Dynamic Interrelationship between Major Crude Oil Prices: Estimation by Multiple Sub-Periods regarding Key Global Events and Time-varying Coefficient

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Abstract:

The aim of this paper is to investigate dynamic interrelationship between four major crude oil prices, Western Texas Intermediate, Brent, Dubai, and Oman, by multiple sub-periods analysis as well as time-varying coefficient from January 1, 2007 to December 31, 2019.The multiple sub-periods are quantitatively constructed by the structural breakpoints identification method and then qualitatively justified by matching those with key economic and political events. GARCH family models, such as an extended GARCH (1,1) and Diagonal BEKK-GARCH model find that (1) volatility spillover and correlations between the selected four crude prices, in general, varied over time, (2) Dubai prices tended to be followed by all other prices over the years, (3) Prediction of oil prices became harder for the Asian crude oil markets, such as, Dubai and Oman, than for the Western markets during the sub-period in which the Arab springs events were involved. These findings shed light on the features of the major crudes oil prices interrelationship for the recent 15 years.

Keywords: volatility spillovers; time-varying correlations; crude oil prices; sub-periods.

JEL Classification: Q40; Q47.

Introduction

In the field of energy economics, a number of studies have been dealing with crude oil prices as a main stream topic. These oil-price studies, in specific, have been focusing on the research question: What determines the oil price movements and how oil price changes driven by these determinants affect the economy? For identifying the determinants, recent studies examined non-fundamental factors, such as, speculative investment (Kaufmann and Ullman 2009, Knittel and Pindyck 2016) and financial liquidity (Ratti and Vespignani 2013). Also, fundamental factors still have been taking attentions, such as, demand-supply, inventories, spare-capacity production (Al-Fattah 2020, Fattouh 2007, Till 2015). To evaluate the oil price effect, researchers often observed changes in macroeconomic variables, such as, GDP, inflation, etc. (Hamilton 2009, Katircioglu *et al.* 2015) or capital markets, such as, stock returns (Boldanov *et al.* 2016, Youssef and Monki 2019).

In spite of its abundance of the main stream studies on oil prices, it is surprising to observe no recent empirical evidence showing how oil prices were interrelated with each other from 2007 to 2019, when the oil markets experienced dramatic turbulences in its prices. Further, because recent studies pointed out that oil prices cointegration became weaker around 2015 (Caporin *et al.* 2019, Lee 2018), it is a timely research to document whether volatility spillover and correlations between crude oil prices may change over the dramatic times through two methodological approaches: multiple sub-periods analysis and time-varying coefficient estimation.

1. Literature Review

A long strand of literature has examined the volatility spillover in crude oil prices movements. As earlier works, Lin and Tamvakis (2001) found the spillover effect of the NYMEX information on the IPE Brent prices and Ewing *et al.* (2002) found that daily oil prices returns were transmitted to other energy markets directly as well as indirectly. Later, Chang *et al.* (2010) also showed that conditional volatility spillover effect and correlations among Brent, WTI and Dubai markets prices. These findings could clarify presence of interdependence, volatility spillover, and asymmetric effects of oil shocks on the conditional variances for oil prices.

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More recently, the oil price spillover studies have been expanding its scope to other markets sectors which were seemingly linked with crude oil prices. Awartani and Maghyereh (2013) showed dynamic spillover between oil prices and equities prices in the Gulf region countries. Mensi *et al.* (2014) found asymmetric volatility spillover effects between energy and cereal commodity prices. Especially, it is surveyed that GARCH family models have been often used for the relationship between oil prices and financial markets. For example, Mensi *et al*. (2015) used a GARCH model to find the spillover between oil prices and USD/euro exchange rates. Salisu and Oloko (2015) used a VARMA-BEKK-AGARCH model for the correlation between oil prices and US stock markets. Ji *et al*. (2020) used an advanced GARCH model to find spillover between oil prices and stock returns in the BRICS. Maraqa and Bein (2020) used DCC-MGARCH model to find the dynamic interrelationship and volatility spillover among stainability stock indices, crude oil prices, and major stock returns of European countries.

Different time phase analysis has been intriguing the oil market researchers as oil price volatility became higher since the new millennium began. The Western Texas Intermediate (hereafter WTI) spot prices began to rise from around 20 US dollars per barrel in 2001 to the record-high price of 145.16 dollars in July 2008 right before the global financial crisis occurred. The price collapsed to about 30 dollars due to the global financial crisis doom and then recovered up to around 100 dollars from early 2011 to mid-2014. The prices dropped again to around 50 dollars in the beginning of 2015 and kept the level until the end of 2019. Erdos (2012) found that the correlation among crude prices and gas prices have been insignificant since 2009 although they were co-moved from 1997 to 2008. Asche *et al.* (2012) suggested a similar result that oil and gas prices presented high differences in short-term, but these were eliminated in long-term. Geng *et al*. (2016) pointed out the time of the shale gas revolution as the breaking point for changing the correlation between oil prices and natural gas prices. Most recently, Perifanis and Dagoumas (2018) constructed three sub-periods based on the whole time from 1990 and 2017 to find the time-varying correlation between oil prices and natural gas prices, and Maraqa and Bein (2020) found that the correlation between oil and stock returns became higher during and after the 2008 global financial crisis time.

Distinguished from the existing literature on the oil and other related price correlations, this paper focuses on four major crude oil prices and tests whether the oil prices interrelationship measured by spillover and correlations may change by different time periods. The different time periods are quantitatively constructed by the Bai-Perron breakpoints identification methods as Lee (2018) suggested. In addition, the quantitatively constructed sub-periods are explained by key global economic and political events which actually occurred in the sub-period, which gives qualitative justification to the sub-period. Such justification work contributes to fill the voids in most of existing literature which simply made quantitative work for constructing sub-periods because it suggests rational background to each sub-period. In addition, another contribution of this paper is to provide a timely empirical evidence about the features of the dynamic interrelationship between crude oil prices over the recent 15 years, which has been not yet documented according to within the best of our knowledge.

2. Methodology

This paper uses daily spot prices of the four benchmarks crude oil, which are WTI, Brent, Dubai and Oman, from January 1, 2007 to December 31, 2019. The data source is the Thomson Reuters Data stream. To construct sub-periods over the whole 15 years, this paper uses the multiple breakpoints identification method originally suggested by Bai and Perron (2003). For all the selected major crude oil prices, the Bai-Perron method identified three structural breakpoints in price volatility over the 15 years, (1) July 1, 2008, (2) December 31, 2010, (3) September 30, 2014, which are very similar with the results from Lee (2011). Thus, these three breakpoints allow constructing four sub-periods, which are 01/01/2007–30/06/2008, 01/07/2008–30/12/2010, 01/01/2011–310/09/2014, 01/10/2014–31/12/2019.

For each sub-period, this paper investigates critical economic and political events characterizing the time horizon. The first sub-period (01/01/2007–30/06/2008) is characterized as "Oil Price Boom Period" because the key events were that crude oil prices rapidly increased to the record-high and USA had the last stage of 2001-2007 stable economic prosperity. The second sub-period (01/07/2008–30/12/2010) is entitled with "Global Financial Crisis Period" since the period is characterized by the crisis even which was initiated by US sub-prime mortgage and depressed the world economy as well as the crude oil markets. The third sub-period (01/01/2011–310/09/2014) is entitled with "Liquidity and Arab Springs Period" because the period was characterized by the key economic and political event: (1) the world economy was supported by expanded money supply (2) A series of anti-government protests occurred in Arab countries, such as Tunisia, Libya, Egypt, Syria, *etc*. Also, nuclear crisis in Iran was one of geopolitical events in the third sub-period. Lastly, the fourth sub-period (01/10/2014–31/12/2019) is characterized as the situation of around $50oil-price because the world economy was under new uncertainties, such as, US-China conflict, US energy policy on crude oil exports expansion and climate change retreat, the world trade protectionism, etc. Table 1 shows the constructed sub-period based on the Bai-Perron method as well as the key events which are corresponding to each sub-period. These events matching with each sub-period establish qualitative justification for the sub-period which is made from the quantitative technique.

Table 1. Construction of sub-period matching with the key economic and political events

Sub-period constructed	Panel Classification	Key economic and political events
01/01/2007 – 30/06/2008	*Panel A* “Oil Price Boom Period”	Unprecedentedly rising oil prices / The last stage of 2001-2007 stable economic prosperity in USA
01/07/2008 – 31/12/2010	*Panel B* “Global Financial Crisis Period”	The global financial crisis initiated by US sub-prime mortgage / Oil prices collapse
01/01/2011 – 30/09/2014	*Panel C* “Liquidity and Arab Springs Period”	The world economy supported by expanded money supply / Arab springs began and spread out
01/10/2014 – 31/12/2019	*Panel D* “New Uncertainties Period”	US-China conflict / Trade protectionism / US energy policies regarding crude export expansion and climate changes treat

Note: Construction of each sub-period is based on the quantitative method of Ba and Perron (2003) and Lee (2018).

This paper calculates the returns of crude oil prices *i* of market *j* at time *t,* in a continuous compound basis are calculated as $r_{ij,t} = \log\ (\frac{p_{ij,t}}{p_{ij,t-1}})$, where $p_{ij,t}$and $p_{ij,t-1}$ are the closing prices of crude oil price *i* in market *j* for days *t* and *t−1*, respectively. The descriptive statistics for all of the daily return series are reported in Table 2. In general, all returns of the crude oil spot prices have mean negative returns during the period. The variation in the returns, measured by standard deviation, is around 0.02 for all four crudes. For example, WTI has the highest variation, 0.0252 which is followed by Brent with 0.0233, Dubai with 0.0211, Oman with 0.0207. The Skewness value is both positive and negative. The positively skewed returns are found in the WTI while the negatively skewed returns are found in the Brent, Dubai and Oman returns, which shows a higher probability for the investor to see positive returns from the WTI index. The Kurtosis values of the returns are over three times the value of the normal distribution, indicating that the return indices have peaks relative to the normal distribution. The Jarque-Bera (J.B.) test, shown in Table 2, rejects the null hypothesis of normal distribution at the 1% significance level for all crude oil return series. Lastly, The ADF test shows that all returns series are stationary.

Table 2. Summary statistics for daily crude oil returns from 01/01/2007 to 31/12/2019

	WTI	Brent	Dubai	Oman
Mean	-0.0000494	-0.0000256	-0.000026	-0.0000258
Median	0.00018	8.88e-05	0.00031	0.00034
Max.	0.1914	0.1171	0.1625	0.161
Min.	-0.1274	-0.1184	-0.1297	-0.125
Std. Dev.	0.0252	0.0233	0.0211	0.0207
Skewness	0.2484	-0.0046	-0.0783	-0.0504
Kurtosis	8.0433	6.0787	7.6851	7.6594
J.B.	2661.21***	982.21***	2277.1***	2250.75***
ADF-test	-8.204***	-11.142***	-11.247***	-11.309***

Note: Construction of each sub-period is based on the quantitative method of Ba and Perron (2003) and Lee (2018).

For the first empirical model, this paper employs GARCH (1,1) process to examine whether crude oil price volatility is persistent over times as follows:

$$r_t = \mu + r_{t-1} + u_t \quad (1)$$

$$h_t^2 = \omega + \alpha u_{t-1}^2 + h_{t-1}^2 \quad (2)$$

As GARCH (*q, p*) is widely defined, the following restrictions must be imposed to ensure that the conditional variance does not take negative values: $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$. In eq. (1) r_t stands for the continuously compounded return on a crude oil price series. This process can vary the conditional variance over time and leave the unconditional variance constant. The coefficient of the squared error term (α) captures the extent to which past news causes volatility today –that is, the existence of volatility clustering in the data. The sum of α and β indicates the persistence of volatility for a given shock. This paper using high-frequency time-series data, such as, daily crude oil returns, is expected to find this sum to be very close to one, indicating that shocks are highly persistent. The unconditional variance is not time-dependent and is given by ($\frac{\omega}{1-\alpha-\beta}$). This process is called an I-GARCH operation by being integrated in the variance process (Engle and Bollerslev 1986) In this case, volatility persistence is permanent while past volatility is significant in predicting future volatility over all finite horizons. The I-GARCH process captures the best temporal pattern of volatility for the major crude returns. If the sum (α + β) is >1, then volatility is explosive.

As the next empirical model, this paper employs an extended GARCH (1,1) model for the volatility spillover effects as recent energy studies used (Karali and Ramirez 2014, Venditti and Veronese 2020). In particular, this paper follows the recent model suggested by Andriosopoulos *et al.* (2017) to establish the variance of each sample market (h_t^2) as a GARCH (1, 1) process in which the conditional variance equation depends on its own past squared residuals and variance. The estimation model is eq. (3) as follows:

$$h_{j,t}^2 = \omega + \alpha_j u_{j,t-1}^2 + \beta_j h_{j,t-1}^2 \tag{3}$$

Eq. (3) allows obtaining the volatility for each market prices returns which are used as a right-hand variable in the variance equation for each market returns variable. So, eq. (4) is constructed as the volatility equation for each returns variable in the left-hand side as well as each crude oil returns variable on the right-hand side as follows:

$$h_{i,t}^2 = \omega + \alpha_i u_{i,t-1}^2 + \beta_i h_{i,t-1}^2 + \gamma_{1,j} h_{j,t}^2 + \gamma_{2,j} h_{j,t-1}^2 \tag{4}$$

Now, eq. (4) shows that the volatility of each of the four major crudes returns variable depends not only on its own past squared residuals and variance, but also on the past variance of each of the four major crudes returns variable. In eq. (4), the dependent variable ($h_{i,t}^2$) is the volatility of each of the crude oil proxies (*i* = WTI, Brent, Dubai, and Oman prices returns) which is estimated against its own past squared innovations and its own past values, along with current and lagged volatility values (also estimated from a GARCH (1,1) model) for the markets of crude oil index returns (*j* = WTI, Brent, Dubai, and Oman prices returns). Statistically significant γ_1 and γ_2 suggest that volatility from one of crude oil markets affects another market; in other words, there are significant volatility spillover effects.

For the last empirical model, this paper employs a BEKK-GARCH model to investigating time-varying correlation between the oil prices used like the recent studies, such as, Jati and Premaratne (2017). The estimation parameters of the Diagonal BEKK are $(n(\iota + k)) + 3$, where *n* is the dimension of the model; *i.e.* the number of dependent variables and *i* and *k* are the lag orders. The time-varying correlation framework conducts a bivariate Diagonal BEKK specification under the Student *t* distribution as follows:

$$S_t - \begin{bmatrix} C_{0,1} \\ C_{0,2} \end{bmatrix} \lceil I_{t-1} \sim t(0, H_t), \tag{5}$$

where $C_0 \equiv [C_{0,1} C_{0,2}]'$ is the mean value, I_{t-1} is the information set at a given time and the bivariate vector $S_t = \begin{bmatrix} CV_{t,1}^{(m)} \\ CV_{t,2}^{(m)} \end{bmatrix}$ denotes the crude oil prices returns

$$H_t = A_0 + \sum_{i=1}^{k} \left(A_i \varepsilon_{t-i} \varepsilon_{t-\iota}' \acute{A}_\iota \right) + \sum_{j=1}^{l} \left(B_j H_{t-j} \acute{B}_\iota \right) \tag{6}$$

In this context, $A_0 = \begin{bmatrix} a_{1,1,0} a_{1,2,0} \\ a_{1,2,0} a_{2,2,0} \end{bmatrix}$ is a $(2{\times}2)$matrix and the A_i and B_j matrices are restricted to be diagonal. Based on this model, the conditional covariance matrix for the two variables is $H_t = \begin{bmatrix} h_{1,1,t} h_{1,2,t} \\ h_{2,1,t} h_{2,2,t} \end{bmatrix}$ and the dynamic conditional correlation between crude oil price returns can be estimated by $\rho_t = \frac{h_{1,2,t}}{\sqrt{h_{1,1,t}}\ \sqrt{h_{2,2,t}}}$.

3. Empirical results

Table 3 shows the results from GARCH (1, 1) model in eq. (2) for each sub-period. The volatility persistence is measured by the sum of the estimated coefficients α + β shown in the 6th column. Positive sign of the ARCH and GARCH parameters suggests a tendency for shocks to increase over time, and that volatility has some memory for its historical levels. Volatility of the returns is observed to be explosive as throughout the sum of the estimated coefficients $\alpha_+ \beta$ is near to one for all crudes returns and all sample periods.

In Panel A of the first sub-period titled with "Oil Price Boom Period", the null hypothesis that ($\alpha + \beta$) = 1 is accepted for all crudes except Brent. It is estimated that for all the crude oil returns, this sum ($\alpha + \beta$) is lower than a full sample period. Also, the "Global Financial Crisis Period" entitled for the second sub-period classified by Panel B accept the null that ($\alpha + \beta$) = 1 for all four crudes with greater ($\alpha + \beta$) than the oil boom sub-period. This result indicates that persistence of the shocks to volatility becomes greater and that past volatility is significant in predicting future volatility. The "Arab Spring Period" classified by panel C showed that Dubai and Oman accepted the null hypothesis that ($\alpha + \beta$) = 1 but WTI and Brent did not accept the hypothesis. This result implies that volatility of the Asian crudes, Dubai and Oman, was more hard to be predicted than that of the Western crudes, WTI and Brent, by the past volatility during the Arab-springs period. It is interpreted that the Arab-springs gave more uncertainty to the Asian crude markets than the Western crude markets. As the last sub-period, the Panel D containing new uncertainties showed that all the crudes did not behave as an I-GARCH procedure because the null ($\alpha + \beta$) = 1 is rejected for all the crudes. It is noticeable that the behavior of this coefficient changed substantially across sub-periods.

Overall, these results express that volatility in the major crudes oil prices returns varies over time. However, the responses of the volatility to these sub-periods were not uniform across the crudes due to the Wald test results. The null hypothesis that ($\alpha + \beta$) = 1 was not accepted in Panel A for Brent; in Panel C for WTI and Brent; Panel D for all the crudes.

Table 3. Volatility persistence between four major crude oil returns for each sub-period

	α	P-Value	β	P-Value	α + β	Wald	P-Value	Log-L	D-W
Panel A. The Oil Price Boom Period: 01/01/2007 – 30/06/2008									
WTI	0.0439	0.112	0.888	0.000	0.9319	1.4	0.24	920.11	2.015
Brent	0.0356	0.1	0.8959	0.000	0.9315	4.12	0.04	931.26	2.046
Dubai	0.0983	0.01	0.8678	0.000	0.9661	1.55	0.21	991.41	2.013
Oman	0.0948	0.01	0.8703	0.000	0.9651	1.63	0.2	1000.89	2.012
Panel B. The Global Financial Crisis Period: 01/07/2008 – 31/12/2010									
WTI	0.1219	0.000	0.8692	0.000	0.2521	5.402	0.02	946.97	2.011
Brent	0.0671	0.04	0.9181	0.000	0.9395	1.77	0.18	951.68	1.97
Dubai	0.0549	0.056	0.9272	0.000	0.951	4.15	0.04	997.95	1.95
Oman	0.0547	0.07	0.9276	0.000	0.9639	4.41	0.04	1014.98	1.98
Panel C. The Liquidity and Arab Springs Period: 01/01/2011 – 30/09/2014									
WTI	0.2676	0.000	0.4523	0.000	0.7199	11.02	0.00	1280.94	2.00
Brent	0.0886	0.047	0.6415	0.000	0.7301	3.55	0.06	1316.95	2.02
Dubai	0.3727	0.000	0.5839	0.000	0.9566	1.29	0.26	1391.35	2.15
Oman	0.4697	0.000	0.4406	0.000	0.9103	1.85	0.17	1387.5	2.00
Panel D. The New Uncertainties Period:01/10/2014 – 31/12/2019									
WTI	0.1095	0.000	0.8355	0.000	0.945	3.6	0.06	1214.95	2.02
Brent	0.0774	0.009	0.8453	0.000	0.9227	3.19	0.07	1230.71	2.04
Dubai	0.0911	0.004	0.8627	0.000	0.9538	3.89	0.05	1256.49	2.04
Oman	0.085	0.004	0.8667	0.000	0.9517	4.16	0.04	1267.21	2.03

Note: Statistically significant values (at 1%, 5%, and 10% level of significance) are denoted in bold.

Next, Table 4 shows the results of volatility spillover for the crude oil returns from the eq. (4). The Ljung-Box test implemented using order up to 36 lags and ARCH LM test to lag-1. GARCH (1,1) tests show standardized residuals and squared standardized residuals, and ARCH tests display significance of GARCH (1,1) model to capture the volatility spillover between four prices returns series.

Table 4. Volatility spillover effects between four major crude oil returns for each sub-period

		Panel A			Panel B					Panel C				Panel D			
I = 1	*J = 1*	γ_1	γ_2	Q-stat (lag 36)	ARCH LM (lag 1)	γ_1	γ_2	Q-stat (lag 36)	ARCH LM (lag 1)	γ_1	γ_2	Q-stat. (lag 36)	ARCH LM (lag 1)	γ_1	γ_2	Q-stat. (lag 36)	ARCH LM (lag 1)
WTI	Brent	1.78 (0.03)	-1.50 (0.11)	39.09 (0.33)	0.96 (0.33)	-0.86 (0.55)	0.94 (0.50)	31.11 (0.70)	0.12 (0.73)	0.21 (0.71)	0.53 (0.36)	50.58 (0.06)	0.42 (0.51)	0.44 (0.33)	-0.45 (0.28)	24.50 (0.93)	0.01 (0.91)
	Dubai	0.59 (0.00)	-0.57 (0.00)	38.47 (0.36)	0.11 (0.75)	-1.16 (0.22)	1.23 (0.18)	30.21 (0.74)	0.05 (0.83)	0.47 (0.01)	-0.14 (0.38)	49.30 (0.07)	0.33 (0.57)	0.64 (0.07)	-0.64 (0.06)	24.68 (0.92)	0.00 (0.93)
	Oman	0.64 (0.00)	-0.62 (0.00)	38.40 (0.36)	0.11 (0.74)	-1.36 (0.19)	1.43 (0.16)	30.51 (0.73)	0.03 (0.86)	0.23 (0.31)	-0.01 (0.97)	49.03 (0.07)	0.30 (0.58)	0.56 (0.18)	-0.54 (0.19)	25.01 (0.92)	0.00 (0.95)
Brent	WTI	0.62 (0.37)	-0.35 (0.67)	43.51 (0.18)	0.16 (0.69)	-0.53 (0.16)	1.14 (0.08)	52.90 (0.03)	0.00 (0.98)	0.38 (0.00)	-0.42 (0.00)	30.13 (0.74)	0.75 (0.39)	0.40 (0.22)	-0.06 (0.95)	22.87 (0.96)	0.57 (0.45)
	Dubai	0.33 (0.00)	-0.30 (0.00)	43.06 (0.19)	0.37 (0.54)	-0.05 (0.96)	0.18 (0.88)	47.39 (0.10)	0.11 (0.74)	0.49 (0.00)	-0.33 (0.02)	31.64 (0.68)	0.43 (0.51)	-0.16 (0.07)	1.57(0.00)	20.87 (0.98)	0.07 (0.79)
	Oman	1.59 (0.19)	-1.06 (0.31)	39.87 (0.30)	0.02 (0.90)	-0.00 (0.99)	0.15 (.91)	47.61 (0.09)	0.10 (0.75)	0.41 (0.04)	-0.30 (0.10)	31.69 (0.67)	0.25 (0.62)	-0.33 (0.50)	1.72 (0.00)	20.75 (0.98)	0.09 (0.75)
Dubai	WTI	-6.46 (0.00)	7.12 (0.00)	41.58 (0.24)	0.03 (0.86)	2.16 (.00)	-1.41 (0.00)	63.18 (0.00)	0.10 (0.75)	1.13 (0.00)	-0.71 (0.00)	29.19 (0.78)	0.11 (0.74)	4.57 (0.00)	-3.29 (0.00)	24.73 (0.92)	1.29 (0.26)
	Brent	-6.12 (0.00)	6.82 (0.00)	44.30 (0.16)	1.10 (0.29)	6.00 (0.00)	-5.32 (0.00)	54.06 (0.03)	0.04 (0.84)	3.62 (0.00)	-2.32 (0.00)	31.76 (0.67)	0.05 (0.82)	7.74 (0.00)	-5.94 (0.00)	27.49 (0.85)	0.58 (0.44)
	Oman	2.84 (0.17)	-2.73 (0.15)	58.28 (0.01)	0.01 (0.92)	-3.50 (0.79)	3.91 (0.76)	36.78 (0.43)	0.01 (0.91)	-0.09 (0.76)	-0.07 (0.79)	26.65 (0.87)	0.66 (0.42)	-3.89 (0.12)	3.74 (0.11)	21.91 (0.97)	0.45 (0.50)
Oman	WTI	-5.73 (0.00)	6.33 (0.00)	43.64 (0.18)	0.02 (0.9)	2.09 (0.00)	-1.38 (0.04)	63.36 (0.00)	0.03 (0.87)	1.03 (0.00)	-0.76 (0.00)	25.45 (0.91)	0.00 (0.97)	4.67 (0.00)	-3.46 (0.00)	22.67 (0.96)	1.42 (0.23)
	Brent	-5.54 (0.00)	6.18 (0.00)	45.75 (0.13)	0.88 (0.35)	5.79 (0.00)	-5.15 (0.00)	55.05 (0.02)	0.14 (0.71)	3.88 (0.00)	-2.17 (0.00)	30.12 (0.74)	0.24 (0.62)	4.73 (0.00)	-3.17 (0.00)	23.59 (0.94)	0.19 (0.67)
	Dubai	-3.19 (0.05)	3.66 (0.49)	56.09 (0.02)	0.01 (0.90)	1.83 (0.85)	-1.23 (0.89)	36.52 (0..44	0.02 (0.88)	0.00 (0.09)	1.24 (0.00)	23.80 (0.94)	0.01 (0.93)	4.38 (0.04)	-3.40 (0.05)	22.61 (0.96)	0.23 (0.63)

Note: Statistically significant values (at 1%, 5%, and 10% level of significance) are denoted in shade.

The primary findings are as follows: First, Brent volatility spillover effects on WTI existed for the Panel A (The Oil Price Boom Period: 01/01/2007 – 30/06/2008) with current volatility. Also, Dubai volatility spillover effect on WTI existed in Panel B, with current and lagged volatility but in the Panel C (The Liquidity and Arab Springs Period: 01/01/2011 – 30/09/2014) only with current volatility significant. Yet, Oman volatility spillover effect on WTI was only in the sub-period of Panel A. Second, Dubai volatility spillover on Brent existed all the sub-periods with current and lagged volatility except only the Panel B (The Global Financial Crisis Period: 01/07/2008 – 31/12/2010) with current and lagged volatility. Oman volatility spillover on Brent also existed in the Panel D (The New Uncertainties Period: 01/10/2014 – 31/12/2019) with lagged volatility and the Panel C with current and lagged volatility. Third, volatility of WTI and Brent was transmitted on Dubai volatility for all the sub-periods with current and lagged volatility.

In summary, it is suggested that volatility of WTI and Brent was transmitted to the volatility of Dubai and Oman in all sub-periods although no significant transmission was found between WTI and Brent. This is an interesting result that the spillover effect of crude oil prices existed only from the Western markets to the Asian markets. Further, Dubai exhibited a high responsiveness to volatility spillover in these crude oil markets and their magnitudes were higher than WTI, Brent and Oman. These findings show the position of Dubai, which was followed by WTI, Brent and Oman over the 15 years from 2007 to 2019.

Lastly, this paper confirms the dynamic interrelationship between major crude oil prices through time-varying coefficient estimation. Table 5 presents the results on time-varying conditional correlations between crude oil returns estimated by the Diagonal BEKK model as specified above. The results show that all coefficients of variance equation were significant for all major crudes returns, except α (1,2) of Brent and Dubai, WTI and Oman, WTI and Dubai, Brent and Oman. For the mean equation, it is found that only Dubai and Oman correlation was estimated significant at 1% with value of 0.0005 but all other correlations were estimated insignificant. Thus, it is concluded that the oil prices correlations vary with time, which is consistent with the above results through the multiple sub-periods analysis in 3 and 4.

Table 5. Dynamic conditional correlation results: Variance Equation Diagonal BEKK model using time-varying coefficients

	WTI-Brent	Brent-Dubai	Dubai-Oman	WTI-Oman	WTI-Dubai	Brent-Oman
α(1,1)	6.84E-06*** (1.53E-06)	9.97E-07** (4.25E-07)	3.32E-05*** (5.02E-06)	2.57E-06*** (9.22E-07)	1.77E-06*** (6.20E-07)	1.66E-06** (6.75E-07)
α(1,2)	4.69E-06*** (1.01E-06)	6.20E-08 (2.18E-07)	3.28E-05*** (4.96E-06)	2.61E-07 (2.02E-07)	4.17E-07 (3.94E-07)	7.00E-08 (2.20E-07)
α(2,2)	4.58E-06*** (1.08E-06)	1.65E-06** (6.75E-07)	3.26E-05*** (4.95E-06)	1.02E-06** (4.12E-07)	4.30E-06*** (1.40E-06)	1.04E-06** (4.25E-07)
A(1,1)	0.29*** (0.01)	0.23*** (0.015)	0.50*** (0.03)	0.23*** (0.02)	0.28*** (0.02)	0.203*** (0.02)
A(2,2)	0.23*** (0.01)	0.20*** (0.02)	0.49*** (0.03)	0.22*** (0.02)	0.29*** (0.02)	0.23*** (0.02)
B(1,1)	0.95*** (0.00)	0.97*** (0.00)	0.89*** (0.01)	0.97*** (0.00)	0.96*** (0.00)	0.98*** (0.00)
B(2,2)	0.97*** (0.00)	0.98*** (0.00)	0.90*** (0.01)	0.97*** (0.00)	0.95*** (0.01)	0.97*** (0.00)
Ω	6.68*** (0.61)	7.77*** (0.72)	3.10*** (0.18)	7.83*** (0.72)	7.00*** (0.64)	7.58*** (0.69)
Log L	13720.91	12846.83	18300.68	12779.03	12708.6-	12894.55
SBC	-11.00	-10.3	-14686	-10.25	-10.188	-10.34
J-B test	590.47***	1151.56***	85740.06***	1710.69***	1138.77***	1766.57***

Note: ***, **, * indicates significance at 1%, 5% and 10% level, respectively. Standard error statistics are in parentheses.

Conclusion

These findings provide important implications to the academic researchers as well as policy makers. First, it is the first empirical evidence showing the features of dynamic interrelationships between four major crude oil prices over the recent 15 years from 2007 to 2019. In terms of 10 year increments, the decade from 2007 to 2016 was very meaningful for the crude oil markets because the time span contains the most turbulent price movements in the past two decades since the new millennium began. The second finding on the Dubai spillover transmission shows that Dubai oil market power seemed to be dominated by Oman oil market in the Asian markets. I suggest a reason that the Dubai oil trading volume has been dramatically declined since 2000 while Oman has been gradually increasing and taking China as the top consumer since 2010. Lastly, the third finding shows distinction of Asian crude oil markets from Western markets by the Asia-specific characteristics of the events, such as, the Arab springs. Thus, oil importers should be aware of regional geopolitical risk involved in the oil producing countries which they are making contracts with because their energy security will be more vulnerable to the risk and uncertainty in the countries.

However, further studies still remain. It is necessary to evaluate whether the features from 2007 to 2019 might be altered when the COVID-19 pandemic period is included. Because the pandemic depressed the oil prices as well as the world economy, the pandemic sub-period is expected to produce new findings. Also, regarding the methodological issue, the event study method is an alternative way to directly access the effect of specific global events on the correlation and volatility spillover between crude oil prices.

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