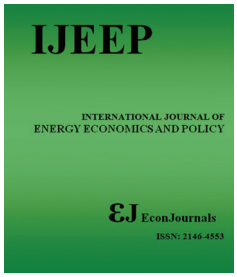

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2020, 10(1), 377-383.

Dynamic Linkages Between the Oil Spot, Oil Futures, and Stock Markets: Evidence from Dubai

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Received: 12 August 2019 **Accepted:** 01 November 2019 **DOI:** https://doi.org/10.32479/ijeep.8705

ABSTRACT

In this paper, we investigate the dynamic linkages between prices on the oil spot, oil futures, and energy stock markets in Dubai between June 29, 2010 and November 02, 2018. We apply a class of multivariate GARCH model to analyze this relationship. We also consider the corresponding markets in the United States, and in order to examine the volatility transmission among the three markets, we use the HAR model. Our empirical results reveal that the correlations between the three markets in Dubai are lower than in the US. We observe high levels of correlations before crises, but this was not the case during the crises themselves. Furthermore, we demonstrate the existence of volatility transmission between the oil spot and futures markets and the oil spot and energy stocks markets, while there is only a unidirectional effect from the energy stock market to the oil futures market. Overall, our findings are crucial for understanding the dynamics that exist between the three markets.

Keywords: Oil Prices, Stock Market, DCC-GARCH, VAR
JEL Classifications: G12, Q43

1. INTRODUCTION

The opening up of economies and the onset of financial liberalization has considerably contributed to increasing market volatility. This fact has attracted growing interest in understanding market volatility and the mechanisms for volatility transmission between financial markets, because this is vital for international investors and policy makers. Oil has been considered a major economic growth catalyst since the 19th century, and several economies in the world depend on oil, especially given the increased integration between commodity markets and financial markets. It is therefore imperative to comprehend the linkage between the crude oil and stock markets. A massive body of literature has revealed results for many countries about the relationship between oil price shocks and aggregate activity, which suggests that a similar relationship also exists between oil price movements and stock markets (Jones and Kaul, 1996; Gjerde and Saettem, 1999; Park and Ratti, 2008; Miller and Ratti, 2009; and Narayan and Sharma, 2011). Hence, understanding the price behavior of oil and stock markets and the volatility transmission mechanism between these markets is essential for traders and portfolio managers, as well as governments.

The literature investigating the relationships between the stock and oil markets continues to expand. However, studies focusing on the dynamic correlation between these markets are limited, but we will summarize the previous findings in this area. Sadorsky (1999) used a VAR model to demonstrate that oil prices and oil price volatility affect stock returns. They suggest that movements in oil prices impact stock returns, but movements in stock returns have little impact on oil prices. Hammoudeh and Aleisa (2004), meanwhile, investigated the linkages among the stock markets of Gulf Cooperation Council (GCC) members, demonstrating a bidirectional relationship between stock markets and oil futures

prices. They also suggest that the impact of oil price changes is weak for GCC members nevertheless consistent with results for the United States' stock market. Park and Ratti (2008) examined the relationship between oil prices and real stock prices for the United States and thirteen European countries over 20 years. They found a significant positive reaction of real stock volatility to a rise in oil price volatility for many European countries. In addition, increased volatility for oil prices significantly reduced real stock returns.

Recently, studies interested in the volatility transmission between the oil and stock markets have been increasing. Malik and Ewing (2009) tried to understand the volatility transmission across sector indexes and oil prices in the United States. The estimation results of a bivariate GARCH (generalized autoregressive conditional heteroskedasticity model) showed evidence of significant volatility transmission between oil prices and several market sectors. The authors followed up on the idea by supporting cross-market hedging and allocating common information by investors. Mensi et al. (2013), meanwhile, examined volatility transmission across commodity and stock markets. The authors linked the S&P 500 with commodity price indexes for energy, food, and gold, finding significant transmission among these markets. Guesmi and Fattoum (2014) investigated the dynamics of volatility between stock markets and oil prices for some oil-importing countries and some oil-exporting countries. Through a multivariate GJR-DCC-GARCH approach, as proposed by Glosten et al. (1993), they showed that the dynamics of the correlations are similar for oil-importing and oil-exporting countries and that oil prices reveal a positive correlation with stock markets. In addition, Souček and Todorova (2013) demonstrated a considerable spillover effect between the realized volatility of the S&P500 and WTI crude oil futures contracts. The authors used a multivariate orthogonalized HAR model to distinguish the short-, mid- and long-term transmission effects.

A considerable number of studies have focused on investigating the interaction between oil and stock markets (Filis et al., 2011; Sadorsky, 2012; Phan et al., 2016). Bhar and Nikolovann (2010) used a bivariate EGARCH model to inspect the dynamic correlation between oil prices and the stock market in Russia. They detected three main historical events (i.e. the September 11, 2001 terrorist attack, the 2003 Iraq war, and the civil war in Iraq in 2006) and revealed a negative correlation between oil prices and the Russian stock market. Cifarelli and Paladino (2010), meanwhile, employed a multivariate CCC-GARCH model and stipulated that oil price movements are negatively linked with stock price and exchange rate variations. Chang et al. (2010) demonstrated the volatility transmission between the WTI and Brent oil markets and the US stock market using a symmetric extension of the DCC-GARCH model. Olson et al. (2014), for their part, used the multivariate BEKK model to examine the linkage between the S&P 500 and Goldman Sach's Energy Index. They concluded that S&P 500 returns positively influence volatility in the energy index, whereas energy price shocks had no strong impact on S&P 500 volatility.

The class of GARCH model developed by Bollerslev (1986) is frequently applied to examine volatility and relationships among markets. The Constant Correlation Coefficient GARCH model, which was the first multivariate extension in its class, was initiated by Bollerslev (1990). Engle (2002), however, suggests that in the real world, the CCC-GARCH model is incapable of capturing the dynamic correlation between financial markets. Hence, the author proposed the Dynamic Condition Correlation multivariate GARCH model to better estimate the time-varying correlation between parameters. Since then, several studies have demonstrated the DCC-GARCH model's superiority in modelling the linkage between variables in financial markets (Ji and Fan, 2010; Creti et al., 2013; Lin et al., 2014). Sadorsky (2014) explored the conditional correlations among emerging markets' stock prices, oil prices, copper prices, and wheat prices using the DCC-AGARCH and VARMA-AGARCH models, demonstrating that the DCC model better fits the data. More recently, Ping et al. (2018) examined the linkage between China's fuel oil spot, fuel oil futures, and energy stock markets using the multivariate DCC-GARCH model. Comparing it to the corresponding markets in the United States, they concluded that the correlations between the three Chinese markets are less significant.

The literature on return and volatility linkage in Gulf countries is not considerable. We did, however, identify a few studies that investigated the intra- and inter-regional linkage and cross-market volatility transmission (Al-Khazali et al., 2006; Bley and Chen, 2006; Suliman, 2011).

The Dubai Fateh Market is of particular interest for several reasons. Primarily, the market has experienced fast growth over the last decade. Moreover, the income for Dubai's economy comes principally from the oil industry, trade, and financial services. Hence, by focusing on Dubai's markets, we seek to arrive at new conclusions and supply several suggestions for investors and policymakers. Indeed, the introduction of crude oil futures to the Dubai exchange market gives the opportunity to study the associated topic in Dubai's oil markets. This study is therefore the first to investigate the relationship between these three markets in Dubai using a multivariate model.

Our primary goal is to model the dynamic relationship between oil spot prices, oil futures prices, and energy stock markets in Dubai from June 29, 2010 to November 02, 2018. The empirical model for our study associates these three markets with a multivariate GARCH framework. We compare our results to the equivalent markets in the United States. To the best of our knowledge, the linkages between these three markets in Dubai have not been previously investigated.

Table 1: Variables explanation

Variables	Dubai Fateh oil spot	Dubai Fateh oil futures	Dubai energy	WTI crude oil spot	WTI crude oil futures	S&P 500 energy
Symbols	DFOS	DFOF	DFOGI	WTIS	WTIF	SP500

The remainder of this paper is organized as follows: We introduce the methodology in the following section. The data and main variables are then described in section 3, while in section 4, we present the empirical findings. We finally conclude the paper in section 5.

2. METHODOLOGY

To analyze the relationship between the oil spot, oil futures, and energy stock markets, we apply the DCC-GARCH model proposed by Engle (2002), following the work of Ping et al. (2018). This model is a generalization of the CCC-GARCH (Constant Conditional Correlation) model of Bollerslev (1990), and it is defined below:

$$y_t = \phi_0 + \sum_{i=1}^{k} \phi_0 y_{t-i} + \varepsilon_t = \mu_t + \varepsilon_t \quad (1)$$

$$\mu_t = E[y_t \mid \Omega_{t1}] \quad (2)$$

$$\varepsilon_t = H_t^{t/2} z_t \quad (3)$$

$$H_t = D_t R D_t \quad (4)$$

Where y_t represents the $n \times 1$ vector of asset returns, the mean is indicated by μ_t, and the residual ε_t meets $\varepsilon_t \mid \Omega_{t-1} \sim N(0, H_t)$.

H_t denotes the conditional covariance matrix and assures equation (4), where $D_t = diag\{\sqrt{h_{ii,t}}\}$, and $R = (\rho_{ij})\ N \times N$ is the matrix of constant conditional correlation coefficients. Ω_t designates the information set at t, while z_t represents the standardized residual. $h_{ii,t}$, which is described by a univariate GARCH model:

$$h_{ii,t} = \omega + \sum_{p=1}^{P_i} \alpha_{ip} \varepsilon_{i,t-p}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{ii,t-q} \quad (5)$$

The assumption that the correlation coefficient among assets is constant is deemed a limitation of the CCC model, so Engle (2002) proposed the DCC-GARCH model and demonstrated its advantage under the assumption that the correlation coefficients vary over time. The mean equation of the DCC model is equivalent to equation (1), but the residual equation is switched to,

$$H_t = D_t R_t D_t \quad (6)$$

Where $R_t = diag\left(q_{11,t}^{-1/2}, \ldots, q_{nn,t}^{-1/2}\right) Q_t diag(q_{11,t}^{-1/2}, \ldots, q_{nn,t}^{-1/2})$ (7)

With $\eta_t = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$ representing the standardized residuals

And Q_t being the symmetric positive definite matrix:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha z_{t-1} z_{t-1}^{'} + \beta Q_{t-1} \quad (8)$$

Where $\bar{Q} = T^{-1} \sum_{t=1}^{T} \eta_t \eta_t^{'}$ is the $n \times n$ unconditional correlation matrix of η_t. The parameters α and β are non-negative and satisfy the condition that $\alpha+\beta<1$, implying that the DCC model is mean reverting. The impact of previous shocks on present volatility is determined by $(\alpha+\beta)$. The greater $(\alpha+\beta)$ is, the slower that shock impacts decline.

To examine the directional relationships for the volatility spillover effect between markets, we apply the VAR(1)-BEKK-GARCH model. The VAR(1) model of Sims (1980) is used to fit the mean equation, while the BEKK-GARCH(1,1) model of Engle and Kroner (1995) is employed to fit the variance equation:

$$y_t = \gamma + \prod y_{t-1} + \varepsilon_t \quad (9)$$

$$H_t = CC^{'} + A^{'}\varepsilon_{t-1}\varepsilon_{t-1}^{'} A + B^{'} H_{t-1} B \quad (10)$$

Where y_t represents an $n \times 1$ vector of asset returns; γ denotes an $n \times 1$ constant vector; H_t denotes the conditional covariance matrix; $A = (a_{ij})$ and $B = (b_{ij})$ represent all $n \times n$ parameter matrices; and C is a lower triangular matrix. Hence, the volatility spillover effects can be investigated through a_{ij} and b_{ij}, which represent the volatility spillover effect from variable i to j. The maximum likelihood estimation (MLE) will be employed to estimate the parameters of the present models.

3. DATA AND DESCRIPTIVE STATISTICS

We aim to analyze the relationships between oil spot prices, oil futures prices, and the energy stock index of Dubai, but in order to compare this with the equivalent US markets, we examine the WTI (West Texas intermediate) crude spot and futures prices and data for the S&P 500 energy index, as traded on the New York Mercantile Exchange. The symbols of the variables to be exploited are presented in Table 1. The database used, which was sourced from Bloomberg, comprised daily closing prices from June 29, 2010 to November 02, 2018. We computed daily returns ($r_{i,t}$) from the fluctuations between t and $t + 1$ by employing the following logarithmic filter:

$$r_{i,t} = 100\text{Ln}(P_{i,t} / P_{i,t-1}), \text{ for } t = 1, 2, \ldots, T \quad (9)$$

Where $P_{i,t}$ is the current price and $P_{i,t-1}$ denotes the preceding price of index i. We measure the daily actual volatility in line with Sadorsky (2006) by using daily squZared returns (r_t^2).

Table 2 gives the descriptive statistics for all the daily return series over the sample period. It shows that the mean of all the examined series was around zero over the sample period. The highest standard deviation (0.0203) was found for the WTI crude oil futures, suggesting this market had the greatest risk, followed by the WTI crude spot market (0.020). The skewness values were positive for the returns on Dubai Fateh crude futures, WTI crude spot, and WTI crude futures, while they were negative for returns on the Dubai Fateh crude oil spot, the Dubai Fateh energy index, and the S&P 500 energy index. Investors therefore had more chance of positive returns from Dubai Fateh crude oil futures, WTI crude oil spot, and the WTI crude oil futures markets than those market series with a negative skewness. Moreover, the excess kurtosis values of the index returns are above the value of the normal distribution, denoting that the return indices have peaks when compared to the normal distribution. Regarding the Jarque-Bera test, the results indicate that the variables demonstrate a significant departure from the normal distribution.

Table 2: Descriptive statistics

Variables	Mean	Median	Maximum	Minimum	Standard deviation	Skewness	Excess Kurtosis	Jarque-Bera
DFOS	−0.0001	−0.0002	0.1197	−0.1208	0.0190	−0.004	3.8700	1767.546 (0.000)
DFOF	0.0002	0.0003	0.1477	−0.0872	0.0196	0.5591	9.3599	3650.41 (0.000)
DFGI	−0.0002	−0.0001	0.0791	−0.1220	0.0135	−0.0308	6.0133	7146.952 (0.000)
WTIS	0.0000	0.0006	0.1162	−0.1079	0.0201	0.0383	3.256	757.413 (0.000)
WTIF	0.0001	0.0004	0.1162	−0.1079	0.0203	0.0547	3.061	852.5105 (0.000)
SP500	0.0002	0.0003	0.0535	−0.0863	0.0131	−0.3436	2.7555	812.2914 (0.000)

The results of the ADF and ARCH tests are reported in Table 3. The ADF test results reveal that all the return series represent a stationary process. The test results show the presence of ARCH effects, implying that the series are integrated of order 1 and can be estimated with a class of GARCH model involving a constant in the mean equation and a GARCH(1,1) variance equation.

Table 3: Statistical tests

Variables	ADF test	P-value	ARCH test	P-value
DFOS	−46.018	0.000	95.031	0.000
DFOF	−44.422	0.000	75.152	0.000
DFGI	−41.477	0.000	96.142	0.000
WTIS	−49.243	0.000	58.659	0.000
WTIF	−48.890	0.000	64.765	0.000
SP500	−46.413	0.000	79.074	0.000

4. EMPIRICAL RESULTS AND ESTIMATIONS

In this section, we proceed to analyzing the correlation among the daily returns series using the CCC and DCC models. Table 4 reports the results for the constant conditional correlations obtained from the CCC model. For the Dubai markets, the estimated correlations reveal that the correlation among crude oil spot and crude oil futures (DFOS and DFOF) is 0.0076, while for crude oil spot and the global index (DFOS and DFGI), it is 0.026. For crude oil futures and the global index (DFOF and DFGI), meanwhile, it is −0.0078. These correlations are at a low level, implying that correlations between the three markets are not particularly strong and at a low level of statistical significance. The crude oil price in Dubai is not directly related to international crude oil prices. For the American markets, the correlations are 0.2145 (WTIS and WTIF), 0.2852 (WTIS and SP500E), and 0.1463 (WTIF and SP500). Compared to previous studies (e.g., Ping et al., 2018), the correlations are less strong, but we do find a low-significance positive correlation between the three markets. This does not support the idea that oil price movements lead to energy stock price transformations. An increasing oil price does lead to a higher stock price, suggesting a positive correlation between the oil spot price and the energy stock index. This finding can be supported by the fact that the energy stock index increases in response to rising oil prices in the short term but not in the long term. On the contrary, there is no clear indication that there will be any continuation of short-term effects in the long run. It is therefore considered that any changes in oil spot prices lead to a short-run rather than a long-run phenomenon. The results primarily indicate that oil prices are negatively correlated with stock markets during periods of either precautionary demand shock or aggregate demand shock. This shows that the stock market correlation can be greater, with positive changes occurring in the long-run without the effect of oil prices. However, it should be noted that the stock market correlation cannot be affected by supply-side oil price shocks. It is already clear that supply-side oil price shocks do not exert any influence on stock market performance, so it follows that such shocks will not impact the stock market correlation.

However, the limited correlations between Dubai markets can be explicated by the oil price policy. The liberalization of the oil prices from 2015 has diminished the linkage between oil prices and the stock market in Dubai. The correlation between DFOF and DFGI is more important than that between DFOS and DFGI, and this can be explained by the fact that financial derivatives (DFOF) can capture more market information because they are driven by speculative demand. In addition, the low correlation between DFOF and DFOS suggests that the futures market is unable to precisely reflect future prices. Based on these findings, it can be noted that the correlation between DFOS and DFGI indirectly affects the derivatives market. The impact of oil price on Dubai stock prices succeed in the long-run because macroeconomic indicators are influenced by oil price effects that influence liquidity of these markets. This implies that the influence of oil price modifies to important macroeconomic indicators, which particularly affect the association between oil prices and stock exchange in Dubai in the long-term equilibrium. Changes are observed from conditions that emphasize observable factors to influence an economy. In addition, speculative factors operate over short periods comprehensively within a market. Therefore, Dubai market can be significantly strong but fundamentally weak or the vice versa. In the present study context, the long-term is accounted when changes made in oil price transmits to major macroeconomic predictors that impact the firms profitability traded in stock market.

Table 4: Correlations results of CCC-GARCH(1,1) model

Variables	DFOS	DFOF	DFGI	WTIS	WTIF	SPE
DFOS	1	0.0076	0.026			
DFOF	0.0076	1	−0.0078			
DFGI	0.026	−0.0078	1			
WTIS				1	0.2145	0.2852
WTIF				0.2145	1	0.1463
SP500				0.2852	0.1463	1

Table 5: Estimation results of DCC-GARCH(1,1)

Parameters	w	α	β	$\alpha+\beta$
DFOS	1.33E-04	0.0659	0.9327	0.9987
DFOF	1.94E-05	0.3213	0.6085	0.9298
DFGI	4.47E-06	0.1256	0.8505	0.9761
WTIS	8.1E-05	0.0541	0.9410	0.9951
WTIF	1.3E-06	0.0526	0.9423	0.9949
SP500	2.74E-06	0.0793	0.9057	0.985
DCC		0.0067	0.9894	0.9961

Table 5 shows the DCC model estimation for each variable. According to the results of the $\alpha+\beta$ parameters, which are close to 1, we can assume that all variables indicate volatility clustering.

Figures 1-3 show the dynamic conditional correlations between the energy stock index, oil spot, and oil futures return series for Dubai and the United States. We can see how the correlation sequences between the Dubai markets are less volatile, which is likely due to Dubai's policy of controlling oil prices. The correlations between oil spot and futures prices are at low levels (mostly between 0 and 0.2), which is comparable to the results achieved with the CCC model. We analyze these results by referring to the spot oil price and stock indices. Figure 4 displays the spot oil price in both Dubai and the USA for the studied period, and we can observe how the DFOS generally shadows the WTIS. Figure 5, however, shows a distinct differences between the DFGI and SPEP, with the Dubai stock market being more volatile than the American stock market.

Due to the importance of oil to the economy, its price is principally affected by real demand and speculative demand. In Figure 6, oil prices in the Dubai market show a high level of volatility, indicating the financial phenomenon of oil and demonstrating the strong dominance of speculative demand over real demand, with this dominating the first sample period. During the second period, the oil prices reflect more real demand, with a decline in the relationship between oil and stock. The inconsistency between the futures market and the spot market is due to futures prices being governed by current transactions for future exchanges, thus improving price transparency and limiting the spot market's role in price discovery.

We studied the volatility transmission between the three markets in Dubai using a VAR(1)-BEKK-GARCH(1,1) model. Tables 6

Figure 1: Dynamic conditional correlation between oil spot and futures prices in Dubai and the USA (DFOS/DFOF and WTIS/WTIF)

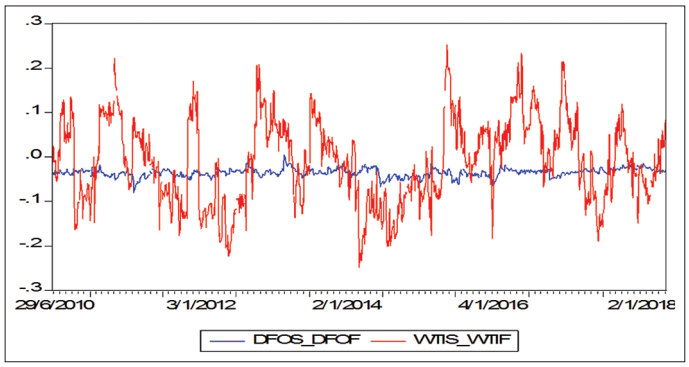

Figure 2: Dynamic conditional correlation between oil spot and futures prices in Dubai and the USA (DFOS/DFGI and WTIS/SP500)

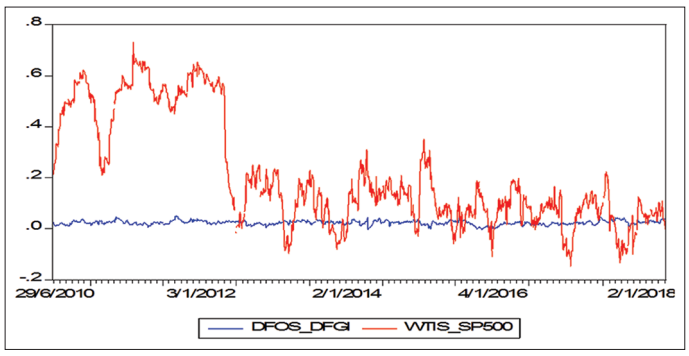

Figure 3: Dynamic conditional correlation between oil spot and futures prices in Dubai and the USA (DFOF/DFGI) and (WTIF/SP500)

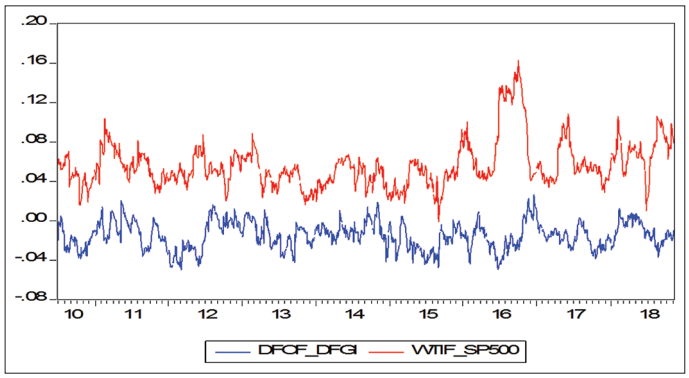

Figure 4: The spot prices of Dubai Fateh spot oil and WTI crude oil

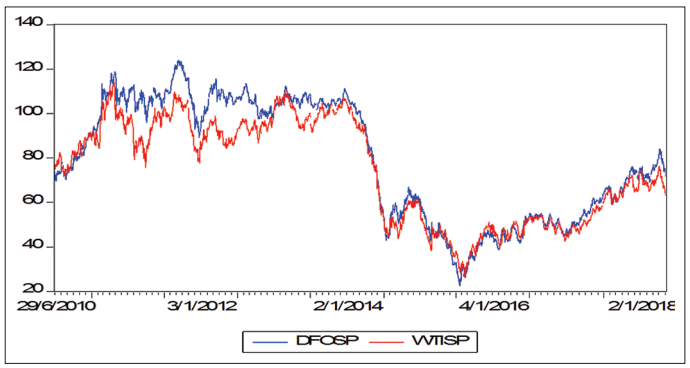

Figure 5: The energy stock indices for Dubai and the USA

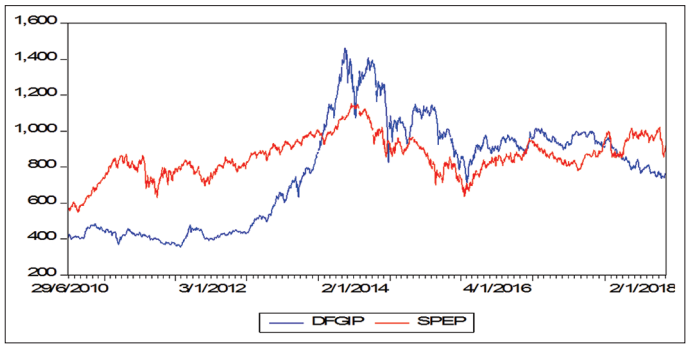

Figure 6: Volatility of Dubai's oil spot, oil futures, and energy stock returns (June 29, 2010-November 02, 2018)

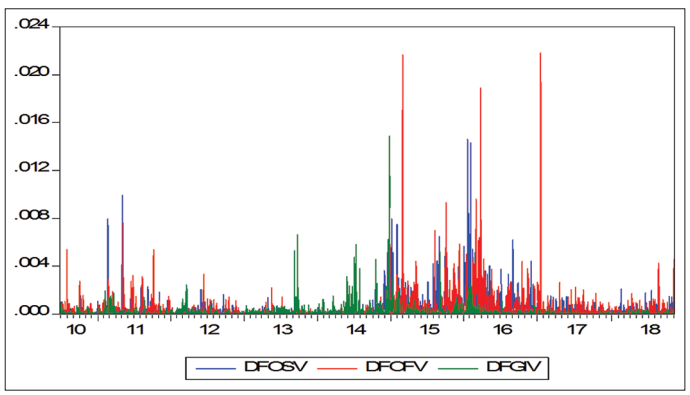

Table 6: VAR(1) model's parameter estimates for the three Dubai markets

Parameters	DFOSR	DFOFR	DFGIR
C	−1.04E5*	0.0003	−0.0002
	(−0.025)	(0.7088)	(−0.9008)
DFOSR(−1)	−0.0046**	−0.0102**	0.0073
	(−0.1856)	(−0.4570)	(0.474)
DFOFR(−1)	−0.0137**	−0.0759	0.0015
	(−0.6487)	(−3.4849)	(0.1007)
DFGIR(−1)	−0.0141**	0.0141**	0.0973**
	(−0.475)	(0.6561)	(4.4615)

1. *, **, *** denote significance at the 10%, 5%, 1% levels, respectively. 2. The t-statistics are shown in parentheses

Table 7: VAR(1) model parameter estimates for Dubai three markets

Parameters	Estimation results		
C	0.0012***		
	(3.9010)		
	0.0016***	0.0010**	
	(2.5755)	(3.2135)	
	0.0002	−0.0000	0.0000
	(0.8467)	(−0.0942)	(0.0915)
A	0.9740***	0.8814***	1.5126**
	(14.04)	(14.15)	(5.5895)
	−0.2856***	0.3013***	−0.0263
	(−5.9602)	(3.9061)	(−0.6301)
	−0.08814***	−0.0687**	0.2213***
	(−7.16)	(−2.1058)	(2.4602)
B	0.5329***	−0.0754	1.3654***
	(5.348)	(−0.6789)	(5.8745)
	0.0438	0.9846	−0.2875
	(0.3245)	(24.7841)	(−0.8415)
	0.2856***	−0.4080***	−0.9984***
	(5.960)	(−3.906)	−15.8321

1. *, **, *** denote significance at the 10%, 5%, 1% levels, respectively. 2. The t-statistics are shown in parentheses. 3. a_{ij} and b_{ij} denote volatility spillover effects from variables i to j. For example, a_{23} (−0.0263) and b_{23} (−0.2875) are insignificant, indicating the absence of any volatility spillover effect from DFOFR to DFGIR

Table 8: VAR(1) model's parameter estimates for Dubai's three markets

Volatility transmission	Null hypothesis	Wald test	P-value
Between DFOS and DFOF	$a_{12}=a_{21}=b_{12}=b_{21}=0$	53.5361	0.0000
From DFOS to DFOF	$a_{12}=b_{12}=0$	5.6596	0.0000
From DFOF to DFOS	$a_{21}=b_{21}=0$	10.6887	0.0000
Between DFOS and DFGI	$a_{13}=a_{31}=b_{13}=b_{31}=0$	32.0312	0.0000
From DFOS to DFGI	$a_{13}=b_{13}=0$	2.6871	0.0073
From DFGI to DFOS	$a_{31}=b_{31}=0$	7.3168	0.0000
Between DFOF and DFGI	$a_{23}=a_{32}=b_{23}=b_{32}=0$	13.7256	0.0000
From DFOF to DFGI	$a_{23}=b_{23}=0$	0.6673	0.5236
From DFGI to DFOF	$a_{32}=b_{32}=0$	3.7256	0.0002

and 7 supply the model's parameter estimates. Table 8, meanwhile, shows the first-order autocorrelation significance related to all series. The DFOSR series is impacted by the first-order lag items of all series present, while DFOFR is influenced by the first-order lag items of DFOSR and DFGIR. We can assume the existence of bilateral mean spillover effects between DFOSR and DFOFR. In addition, the results demonstrate only unidirectional influences from DFGIR to DFOSR and DFOFR. We can observe that the coefficient between DFOSR and DFGIR(−1) is negative, and this relates to the oil price policy of Dubai.

Table 7 shows the volatility spillover effects between variables. The results show that at the 1% level, the parameters a_{11}, a_{22}, a_{33}, b_{11}, b_{22} and b_{33} are all significant, implying that DFOSR, DFOFR, and DFGIR exhibit volatility clustering. In addition, all significant parameters show a volatility spillover effect between variables. For example, for the significance of a_{31} and b_{31}, a volatility variation in the oil spot market after a shock in the energy stock market can be expected.

In order to investigate the accuracy of the volatility spillover effect, we proceed to the Wald test. The results in Table 8 suggest significance at a 10% level for most of the volatility spillover impacts. However, this significance is absent for DFOFR and DFGIR. The results demonstrate how bilateral volatility spillover exists between oil spot and futures prices, as well as oil spot prices and the energy stock index. There is also a unidirectional effect from the energy stock market to the oil futures market, and this may be attributed to speculative demand in the energy stock market affecting the oil futures market.

5. CONCLUSION

This study aimed to examine the dynamic relationship between oil futures prices, oil spot prices, and energy stock markets in Dubai. In this study, the empirical model correlates the three markets using a multivariate GARCH and VAR-BEKK-GARCH framework. A comparison was also made between the markets of Dubai and their equivalents in the United States. It can be concluded that there is an indirect correlation between crude oil prices in the Dubai markets when compared to international crude oil prices and the United States markets. Similarly, the correlation between oil prices and the stock market in Dubai has decreased due to the liberalization of oil prices that began in 2015. The study also showed a week correlation between Dubai's oil spot and futures prices. During the second period, oil prices reflected real demand, with there being a decline in the relationship between oil and stock. In addition, because oil is important to the economy, its price is principally affected by real and speculative demand.

Based on these findings, this study concludes that the relationship between oil and energy stocks is not strong. This result implies that oil cannot represent a useful hedging tool for enrgy stocks. Nevertheless, investors can employ the volatility transmission between markets to moderate their expectations.

For Dubai market, we can advance that the control policy affects the linkage among oil spot and futures markets in two ways. Firstly, the hedging against loss of futures becomes absent. Secondly, the expansion of the Dubai oil futures, as a hedging instrument, will be useful for oil corporations. Besides, the size of the derivatives

market can also be stimulated by improving or fostering size, specifically in developing and emerging countries by encouraging energy stock markets. Unobserved outcomes should be prevented, however, because they exert a negative effect in the short-term effect and cause growth volatility when using an appropriate regulatory framework.

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