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Original Paper

# A spillover network analysis of the global crude oil market: Evidence from the post-financial crisis era

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ABSTRACT

The frequent occurrence of geopolitical crises in the post-financial crisis era is driving the rethinking behind whether the global crude oil market is still a highly connected “great pool”. Using the spillover network model suggested by Baruník and Křehlík (2018), and the daily data of 31 global crude oil markets from 2009 to 2019, this study examines the return and volatility spillover effects and their time-varying behavior in six crude oil market segments at different timescales. The findings indicate that heterogeneity exists in the co-movements between global crude oil markets in the post-financial crisis era. In the medium term, both return and volatility spillover effects are not significant, which makes the diversified portfolio strategy useful. Prices in the Europe and Central Asian regions take the lead in return spillovers. In contrast, Asia-Pacific regional prices contribute the most in terms of volatility spillovers. Long-term volatility spillovers increase sharply when confronted with oil-related events in the post-financial crisis era. Therefore, policymakers should take effective measures to prevent any large-scale risk transmission in the long run.
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## 1. Introduction

An investigation of the spillovers of the global crude oil market helps in understanding the effectiveness of energy policies and market efficiency (Fattouh et al., 2013; Weiner, 1991). Likewise, co-movements between global crude oil markets have significant implications for market participants seeking to form investment portfolios (Reboredo, 2011) and to manage risks (Ji and Fan, 2016). Since the 1990s, most studies have reached a consensus that the global crude oil market is a “great pool”, where the price changes in one market will quickly transmit to other regional crude oil markets (Adelman, 1984; Gülen 1997, 1999; Hammoudeh et al., 2008; Kleit, 2001). Since the start of the new millennium, crude oil prices have been shown to contain characteristics that are similar to a typical financial product (Zhang, 2017). The connections between the crude oil markets in various regions seem to be enhanced (Silvapulle and Moosa, 1999; Silvério and Szklo, 2012).

However, the co-movements between global crude oil markets need to be reconsidered, given that oil-related events in the post-financial crisis era seem to have regionalized the world market. The geopolitical events that have broken out worldwide (Gozgor et al., 2021) have increased the complexity of the global crude oil markets (Ji and Guo, 2015). Instability has caused crude oil prices to change significantly. Examples include military conflicts in the Middle East, the shale gas revolution in the United States, and the economic slowdown in emerging economies (Ferrer et al., 2018; Gupta et al., 2020). Especially after 2010, oil prices diverged in response to specific geopolitical risks (Ji and Fan, 2015), local crude oil supply and demand, and energy policies. During this period, the spillovers of the crude oil markets started to present regional characteristics. The integration of global crude oil markets has gained fresh prominence, due to the changes in the supply and demand pattern of regional crude oil markets (Ji and Fan, 2016; Zhang et al., 2019). However, there has been little agreement on either the spillover characteristics or the leadership between the global crude oil markets in the post-financial crisis era to date. This paper analyzes the spillovers and the leading-lagging relationship of crude oil markets from a new perspective, which helps to

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regulate the global crude oil market risks and prevent significant systemic risks (Huang et al., 2021).

Most early studies examined the leading-lagging relationship between the prices of several benchmark crude oils in the world and then constructed spillover networks by using co-integration or Granger causality tests (Bentzen, 2007; Ewing and Harter, 2000; Milonas and Henker, 2001; Rodriguez and Williams, 1993). Such pairwise approaches, however, fail to reveal the complexity of the spillover characteristics of crude oil markets. Some new studies have revealed the linkages of the global crude oil market by building a multi-network model. Ji and Fan (2016) used a directed acyclic graph approach to study the dynamic integration of the global crude oil market. The spillover index model proposed by Diebold and Yilmaz (DY) (2012, 2014) can accurately describe the interactions within a system. Thus, the model has been widely used in researches investigating the network linkages of energy markets (Awartani and Maghyereh, 2013; Kang et al., 2017). Zhang et al. (2019) used the DY spillover index model to build the return and volatility spillover networks of seven major crude oils in the world. The study found that Brent and Bonny crude oils are at the core of the return spillover networks, and Dubai crude oil is dominant in the volatility spillover networks. By building spillover networks, the leading-lagging relationship and transmission mechanism of global oil prices can be intuitively displayed.

However, the above studies ignore the fact that the spillover network characteristics of the global crude oil market may vary at different timescales.[1] Crude oil market participants have different beliefs, objectives, preferences, institutional constraints, levels of information assimilation and risk tolerance (Dew-Becker and Giglio, 2016; Gençay et al., 2010). They engage in market transactions at different timescales, ranging from seconds to years. Therefore, energy market participants operating at different timescales have significant heterogeneity (Dai et al., 2020; Wang et al., 2020). Through the different behaviors of crude oil market participants, economic and financial shocks have different effects on the spillovers of the crude oil markets at different timescales. Many studies have shown that the pattern of crude oil prices varies at different timescales.[2] These studies use multiscale analyses to explore the oil price cycle (Naccache, 2011), analyze the efficiency of the crude oil markets (Martina et al., 2011; Wang and Liu, 2010), predict oil prices (He et al., 2012; Jammazi and Aloui, 2012), and study the co-movements of oil prices and stock prices (Reboredo et al., 2017). Investors, regulators, and other market participants need to make decisions based on the spillovers of oil prices at different timescales (Tiwari et al., 2018). Therefore, it is necessary to explore the co-movements of the global crude oil market from a timescale perspective (short-term, medium-term and long-term).

Based on the discussions above, this article attempts to solve the following questions: What have the spillover characteristics of the global crude oil market been at different timescales in the post-financial crisis era? Which crude oil market regions play a leading role in the price transmission mechanism? Do price spillovers and the influences of various regional crude oil markets have time-varying patterns in the post-financial crisis era? The resolution of these issues will generate fresh insight into global crude oil market integration in the post-financial crisis era. Moreover, the results will guide market participants with different investment horizons to implement better portfolio construction, arbitrage and risk management.

This research makes three contributions to existing literature. First, this is perhaps the first study to undertake a spillover network analysis of the global crude oil markets' return and volatility spillovers at different timescales. Using the spillover index model proposed by Baruník and Křehlík (2018), this paper examines the strength and direction of the return and volatility spillovers in the global crude oil market at different timescales. Unlike traditional approaches without consideration of timescales (Hammoudeh et al., 2008; Lu et al., 2014; Wlazlowski et al., 2011), this study uses a multivariate network model to build return and volatility spillover networks of global crude oil markets at different timescales. Then, a rolling window is used to depict the time-varying characteristics of return and volatility spillovers at different timescales. This study conducts a multi-scale analysis to discover the price setters in various timescales and the dynamic evolution process of their price leadership. The results provide an essential reference for decision-makers and market participants with different investment horizons.

Second, the supply and demand pattern of global crude oil markets changed significantly after the global financial crisis. Given the defects in the sample period of traditional research, this study uses daily spot price data from 2009 to 2019, as this more recent data can better reveal the spillovers of the global crude oil markets in the post-financial crisis era.

Finally, 31 regional crude oil markets are selected to gain a detailed understanding of the general characteristics of global crude oil markets' co-movements. The co-movements of oil prices depend on many factors, such as geographical location and political conflicts.[3] Compared to the limited sample selection in the previous literature (Chang et al., 2010; Lin and Tamvakis, 2001; Milonas and Henker, 2001), the numbers of crude oil types and sources in this paper is larger, covering crude oils of different qualities and different geographical locations. Moreover, the 31 crude oil markets are divided into six market regions on a geographical basis.[4] This paper attempts to discuss spillovers and the leading-lagging relationship among crude oil market regions, rather than the relationship between individual markets. The findings are useful for investors who choose crude oil products from different regions to build investment portfolios and carry out arbitrage.

The remainder of the paper is organized as follows: Section 2 introduces the method of this article. Section 3 introduces the data and the related summary statistics. Section 4 presents and discusses the empirical results, and Section 5 summarizes the full text and makes a number of comments.

## 2. Methodology

To explore the heterogeneity of return and volatility spillovers at different timescales in different regions, this paper adopts the analytical framework of Fig. 1. A classical way to explore the

[1] Following Ferrer et al. (2018), and Wang and Wang (2019), investors' timescales are similar to their investment period. Agents with shorter investment horizons (such as traders or hedge funds on the day) pay more attention to the short-term performance of the market. They have a shorter timescale. Large institutional investors focus on long-term market performance, so they have a longer timescale.

[2] Multiscale analysis refers to the analysis of a problem from the perspective of different timescales (short-term, medium-term, and long-term). Decision making based on the conditions at a single timescale often leads to mistakes.

[3] Crude oil market conditions (like crude oil refining technology, cross-regional transport costs, the country's economic development level, and political risks) may change. These changes will affect oil prices through market arbitrage, resulting in varying price differences among crude oils with different properties and different external environments (Kaufmann and Banerjee, 2014; Kaufmann, 2016).

[4] It may be difficult to analyze a large number of crude oil samples. Some studies classify the samples according to their characteristics, such as sulfur content, weight, and geographic region, and discuss each type of crude oil samples separately. Following Ji and Fan (2016) and Wlazlowski et al. (2011), we classified 31 crude oil markets on a geographical basis.

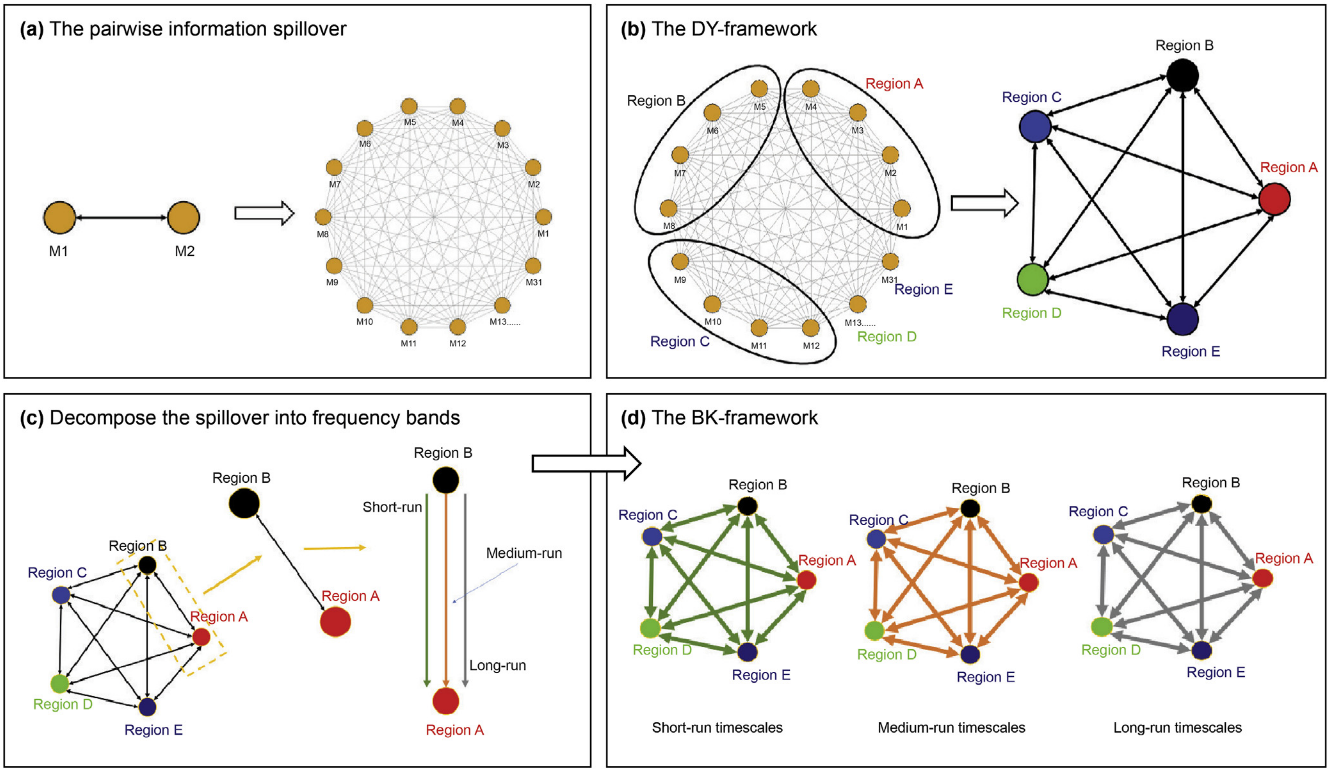


**Fig. 1.** Analytical framework for crude oil market system. Notes: M1-M31 represent the 31 crude oil markets; Region A-Region F represent the six regions of the world (America, Europe, Middle East, Asia-Pacific, Central Asia and Africa). This paper divides 31 crude oil markets according to their geographic locations.

interactions between crude oils is to use the spillover index model proposed by Diebold and Yilmaz (2012) and build the spillover networks (panel A). This paper selects 31 crude oils and divides them into six regions. Then, the spillovers between individual markets are added up to get the spillovers between regional markets. In this way, the traditional spillover network consisting of 31 single markets transforms into a spillover network consisting of six regional markets (panel B). Next, the Baruník and Křehlík (2018) model is introduced to investigate the spillover effects at different timescales. This paper decomposes the connectedness of regional markets into three timescales and further explores the spillovers between six regions at three different timescales (short-term, medium-term, and long-term), as shown in panel D.

While employing the Diebold-Yilmaz method, this study first assumes the following$n$-dimensional VAR ($p$) model with $n$ variables and $p$ lags:

$$X_t = \Phi_1 X_{t-1} + \Phi_2 X_{t-2} + \ldots + \Phi_p X_{t-p} + \xi_t \tag{1}$$

where $X_t = (X_{1t}, X_{2t}, \ldots, X_{nt})'$ denotes an $n$-dimensional vector of $n$ crude oil markets' price return or volatility series; $\xi_t$ represents a white noise error vector with zero mean and covariance matrix $\sum$, and $\Phi_1, \ldots, \Phi_p$ are coefficient matrices. Also, $p$ is determined according to the AIC criterion. The moving average process of Eq. (1) can be expressed as:$X_t = \Psi(L)\xi_t$.

The variance decomposition method measures the proportion of the variance of the prediction error of an endogenous variable in the VAR system affected by different information shocks. This information can reveal to what extent the trajectory of a variable is influenced by itself or other variables in the system. Hence, the contribution of variable $j$ to the variance of the forecast error of variable $i$ at horizon $H$ can be written as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}{}^{-1} \sum_{h=0}^{H} \left( (\Psi_h \sum)_{ij} \right)^2}{\sum_{h=0}^{H} (\Psi_h \sum \Psi_h{}')_{ii}} \tag{2}$$

Each variance decomposition matrix can be normalized as $\widetilde{\theta_{ij}(H)} = \frac{\theta_{ij}(H)}{\sum_{j=1}^{n} \theta_{ij}(H)}$, where $\widetilde{\theta_{ij}(H)}$ provides a measure of pairwise connectedness from $j$ to $i$ at horizon $H$ in the time domain.

In order to measure the total spillover of the crude oil system, $S(H)$, a total spillover index is constructed to reveal the impact of information spillovers between markets on the changes of crude oil systems:

$$S(H) = \frac{1}{n} \sum_{i,j=1}^{n} \widetilde{\theta_{ij}(H)} \tag{3}$$

Following the framework of panel B in Fig. 1, this study divides 31 global crude oil markets into six regions by their geographic locations. Since the spillovers can be added up when the DY method is used, the spillover of region $m$ to region $n$ can be defined as:

$$\widetilde{\theta_{mn}} = \sum_{i \in m} \sum_{j \in n} \widetilde{\theta_{ij}} \tag{4}$$

Here, $m$, $n \in \{$A, B, C, D, E, F$\}$; region $m$ contains crude oil markets $i$, and region $n$ contains crude oil markets $j$.

In addition, this paper investigates the transmission mechanism of the return and volatility of different crude oil markets or regions at different timescales (short-term, medium-term, and long-term). The choice of time scale depends on the time interval of the original return series. As shown in panel C and panel D of Fig. 1, this study attempts to decompose the total spillover into three timescales. The spillover characteristics of different regions are also investigated, in order to find whether they are the same at different timescales. We introduce the Fourier transform employed by BK, which can calculate the generalized prediction error variance decomposition at a specific frequency $\omega$ as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}{}^{-1}\sum_{h=0}^{\infty}\left(\Psi\left(e^{-ih\omega}\right)\sum\right)_{ij}^{2}}{\sum_{h=0}^{\infty}\left(\Psi\left(e^{-ih\omega}\right)\sum\Psi\left(e^{ih\omega}\right)\right)_{ii}} \tag{5}$$

Here, $\theta_{ij}(\omega)$represents the spectrum part of the variable $i$ at a given frequency $\omega$, which can be attributed to the impact of variable $j$. As with a time-domain analysis, Eq. (5) can be normalized to: $\widetilde{\theta_{ij}(\omega)} = \frac{\theta_{ij}(\omega)}{\sum_{h=1}^{n}\theta_{ij}(\omega)}$, where $\widetilde{\theta_{ij}(\omega)}$ is the information spillover from market $j$ to $i$ at a given frequency $\omega$.

Since evaluating the connectivity within a frequency band is more valuable than the connectivity of a single frequency, the cumulative connectivity in any frequency band $d = (a, b)$ can be defined as:

$$\widetilde{\theta_{ij}(d)} = \int_{a}^{b}\widetilde{\theta_{ij}(\omega)}d\omega \tag{6}$$

In order to measure the overall spillover level of the global crude oil markets, a total spillover index $C^d$ can be constructed, in order to reveal the impact of the information spillover between markets on global crude oil markets. The total spillover in all market bands $d$ is expressed as:

$$C^{d} = \frac{\sum_{i=1, i\neq j}^{n}\widetilde{\theta_{ij}(d)}}{\sum_{ij}\widetilde{\theta_{ij}(d)}} \tag{7}$$

Specifically, the portion of the variance of variable $i$ contributed by all the other variables ($i\neq j$), which is called "within from connectedness", at the frequency band $d$ can be computed as:

$$C_{i\leftarrow}^{d} = \sum_{j=1, i\neq j}^{n}\widetilde{\theta_{ij}(d)} \tag{8}$$

Analogously, the contribution of variable $i$ to all other variables $j$ ($i\neq j$) is called "within to connectedness" on the spectral band d and is given by:

$$C_{i\rightarrow}^{d} = \sum_{j=1, i\neq j}^{n}\widetilde{\theta_{ji}(d)} \tag{9}$$

In addition, the so-called within net connectedness, which quantifies the difference between the variance transmitted and received by a given variable, is defined as:

$$NC_{i}^{d} = C_{i\leftarrow}^{d} - C_{i\rightarrow}^{d} \tag{10}$$

It is not sufficient to focus on static spillover indicators, which are calculated by the DY and BK for the entire period. We employ the rolling window approach to capture the dynamics of the spillover effects. The choice of window width is a trade-off between noisy data (with small window widths) and smooth data (with large window widths) (Ji and Fan, 2016). As shown in Fig. 2, this study fixes the moving window sample size to 500 trading days and offsets the window by one business day every time we perform an analysis. This paper selects the data from September 9, 2009, to July 25, 2019 (2155 observations and 1654 windows in total), as shown in Fig. 2.

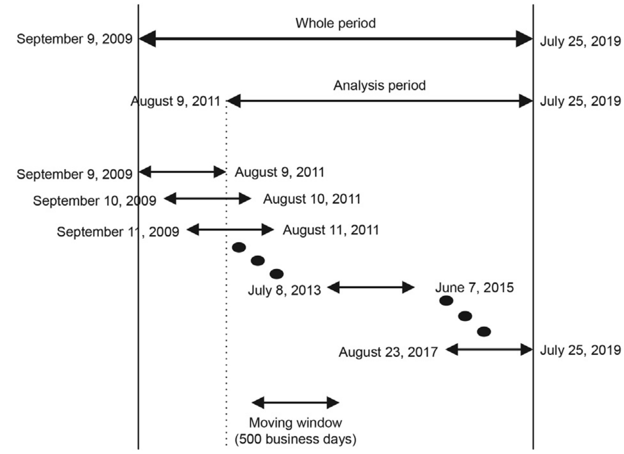


**Fig. 2.** Framework of the rolling window analysis method.

## 3. Data

We compiled daily observations for the prices ($/Bbl) of the 31 crude oils (Table 1) reported by *Wind* and *Thomson Reuters DataStream* databases. The sample also includes 2155 daily observations from September 9, 2009, to July 25, 2019. These 31 crude oils cover six regions of the world, with distinct differences in gravity and sulfur content (Fattouh, 2010; Reboredo, 2011). Also, the production and sales volumes of these crudes are high (Chen et al., 2009). Therefore, this sample can effectively reveal the geographical characteristics of the global crude oil market (Li and Leung, 2011), increase the richness of existing research and more accurately reflect the co-movements of world crude oil market prices. This paper uses a logarithmic transformation to calculate return series, $r_t = 100{*}\ln(p_t / p_{t-1})$, with $p_t$ being the current spot price of crude oil. To avoid the issue of errors in the calculation of volatility, the volatility series of 31 crude oil markets is calculated using the GARCH model.

Table 1 lists the regions and abbreviations of 31 crude oils. Table 2 presents the summary statistics of the return series of each crude oil. As can be seen, the average returns of the 31 crude oil markets is almost all zero. Positive skewness (right deviation) shows that the oil price has a higher probability of rising. The high value of kurtosis indicates that, when the return distribution has a thick tail, extreme price changes are more frequent. The Jarque-Bera test rejects the assumption of normal distribution. The

**Table 1**
Regions of 31 crude oils and their abbreviations.

| Crude oil markets | | Ticker | Crude oil markets | | Ticker |
|---|---|---|---|---|---|
| Americas | ANS | ANS | Asia Pacific | Cossack | COS |
| | Bonito | BON | | Gippsland | GIP |
| | Isthmus | IST | | Sokol | SOK |
| | Mars | MAR | | Tapis | TAP |
| | Olmeca | OLM | | Shengli | SHE |
| | Poseidon | POS | | Daqing | DAQ |
| | WTI | WTI | | Minas | MIN |
| Europe | Oseberg | OSE | | Cinta | CIN |
| | Brent | BRE | | Duri | DUR |
| Middle East | Arab Heavy | ARH | Central Asia | Azeri Light | AZE |
| | Arab Medium | ARN | | CPC | CPC |
| | Iran Heavy | IRH | Africa | Bonny Light | BOL |
| | Iran Light | IRL | | Bonny Medium | BOM |
| | Murban | MUR | | Girassol | GIR |
| | Dubai | DUB | | Zafiro | ZAF |
| | Kuwait | KUW | | | |

**Table 2**
Summary statistics for regions' crude oil returns (2009.9.9–2019.7.25).

| Ticker | A: return | | | | | | |
|---|---|---|---|---|---|---|---|
| | Mean | Skewness | Kurtosis | Jarque-Bera | ADF | Q(36) | ARCH-LM |
| ANS | −0.01 | −0.01 | 6.62 | 3938.8* | −31.90* | 110.45* | 219.27* |
| BON | −0.01 | 0.43 | 9.72 | 8559.1* | −34.19* | 124.49* | 254.24* |
| IST | 0.00 | 0.39 | 14.46 | 18858.0* | −32.45* | 86.37* | 239.00* |
| MAR | 0.00 | 0.42 | 10.72 | 10407.0* | −33.78* | 118.31* | 251.54* |
| OLM | 0.00 | 0.19 | 58.64 | 309248.0* | −38.39* | 156.36* | 955.56* |
| POS | −0.01 | 0.47 | 10.87 | 10702.0* | −34.15* | 117.21* | 238.61* |
| WTI | −0.01 | 0.04 | 5.93 | 3162.6* | −31.59* | 113.29* | 260.25* |
| OSE | 0.00 | 0.45 | 5.65 | 2945.2* | −31.20* | 78.45* | 224.11* |
| BRE | 0.00 | 0.41 | 5.47 | 2748.3* | −30.84* | 84.29* | 216.87* |
| ARH | 0.00 | 0.62 | 14.76 | 19734.0* | −32.45* | 98.29* | 230.51* |
| ARN | 0.00 | 0.58 | 14.07 | 17920.0* | −32.49* | 94.94* | 218.97* |
| IRH | 0.00 | 0.55 | 14.23 | 18330.0* | −32.36* | 85.61* | 207.86* |
| IRL | 0.00 | 0.53 | 13.38 | 16192.0* | −32.25* | 82.73* | 188.03* |
| MUR | 0.00 | −0.04 | 4.84 | 2110.2* | −33.22* | 63.42* | 324.43* |
| DUB | 0.00 | 0.33 | 8.24 | 6145.2* | −32.08* | 81.67* | 267.51* |
| KUW | 0.00 | 0.47 | 10.11 | 9267.6* | −33.45* | 90.24* | 172.41* |
| COS | −0.01 | 0.23 | 5.95 | 2934.5* | −31.04* | 52.65* | 204.05* |
| GIP | 0.00 | 0.82 | 36.85 | 106006.0* | −34.70* | 92.49* | 535.67* |
| SOK | 0.00 | −0.12 | 5.16 | 2399.1* | −33.00* | 67.49* | 310.35* |
| TAP | 0.00 | 0.18 | 7.50 | 5080.0* | −32.63* | 73.16* | 120.96* |
| SHE | 0.00 | 0.35 | 9.53 | 8222.8* | −33.14* | 94.36* | 178.03* |
| DAQ | −0.01 | 0.46 | 10.03 | 9123.2* | −32.66* | 97.81* | 193.08* |
| MIN | 0.00 | 0.15 | 7.18 | 4653.6* | −32.25* | 78.96* | 211.30* |
| CIN | −0.01 | 0.42 | 8.39 | 6395.4* | −32.22* | 81.61* | 168.14* |
| DUR | −0.01 | 0.47 | 9.77 | 8662.6* | −32.57* | 96.84* | 167.45* |
| AZE | 0.00 | 0.47 | 5.31 | 2615.5* | −31.19* | 70.33* | 233.15* |
| CPC | −0.01 | 0.45 | 5.54 | 2836.6* | −31.27* | 73.96* | 195.32* |
| BOL | 0.00 | 0.46 | 5.63 | 3200.5* | −33.41* | 75.90* | 225.15* |
| BOM | 0.00 | 0.83 | 34.29 | 122367.0* | −35.32* | 74.39* | 531.44* |
| GIR | 0.00 | 0.82 | 36.85 | 3207.9* | −31.10* | 77.88* | 231.52* |
| ZAF | 0.00 | 1.65 | 258.51 | 6009897.0* | −41.37* | 172.15* | 868.85* |

Notes: Jarque–Bera is the $\chi^2$ statistic for the test of normality; $Q(k)$ is the Ljung–Box statistics for serial correlation in the squared return computed with $k$ lags. ARCH–LM is Engel's LM test for heteroscedasticity, conducted using 10 lags. * Denotes rejection of the null hypothesis at a 1% significance level.

**Table 3**
Summary statistics for regions' crude oil volatility (2009.9.9–2019.7.25).

| Ticker | B: volatility | | | | | | |
|---|---|---|---|---|---|---|---|
| | Mean | Skewness | Kurtosis | Jarque-Bera | ADF | Q(36) | ARCH-LM |
| ANS | 202.99 | 1.57 | 3.33 | 1889.1* | −2.88 | 58554* | 2112.7* |
| BON | 216.50 | 2.51 | 8.11 | 8181.6* | −3.82 | 49995* | 2075.8* |
| IST | 192.90 | 2.38 | 8.03 | 7840.3* | −3.65 | 49579* | 2078.2* |
| MAR | 215.38 | 2.44 | 8.05 | 7966.0* | −4.13* | 46091* | 2058.6* |
| OLM | 202.06 | 7.90 | 84.69 | 667391.0* | −8.04* | 14042* | 2016.2* |
| POS | 228.82 | 2.46 | 7.75 | 1642.2* | −2.81* | 46250* | 2059.9* |
| WTI | 202.82 | 1.80 | 4.30 | 7569.4* | −4.03 | 52516* | 2089.6* |
| OSE | 190.33 | 1.54 | 2.97 | 2827.2* | −3.41 | 59976* | 2104.2* |
| BRE | 192.10 | 1.51 | 2.97 | 1612.2* | −3.28 | 56358* | 2102.5* |
| ARH | 190.74 | 2.43 | 8.04 | 7946.4* | −3.15 | 54464* | 2089.0* |
| ARN | 185.45 | 2.33 | 7.35 | 6812.9* | −3.13 | 55109* | 2091.4* |
| IRH | 188.99 | 2.35 | 7.71 | 7319.8* | −3.77 | 48604* | 2073.6* |
| IRL | 183.78 | 2.20 | 6.71 | 5785.6* | −3.76 | 49094* | 2073.3* |
| MUR | 179.33 | 1.84 | 4.97 | 3434.7* | −4.22* | 42380* | 2075.2* |
| DUB | 187.30 | 2.04 | 6.26 | 5022.2* | −4.06* | 46294* | 2069.6* |
| KUW | 205.30 | 1.78 | 3.67 | 2351.7* | −3.43 | 53811* | 2086.7* |
| COS | 201.01 | 1.82 | 4.50 | 1572.4* | −2.73* | 40722* | 2052.8* |
| GIP | 177.74 | 4.62 | 33.41 | 72217.0* | −7.33 | 18883* | 1960.5* |
| SOK | 177.46 | 1.86 | 5.12 | 3613.4* | −3.80 | 46903* | 2086.6* |
| TAP | 180.20 | 1.37 | 2.32 | 1158.7* | −3.59 | 51565* | 2079.0* |
| SHE | 203.13 | 1.80 | 3.91 | 2539.5* | −3.59 | 51859* | 2080.2* |
| DAQ | 204.19 | 1.91 | 4.45 | 3093.3* | −3.57 | 52484* | 2082.8* |
| MIN | 186.66 | 1.67 | 3.88 | 2360.2* | −3.88 | 48642* | 2078.8* |
| CIN | 206.21 | 1.87 | 4.12 | 2790.2* | −3.69 | 52199* | 2084.4* |
| DUR | 200.19 | 1.80 | 3.94 | 2560.4* | −3.61 | 52327* | 2080.8* |
| AZE | 186.15 | 1.46 | 2.54 | 1354.4* | −2.73 | 60628* | 2106.7* |
| CPC | 193.23 | 1.39 | 2.21 | 1138.1* | −2.81 | 60254* | 2103.2* |
| BOL | 187.94 | 1.53 | 2.85 | 3014.8* | −4.44 | 60573* | 2106.7* |
| BOM | 184.24 | 4.14 | 27.10 | 108059.0* | −7.64* | 21568* | 1968.0* |
| GIR | 190.97 | 1.55 | 2.88 | 1616.8* | −2.65 | 61491* | 2108.4* |
| ZAF | 196.29 | 12.87 | 210.19 | 4032259.0* | −14.68* | 5244* | 1733.9* |

Notes: See Table 2.

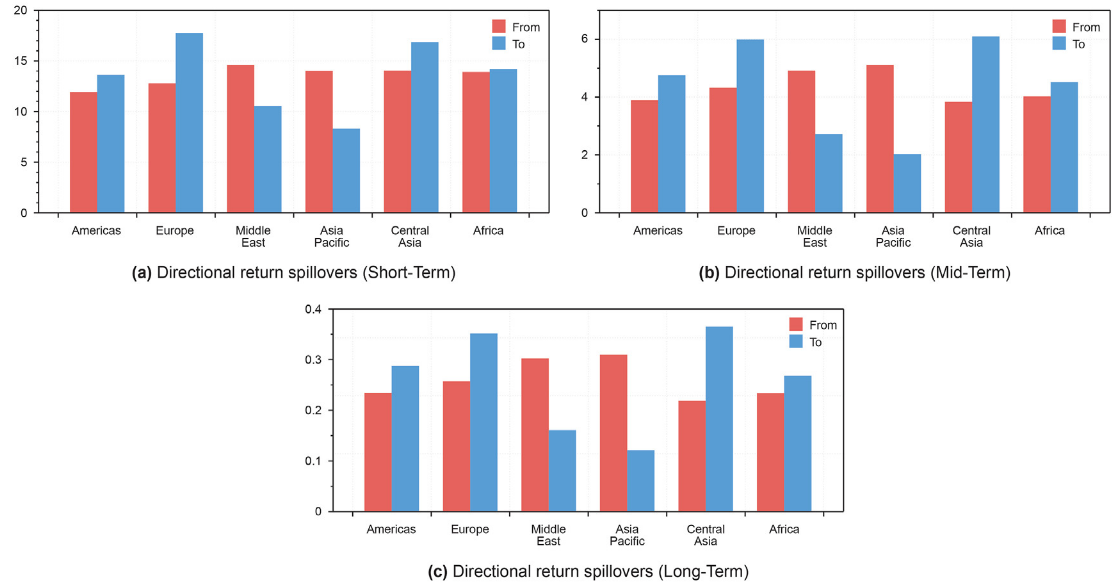


**Fig. 3.** "To" and "From" return spillovers at different timescales
Notes: In Fig. 3, blue represents the "To" return spillover, red represents the "From" return spillover. The "To" return spillover reflects the contribution of one crude market to other markets. The "From" return spillover represents the gain that one crude market obtains from other markets.

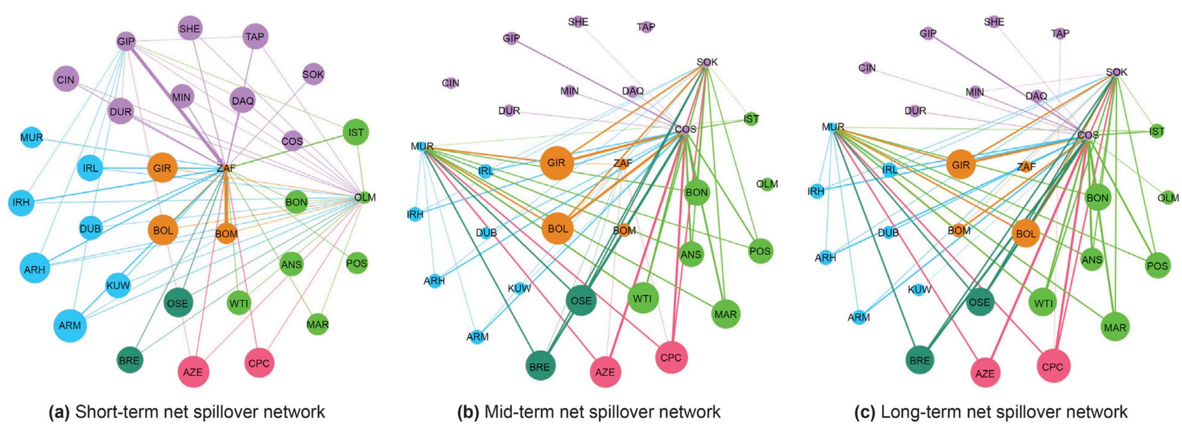


**Fig. 4.** Net return spillover networks at different timescales
Notes: The node represents the 31 crude oil market prices selected in this article. The directed edges between nodes represent the net spillover index between crude oil market returns (volatility). The nodes in the figure have six colors, representing the crude oil markets in different regions. Range green represents crude oils in the Americas, pink represents crude oils in Central Asia, orange represents crude oils in Africa, dark green represents crude oils in Europe, blue represents crude oils in the Middle East, and purple represents crude oils in the Asia-Pacific region. The size of the node represents the total net spillover index of the crude oil market returns (volatility). The stronger the leadership of crude oil market returns (volatility) is, the higher will be the total net spillover index and the larger the node. The directed edges in the graph have six colors, which are determined by the node color of the starting point of the directed edges. The thickness of the edge represents the level of the net income spillover. The thicker the directed edge is, the greater is the net return spillover between the two crude oil markets connecting the directed edge.

stability of the return series can be derived from ADF test results. The $Q$ (36) test result based on the Ljung–Box shows that the return series has no correlation. Thus, the VAR model in Eq. (1) can be used. Finally, the ARCH–LM test demonstrates the rationality of using the GARCH model to calculate volatility. As can be seen from Table 3, compared with the return series, the mean and variance of the volatility series over the entire sample period are significantly higher than the return series. The skewness and kurtosis of the volatility series are similar to the return series, but the degree of right deviation is more obvious than in the return series. The Jarque–Bera test, $Q$ (36) test and ARCH–LM test of the volatility series are all consistent with the results of the return series.

## 4. Empirical analysis

Following the spillover index model of Baruník and Křehlík (2018), this paper decomposes the total connectedness into three timescales, in order to show the spillovers of global crude oil

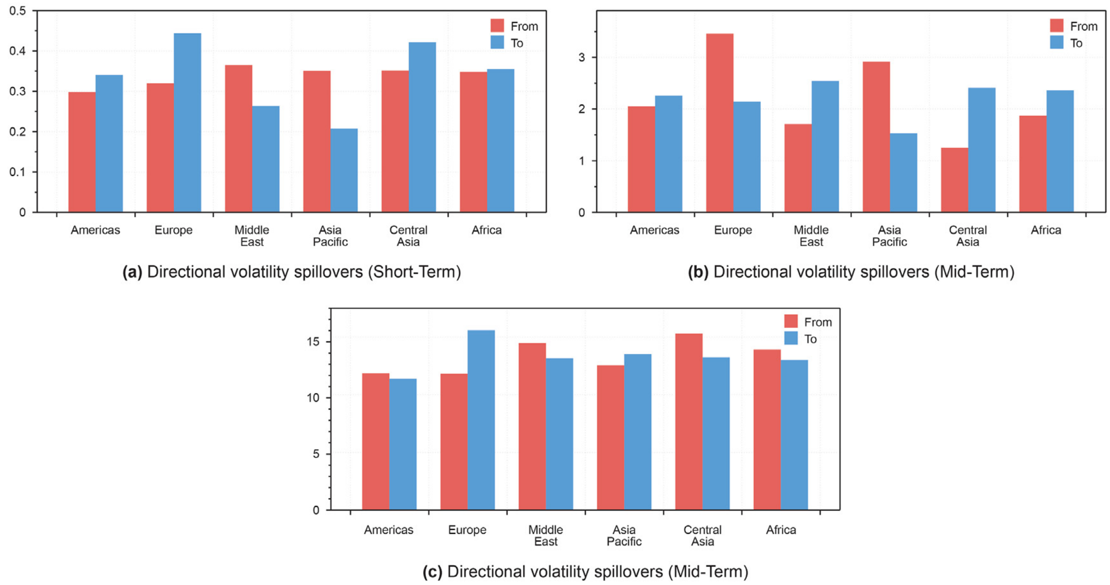


**Fig. 5.** "To" and "From" volatility spillovers at different timescales
Notes: See Fig. 3.

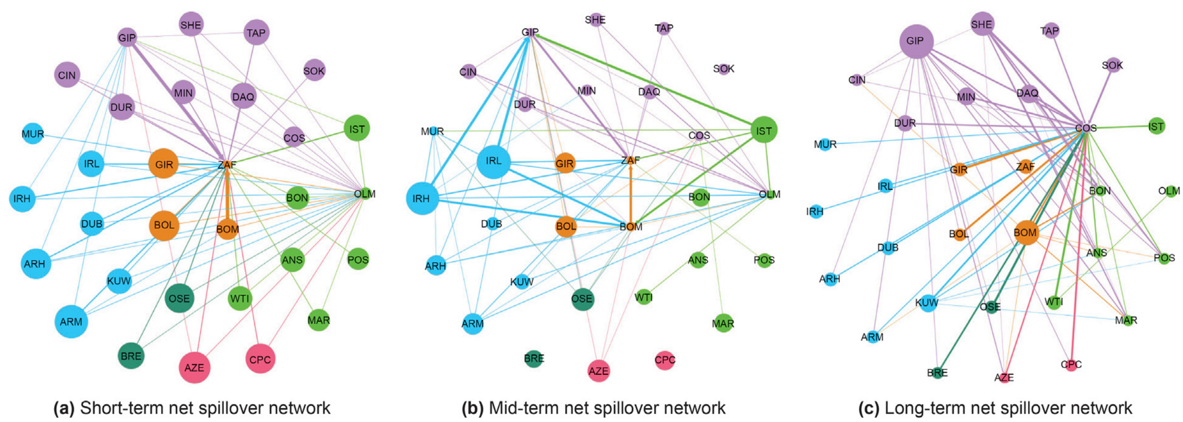


**Fig. 6.** Net volatility spillover networks at different timescales
Notes: See Fig. 4.

markets in the short-term (day-to-week length), in the medium-term (week-to-quarter length (three months)) and in the long-term (more than one quarter).[5] This study divides 31 crude oil markets into six regions, according to their geographic locations. In Sections 4.1 and 4.2, this paper presents the static spillover characteristics of oil price returns and volatility at different timescales, and further builds return and volatility spillover networks to show the price transmission of crude oil markets. In Section 4.3, we use a rolling window analysis to describe the dynamic changes of the influence of oil prices in various regions under different timescales.

### 4.1. Multiscale analysis on the static return spillover

This study first observes the static spillover characteristics of oil price returns at different timescales. Through the calculation of Eq. (3), we find that 92.9% of the total return spillover index is consistent with the assumption of Adelman (1984), i.e., that global crude oil markets are in reality "one great pool". However, heterogeneity exists in the return spillover characteristics of global crude oil markets. The short-term global crude oil markets' spillover index is 67.1%,[6] the medium-term accounts for 24.3%, while the long-term is only 1.5%. Changes in the price return can quickly transmit to other markets (within one week), while in the long-

[5] The choice of timescales depends on the time interval of the original return series. Since this article uses the daily data of crude oil for modelling, we use a week (1–5 days) as the short-term. The sample period selected in this paper is long, so we take one week to three months (5–66 days) as the medium-term, and more than 66 days as the long-term.

[6] We can obtain this value from Eq. (7). The proportion of the short-term return spillover to the total change (equal to the number of 31 crude oil types in the system) can measure the integration of the short-term crude oil markets. The sum of the short-term, medium-term and long-term return spillover is the total return spillover. The closer to 100% the sum is, the higher is the integration of the global crude oil market under this timescale.

term, almost no return spillover will occur. This finding is consistent with the widely accepted view that short-term changes in oil prices in various regions are mainly driven by exogenous factors, whereas local demand and supply and overall economic prospects play a major role in the long-term (Ferrer, 2018; Wang and Liu, 2010). Therefore, the interaction of changes in oil price in various regions mainly occurs in the short-term. This finding makes up for the shortcomings in previous literature (Ji and Fan, 2016; Zhang et al., 2019), which ignores the linkage of the crude oil markets at different timescales.

Then, this paper analyzes the strength and transmission direction of the return spillovers between the crude oil markets in different regions. Fig. 3 shows the contribution and gains of various regional crude oil returns in the short-term, medium-term and long-term horizons. As shown in panels A in Fig. 3, the European, Central Asia and African region contribute more short-term return spillovers than other regional market, which shows that they play an essential role in the short-term cross-market contagion of price changes. The contributions and gains of the African region returns are roughly equivalent, which means the African region serves as a bridge for cross-regional return transmission.

Panels B in Fig. 3 illustrate that the return spillover effects in the medium-term are significantly lower than in the short-term. However, the leading-lagging relationship of crude oil returns in the medium-term is more evident than that in the short-term. The contributions of the crude oil returns in Central Asia, Europe, the Americas, and Africa are significantly larger than those in the Middle East and Asia-Pacific regions. In contrast, the Middle East and Asia-Pacific region markets gain more return spillovers than other markets. It can be seen from the spillovers in panels C in Fig. 3 that the linkages of the long-term crude oil market returns are weak.

The net influences between crude oil returns allow us to have a deeper understanding of the transmission mechanism of global crude oil returns. Fig. 4 shows the net return spillover networks of the crude oil markets at different timescales. Crude oil markets in different regions have similar influences in the short-term. Compared with the short-term, however, the influences of the crude oil returns of various regions in the medium-term is significantly different. The status of the American region crude oil markets has increased, while Asia-Pacific and Middle East markets have become less influential. In the medium- and long-term, net return spillovers mainly spread from the markets in Europe, America and Central Asia to the markets in the Asia Pacific and the Middle East.

These results suggest that the integration degree and transmission of crude oil returns are heterogeneous under different timescales. First, the short-term linkages between global oil price returns are stronger than the medium-term, and they are significantly stronger than the long-term. Second, there is no significant leading-lagging relationship in the short-term. However, the return spillovers in the medium- and long-term are mainly transmitted from the European, American and Central Asia markets to the Asia Pacific and Middle East markets. Different drivers of return spillovers in the short-term, medium-term, and long-term result in this heterogeneous feature. Speculation and inventory levels (Merino and Ortiz, 2005) affect short-term return spillovers. Medium-term and long-term return spillovers depend more on structural factors, such as sovereign production plants, macroeconomics, and political environment (Martina et al., 2011). The crude oil supply and demand pattern, and the global economic and political power in each region are different. This results in significant differences between the influences of various regional crude oil market returns in the medium- and long-term.

Third, the direction of return spillovers reveals the pricing power of various crude oil market regions. In the medium- and long-term, crude oil returns in Europe, the Americas, and Central Asia dominate the market, while returns in Asia-Pacific and the Middle East follow changes in other markets. There are well-developed financial markets and mature futures trading markets in Europe and America. The International Petroleum Exchange and the New York Mercantile Exchange have the world's largest crude oil futures trading volume. In addition, crude oil is priced in the U.S. dollars. These factors have led to the dominance of the European and American crude oil returns in the global crude oil market. Central Asia is rich in oil reserves and is the world's main oil export region. Its stable political environment and unique geographical location, known as “the crossroads of east and west”, facilitate the export of its oil to European countries and China. Therefore, Central Asia's crude oil price dominates changes in oil prices in different regions. The Middle East and the Asia-Pacific region do not have pricing power. The Middle East has abundant oil reserves, but its political environment is complicated. The Asia-Pacific region lacks pricing benchmarks, so the oil prices in Asia are based on oil prices in the Middle East (Ji and Fan, 2016).

The heterogeneous performances of global oil price returns at different timescales can serve as an important reference for investors seeking to adopt diversified investment strategies. Because the prices of crude oil markets in various regions will quickly converge, it is more difficult for short-term investors to profit from diversification strategies than it is for medium-term and long-term investors. Moreover, it is difficult for long-term investors to arbitrage by focusing on oil price changes in specific markets, because crude oil markets in any region have little effect on global oil price returns in the long-term. Market conditions such as crude oil refining technologies, each country's economic development level, political risks, and environmental protection policies will change (Kaufmann and Banerjee, 2014; Wlazlowski et al., 2011), thus making it difficult for the returns of crude oils of different properties and different external environments to co-move in the long-term. There are profit opportunities in the medium-term for investors who focus on oil price changes in Europe, the Americas, and Central Asia. This is because the crude oil markets in these regions have the largest impacts on global oil price returns. When constructing crude oil product investment portfolios in various regions, medium-term investors should reduce their investment in crude oil in Europe and Central Asia to avoid excessive convergence of their investment portfolios. When conducting market arbitrage, medium-term investors should pay attention to the changes in oil prices in these two regions to take advantage of time arbitrage.

### *4.2. Multiscale analysis of the static volatility spillover*

Volatility transmission in the global crude oil market is of great significance for the hedging of risks (Chang et al., 2010). Similar to return spillovers, heterogeneity exists in the volatility spillovers at different timescales. The short-term volatility spillover index of the global crude oil markets is only 1.8%,[7] the medium-term is 15.5%, and the long-term is 75.3%. Price volatilities are mainly transmitted in the long-term, whilst almost no volatility spillover will occur in the short-term. This characteristic is the exact opposite of that found in return spillovers.

Then, we analyze in detail the level and direction of the volatility

[7] This value is calculated by Eq. (7). The proportion of the short-term volatility spillover of oil prices across the market to the total change (equal to the number of crude oils (31) in the system) can measure the linkage of the short-term crude oil market. The sum of the short-term, medium-term and long-term volatility spillovers is the total volatility spillover. The closer to 100% the total is, the higher the integration of the global crude oil market at this time scale.

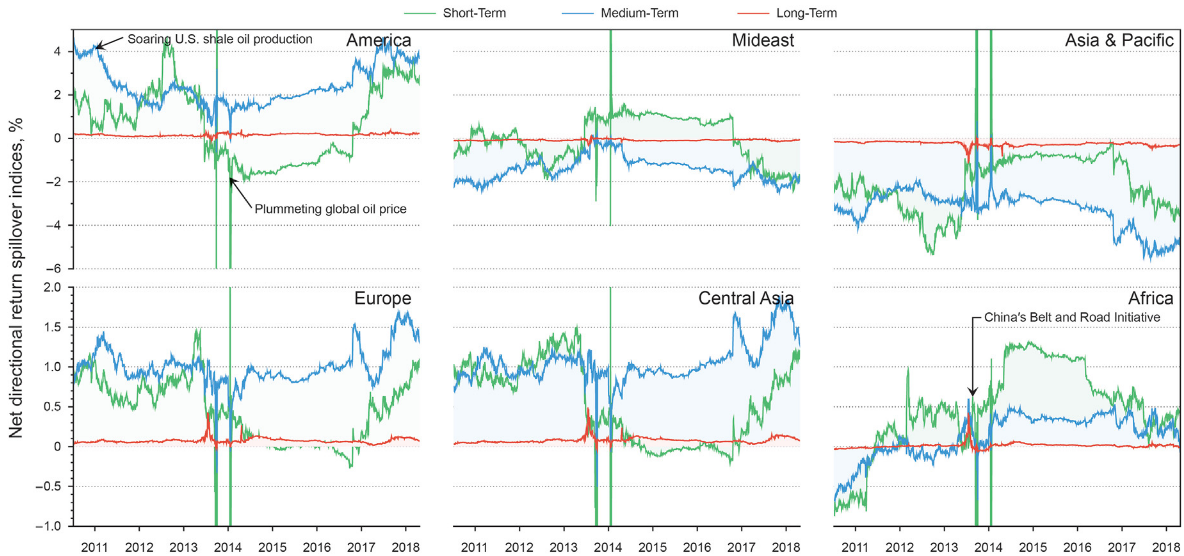


**Fig. 7.** Net directional return spillovers of six regions at different timescales

Notes: This graph shows the time-varying characteristics of the total net spillover index of crude oil markets in various regions under different timescales. The total net spillover index of a crude oil market can be obtained by subtracting the spillover of a crude oil market' contribution to other crude oil markets from the gain from other crude oil markets. Also, one regional market's total net spillover index is obtained by adding up the net spillover indexes of all crude oil markets in this region. A positive value indicates that the regional market is a net contributor to the system; a negative value indicates that the regional market is a net receiver of the system. The green area represents the short-term (within one week) total net spillover; the blue area represents the mid-term (one week to one quarter) total net spillover, and the pink area represents the long-term (over one quarter) total net spillover.

spillovers among crude oil markets. As can be seen from panels A in Fig. 5, the short-term volatility spillovers between markets are minor. This is different from the pronounced short-term return spillover effects. However, the short-term volatility spillovers received by the Europe crude oil markets far exceed those of other regional markets. Compared with the short term effects, the cross-regional volatility spillover effects have significantly increased in the medium-term (Fig. 5 panel B). The Europe and Asia Pacific regional market receive more volatility spillovers, and the Middle East, Central Asia regional markets contribute more volatility spillovers. In the long-term (Fig. 5 panel C), the European and the Asia-Pacific region become net contributors, and crude oil markets in other regions are net absorbers.

Fig. 6 shows the net volatility spillover networks of crude oil markets at different timescales. In the short horizon, various crude oil regions play similar roles in volatility transmission. Compared with the short-term, the impacts of various regional crude oil volatilities in the medium-term have diverged. The Middle East regional market makes the largest contribution to other volatilities, followed by Central Asia, Europe, and the Americas regional crude markets. The net long-term volatility spillover network of crude oil markets is significantly different from that of the short-term and medium-term. The Asia-Pacific regional market (SHE, DAQ, GIP) takes the lead in volatilities, followed by the Middle East region.

The co-movements and transmission mechanism of global oil price volatilities vary under different timescales. The long-term volatility spillovers of the global oil price are larger than with other timescales. Oil price volatilities in various regions have seemingly different influences in the medium- and long-term, while the short-term impacts are not much different. This inconsistency may be due to the different driving factors of volatility spillovers at each of the different timescales. The medium-term volatility spillovers mainly reflect the impact of temporary crude oil supply and demand shocks on the market. Frequent geopolitical conflicts in the Middle East and North Africa (Ji and Fan, 2015) have increased the fluctuations in oil prices in these regions (Hamilton, 2009), so these regions have taken up a central role in the medium-term volatility spillover. Long-term volatility spillovers are mainly driven by economic cycles and the fundamentals of crude oil supply and demand. The Asia-Pacific region is the main crude oil import region. From 2007, due to the rapid economic development of the Asia-Pacific region, the world's total crude oil demand has maintained a strong growth trend (Jia et al., 2017). After 2014, China, India, and other emerging countries in Asia-Pacific have slowed down, and the demand for crude oil in emerging market countries has stagnated (Ferrer et al., 2018). Uncertainty with regard to economic growth in the Asia-Pacific region, combined with the worldwide overproduction of crude oil, has created the dominant role of the Asia-Pacific crude oil markets in long-term volatilities. Zhang et al. (2019) found that Asian oil prices are the net receivers of global oil price volatility spillovers. This finding differs from the findings presented here. A possible explanation for this discrepancy might be that this paper considers the volatility spillovers of crude oil markets in various regions from a multiscale perspective, and chooses more types of crude oils in the Asia-Pacific region.

Oil price volatilities reflect market risks. Therefore, the regional crude oil markets that dominate oil price fluctuations at different timescales can be used as a monitoring mechanism to reduce the spread of market risks. The heterogeneous performances of volatility spillovers at different timescales help both investors and market regulators to manage risks. Short-term investors face little risk. In the medium-term, investors face certain market risks. Medium-term investors need to focus on the volatilities of the crude oil markets in the Middle East, Central Asia, Europe, and the Americas regions, which have the largest impacts on global oil price

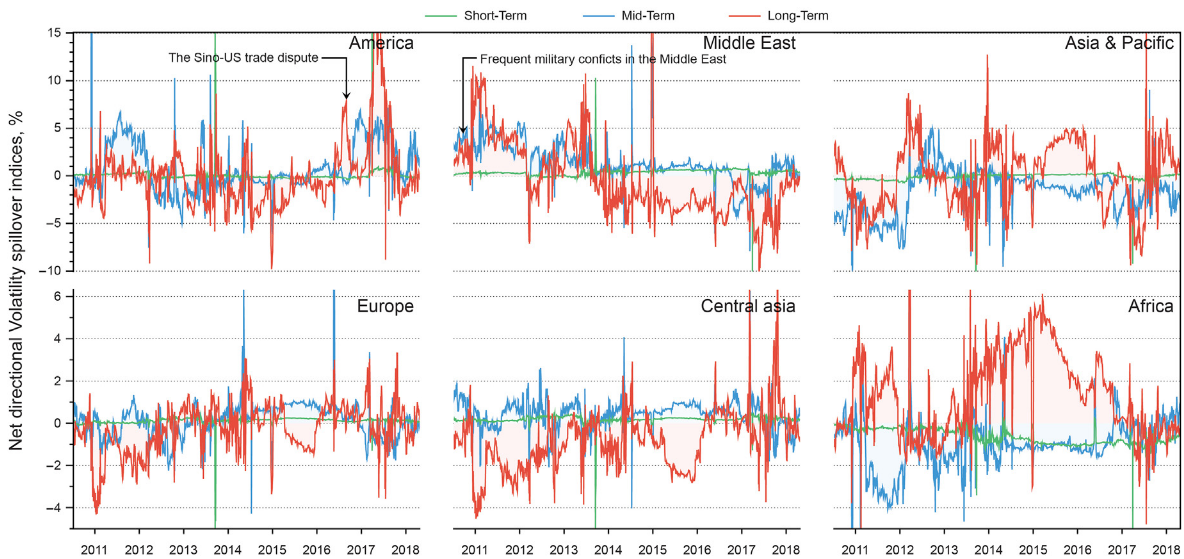


**Fig. 8.** Net directional volatility spillovers of six regions at different timescales
Notes: See Fig. 7.

volatilities. The market risks faced by long-term investors are the most significant. Reducing risks through diversified portfolios strategies is also a significant challenge. Regulators should set up effective regulatory policies to reduce market risks, especially long-term market risks. Moreover, regulators cannot ignore the critical position of the Asia-Pacific and Middle East regional crude oil markets in long-term oil price risk contagion.

### 4.3. Multiscale analysis of the dynamic spillover

In this section, this paper uses a rolling window analysis to show the time-varying characteristics of oil price spillovers in various regions at different timescales. Fig. 7 shows the dynamic pattern of the net return spillover index of six regional crude oil markets under different timescales. The short- and medium-term cross-regional return spillovers are significant, while the long-term spillovers fluctuate around zero. This is consistent with the patterns of static return spillovers.

Although the strengths of the net short- and medium-term return spillovers are similar, the net short-term spillovers have more pronounced time-varying characteristics. Furthermore, massive shocks to the markets have a more considerable and long-lasting impact on short-term return spillovers than on medium-term ones. In other words, in the medium and long-term, the price leadership of the crude oil market in various regions is relatively stable, and the impact of oil-related events is relatively small.

Since 2011, crude oil production in the U.S has increased significantly. Oil prices in the Americas, represented by WTI crude oil, are more inclined to respond to changes in local market conditions and do not play a benchmark role in international oil prices (Chen et al., 2015; Ji and Fan, 2015). Therefore, from 2011, the medium-term net directional return spillover index of the American crude oil market has continued to decrease. In 2014, due to factors such as the shale gas revolution in the United States and the economic slowdown in the Asia-Pacific region, global oil prices fell sharply (Ferrer et al., 2018). During this period, the Americas regional market changed from net short-term return spillover contributors to net short-term return spillover absorbers, while the Middle East regional market changed from a net absorber to a net contributor. The short-term market status change of the Americas and the Middle East regions continued for three years. After 2014, the net medium-term return spillover index of crude oil markets showed a similar trend to that of the short-term index. The influences of Europe, the Americas, and Central Asia crude oil returns decreased, and the pricing power of Africa and the Middle East returns strengthened. However, the changes in the market's net medium-term spillover index did not last for as long a time as in the short term. A possible explanation for this might be that market shocks continue to affect the short-term return spillovers through speculation. However, market shocks have not affected the market fundamentals and the system's underlying pricing mechanism. The medium-term return spillovers are mainly driven by the internal structures of the crude oil markets. Consequently, the net spillovers of the medium-term return to the original level faster than do those of the short-term.

As shown in Fig. 7, Europe and Central Asia regional returns have always been net contributors at various timescales. The Asia-Pacific region has been a receiver of return spillovers and has shown a significant lack of any pricing power. It is worth noting that the short-term and medium-term net return spillover index of African regional markets have risen significantly since 2014, especially the short-term index. It seems possible that the increase in the influence of the Africa region is due to China's Belt and Road policy.

Fig. 8 shows the dynamic pattern of the net volatility spillover index of various regional crude oil markets under different timescales. The cross-regional volatility spillovers in the short-term fluctuate around zero. The Africa regional market, which has been a short-term spillover receiver since 2014, is the exception. Although the cross-regional volatility spillovers are significant in the medium- and long-term, heterogeneity exists in the strength and direction of risk transmission, as well as the degree of impacts from market shocks.

The notable time-varying characteristics of the net volatility spillover index under different timescales indicate that market shocks will change the influences of regional crude oil volatilities.

From 2011 to 2012, military conflicts in the Middle East and North Africa occurred frequently. This caused the long-term volatility spillovers of the Middle East and Africa regional markets to be significantly higher than those in other regions. During this period, the medium-term net volatility spillover in the Americas regional market was comparable to that in the Middle East, indicating that the price volatilities of the Americas region were also the primary source of information. After 2014, the global crude oil supply has increased substantially, while the market share of Middle East crude oil has decreased, because of the shale gas revolution. These changes in market conditions caused the Middle East regional market to turn from being a long-term net volatility spillover contributor to becoming a net receiver. The significant increase in the long-term volatility spillover of the African regional crude oil markets after 2014 may be related to China's Belt and Road policy. The Sino-US trade dispute can explain the rises in the medium-term and long-term volatility spillover of the Americas regional market after 2017. In the context of the global economic slowdown, the most active region (Asia-Pacific) is also facing growth uncertainty. Therefore, the Asia-Pacific regional market has played a leading role in long-term risk transmission, except for the period dominated by the Middle East conflict and the Sino-US trade dispute. However, the Asia-Pacific regional market has been a receiver of volatility spillovers in the medium-term. In general, the impact of market shocks on long-term volatility spillovers is more significant than the impact on medium-term ones.

The dynamic characteristics of global oil price spillovers at different timescales are vital to market participants with varied investment horizons. Short-term investors face little risk, but they should only cautiously invest in the African crude oil markets, as this region has been the only receiver of global oil price volatilities since 2014. Compared with the strong time-varying characteristics of the influences of some regional markets, several regional markets have always been net contributors to oil price information in the medium term. Medium-term investors should focus on price movements in the European, Americas, and Central Asia regional markets to obtain arbitrage opportunities. Moreover, these investors can prevent market risks by paying attention to the European, Americas, Middle East and Central Asia regional crude oil markets. Because of the weak long-term return spillovers, it is difficult for long-term investors to profit from arbitrage. The long-term risk transmission is huge; investors with a long-term investment horizon could prevent themselves from market risks by focusing on the risks of the crude oil markets in the Asia-Pacific, Africa, and regions related to specific oil events. From a regulatory perspective, after certain huge events (such as the Middle East conflict and the Sino-US trade war), the crude oil markets in the Americas and the Middle East regions will have tremendous impacts on medium- and long-term global crude oil volatilities. Regulators should introduce effective regulatory policies to avoid large-scale risks and cross-market contagion during any crisis.

## 5. Conclusion

The issue of rethinking the integration of the global crude oil market has grown in importance in light of the new global economic and energy environment in the post-financial crisis era. Using the spillover index model proposed by Baruník and Křehlík (2018), this paper selects 31 types of regionally-representative crude oils. The purpose of this study is to explore the return and volatility spillover network characteristics of the global crude oil market in the post-financial crisis era, using a multiscale analysis.

Our findings are three-fold. Firstly, the patterns of global oil price returns and volatility spillovers vary across timescales. Global oil price return spillovers mainly occur in the short-term. Also, the short-term influences of various regions are similar. In the medium- and long-term, the price movements in Central Asia, Europe and the American regions transmit to the Middle East and the Asia-Pacific regions. Secondly, long-term volatility spillovers are significantly larger than volatility spillovers at other timescales. In the short-term, volatilities of various regions have similar impacts. The Middle East regional market dominates the medium-term volatility spillover. In contrast, the Asia-Pacific regional market plays a leading role in long-term volatility transmission. Thirdly, heterogeneity exists in the evolution of returns and volatility spillovers under different timescales in the post-financial crisis era. Massive shocks to the markets have a considerable impact on short-term return spillovers and long-term volatility spillovers. When an oil-related event occurs, the volatility spillovers in the regional markets associated with that event will increase significantly. In contrast, the short- and medium-term volatility spillovers are less affected by market shocks.

With the new global environment in the post-financial crisis era, crude oil market investors and policymakers should change their behaviors according to their investment horizons. Constructing diversified investment portfolios is very challenging for short-term crude oil markets investors, because the price movements in one regional market will quickly transmit to other regions. In contrast, short-term investors face fewer market risks. Medium-term investors can benefit from diversified portfolios and can, to some extent, prevent risks. Medium-term investors have potential arbitrage opportunities if they pay attention to oil price movements in the European, American, and Central Asia regional markets. Moreover, they can focus on the price volatilities of the Middle East and American regional markets to prevent risks in other regions. Long-term investors can profit from diversified portfolios. However, it is difficult for long-term investors to carry out effective risk management, because the risk contagion in the long-term is significant, especially when some huge oil-related events occur. Policymakers should introduce some regulatory measures to reduce long-term cross-market oil price risk transmission.

## Acknowledgement

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## Appendix

Fig. 9 and Fig. 10 contain spillovers for all the 31 crude oil markets, are an extension of Figs. 3 and 5. From Figs. 9 and 10, readers can know the details and compare the results for different regions.

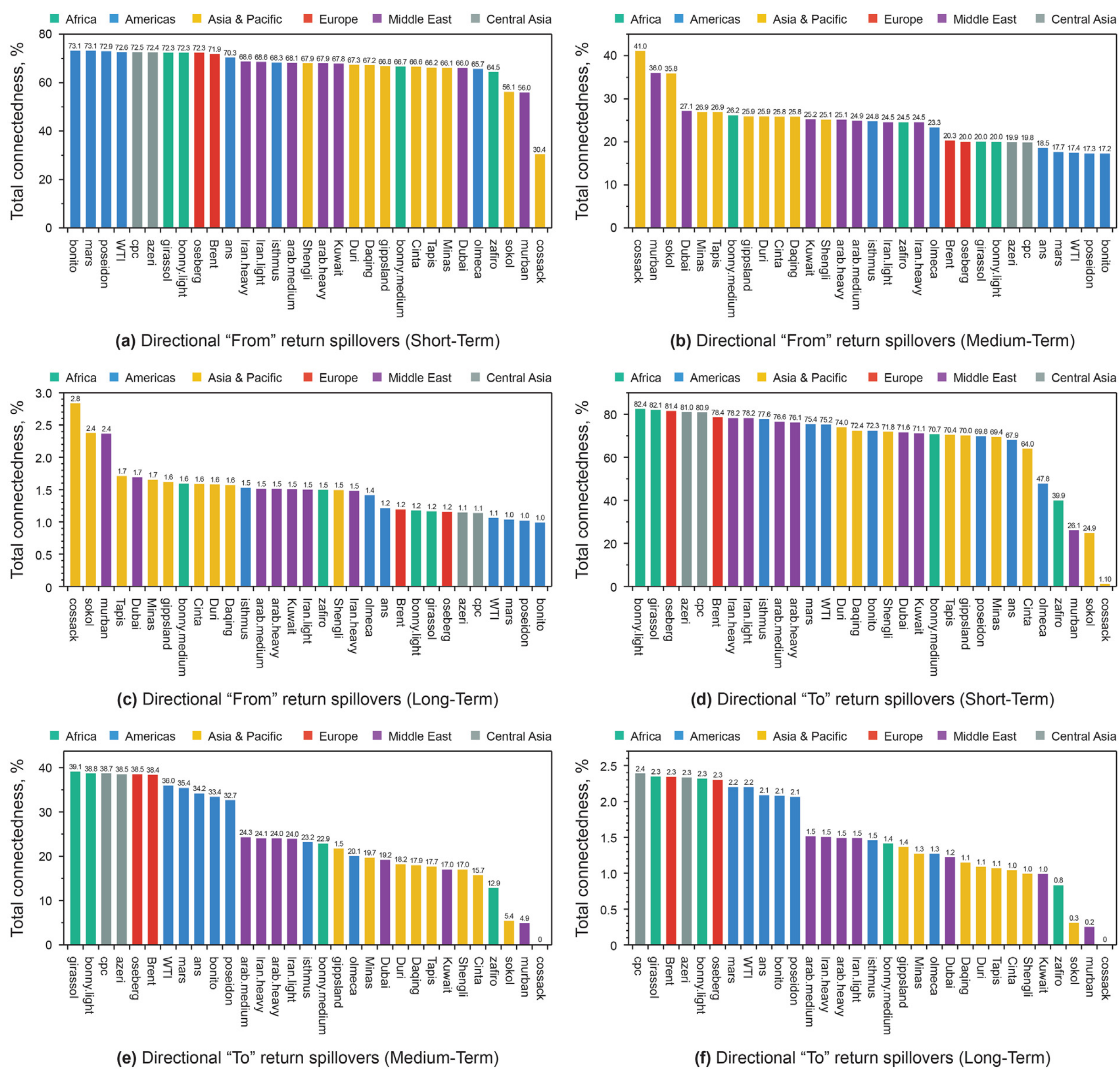


**Fig. 9.** Directional "To" and "From" return spillovers at different timescales (31 specific crude oil markets)

Notes: In Fig. 9, green represents the African market, blue represents the American market, yellow represents the Asia-Pacific market, red represents the European market, purple represents the Middle East market, and grey represents the Central Asian market. The "To" return spillover reflects the contribution of one crude market to other markets. The "From" return spillover represents the gain that one crude market obtains from other markets.

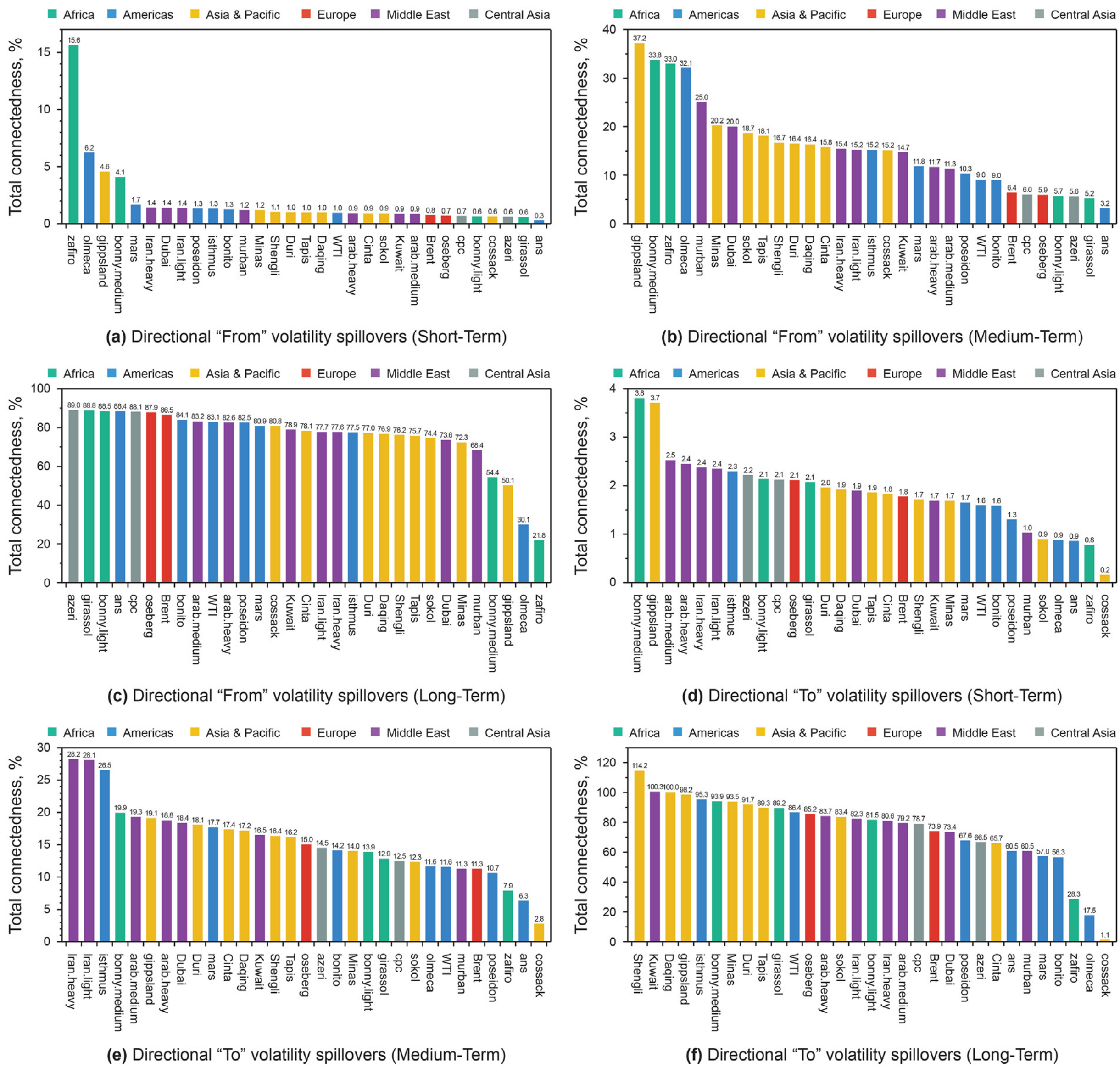


**Fig. 10.** Directional “To” and “From” volatility spillovers at different timescales (31 specific crude oil markets)
Notes: See Fig. 9.

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