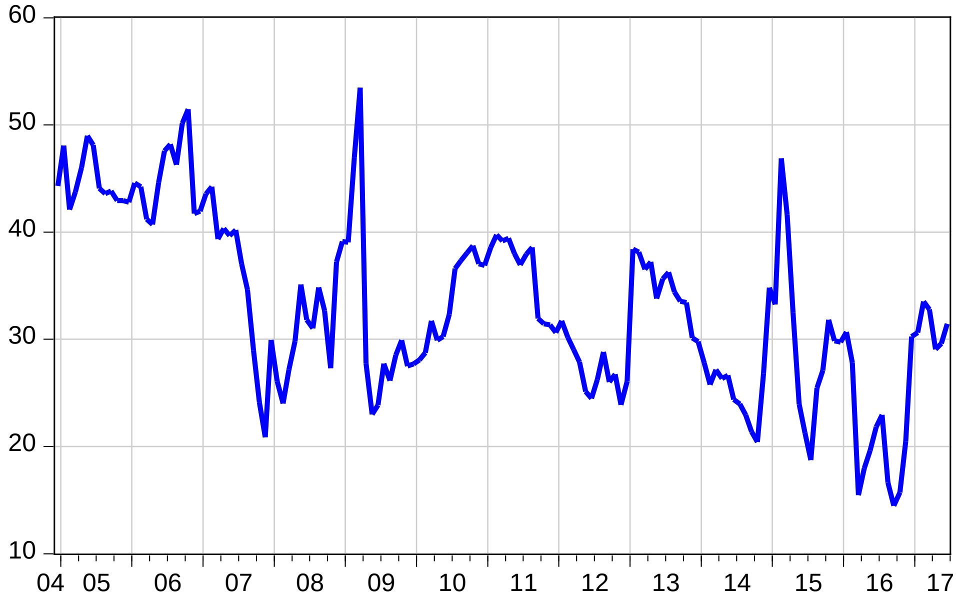

Figure 3. Dynamic total spillover for original returns. (The VAR lag used in the estimation is 1, step of forecasting horizon is 24-month and rolling window length is 36-month).

The spillover of crude oil and natural gas price has a significant time-varying feature and a strong correlation with specific events. As shown in Figure 3, images start from a total spillover of almost 50%, even over 50% in 2006. This shows that there is a relationship of spillover between crude oil and natural gas. The reason might be that the total investment in the UK offshore oil and gas exploration development and operations continue its year on year upward trend, rising 15%. With the change of time, we can clearly see that the total spillover of five groups of data is as high as about 54% in 2009. Part of the reason for this situation may be the financial crisis in 2008, which is considered the worst since the great depression, and it severely affected oil and gas prices. There is a sudden increase between 2014 and 2015. The reason for this may be related to the sudden decline of the Brent crude oil in 2014. The price of crude oil fell from $100 to $50 a barrel, creating high uncertainty for the market. In general, the total spillover of crude oil and natural gas prices in different regions is largely affected by specific events.

4.2. *Results on the volatility system*

The spillover effects of oil and natural gas volatility are also calculated. Using these volatility series, we then estimate five variables of the VAR model presented in Equation 2, selecting the lag using the Schwarz Criterion. From these estimations, we compute the given spillover as in Equation 7. A 24-month ahead forecasting horizon (H) for variance decomposition is used to construct the spillover table. All of these results are presented in Table 5.

Table 5. Full-sample spillover connectedness for original volatility.

	WTI	Brent	Daqing	USAG	EURG	From
WTI	34.850	31.538	6.362	5.737	21.513	13.030
Brent	23.944	36.945	3.520	8.510	27.080	12.611
Daqing	16.644	47.918	24.394	2.367	8.677	15.121
USAG	15.947	36.533	21.285	21.069	5.167	15.786
EURG	19.292	48.924	13.188	1.941	16.656	16.669
To	15.165	32.983	8.871	3.711	12.487	TSI = 73.217
NS	2.135	20.372	−6.250	−12.075	−4.182	

There are volatility spillover interaction and connectedness between emerging and developed markets. In this section, we use the volatility of each market to establish a volatility system and see how markets interact dynamically. Table 4 reports the volatility spillover connectedness and the sum of “From” and “To” measures for each variable, showing that the table is reasonably similar to the returns system. First, the total spillover index shows in the lower right corner rises to 73.217%, about 10% higher than the return system. And the self-contribution of volatility system is lower than that of the return system. But the crude oil of the Brent still has the largest self-explanatory power with 36.945%, followed by the WTI (34.85%) and the Daqing (24.394%). Moreover, the “From” column that represents the volatility spillover from others to the EURG is largest at 16.669%. The next are the USAG (15.786%) and WTI (15.121%). From the “To” row, the volatility spillover to others from the Brent is the largest at 32.983%, followed by the WTI (15.165%) and the EURG (12.487%). The crude oil of the Brent is the largest net contribution at 20.372%, followed by the WTI (2.135%), and the rest of others are net receivers. In addition, the largest contributor of the Daqing crude oil also is the Brent in the volatility spillover system, but the contribution of the Brent is about twice higher than the return system. It is indicated that the crude oil of the Daqing and the Brent are more closely linked.

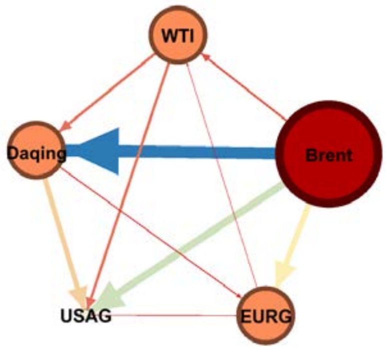

Figure 4. Full-sample directional spillover connectedness network for original volatility.

The fluctuation of the crude oil price in emerging markets can affect the natural gas price in developed markets in the volatility spillover system. Figure 4 describes the directional volatility spillover connectedness network, showing a picture reasonably similar to that of the returns system. In this figure, the Brent is the largest net contributor to the other four nodes. There are the greatest number of outward arrows and the largest size. It shows that crude oil of the Brent has a great influence on this market. Not only the volatility of the Brent price can affect the crude oil of the Daqing price, the most important is that the Brent price can affect the price of natural gas in Europe and the United States. This situation shows that the volatility spillover of crude oil price can influence the natural gas price volatility. Moreover, the nodes of the Daqing crude oil have the less net influence and the smaller size, but the only two arrows are spillover to the natural gas markets of Europe and the United States respectively. This means that although emerging markets have little influence, the volatility spillover of crude oil prices in emerging market can affect the price of natural gas in the developed world.

The volatility spillover of energy prices is heterogeneous before and after the economic crisis. As shown in Figure 5, the total spillover index of the volatility spillover system is higher than that of the returns spillover system. The level of fluctuation in the volatility spillover system is between about 57% and 84%. And the floating level of the returns spillover system is between approximately 15% and 52%. Consisting with the findings of a majority of previous studies (e.g., Shahzad et al., 2017), we find that the total volatility spillover index exhibits a rather similar pattern to that of the total return spillover index, and it is slightly higher than that of returns spillovers throughout the sample. Moreover, between 2007 and 2011, the volume of volatility spillover is very large. Since the outbreak of the subprime mortgage crisis in the second quarter of 2007, investors began to lose confidence in the value of mortgage securities, triggering a liquidity crisis. So, the total volatility spillover in the second to third quarters fell to 64%. After 2009, the volatility spillover reaches its lowest level in history because of the global economic recession in 2008. In addition, the volatility spillover has been in a moderate state between 75% and 80% from 2014 to 2017. The reason is that after the Great Depression, many European countries began to restore the economic growth and improve the structural deficits in 2014.

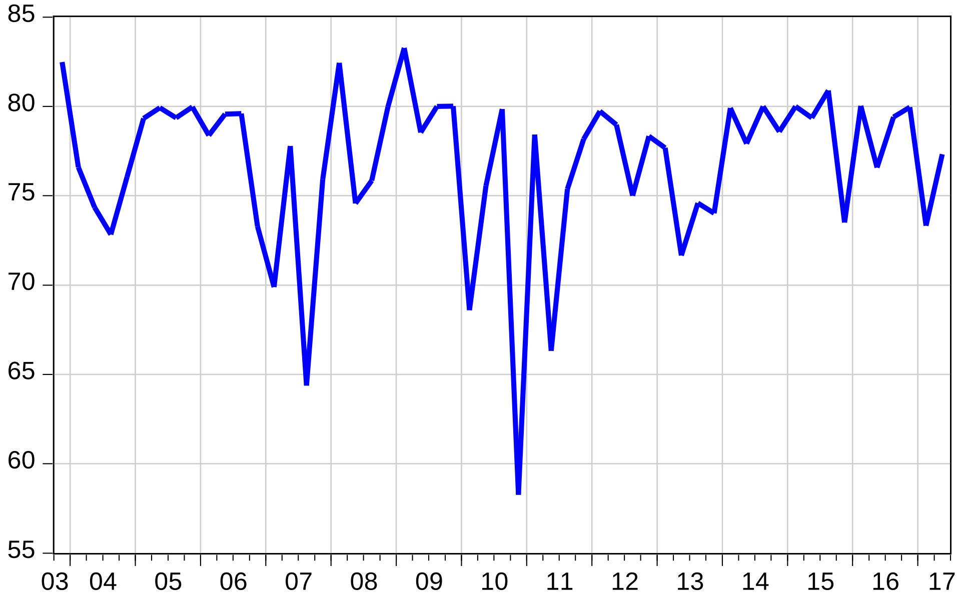

Figure 5. Dynamic total spillover for original volatility. (The VAR lag used in the estimation is 1, step of forecasting horizon is 24-month and rolling window length is 36-month).

4.3. Robustness tests

We now perform some simple variations on our basic analysis toward checking robustness with respect to the rolling window length and the forecast horizon.

Using a longer 36-month and 48-month rolling window length, and two different variance decomposition forecast horizons, with 48-month and 60-month horizon, our results remain robust.

The results appear largely robust to variation in window length and forecast horizon. The returns and volatility spillover index for the 36-month and 48-month rolling window are more stable over time. The reason is that it uses more observations but generally has a similar path to the 24-month rolling window length. It is worth noting that the returns and volatility spillover index matrix may change if forecast horizon (H) is set to be too small. The matrix, however, converges quickly to a stable value when H goes higher, which is consistent with findings of Diebold and Yilmaz (2009).

5. Conclusions

In this paper, we highlight and empirically analyze spillover effects of oil and natural gas prices between emerging and developed markets over the period from December 2001 to Jun 2017. A Granger causality test is the initial work. Subsequently, our study follows the settings presented in the DY spillover index (Diebold and Yilmaz, 2012) to investigate the returns and volatility spillovers for the USA, Europe and China markets. Our main findings can be summarized as follows.

Oil and natural gas markets have significant Granger causality. The co-integration relationship between the five oil and natural gas prices is proved. We use the Granger causality test with 1–3 lags to justify the causality of five prices, and there are three main findings: (1) Daqing Granger causes the WTI and the Brent; (2) the USAG Granger causes the EURG; (3) the bi-directional causality between crude oil and natural gas indicates that there is a certain relationship between their prices.

Furthermore, the emerging market plays an important role for influencing many developed markets both in returns and volatility spillover systems. Daqing has about 20% contributions to other energy markets in the returns system and about 10% in the volatility system. The spillover index shows a strong interaction and connectedness between emerging and developed markets. Moreover, this connectedness of energy markets in both the returns and volatility systems has clear time-varying characteristics. The fluctuation of the spillover index has a strong correlation with specific events, such as the financial crisis.

These results can have good applicability in practice. From the returns and volatility spillover index trend, the market response to information can be extracted to help investors predict the trend, facilitating their reasonable asset allocation. Since there are strong connections among oil and natural gas markets of the USA, Europe, and China, the volatility mechanism can help investors consider the dynamic of each market to diversify their investment portfolio and construct the advantageous investment and arbitrage portfolios related to the oil or natural gas futures.

Conflict of interest

The authors declare no conflict of interest.

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