Energy Economics 80 (2019) 310–320

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Asymmetric volatility spillovers between oil and stock markets: Evidence from China and the United States

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ARTICLE INFO

Article history:
Received 31 July 2018
Received in revised form 18 November 2018
Accepted 17 January 2019
Available online 28 January 2019

Keywords:
Volatility spillover
Asymmetric effects
Oil market
Stock market

ABSTRACT

The relationship between oil and stock markets is a hot topic, but little research has focused on the time-varying asymmetric volatility spillover in a quantitative manner. In this study, we use a new spillover directional measure and asymmetric spillover measures to investigate the dynamic asymmetric volatility spillover between oil and stock markets during the period of 2007 to 2016. Using the intra-day data of WTI future prices, the S&P 500 index, and the Shanghai stock market composite index, we find that there exists an asymmetric spillover effect between the oil market and stock markets and that bad volatility spillovers dominate good volatility spillovers for most of the sampling period. In addition, participants are more pessimistic about the oil market than they are about the stock market. We further investigate the presence of asymmetric response to volatility shocks using the asymmetric generalized dynamic conditional correlation (AG-DCC) model; the results also show strong evidence of asymmetries in volatility shocks between the oil and stock markets due to bad volatility.

1. Introduction

The international oil market has experienced a sharp rise and fall over the past 10 years, showing extremely high price fluctuations. Crude oil has a significant influence on the economy as well as financial markets (Hamilton, 1983, 2003; Chen et al., 1986; Huang et al., 1996; Jones and Kaul, 1996; Hammoudeh et al., 2004; Kilian, 2008; Kilian and Park, 2009; Aloui and Jammazi, 2009; Scholtens and Yurtsever, 2012; Wen et al., 2012; Yaya et al., 2016; Ji et al., 2018; Gong and Lin, 2018a, 2018b). Therefore, volatility spillovers between the oil market and stock markets are crucial for energy policy-makers, market participants, portfolio diversification and energy risk management; as such, this linkage between the oil market and stock markets has attracted more attention around the world (Filis et al., 2011; Wen et al., 2012; Awartani and Maghyereh, 2013; Ewing and Malik, 2016; Maghyereh et al., 2017; Kang et al., 2017). However, despite the fact that the presence of asymmetric volatility in financial markets has long been recognized in the literature (Christie, 1982; French et al., 1987; Bollerslev et al., 2006; Chiou and Lee, 2009; Filis et al., 2011; Wen et al., 2012), and the proper quantification of such asymmetries is highly relevant to risk valuation and portfolio diversification strategies (Patton, 2004; Knott et al., 2009; Garcia and Tsafack, 2011), little research has focused on the time-varying asymmetric volatility spillover between oil and stock markets in a quantitative way; our paper fills this gap.

The early literature focused on the return spillovers between oil and stock markets, wherein the common econometric methodologies applied to the return spillovers between crude oil and stock markets were the traditional vector autoregressive (VAR) or vector error correction models (VECM) (Huang et al., 1996; Cong et al., 2008; Miller and Ratti, 2009; Gupta and Modise, 2013). For example, Huang et al. (1996) used a VAR model to test the dynamics of interactions between oil futures returns and U.S stock returns during the 1980s, and they found that oil futures affect individual oil companies but not U.S stock returns. Cong et al. (2008) used a VAR model to test the correlation between international oil price returns and Chinese stock returns, and they found no statistically significant impact from international oil price shocks on most Chinese stock price indices. Miller and Ratti (2009) analyzed the long-term relationship between the world price of crude oil and international stock markets over 1971:1–2008:3 using VECM. Gupta and Modise (2013) used a sign restriction structural VAR to test the dynamics between oil price shocks and South African stock returns. They found that stock returns only increase with oil prices when global economic activity improves.

Moreover, studies addressing the issue of volatility spillovers between oil and stock markets use the common econometric methodologies of the multivariate GARCH-type models (Hammoudeh et al., 2004; Accioly and Aiube, 2008; Chang et al., 2010; Hammoudeh et al., 2010; Filis et al., 2011; Wen et al., 2012; Chkili et al., 2014; Guesmi and Fattoum, 2014;

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https://doi.org/10.1016/j.eneco.2019.01.014
0140-9883/

Kang et al., 2017). For instance, Hammoudeh et al. (2010) examined the impacts of world-, country-, and sector-specific variables on the stock return volatility of twenty-seven US sectors in the short- and long-run and accounted for their asymmetric shocks based on GARCH models. Filis et al. (2011) investigated the time-varying correlations between Brent oil prices and stock markets on both oil-importing and oil-exporting countries. Using a multivariate asymmetric DCC-GARCH approach, they found that the conditional variance of oil and stock prices remains the same for oil-importing and oil-exporting economies. However, time-varying correlations depend on the origin of the oil shocks: the response from aggregate demand-related shocks is much greater than supply-related shocks originating from OPEC's production cuts. Guesmi and Fattoum (2014) use a multivariate GJR-DCC-GARCH approach to investigate the co-movements and dynamic volatility spillovers between oil prices and oil-exporting and oil-importing countries; they determined that oil assets are not a good 'safe haven' for protection against stock market losses during periods of turmoil.

However, the ability to measure spillovers by using the above types of models is limited; more specifically, merely measuring the return and volatility spillover through the significance of parameters by estimation under a special variance structure cannot measure the extent of spillovers or capture the direction of spillovers (Zhou et al., 2012; Kang et al., 2017; Wang and Guo, 2018).

To overcome the limitations evident in the abovementioned literature, Diebold and Yilmaz (2009) provided new versatile measures based on forecast error variance decompositions in a vector autoregressive framework to quantitatively measure the extent of spillover transfer among markets. Further, this methodology was further improved by Diebold and Yilmaz (2012), which has since allowed us to track down dynamically directional spillover in a quantitative way. That is, it not only indicates the direction of the spillover but also provides the value of directional spillovers between any two markets. In addition, it avoids the controversial issues associated with the definition and existence of episodes of "contagion" or "herd behavior." A fairly sizable amount of studies have using the spillover directional measure introduced by Diebold and Yilmaz (2009, 2012) to investigate dynamic spillovers in different financial markets (Zhou et al., 2012; Awartani and Maghyereh, 2013; Ewing and Malik, 2016; Maghyereh et al., 2016; Zhang, 2017; Yang and Zhou, 2017). Awartani and Maghyereh (2013) used a spillover index proposed by Diebold and Yilmaz (2009, 2012) to investigate the dynamic spillover of return and volatility between oil and equities in the Gulf Cooperation Council countries; they found that return and volatility transmissions are bi-directional, albeit asymmetric. Maghyereh et al. (2016) used a set of newly introduced implied volatility indices to investigate the directional connectedness between oil and equities in eleven major stock exchanges, and they found that volatility transmissions are bi-directional and that the bulk of association is largely dominated by the transmissions from the oil market to equity markets and not the other way around. Yang and Zhou (2017) used a new spillover index, similar to that employed by Diebold and Yilmaz (2009, 2012), with the DAG technique to investigate the dynamic spillover of U.S. Treasury bonds, global stock indices, and commodities; as a result, they found that the U.S. stock market is the center of the international volatility spillover network, and its volatility spillover to other markets has intensified since 2008.

Although the presence of asymmetric volatility in financial markets has long been recognized in the literature, surprisingly, previous studies of asymmetries in volatility spillovers have not yet received the same attention. With the availability of high-frequency data, research on financial market volatility has taken new avenues. Andersen and Bollerslev (1998) proposed a robust measure for actual market volatility, called the realized volatility (RV). Barndorff-Nielsen et al. (2010) proposed realized semivariance (RS) that decomposes RV into good and bad volatility due to positive or negative returns. Baruník et al. (2016) were the first to propose how to quantify asymmetries in volatility spillovers that emerge due to bad and good volatility, and they found that ample evidence of the asymmetric connectedness of stocks at the disaggregate level and the spillovers of bad and good volatility are transmitted at different magnitudes that change substantially over time in different sectors. Furthermore, Baruník et al. (2017) revised directional asymmetries in volatility spillovers, thus making their interpretation straightforward.

There is some literature examining the relationship between oil price and the Chinese stock market (Wen et al., 2012; Zhou et al., 2012; Broadstock et al., 2012; Zhang and Wang, 2014; Broadstock and Filis, 2014). Broadstock et al. (2012) used the BEKK method to investigate the relationship between international oil prices and energy-related stocks in China, they found that international oil price changes are correlated with energy-related stock returns in the context of China, but in a time-dependent manner; the results show a much stronger relationship following the 2008 financial crisis. Wen et al. (2012) used time-varying copulas and the GJR model to study the contagion effect between crude oil and US/Chinese stock markets, and they found that the dependence between crude oil and stock markets significantly increases after the failure of Lehman Brothers. Zhang and Wang (2014) examined the return and volatility spillovers between China and world oil markets, extending Diebold and Yilmaz's (2012) method of catching spillover dynamics, and they found that the return and volatility spillover between China and world oil markets are bi-directional and asymmetric; the Chinese oil market is highly affected by world oil markets and exerts an influence on world oil markets, although to a lesser extent. However, although the US/Chinese stock markets are the first- and second-largest stock markets in the world, few studies have examined the asymmetric volatility spillover between oil and the US/Chinese stock market.

In this study, we aim to fill the gap and use the volatility spillover index introduced by Diebold and Yilmaz (2009, 2012) and the realized semivariances introduced by Baruník et al. (2017) to investigate the dynamic asymmetric volatility spillover between oil and US/Chinese stock markets during the period of 2007 to 2016.[1] Why we choose the Chinses stock market to do our research is that because the Chinese stock market is one of the largest and fastest-growing emerging stock markets in the world. By the end of 2017, the total market capitalization of the Chinese stock market had broken 56.62 trillion yuan. More importantly, the Chinese stock market has gradually integrated into the global economy after a series of liberalization policies, such as those of the World Trade Organization (WTO), Qualified Foreign Institutional Investors (QFII) and RMB Qualified Foreign Institutional Investors (RQFII). Considering these factors, the Chinese stock market has received more attention from scholars and investors. Overall, this study extends the previous literature in three dimensions: (a) using high-frequency, intra-day data of WTI future prices, the S&P500 index, the Shanghai stock market composite index, we analyze the total and directional connectedness between the oil and stock markets in a quantitative way; (b) combining the volatility spillover index introduced by Diebold and Yilmaz (2012) and the realized semivariances introduced by Baruník et al. (2017), we are the first to analyze the dynamic asymmetric volatility spillover between oil and US/Chinese stock markets; and (c) we use the asymmetric generalized dynamic conditional correlation (AG-DCC) model developed by Cappiello et al. (2006) to investigate the presence of asymmetric response to volatility shocks.

In this research, we have several noteworthy findings. First, our empirical results reveal the asymmetric spillover effect between oil and stock markets. Second, the asymmetric volatility spillovers between oil and stock markets are time-varying, and the interdependence between oil and stock markets strengthened during the financial crisis; this underscores the conclusion that economic events have a strong influence on the global oil and stock markets. Third, our results indicate that bad volatility spillovers dominate good volatility spillovers for most of the sampling period, and participants' pessimistic mood about the oil market is larger

[1] Our estimation sample length includes both the global financial crisis and the Eurozone debt crisis.

than that about the stock market. In addition, our conclusions are robust to different windows and models (e.g., Markov-regime VAR).

The rest of this paper is organized as follows. Section 2 introduces the methodological approach, including realized volatility, semivariance measures and asymmetric spillovers. Section 3 provides the data description. Section 4 reports our main empirical results. Section 5 reports the robustness check. Section 6 reports Markov regime-switching asymmetric volatility spillovers. Section 7 concludes the paper.

2. Empirical methodology

This section introduces the methodology used to capture asymmetric volatility spillovers using high-frequency measures. First, we introduce the concept to describe how to measure realized volatility and semivariance measures. Second, we introduce the concept to describe how to measure volatility spillovers. Third, we introduce the concept to describe how to measure asymmetric volatility spillovers.

2.1. Realized volatility and semivariance measures

According to Andersen and Bollerslev (1998), the realized volatility is defined as the sum of intraday squared returns, which can be calculated as:

$$RV_t = \sum_{j=1}^{1/\Delta} r^2_{(t-1)+j\,\Delta,\Delta} \tag{1}$$

where Δ and $r_{(t-1)+j\Delta,\,\Delta}$ represents the sampling interval and the intraday return during day t, respectively. As pointed out by Barndorff-Nielsen and Shephard (2004), for $\triangle \to 0$,

$$RV_t \to \int_0^t \sigma^2(s)ds + \sum_{0<s\le t} \kappa^2(s) \tag{2}$$

where $\int_0^t \sigma^2(s)ds$ is the integrated variance (IV) and $\sum_{0<s\le t}\kappa^2(s)$ is the discontinuous jump part of the quadratic variation (QV). IV can be computed by realized bipower variation (RBV), which is defined as follows:

$$RBV_t = \mu_1^{-2} \sum_{j=2}^{1/\Delta} \left| r_{(t-1)+j\,\Delta} \right| \left| r_{(t-1)+(j-1)\,\Delta} \right| \to \int_0^t \sigma^2(s)ds \tag{3}$$

where $\mu_1 = (2/\pi)^{0.5} \simeq 0.7979$, and $\sum_{0<s\le t}\kappa^2(s)$ is the jump component (J_t), which is defined as $J_t = \max(RV_t - BPV_t, 0)$.

Recently, Barndorff-Nielsen et al. (2010) proposed that RS decomposes RV due to positive or negative returns. The positive realized semivariances (RS$^+$) and negative realized semivariances (RS$^-$) can be computed as follows:

$$RS_t^+ = \sum_{j=1}^{1/\Delta} r^2_{(t-1)+j\,\Delta,\Delta} I\left(r_{(t-1)+j\,\Delta}>0\right) \to \frac{1}{2}\int_0^t \sigma^2(s)ds + \sum_{0<s\le t} \kappa^2(s) I(\kappa_s>0) \tag{4}$$

$$RS_t^- = \sum_{j=1}^{1/\Delta} r^2_{(t-1)+j\,\Delta,\Delta} I\left(r_{(t-1)+j\,\Delta}<0\right) \to \frac{1}{2}\int_0^t \sigma^2(s)ds + \sum_{0<s\le t} \kappa^2(s) I(\kappa_s<0) \tag{5}$$

where $I(\bullet)$ is the indicator function. Barndorff-Nielsen et al. (2010) proved that RV is the sum of RS$^+$ and RS$^-$, $RV_t = RS_t^+ + RS_t^-$. The realized semivariances can serve as a measure of estimating volatility spillovers due to good or bad volatility and quantify asymmetries in spillovers in different financial markets.[2]

[2] See details in Sections 2.2–2.3, Baruník et al. (2017).

2.2. Measuring volatility spillovers

This sub-section uses the core method developed by Diebold and Yilmaz (2009, 2012) to describe how to measure volatility spillovers based on the forecast error variance decompositions in a generalized vector autoregressive framework. This is widely used to quantify volatility spillovers in different financial markets.

Consider a covariance stationary of realized variance, $RV_t = (RV_{1t}, \cdots, RV_{nt})'$ in N different assets, with a lag length P-th, such that VAR(P) can be calculated by:

$$RV_t = \sum_{i=1}^{p} \phi_i RV_{t-i} + \varepsilon_t, \tag{6}$$

where $\varepsilon_t \sim i.i.d.(0, \Sigma_\varepsilon)$ is a vector of disturbances and ϕ_t is for $i = 1, \ldots, p$. Eq. (1) can be rewritten as the infinite moving average representation:

$$RV_t = \sum_{i=1}^{\infty} A_i \varepsilon_{t-i}, \tag{7}$$

where the $N \times N$ coefficient matrices A_i obey the recursion of the form $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \cdots + \phi_p A_{i-p}$, with A_0 being the identity matrix and where $A_i = 0$ for $i < 0$.

The moving average coefficients are the key to understanding the dynamics of the system given the variance decompositions, which allow us to split the H-step-ahead forecast error variances of each variable into parts that are attributable to the various system shocks. However, in order to produce variance decompositions that are invariant with the ordering, which allows for correlated shocks but accounts for them appropriately, Diebold and Yilmaz (2012) used the generalized VAR of Koop et al. (1996) and Pesaran and Shin (1998).

Following Diebold and Yilmaz (2012), we consider: (i) the assets' own variance shares as fractions of the H-step-ahead error variances in forecasting the i-th variable that are due to the assets' own shocks to i for $i = 1,2\ldots,N$, and (ii) spillovers, or the cross variance shares, as fractions of the H-step-ahead error variances in forecasting the i-th variable that are due to shocks to the j-th variable, for $i,j = 1,2\ldots,N$, $i \ne j$. The H-step-ahead generalized forecast error variance decompositions[3] $\theta_{ij}^g(H)$ and its normalization $\tilde{\theta}_{ij}^g(H)$ for $H = 1,2\ldots$, can be respectively calculated by:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_j\right)}, \tag{8}$$

and

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^{N} \theta_{ij}^g(H)}. \tag{9}$$

where Σ is the variance matrix for the error vector ε, σ_{ij} is the standard deviation of the error term for the j-th equation, and e_i is the selection vector, with one as the i-th element and zeros otherwise.

Note that $\sum_{j=1}^{N} \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H) = N$. $\tilde{\theta}_{ij}^g(H)$ can be seen as a natural measure of the contribution of the forecast H step-ahead error variance from market j to market i at horizon H. The main diagonal elements of $\tilde{\theta}_{ij}^g(H)$ can be seen as a measure of the contributions of the forecast error variance to market i to its own forecast H step-ahead error variance at horizon H.

[3] The sum of the elements in each row of the variance decomposition table is not equal to one. $\sum_{j=1}^{N} \theta_{ij}^g(H) \ne 1$, as the shocks are not necessarily orthogonal.

Table 1
Spillover matrix ($2N \times 2N$).

		Panel B: realized semivariances					
		RS^+			RS^-		
		Crude oil	US	CN	Crude oil	US	CN
RS^+	Crude oil	$\omega_{1,1}$	$\omega_{2,2}$	$\omega_{1,3}$	$\omega_{1,4}$	$\omega_{1,5}$	$\omega_{1,6}$
	US	$\omega_{2,1}$	$\omega_{2,2}$	$\omega_{2,3}$	$\omega_{2,4}$	$\omega_{2,5}$	$\omega_{2,6}$
	CN	$\omega_{3,1}$	$\omega_{1,2}$	$\omega_{3,3}$	$\omega_{3,4}$	$\omega_{3,5}$	$\omega_{3,6}$
RS^-	Crude oil	$\omega_{4,1}$	$\omega_{4,2}$	$\omega_{4,3}$	$\omega_{4,4}$	$\omega_{4,5}$	$\omega_{4,6}$
	US	$\omega_{5,1}$	$\omega_{5,2}$	$\omega_{5,3}$	$\omega_{5,4}$	$\omega_{5,5}$	$\omega_{5,6}$
	CN	$\omega_{6,1}$	$\omega_{6,2}$	$\omega_{6,3}$	$\omega_{6,4}$	$\omega_{6,5}$	$\omega_{6,6}$

2.2.1. Total spillovers

Using the volatility contributions from the variance decomposition, according to Diebold and Yilmaz (2012), the total volatility spillover index can be constructed as follow:

$$S^g(H) = \frac{\sum\limits_{\substack{i,j=1\\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum\limits_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum\limits_{\substack{i,j=1\\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100. \tag{10}$$

The main advantage of the total spillover index is the measurement of the contribution of the spillovers of volatility shocks to the total forecast error variance. The total connectedness is the ratio of the sum of the off-diagonal elements of $\tilde{\theta}_{ij}^{g}(H)$ to the sum of all its elements.

2.2.2. Directional spillovers

According to Diebold and Yilmaz (2012), we can measure the directional volatility spillovers received by market i from all other markets j (FROM others) and the reverse direction of transmission from market i to all markets j (TO others), as shown below:

$$S_{i\leftarrow\cdot}^{g}(H) = \frac{\sum\limits_{\substack{j=1\\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum\limits_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum\limits_{\substack{j=1\\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100 \tag{11}$$

and

$$S_{i\rightarrow\cdot}^{g}(H) = \frac{\sum\limits_{\substack{j=1\\ i\neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum\limits_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \cdot 100 = \frac{\sum\limits_{\substack{j=1\\ i\neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \cdot 100 \tag{12}$$

The main advantage of directional spillovers is to further provide a decomposition of the total spillovers to those coming from (or to) a particular market in the system, which can reveal the spillover transmission mechanism.

2.2.3. Net spillovers

According to Diebold and Yilmaz (2012), the net volatility spillover from market i to all other markets j can be calculated as follows:

$$S_i^g(H) = S_{i\rightarrow\cdot}^{g}(H) - S_{i\leftarrow\cdot}^{g}(H). \tag{13}$$

The main advantage of the net volatility spillover is to compute how much each market i contributes to the volatility in other assets in net terms, which can distinguish who is the net-contributor and net-recipient of volatility shocks. if $S_i^g(H) > 0$, we say that the market i a 'net-contributor', otherwise, market i is a 'net-recipient'.

2.3. Measuring asymmetric spillovers

Using the realized semivariance framework of Barndorff-Nielsen et al. (2010) and the volatility spillover index of Diebold and Yilmaz (2009, 2012), Baruník et al. (2016) first defined asymmetry as the difference between positive and negative spillovers, where the authors defined measures using two separate VAR systems for negative and positive semivariances. Further, Baruník et al. (2017) revised directional asymmetries in volatility spillovers with a single VAR system and used the direction TO to have a straightforward interpretation in the $2N \times 2N$ spillover matrix setting, while the interpretation of FROM is quite vague. Next, we introduce the measures of the directional spillover asymmetry and Total Spillover asymmetry of Baruník et al. (2017).

Due to the advantages of high-frequency data, we can disentangle realized volatility into negative and positive realized semivariances in N different assets. We replace the vector of the realized volatilities $RV_t = (RV_{1t}, \cdots, RV_{nt})'$ defined in Eq. (1) with the vector of negative and positive semivariances $RS_t = (RS_{1t}^{+}, \cdots, RS_{nt}^{+}, RS_{1t}^{-}, \cdots, RS_{nt}^{-})'$; finally, we get the $2N \times 2N$ H-step-ahead generalized forecast error variance decomposition matrix $\theta_{ij}^{g}(H)$. Thus, we estimate a $2N$-dimensional VAR, resulting in a $2N \times 2N$ system of forecast variance error decompositions.

2.3.1. Directional spillover asymmetry measure

In Table 1, we show the elements of the $2N \times 2N$ H-step-ahead generalized forecast error variance decomposition matrix for a specific case of three assets. To compute the directional spillovers in the direction TO, we not only remove the main diagonal elements, $i \neq j$, but also exclude the diagonal elements in the $N \times N$ sub-matrices (lower left and upper right), $|i\text{-}j| \neq N$. All excluded numbers are highlighted in bold in Table 1; hence, for each row and column, we sum $2N$-2 numbers.

The directional spillover from an asset i to all other assets can be calculated as follows:

$$S_{2N,i\rightarrow\bullet}^{g}(H) = \frac{1}{2N} \sum_{\substack{j=1, i\neq j\\ |i-j|\neq N}}^{2N} \tilde{\theta}_{ji}^{g}(H) \times 100, i, j = 1, \ldots 2N. \tag{14}$$

According to Baruník et al. (2017), the directional spillover asymmetry measure is defined as the difference of the response to a shock from good or bad volatility from asset i to other assets. Thus, for asset i, we subtract the effect of the $(N+i)$-th column of a spillover matrix from the effect of the i-th column; then, the directional asymmetry measure spillover from an asset i to all other assets with an H-step-ahead forecast at time t can be calculated as follows:

$$SAM_{2N,i\rightarrow\cdot}^{g}(H) = S_{2N,i\rightarrow\cdot}^{g}(H) - S_{2N,(i+N)\rightarrow\cdot}^{g}(H), i = 1, \ldots, N. \tag{15}$$

If the $SAM_{2N,\, i\rightarrow\cdot}^{g}(H)$ is positive (negative), it reflects the stronger effect of the good (bad) volatility of asset i to other assets.

2.3.2. Total spillover asymmetry measure

According to Baruník et al. (2017), we define the Total Spillover asymmetry measure with an H-step-ahead forecast at time t, $SAM_{2N}^{g}(H)$, as the difference between volatility spillovers due to the negative and positive returns for all assets N:

$$SAM_{2N}^{g}(H) = \sum_{i=1}^{N} SAM_{2N,i\rightarrow\cdot}^{g}(H) - \sum_{i=N+1}^{2N} SAM_{2N,i\rightarrow\cdot}^{g}(H) \tag{16}$$

The main advantage of the Total Spillover asymmetry measure $SAM_{2N}^{g}(H)$ is to better understand the behavior of total volatility

Table 2
Descriptive statistics of realized volatilities and semivariances.

	Mean	St. dev.	Min	Max	Skewness	Kurtosis	Jarque-Bera	Q(10)	ADF
Panel A: Realized volatilities									
Oil	0.542	1.061	0.017	23.518	10.301	171.630[a]	2,669,390.844[a]	2961.006[a]	−5.806[a]
US	0.117	0.331	0.003	9.415	14.124	318.865[a]	9,154,215.054[a]	4787.499[a]	−5.669[a]
CN	0.250	0.364	0.012	4.328	4.711	33.254[a]	106,713.570[a]	4094.493[a]	−10.664[a]
Panel B: The positive realized semivariances (RS^{+})									
Oil	0.268	0.785	0.006	21.856	17.793	419.711[a]	15,849,826.182[a]	662.868[a]	−7.944[a]
US	0.058	0.159	0.001	3.954	11.744	213.382[a]	4,116,787.984[a]	5088.072[a]	−5.850[a]
CN	0.126	0.196	0.002	2.740	5.462	44.616[a]	188,489.582[a]	3216.380[a]	−10.991[a]
Panel C: The negative realized semivariances (RS^{-})									
Oil	0.273	0.556	0.006	9.728	7.611	86.200[a]	684,486.969[a]	2232.988[a]	−4.275[a]
US	0.059	0.181	0.001	5.461	15.934	397.295[a]	14,191,391.065[a]	3694.746[a]	−5.330[a]
CN	0.124	0.193	0.003	2.036	4.460	28.588[a]	80,120.456[a]	3149.723[a]	−11.600[a]

Notes: This table reports summary statistics of realized volatilities and semivariances. In the table, Crude Oil, US, and CN denote crude futures oil market, the US Stock Market, and the Chinese Stock Market, respectively. The Jarque-Bera statistic (Jarque and Bera, 1987) tests are for the null hypothesis of normality for the distribution of the series. Q(10) is the Ljung–Box statistics for serial correlation. ADF is the t-statistics for Augmented Dickey–Fuller test. All data are multiplied by 1000.
[a] Indicates the rejection of the null hypothesis at the % levels.

spillovers for a given portfolio of assets, $SAM_{2N}^{g}(H) = 0$, where there is no spillover asymmetry.

3. Data

In this paper, we employ high-frequency data to compute the volatility spillovers on three markets: the oil market, the stock market in the US and the stock market in China. We select data from the Light Sweet Crude Oil (WTI) futures contract with a maturity of one month trade on the NYMEX to represent the Crude Oil market as WTI futures traded on the NYMEX, which is a widely traded energy commodity, to provide the reference crude oil price benchmark. Furthermore, we use the S&P 500 index and the Shanghai Stock Exchange Composite index (SSEC)[4] to represent the stock markets in the US and China. These data were obtained from the Thomson Reuters Tick History (TRTH) and the RESSET Financial Research Database, respectively. Note that the Chinese stock market is open when the US stock market is closed. To tackle the nonsynchronous trading problem, following Cai et al. (2009) and Zhang and Wang (2014), the daily volatility of the US is lagged by one day. However, our results show that there is little difference before and after this adjustment. In this paper, we mainly present the empirical results with this adjustment and discuss their associated economic implications. We examine the sample period from January 4, 2007 to April 28, 2016, which, after deleting non-match data, includes 2144 trading days.[5]

Given consideration to both the measurement accuracy and market microstructure noise, it is found that 5 min of sampling frequency is the optimal sampling frequency (e.g., Andersen and Bollerslev, 1998; Andersen et al., 2007; Corsi et al., 2010; Sévi, 2014; Liu et al., 2015); thus, we choose a 5-min sampling frequency.

The descriptive statistics for realized volatilities and semivariances are summarized in Table 2. In terms of the mean and standard errors of realized volatilities and semivariances, Crude Oil displays the highest price volatility, while that of the US is the lowest. The skew of all data is positive, and all of the excess kurtosis values are above three, indicating the presence of sharp peaks and fat tail distribution. The results of the Ljung-Box Q test show evidence of serial correlation up to an order of 10 for all of the series, indicating the existence of a correlation. The unit root tests based on the Augmented Dickey-Fuller (ADF) procedure support the conclusion that all series are stationary at the 1% significance level, indicating that they can be used in the VAR analysis.

4. Empirical analysis

4.1. Full sample analysis

Table 3 reports the full sample spillover table of volatilities. The (i, j) entry in each panel is the estimated contribution to the forecast error variance of market i coming from innovations to market j. The diagonal elements of the matrix are not particularly interesting in our context, as they represent the own shock, which is not the point of our discussion. The off-diagonal elements (i, j) capture directional spillovers from market i to market j. For example, the element in row 2, column 1 (13.66%) is the directional spillover from Oil to the US stock market. The highest oil directional connectedness of approximately 31.90% is observed from Oil to the US stock market (see first column, second row), while 13.66% is from the US to oil (see first row, second column). From the empirical results of Table 3, we find that the volatility connectedness from oil to stock markets (US and China) is 38.49% (see first column, fourth row), and from stock markets (US and China) to oil is 15.29% (see first row, fourth column). The difference between two pairwise connectedness measures is 23.20% (38.49% − 15.29%), implying that the net pairwise connectedness is from oil volatility to the volatility of stock markets (US and China). Specifically, the spillover index is 31.90% from oil to US and is 6.59% from oil to China. In return the connectedness is 13.66% from US to oil and 1.64% from China to oil. Consequently, we find that the connectedness between oil and US is more strong than the connection between oil and China. Obviously, our empirical results indicate that the impacts of oil risk on US investors are larger than the Chinese investors.

In the TO others row, the directional spillovers from the CN market to all other markets is the least (3.31%), indicate that the CN stock market has no significant impact on the oil market or US stock market.

Table 3
Full-sample volatility spillover table for N-dimensional VAR model.

	Crude oil	US	CN	From others	Net	Conclusion
Crude oil	84.71	13.66	1.64	15.29	23.20	Net-contributor
US	31.90	66.43	1.67	33.57	−11.18	Net-recipient
CN	6.59	8.73	84.68	15.32	−12.01	Net-recipient
TO others	38.49	22.39	3.31			Total spillover
including own	138.76	72.77	88.48			Index: 21.39

Notes: The (i,j) entry is the estimated contribution to the forecast error variance of market i coming from innovations to market j. TO others are the directional spillovers from a market to all other markets. FROM others are the directional spillovers from all markets to a particular market. The total spillover index, as defined in Eq. (1), is reported in the lower right corner of the table. Oil, US, and CN represent WTI future oil, the US stock market, and the Chinese stock market, respectively.

[4] The Shanghai stock market is the largest stock market in China, so the Shanghai Stock Exchange Composite index (SSEC) can be used to represent the Chinses stock market.
[5] Methodologies on data clearing are based on Sévi (2014) and Ma et al. (2017).

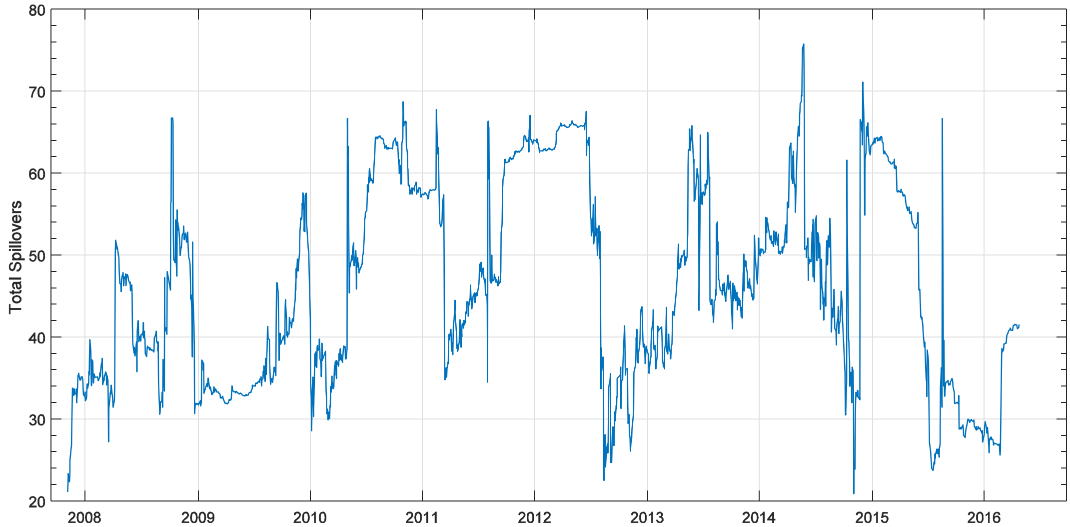

Fig. 1. Dynamic total volatility spillovers using 200-day rolling-sample window between oil and the US/Chinese Stock Market.

In the FROM others column, the oil markets are the least affected by other markets during the time under consideration (15.29%), which is consistent with the conclusion of Maghyereh et al. (2016). The US market is the most affected by other markets (33.57%).

In the net column, oil is the only positive value (23.20%), indicating that oil contributes more than it receives from the system and that the oil market is a net contributor. The US and CN stock market are the net recipients. The total spillover index for all markets is 21.39%.

4.2. Rolling-windows analysis

4.2.1. Total volatility spillover

Full sample analysis is insufficient to reveal the time-varying nature of volatility spillovers. Due to this consideration, we compute the volatility spillovers indices using a 200-day rolling window, the generalized variance decompositions of 10-day-ahead forecast errors horizon ($H = 10$), and a VAR lag length of $5 (p = 5)$.[6]

Fig. 1 presents the total spillover index for the volatility series among the three markets over the sample period. We highlight some characteristics in these plots: the total spillover index ranges from 20.88% to 75.75%; from November 2007 to late October 2008, there are sharp upticks in the volatility spillover, indicating that the interdependence between oil price and the stock market strengthened during the financial crisis. A plausible explanation is that investors in the stock market are more sensitive to price volatility in crude oil market. Sudden increases in oil prices will boost returns in investment and a consequence of the financial crisis was that oil markets became more volatile, hence results in higher returns. Another possible explanation is that high oil risk can remarkably increase market uncertainty, and naturally increase the uncertainty of the oil-related industries, which can lead to increase the fluctuations of the stock markets. In addition, Zhang (2017) demonstrate that financial markets have increasing impacts on commodity markets (i.e., oil) during the financial crisis. Generally, our finding is consistent with previous studies (Diebold and Yilmaz, 2012; Broadstock et al., 2012; Wen et al., 2012; Awartani and Maghyereh, 2013; Zhang and Wang, 2014; Wang and Wu, 2018).

From November 2008 through the end of 2008, the spillover decreased rapidly; however, beginning in January 2009, the spillover increased gradually. Subsequently, there are sharp peaks and valleys in the volatility spillover due to the Eurozone debt crisis, the collapse of co-operation among OPEC members and the slowdown of China. This indicates that economic and political events have a strong influence on the world oil and stock markets.

4.2.2. Directional spillovers

To understand how directional volatility spillovers between oil and the stock markets change over time, Fig. 2 reports directional volatility spillovers, while net spillovers are calculated by subtracting directional 'TO' spillovers from directional 'FROM' spillovers. Directional spillovers show time-varying patterns in the oil and stock markets. Taking the oil market as an example, in Fig. 2 in the first column, in 2008 (in the upper panel), the directional spillover from stock markets to the oil market is high, while in middle panel, the directional spillover from the oil market to the stock markets is low; thus, in the third row, the net spillover of oil has a negative value, indicating that oil is a 'net-recipient' and thus that the spillover during that period was dominated by stock markets. Meanwhile, in the third row and second column, the US stock market is a 'net-contributor', which can be explained by noting that during the financial crisis, the US market dominated the information transmission across global markets, including the oil market. It is worth mentioning that since the middle of 2013, with the exception of the first half of 2015, the Chinese market is nearly a 'net-contributor' while the US market is almost a 'net- recipient', which may be explained by the recovery of the Chinese economy. We find that net spillovers show time-varying patterns and that spillovers are asymmetric; there is no clear-cut evidence concerning which of the three markets leads to the spillovers to the others. Those findings are clear supported that modeling and forecasting stock market prices volatility should be considered the impacts of oil uncertainty, especially bad shocks. Additionally, the impacts of oil risk on stock market volatility are also time-varying. Moreover, our findings are important for investors who have exposures to oil and equity such as hedge funds. For example, the strong links between oil and equity can reduce the diversification benefits strategy when investor hold a portfolio that includes both of oil and equity.

4.3. Total asymmetries in volatility spillovers

This section reports the asymmetric volatility spillovers between the oil and stock markets. Fig. 3 presents the spillover asymmetry measure, with positive values suggesting that the volatility spillovers due to positive/good volatility are larger than those due to negative/bad volatility. Negative values of SAM suggest that volatility spillovers due to

[6] Rolling window of 200 and H-values = 10 follow Diebold and Yilmaz (2009, 2012, 2016); for a robustness check, we also use different rolling window lengths and h-values and find that the results are robust (see Section 5). The VAR optimal lag length was chosen according to the Schwarz's Bayesian Information Criterion (SIC).

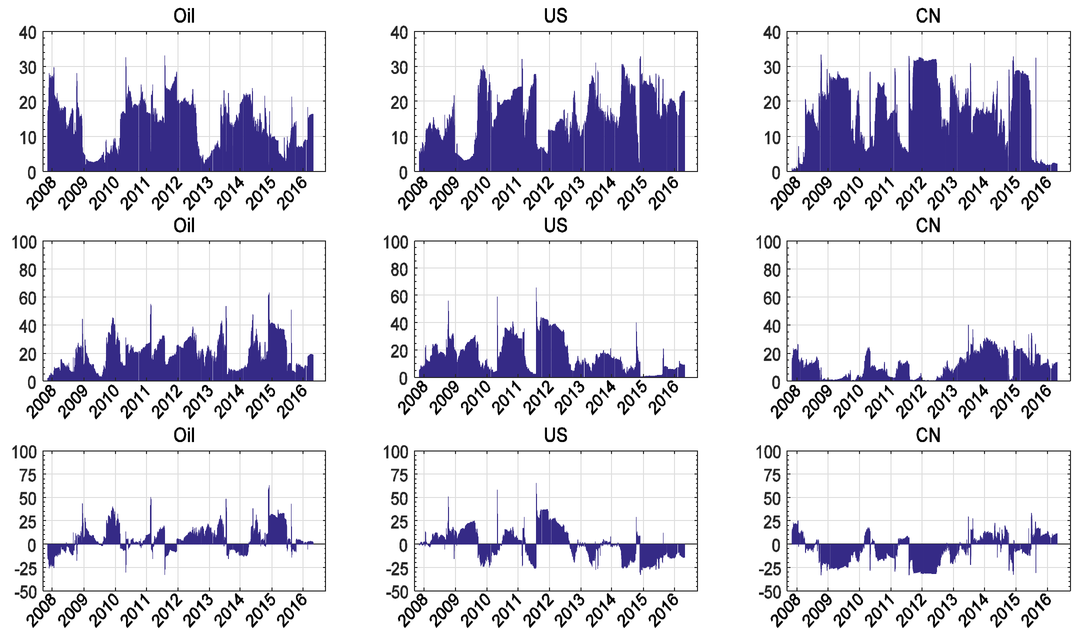

Fig. 2. Upper panel: directional 'FROM', middle panel: directional 'TO', lower panel: net spillovers (third row) on RV.

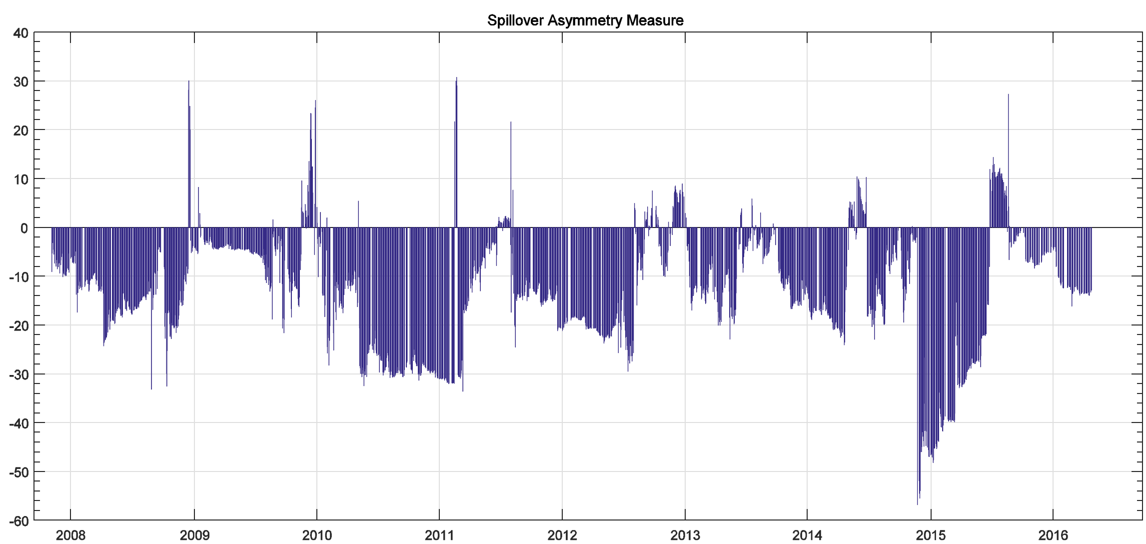

Fig. 3. Spillover asymmetry measure.

negative/bad volatility are larger than spillovers due to positive/good volatility. A zero SAM shows that the influences of both negative and positive spillovers are equivalent; in other words, there is no spillover asymmetry.

In Fig. 3, the asymmetries are pronounced, and bad volatility spillovers dominate good volatility spillovers. Thus, we conclude that during the most of our sample period, negative shocks drove volatility spillovers, which is consistent with Wang and Wu (2018). This conclusion

Table 4
Full-sample Volatility spillover table for 2*N*-dimensional VAR model with realized semivariances.

		Realized semivariances						From others	Net	Conclusion
		RS^+			RS^-					
		Oil	US	CH	Oil	US	CH			
RS^+	Oil		4.57	0.52		4.28	0.57	9.93	−7.60	Net-recipient
	US	1.03		1.12	31.88		0.68	34.70	−12.94	Net-recipient
	CH	0.41	2.91		7.36	4.32		15.01	−10.79	Net-recipient
RS^-	Oil⁻		12.42	1.60		12.85	1.31	28.17	49.46	Net-contributor
	US	0.72		0.98	31.94		0.54	34.18	−10.16	Net-recipient
	CH	0.18	1.86		6.45	2.57		11.06	−7.96	Net-recipient
	Toothers including own	2.33	21.76	4.21	77.63	24.02	3.10			Total: 22.18
		92.40	87.06	89.21	149.46	89.84	92.04			

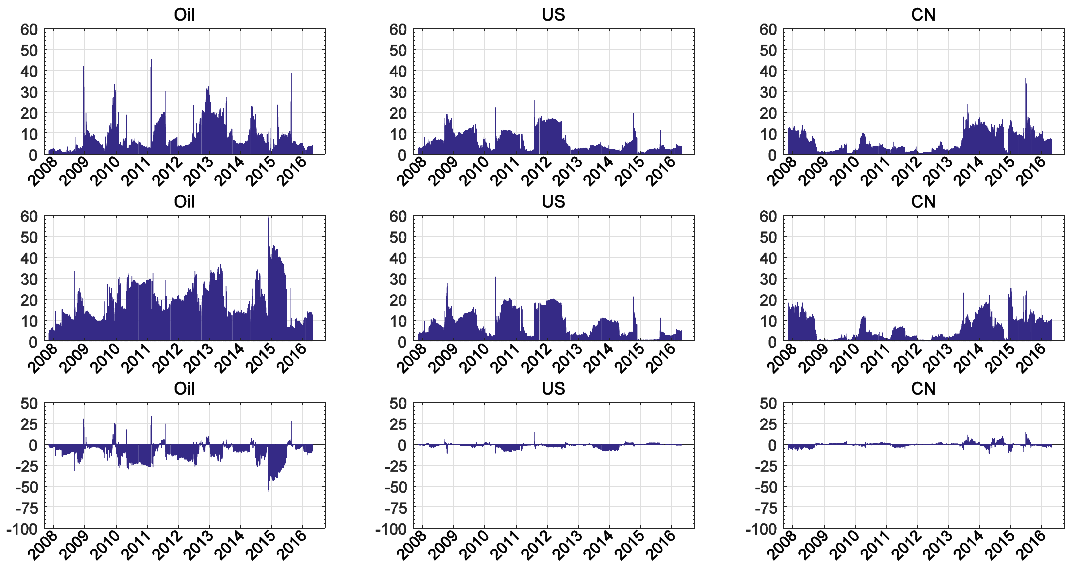

Fig. 4. Upper panel: directional spillovers, direction to, from good volatility, middle panel: directional spillovers, direction to, from bad volatility, lower panel: the directional spillover asymmetry measure.

differs from that of Baruník et al. (2017), who determined that during the period of the global financial crisis, the U.S. was characterized by good volatility spillovers on the forex market. According to Wang and Wu (2018), SAM can also be a good indicator of whether the markets are in an optimistic or pessimistic mood and what their expectations are. Therefore, the evidence of prominent negative spillovers suggests that a pessimistic mood dominates much of the sample period. The largest values occur at the end of 2014 due to the pessimistic mood about the Organization of Petroleum Exporting Countries (OPEC) announcing no reduction and the slowdown of the Chinese economy reaching its highest level.

4.4. Asymmetries in directional volatility spillovers

Table 4 reports the Full-sample Volatility spillover table for the 2N-dimensional VAR model with realized semivariances. Table 4, excluding all diagonals of all four 3×3 block-matrices, intuitively shows how the asymmetries in directional spillovers propagate. The total spillover index for the 2N-dimensional VAR model with realized semivariances is 22.18, which is almost the same as the total spillover index for the N-dimensional VAR model. Based on the empirical results, we find that only net spillover of the RS^- of oil is positive. The RS^- of oil is the only 'Net- contributor'; in other words, the spillovers during that full-sample period are dominated by the bad volatility of the oil market.

Furthermore, we study the dynamics of the asymmetrical volatility spillovers of individual markets, which reveal further information about asymmetries. The detailed dynamics of the asymmetrical volatility spillovers of individual markets are plotted in Fig. 4. In the upper panel, the good volatility of a specific market influences the volatility of the other markets, excluding the bad volatility of the specific market, which can isolate the effects of the bad volatility of the specific market. In a similar fashion, in the middle panel, bad volatility spillovers coming from a specific market are presented, excluding the good volatility of the specific market. Finally, in the lower panel, we present the asymmetric directional spillovers constructed as the difference between the values plotted in the upper and middle panels.

The asymmetric directional spillovers of individual markets (in lower panel) are our focus. In the lower panel, we can see that the values

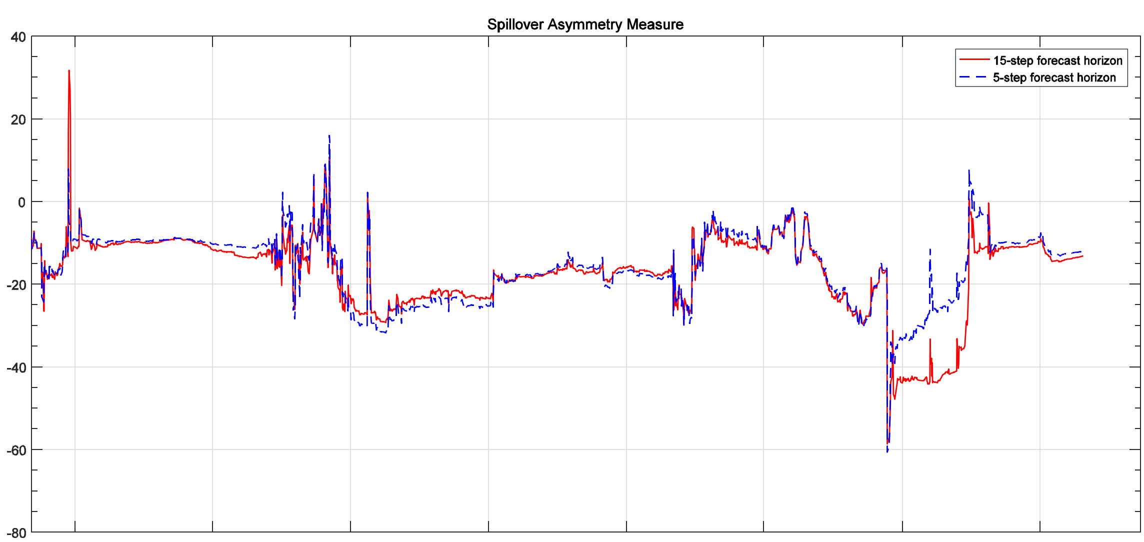

Fig. 5. Spillover asymmetry measure.

Table 5
Results of parameter estimates for the asymmetric DCC-GARCH models.

	RV		
	a_i^2	g_i^2	b_i^2
Oil	0.1653[a]	0.2306[a]	0.9528[a]
US	0.0822[a]	0.6118[a]	0.9580[a]
CN	0.2174[a]	0.1771[a]	0.9809[a]

[a] Indicates the rejection of the null hypothesis at the 1% level.

of the directional spillover asymmetry measure for the oil market are negative during the majority of the sample period; furthermore, we can see that the magnitude of the directional spillover asymmetry measure for the oil market is larger than that of the US/Chinese stock market, which indicates that the pessimistic mood about the oil market is larger than that about the stock markets. For the Chinese stock market, we can see the directional spillover asymmetry measure is time-varying; since the middle of 2013, positive and negative values occur alternatingly, which may indicate participants' mood about the uncertainty of the Chinese economy because China is the largest importer of oil.

5. Robustness check

To check robustness, first, we use different rolling window widths and forecast horizons. In Fig. 5, we present the spillover asymmetry measure plots obtained using a longer 400-day rolling window width and two different variance decomposition forecast horizons. The results are robust.

Moreover, we further investigate the asymmetric response to volatility shocks using the asymmetric generalized dynamic conditional correlation (AG-DCC) model developed by Cappiello et al. (2006). The AG-DCC specification is well suited to examine the correlation dynamics among different asset classes and investigate the presence of asymmetric responses in conditional variances and correlations to negative returns.

$$Q_t = \left(\overline{P} - A'\overline{P}A - B'\overline{P}B - G'\overline{N}G\right) + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + G'n_{t-1}n'_{t-1}G + B'Q_{t-1}B \tag{17}$$

where A, B and G are $k \times k$ parameter matrices, $n_t = I[\varepsilon_t < 0] \circ \varepsilon_t(\mathrm{I}[\cdot])$ is a $k \times 1$ indicator function, which has a value of 1 if the argument is true and a value of 0 otherwise, while "o" indicates the Hadamard product.

Table 5 shows that all parameters are statistically significant and different from zero, indicating that the data are well fitted with the AG-DCC model. Most notably, the estimate of the asymmetric term (g_i) for all markets is significant at the 1% level. In other words, the results show strong evidence of asymmetries in volatility shocks between the oil and stock markets due to bad volatility.

6. Markov regime-switching asymmetric volatility spillovers

Furthermore, we use two regime Markov-switching-VAR model,[7] volatility spillover index introduced by Diebold and Yilmaz (2012) and realized semi-variances introduced by Baruník et al. (2017) to investigate the dynamic asymmetric volatility spillovers between oil and stock markets during two regimes (i.e., regime 1, a low-risk regime during non-crises (moderate times) and regime 2, a high-risk regime during crises (intense times)). To the best of our knowledge, it is the first study to investigate the dynamic asymmetric volatility spillovers in the framework of Markov regime-switching. Considered the length of the paper, we only present the results of total spillover asymmetry measure plots with the regime-switching model for regime 1 in Fig. 6, and for regime 2 in Fig. 7.

In Fig. 6, we find that the asymmetries are pronounced and bad volatility spillovers dominate good volatility spillovers during regime 1. Thus, we conclude that during the most of our sample period, negative shocks were driving volatility spillovers, which is consistent with Fig. 3 in Section 4.4.

In Fig. 7, the asymmetries are also pronounced during regime 2. However, we notice that there are two significant differences with Fig. 6 as fellows: (1) Bad volatility spillovers and good volatility spillovers appeared in turn, which indicate that during crises (intense times), good volatility spillovers have begun to emerge; (2) the magnitudes of asymmetric volatility spillovers during regime 2 is larger than during regime 1.

7. Conclusions and implications

Our study uses high-frequency, intra-day data of WTI future prices, the S&P 500 index, and the Shanghai stock market composite index during the period of 2007 to 2016. In this study, we use a new spillover directional measure introduced by Diebold and Yilmaz (2012) and an asymmetric spillovers measure introduced by Baruník et al. (2017) to investigate the dynamic asymmetric volatility spillovers between oil and stock markets, and our study extends empirical studies of the relationship between the oil market and stock markets by providing new insights into the time-varying asymmetric volatility spillover in a quantitative way. We have several noteworthy findings. First, the volatility spillovers between the oil and stock markets are time-varying, and the interdependence between the oil and stock markets strengthened during the financial crisis. Economic and political events have a strong influence on the global oil and stock markets. Second, the empirical results reveal the asymmetric spillover effect between oil and stock markets, in which bad volatility spillovers dominate good volatility spillovers for most of the sampling period. Participants' pessimistic mood about oil market is larger than their mood about the stock markets. Third, we further investigate the presence of asymmetric response to volatility shocks using the asymmetric generalized dynamic conditional correlation (AG-DCC) model developed by Cappiello et al. (2006); the results also show strong evidence of asymmetries in volatility shocks between the oil and stock markets due to bad volatility. Finally, we find that different regimes have different connectedness. Bad volatility spillovers and good volatility spillovers appeared in turn, which indicate that during crises (intense times), good volatility spillovers have begun to emerge. In general, the magnitudes of asymmetric volatility spillovers during regime 2 is larger than during regime 1.

To our knowledge, we find that investigating the topic of the spillover is received more attentions by international investors, portfolio managers and policy makers, this is because spillover is a closer tie to portfolio management and hedging strategies, which can be supported by most existing studies (e.g., Arouri et al., 2011; Nazlioglu et al., 2013; Broadstock and Filis, 2014; Ewing and Malik, 2016; Kang et al., 2017; Wang and Wu, 2018). In this study, we use a new spillover directional measure and asymmetric spillover measures to investigate the dynamic asymmetric volatility spillover between oil and stock markets during the period of 2007 to 2016, and then can identify some novel findings, which are important to international investors, portfolio managers and policy makers. For example, there exists an asymmetric spillover effect between the oil market and stock markets and that bad volatility spillovers dominate good volatility spillovers for most of the sampling period. Therefore, international investors, portfolio managers and policy makers should pay more attentions on negative shocks ("bad news") than positive shocks ("good news"). More specifically, our findings are important for investors who have exposures to oil and equity such as

[7] To save space, we don't give the MS-VAR model, and more details on two regime Markov-switching-VAR model can be referred to BenSaïda et al. (2018).

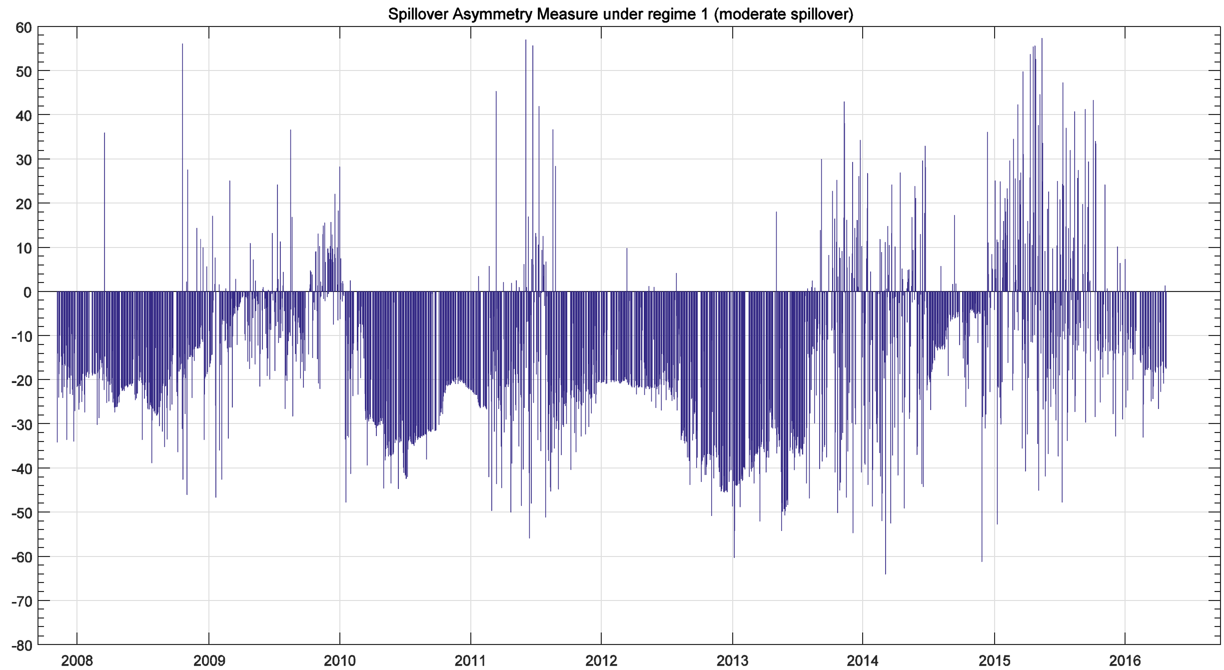

Fig. 6. Spillover asymmetry measure under regime 1 (moderate spillover).

hedge funds. For example, the strong links between oil and equity can reduce the diversification benefits strategy when investor hold a portfolio that includes both of oil and equity. Our empirical results on the connectedness between oil volatility and the volatilities of the US and China stocks are supported to contain useful information for risk management and asset pricing. Specifically, the connectedness between oil and stock markets strongly supports that oil risk cannot be ignored when forecasting stock market volatility and designing equity option.

Acknowledgements

We are thankful to the editor-in-chief, Professor Richard S.J. Tol, and two referees who provided us with invaluable comments to improve the quality of this paper. The authors are grateful to the financial support from the Natural Science Foundation of China [71671145, 71701170], the Humanities and Social Science Fund of the Ministry of Education [17YJC790105, 17XJCZH002], and the

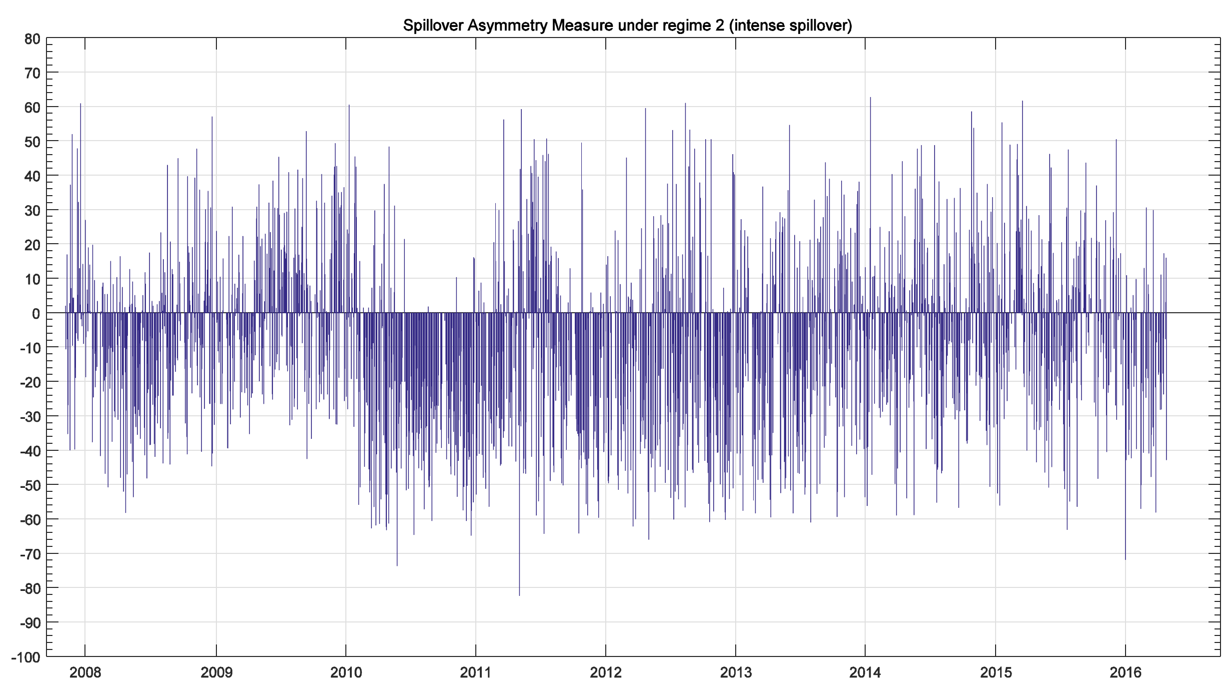

Fig. 7. Spillover asymmetry measure under regime 2 (intense spillover).

Fundamental Research Funds for the Central Universities [682017WCX01, 2682018WXTD05].

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