International Journal of Energy Economics and Policy
Vol. 4, No. 2, 2014, pp.189-197
ISSN: 2146-4553
www.econjournals.com

Does WTI Oil Price Returns Volatility Spillover to the Exchange Rate and Stock Index in the US?

Ching-Chun Wei
Department of Finance, Providence University,
200 Sec 7, Taichung Boulevard, Taichung City, 433, Taiwan.
Email: ccw@pu.edu.tw

Chung-Hsuan Chen
Department of Finance, Providence University,
200 Sec 7, Taichung Boulevard, Taichung City, 433, Taiwan.
Email: sulabiao624@yahoo.com.tw

ABSTRACT: The purpose of this paper is to examine whether the volatility of the West Texas Intermediate oil spot returns (WTIR) is affected by the Texas Light Sweet oil futures returns (FUR), the exchange rate returns between the US dollar and the Euro (ERR), and the S&P 500 energy index returns (EIR), and if any of those have changed over time. The daily data of the WTIR, the FUR, the ERR, and the EIR between the period of January 4, 2000 and September 30, 2009, were utilized. The empirical results of the multivariate GARCH of the BEKK model indicated that the WTIR is significantly affected by its own past volatility, and by the volatility of FUR, ERR, and EIR. Most likely, WTIR employs a structural conversion in our dummy variable for selected time points. This suggests that investors could use the FUR's past volatility as a basis for WTIR purchase. In addition, the changes in ERR's and EIR's past volatility can be partially used as a basis for the same purpose.

Keywords: Oil spot and futures; Exchange rate; Stock index market; Multivariate GARCH-BEKK
JEL Classifications: C32; G32; Q43

1. Introduction

Although some commodities have seen a global boom in recent years, the experience of the crude oil industry is extraordinary. Crude oil acts as a driver of the US economy and sets the standard of living for the people in the USA. It is arguably the world's most influential physical commodity since it provides energy for a variety of human activities. The futures market of crude oil plays an important role in providing efficient prices. Many macroeconomic variables, such as the exchange rate and the stock index, are also important in increasing or decreasing the value of crude oil. In the end, crude oil is a dynamically traded commodity that is affected by many macroeconomics variables.

All things being equal, an ever-decreasing USD rate requires an ever-increasing amount of dollars to allow the purchase of the quantity of oil that the nation consumes. A negative relationship between oil and the USD has been commonly cited in the popular economic press. For example, in mid-December 2008, crude oil futures spiked amid expectations of a production cut by OPEC based on a weakening USD. The rationale was that "a cheaper dollar makes oil priced in US currency an attractive buy for foreign investors, while at the same time acting as a hedge against inflation" (The Wall Street Journal, December 12, 2008).

The present study accommodates market issues from different perspectives. It focuses on the fluctuation of US crude oil, the US oil futures, the US exchange rate, and the US stock index. Over time changes take place in the conditional volatility of the oil market, exchange rate market, and stock index market. Indeed, countless studies have attempted to examine the causes of such changes. There is a considerable amount of literature on the relationship between oil price, financial and macroeconomics variables, and the stock index market. Some of this literature examined the impact of oil prices on macroeconomic variables such as the exchange rate (Zhang et al., 2008; Narayan et al., 2008) or the stock index (Narayan and Narayan, 2010; Cong et al., 2008; Park and Ratti, 2008), while others analyzed the energy futures market (Wu and Yang, 2008; Liao et al., 2008).

There is a significant relationship among oil price returns, exchange rate returns, and stock index returns. Thus, if oil has an impact on real output, a rise in oil price will depress the aggregate stock index price, suggesting that oil prices are associated with stock index returns (Nandha and Faff, 2008; Park and Ratti, 2008). In addition, the exchange rate can be incorporated into the basic model for oil price determination. Lizardo and Mollick (2010) provide evidence of the influence of the exchange rate on oil prices, by explaining the movements in the value of the American dollar (USD) against major currencies from the 1970s to 2008. However, studies examining the links of oil price, exchange rate, and stock index are relatively rare. Therefore, this study focused on the changes in oil price volatility, as opposed to general macroeconomic variables. This study follows the study of Lee and Chung (2007) on time-variation analysis.

The ARCH model, originally developed by Engle (1982) and later generalized by Bollerslev (1986), is by far the most popular method for modeling the volatility of high-frequency financial time series data. Multivariate GARCH models have been popular for estimating the volatility spillover effect in different markets.

The purpose of this paper is to estimate the volatility of the returns in spot and futures prices of West Texas Intermediate (WTI), the exchange rate, and the stock index. These factors are then utilized in the recently developed multivariate generalized autoregressive conditional heteroscedasticity (GARCH) models. In addition, this study aims to test the existence of causal lead-lag relationships in the returns of WTI crude oil spot, Texas Light Sweet oil futures, the US/ Euro exchange rate, and the S&P 500 energy index. Consequently, based on the oil price dynamics, investments can be identified upon the full understanding of the relationships of oil spot and futures markets, exchange rate, and the stock index market.

Recent research has used multivariate GARCH specifications, especially BEKK, to model volatility spillovers into crude oil, exchange rates, and stock markets. Hammoudeh et al. (2004) reported on the two-way interactions between the S&P oil sector stock index and the oil spot and futures prices. Ågren (2006) presents strong evidence of volatility spillovers from oil prices into the stock market using the asymmetric BEKK model of the Japan, Norway, UK, and US stock markets, as well as rather weak evidence of a volatility spillover into the Swedish stock market.

Most of the time-series models experience changes. When these changes are applied to data, the location must be determined. Clearly, any estimation or inference that fails to acknowledge this fact may result in unreliable results. Our study developed several methodologies, such as the augmented Dickey and Fuller (ADF) test, the Granger causality test, the impulse-response function of the vector autoregression (VAR) model, and the multivariate GARCH version of the BEKK model to investigate the impact of oil futures, the US $ / Euro exchange rate and the S&P 500 energy index shocks on oil spot returns.

In this study we assume that oil spot returns are affected by oil futures returns (FUR), the US / Euro exchange rate (ERR), and the S&P 500 energy index return (EIR) shocks. We hypothesize that a relationship exists between oil price returns, exchange rate, and stock index returns. Variations in oil prices are then investigated based on several methods. This is followed by an examination of the effects of the FUR, ERR, and EIR on WTIR using the multivariate GARCH version of the BEKK model.

This paper uses empirical methodology to determine the correlations between the oil market and the exchange rate as well as the correlations between the oil market and the stock index market. Empirical results show significant fluctuations in the WTIR. These changes have a significant impact on FUR, ERR and EIR. We also found that the WTIR were significantly affected by their past volatility and by the volatility of FUR and ERR. It is possible that the WTIR impose a structural conversion on our dummy variable at selected time points.

The remainder of this paper is organized as follows. Section 2 provides a review of the related literature, while section 3 describes the empirical methodology adopted for this study. In section 4 we present the data and the empirical results. Finally, in section 5 we summarize our conclusions.

2. Methodology

In non-stationary time series, this method is common for first identifying the difference in the variables. In stationary time series, the ADF unit root test is employed first, the multivariate GARCH of the BEKK model is utilized to discuss the shock and volatility of the variables returns. A dummy variable is added to represent the financial tsunami of 2008.

The first step in the multivariate GARCH methodology is to specify the mean equation. The commodity in these empirical systems with the WTIR at time t is indexed by 1. Consequently, WTIR, FUR, ERR, and EIR at time t-1 in this empirical systems are indexed by 1, 2, 3, and 4. Meanwhile, n denotes the total number of commodities included in the various models. In each system, all the commodity combinations have four variables, so that n=4. The mean equation for i and j commodities in this system is AR (1). Accordingly, the mean equation for each return series is given by

$$R_{1,t} = a_1 + b_{11}R_{1,t-1} + b_{12}R_{2,t-1} + b_{13}R_{3,t-1} + c_1D + \varepsilon_{1,t} \tag{1}$$

where $R_{1,t}$ is the WTIR at time t, $R_{1,t-1}$, $R_{2,t-1}$, and $R_{3,t-1}$ are the WTIR, the FUR, and the ERR (or the EIR) at time t-1. Herein, a_1, b_{11}, b_{12}, b_{13} and c_1 are long-term drift coefficients. D denotes the dummy variable for the 2008 financial crisis, and is equal to 1 if it represents the period between January 3, 2007 and September 30, 2009. In addition, it is equal to 0 if it represents the period between January 4, 2000 and December 29, 2006. In Eq. (1), $\varepsilon_{i,t}$ is the error term for WTIR at time t. Eq. (1) is tested as described by Engle (1982) for the existence of autoregressive conditional heteroscedasticity (ARCH[1]). All estimated series exhibit evidence of ARCH effects.

There are two popular parameterizations for the multivariate GARCH model mentioned in the literature. The VECH model (Bollerslev, Engle, and Wooldridge, 1988) is given as

$$\mathrm{vech}(H_t) = W_0 + \sum_{j=1}^{q} B_j \mathrm{vech}(H_{t-i}) + \sum_{j=1}^{p} A_j \mathrm{vech}\left(\varepsilon_{t-j}\varepsilon'_{t-j}\right) \tag{2}$$

where $\varepsilon_t = H_t^{1/2}\eta_t$, $\eta_t \overset{iid}{\sim} N(0,1)$, the notation $\mathrm{vech}(H_t)$ is the stack of columns on and below the diagonal of the symmetric matrix X_t, and H_t is the conditional variance matrix. In practice, several simplifying assumptions are imposed to reduce the number of estimated elements. However, the challenge is to constrain all elements as positive during the estimation to ensure a positive semi-definite covariance matrix.

Next we use a convenient alternative parameterization for H_t (Engle and Kroner, 1995). This allows us to examine the direct dependence of the individual conditional variances on its history and cross-innovations, as well as on the association with its own and cross-conditional variances. In the multivariate case of the first order BEKK model,

$$H_t = W_0'W_0 + \sum_{k=1}^{k}\sum_{i=1}^{q} A'_{ik}\varepsilon_{t-i}\varepsilon'_{t-i}A_{ik} + \sum_{k=1}^{k}\sum_{i=1}^{q} B'_{ik}H_{t-i}B_{ik} \tag{3}$$

where the individual elements for the W, A, and B matrices for Eq. (3) are given as

$$W = \begin{bmatrix} w_{11} & 0 & 0 & 0 \\ w_{21} & w_{22} & 0 & 0 \\ w_{31} & w_{32} & w_{33} & 0 \\ w_{41} & w_{42} & w_{43} & w_{44} \end{bmatrix}, \quad A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}, \quad B = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} \end{bmatrix}$$

We set the conditional variance for the equation and for the multivariate GARCH(1,1) as

$$H_t = W_0'W_0 + A'_{11}\varepsilon'_{t-1}\varepsilon_{t-1}A_{11} + B'_{11}H_{t-1}B_{11}$$

---

1. The test statistic is distributed as χ^2 with degrees of freedom equal to the number of restrictions. Each return series exhibits significant ARCH effects, which suggest that the past values of volatility can be used to predict the current volatility.

$$H_t = W_0' W_0 + \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}' \begin{bmatrix} \varepsilon_{1t-1}^2 & \varepsilon_{1t-1}'\varepsilon_{2t-1} & \varepsilon_{1t-1}'\varepsilon_{3t-1} & \varepsilon_{1t-1}'\varepsilon_{4t-1} \\ \varepsilon_{1t-1}'\varepsilon_{2t-1} & \varepsilon_{2t-1}^2 & \varepsilon_{2t-1}'\varepsilon_{3t-1} & \varepsilon_{2t-1}'\varepsilon_{4t-1} \\ \varepsilon_{1t-1}'\varepsilon_{3t-1} & \varepsilon_{2t-1}'\varepsilon_{3t-1} & \varepsilon_{3t-1}^2 & \varepsilon_{4t-1}'\varepsilon_{3t-1} \\ \varepsilon_{1t-1}'\varepsilon_{4t-1} & \varepsilon_{2t-1}'\varepsilon_{4t-1} & \varepsilon_{3t-1}'\varepsilon_{4t-1} & \varepsilon_{4t-1}^2 \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}$$

$$+ \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} \end{bmatrix}' \begin{bmatrix} h_{11t-1} & h_{12t-1} & h_{13t-1} & h_{14t-1} \\ h_{21t-1} & h_{22t-1} & h_{23t-1} & h_{24t-1} \\ h_{31t-1} & h_{32t-1} & h_{33t-1} & h_{34t-1} \\ h_{41t-1} & h_{42t-1} & h_{43t-1} & h_{44t-1} \end{bmatrix} \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} \end{bmatrix} \quad (4)$$

H_t is the conditional variance matrix, W is a 4×4 lower triangular matrix with 10 parameters, and A is a 4×4 square matrix of parameters showing the extent to which conditional variances are correlated with past squared errors (i.e., deviations from the mean). Hence, the elements of A capture the effects of the shocks or unanticipated events on the conditional variances (volatility). B is also a 4×4 square matrix of parameters and shows how the current levels of conditional variances are affected by the past conditional variances. The total number of estimated elements for the variance equations in this study is 42.

We maximize the following likelihood function, assuming that errors are normally distributed, such that:

$$L(\theta) = -T\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left(\ln|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t\right) \quad (5)$$

where θ is the estimated parameter vector and T is the number of observations. Numerical maximization techniques are utilized to maximize this non-linear log likelihood function. Initial conditions are obtained by performing several initial iterations using the simplex algorithm, as recommended by Engle and Kroner (1995). The BFGS algorithm is then used to obtain the final estimate of the variance-covariance matrix with corresponding standard errors.

3. Data and Empirical Results

The sample period runs from January 4, 2000 to September 30, 2009. Daily data on the WTI oil transactions, the US dollar/Euro exchange rate, and the S&P 500 energy index were obtained from C-Money. The data set was subsequently transformed into daily returns, with the returns defined in their logarithmic form as $R_t = \ln(P_t/P_{t-1})$, where P_t is the closing price at time t.

The dummy in this study covering January 4, 2000 to September 30, 2009 is separated into two sample periods: January 4, 2000 to December 29, 2006 and January 3, 2007 to September 30, 2009. This point was chosen because it shows the region with significant increases, as shown in Fig. 2. Hence, it is considered the turning point of the 2008 financial crisis.

The spot and futures prices of WTI, also known as Texas Light Sweet, are used as a benchmark in oil pricing. WTI is the underlying commodity of the New York Mercantile Exchange's oil futures. The US dollar/Euro exchange rate follows Lizardo and Mollick (2010) which we used to determine the highest weight of the USD against the major currencies (Euro: 65%).

3.1. Descriptive statistics and the unit root test results

Table 1 presents a descriptive statistic for the sample means, standard deviations, skewness, kurtosis, Ljung-Box Q (LB-Q), and the Jarque-Bera (JB) statistics of the West Texas Intermediate (WTI) oil spot returns (WTIR) as well as the Texas Light Sweet oil futures returns (FUR), the US dollar/Euro exchange rate returns, and the S&P 500 energy index returns (EIR). The Ljung-Box Q (LB-Q) statistics for 24 lags of returns, as well as squared returns, and the ARCH-LM test statistics for 12 lags, are reported for the daily returns. The skewness of the statistics suggests a lack of normality in the distribution of the return series. The US dollar/Euro exchange rate has a returns distribution that is positively skewed. The value of the kurtosis indicates that the returns series is leptokurtotic. The JB normality test rejects the null hypothesis of normality. The significant value of the LB-Q statistics for the returns series rejects the null hypothesis of white noise, indicating the presence of autocorrelation. The significant value of LB-Q statistics for the squared returns suggests the presence of autocorrelation in the square of variable returns. ARCH-LM indicates the existence of the ARCH phenomena for the variable series. In accordance with the JB normality test, skewness, and kurtosis statistics (Table 1), the daily returns of the spot and futures for the US crude oil exhibit an ARCH effect, which indicates that the GARCH family of models is appropriate for modeling.

Table 1. Descriptive Statistics

Statistic	WTIR	FUR	ERR	EIR
Mean	0.0004	0.0004	0.0001	0.0003
Max.	0.2128	0.1489	0.0034	0.1696
Mini.	-0.1713	-0.1654	-0.0313	-0.1688
S.D.	0.0273	0.0252	0.0068	0.0189
Skewness	-0.1385	-0.2181	0.0883	-0.3118
Kurtosis	7.7146	6.7904	4.6288	13.30615
Jarque-Bera	2269.415	1481.221	273.1056	10847.11
J-B probability	0.0000***	0.0000***	0.0000***	0.0000***
$L-BQ$ (24)	68.973***	62.410***	52.795***	107.53***
$L-BQ^2$ (24)	1142.2***	1539.2***	1148.5***	3635.4***
ARCH-LM (12)	280.2879***	311.8465****	243.9572***	737.4032***
Sample Periods	2000/01/01-2009/09/30	2000/01/01-2009/09/30	2000/01/01-2009/09/30	2000/01/01-2009/09/30
Observation	2442	2442	2442	2442

Note: (1) S.D. represents the standard deviation; Jarque-Bera is the normality test; $L-BQ(k)$ and $L-BQ^2(k)$ are the Ljung-Box statistics for the level and squared terms for the autocorrelations up to k lags.
(2) ***, **, * denote the statistical significance at the 1, 5 and 10% level.

We examined each individual series using the ADF unit root test (Dickey and Fuller, 1981). The lag-length was set to 12 based on the Akaike information criterion. Table 2 lists the results of the application of the ADF unit root test of the returns to the WTI oil spot, the Texas Light Sweet oil futures, the US dollar/Euro exchange rate, and the S&P 500 energy index. The standard econometric practice for the analysis of financial time series data is to start with an examination of the unit roots.

The ADF test is used to test for all returns in each market under the null hypothesis of a unit root against the hypothesis of stationarity. The results from the unit root test are presented in Table 2. The tests yield negative values in all case levels with the result that the individual returns series reject the null hypothesis at the 1% significance level. The values are stationary for each of the returns of WTI oil spot futures, Texas Light Sweet oil futures, the US dollar/Euro exchange rate, and the S&P 500 energy index.

Table 2. Unit root test results

	Augmented Dickey-Fuller
	Level
WTIR	-10.4083***
FUR	-11.2806***
ERR	-9.6495***
EIR	-9.6028***

Note: (1) ***, **, *: statistically significant at the 1, 5 and 10% level, respectively.
(2) ADF tests with constant (level): lags selected with the Akaike Information Criterion.

3.2. The estimate results of the multivariate GARCH (1,1) of BEKK model

The earliest empirical study by Bollerslev (1986) suggested that the results of the GARCH (1,1) model provide a good fitting for time series models. In the present study, the formation of five variables (e.g., WTIR, FUR, ERR, EIR, and the dummy variable occurred at a point with rising significance (D)). We divided them into two regressions (WTIR-FUR-ERR-D and WTIR-FUR-EIR-D) for the purpose of the test. Because the multivariate GARCH model is not suitable for more than four variables, more than four variables will result in a less accurate estimate.

Before estimating the parameters of GARCH (1,1), we first tested this model for the generation of residual items (i.e., whether they exist in the ARCH phenomenon). If they existed, then the parameters were further adopted into the GARCH model and processed for empirical analysis. This study used the Lagrange multiplier (LM) test to examine whether the residual items of a time series existed in the ARCH effects. Table 1 shows that the residual items of the variables exist in the ARCH effects.

In addition, the multivariate GARCH of the BEKK model was used to analyze the volatility of the oil spot prices and futures markets, the exchange rate, and the stock index market. In this paper, we employed the LB-Q test for the residual items of the model and the items of the squared residuals. The results of the ARCH-LM and LB-Q tests are presented in Tables 3 and 4. They show that it is appropriate to consider the variance change over time.

Tables 3 and 4 show the empirical results of the multivariate GARCH of the BEKK model, including the mean equation and the variance equation. The results for Eq. (1) are shown in Table 3. The WTIR are significantly impacted at 1% and 5%, respectively, with a lag of one period by itself, as well as in FUR and ERR. Next, we set up a dummy variable. The time points were 10% significantly correlated with the WTIR. Table 4 shows the results of Eq. (1). These results also show similar findings, such that the WTIR are significantly impacted with a lag of one period by itself at the 1% level, and in FUR and EIR at the 5% and 10% level, respectively. We set up a dummy variable that for a specific point in time has equally a 10% significant effect on the WTIR. The results indicate that the past information of FUR, ERR, and EIR can be used to explain the present WTIR. A one period lag for FUR, ERR, and EIR, makes the impact similar to that of the WTIR. These above mentioned relationships are very strong.

Table 3. The parameter estimation results of the returns of the oil futures and the exchange rate to the oil spot prices

Coefficient	WTIR-FUR-ERR-D						
Mean Equation							
b_{11}	0.0011*** (0.0003)	b_{12}	0.0013*** (0.0003)	b_{13}	0.0003** (0.0001)	b_{14}	0.0009* (0.0004)
Variance Equation							
α_{11}	0.6325*** (0.0126)	α_{12}	-0.0329*** (0.0113)	α_{13}	0.0309** (0.0094)	α_{14}	0.0062* (0.0322)
α_{21}	-0.6829*** (0.0160)	α_{22}	-0.0201** (0.0102)	α_{23}	-0.0250** (0.0098)	α_{24}	-0.0127 (0.0340)
α_{31}	0.8164*** (0.0494)	α_{32}	0.9390*** (0.0401)	α_{33}	0.1121*** (0.0126)	α_{34}	-0.0715 (0.0959)
α_{41}	0.0051*** (0.0010)	α_{42}	0.0036*** (0.0010)	α_{43}	0.0003*** (0.0000)	α_{44}	0.8422*** (0.0243)
β_{11}	0.8189*** (0.0136)	β_{12}	0.0539*** (0.0057)	β_{13}	-0.0315*** (0.0046)	β_{14}	0.0013* (0.0176)
β_{21}	-0.0016 (0.0073)	β_{22}	0.8366*** (0.0088)	β_{23}	0.0317*** (0.0048)	β_{24}	0.0073 (0.0201)
β_{31}	-0.0961*** (0.0231)	β_{32}	-0.1560*** (0.0206)	β_{33}	0.9857*** (0.0018)	β_{34}	-0.0164 (0.0380)
β_{41}	-0.0064*** (0.0007)	β_{42}	-0.0044*** (0.0006)	β_{43}	-0.0003*** (0.0000)	β_{44}	0.6253*** (0.0048)
Log-likelihood	25369.1648						
Diagnostic Checking							
L-BQ(36)	8.5226						
L-BQ^2 (36)	5.7893						
ARCH-LM(36)	4.2839						

Notes: (1) ***, **, *denote the rejection of the hypothesis at the 1%, 5%, 10% level, respectively.

(2) The market described by 1 is the West Texas Intermediate (WTI) crude oil spot returns, 2 is the Texas Light Sweet oil futures returns, 3 is the USD nominal effective exchange rates returns, and 4 is the dummy variable for the 2008 financial crisis.

(3) h_{ii} refers to the variance in market i, while h_{ij} is the covariance of market i in response to past volatility in market j. Shocks are defined similarly.

The variance of the multivariate GARCH of BEKK model in Eq. (4) is then checked. The estimated results are shown in Tables 3 and 4. The diagonal line for A_{11}, i.e., α_{11}, α_{22}, α_{33}, and α_{44} indicates the extent of the correlation of the conditional variance of the WTIR (β_{1t}); FUR (β_{2t}); ERR, and EIR (β_{3t}); and the dummy variable for the 2008 financial crisis (β_{4t}) with the past squared residuals of $\varepsilon^2_{i,t-1}$ for $i = [1,2,3,4]$. The off-diagonal elements (α_{ij}) simultaneously impact the conditional variance of one of the variances originating from past squared shocks of other elements.

The diagonal elements of B_{11} indicate the association of the current conditional volatility with their own past conditional variances. The off-diagonal parameters in B_{11} are of particular interest for our analysis as they show potential WTIR volatility.

The variance in Eq. (4) in Table 3, with respect to WTIR, FUR, ERR, and the dummy variable for the 2008 financial crisis parameters showed results that are significantly influenced by the lagged WTIR squared residuals to the variance of WTIR (α_{11}), FUR (α_{12}), ERR (α_{13}), and D (α_{14}). Data on the conditional variance (volatility; β_{11}) for WTIR is shown in Table 3. In terms of sensitivity to past volatility (β_{11}), the WTIR are 1% significantly affected by past volatility originating only from its own market. The estimation of β_{12}, β_{13} shows that WTIR is both 1% significantly affected by past volatility of FUR and ERR. Finally, for the estimation of h_{14}, the WTIR employed a marked structural conversion on our dummy variable at a selected time point.

Table 4. The parameter estimation results of the oil futures returns and the energy index to the oil spot returns.

Coefficient	WTIR-FUR-EIR-D						
Mean Equation							
b_{11}	-0.0008*** (0.0001)	b_{12}	-0.0004** (0.0002)	b_{13}	0.0004* (0.0003)	b_{14}	0.0005* (0.0005)
Variance Equation							
α_{11}	0.8088*** (0.0038)	α_{12}	0.0512*** (0.0023)	α_{13}	-0.0498*** (0.0090)	α_{14}	0.0297* (0.0229)
α_{21}	-0.5968*** (0.0030)	α_{22}	0.0427*** (0.0028)	α_{23}	0.0003 (0.0100)	α_{24}	-0.0037 (0.0269)
α_{31}	0.0061 (0.0133)	α_{32}	0.1069*** (0.0099)	α_{33}	0.2377*** (0.0120)	α_{34}	-0.0535* (0.0292)
α_{41}	-0.0025*** (0.0001)	α_{42}	-0.0022*** (0.0004)	α_{43}	-0.0021*** (0.0004)	α_{44}	0.5336*** (0.0133)
β_{11}	0.5849*** (0.0097)	β_{12}	-0.0719*** (0.0074)	β_{13}	0.0307*** (0.0017)	β_{14}	0.0492*** (0.0037)
β_{21}	0.3534*** (0.0095)	β_{22}	1.0563*** (0.0067)	β_{23}	-0.0099*** (0.0027)	β_{24}	0.0443*** (0.0033)
β_{31}	-0.0061 (0.0057)	β_{32}	-0.0410 (0.0037)	β_{33}	0.9558 (0.0027)	β_{34}	-0.2272*** (0.0728)
β_{41}	-0.0038*** (0.0007)	β_{42}	-0.0032*** (0.0007)	β_{43}	-0.0003 (0.0011)	β_{44}	-0.8750*** (0.0002)
Log-likelihood	23509.8643						
Diagnostic Checking							
L-BQ(36)	3.8812						
L-BQ^2(36)	5.4773						
ARCH-LM(36)	3.9298						

Notes: (1) ***, **, *denotes rejection of the hypothesis at the 1%, 5%, and the 10% level, respectively.
(2) The market described by 1 is the West Texas Intermediate (WTI) crude oil spot returns, 2 is the Texas Light Sweet oil futures returns, 3 is the S&P 500 energy index returns, and 4 is the dummy variable for the 2008 financial crisis.
(3) h_{ii} refers to the variance in market i, while h_{ij} is the covariance of market i in response to past volatility in market j. Shocks are defined similarly.

The results for the variance in Eq. (4) as shown in Table 4, regarding the WTIR, FUR, EIR, and the dummy variable of the 2008 financial crisis parameters, indicate that significant relations form lagged WTIR squared residuals for the variance of WTIR (α_{11}), FUR (α_{12}),EIR (α_{13}), and D (α_{14}). The conditional variance (volatility) is shown in Table 4. In the first estimation of β_{11}, WTIR is 1% significantly affected by past volatility that originates only from its own market. The estimations of β_{12}, β_{13} ,and β_{14} are the same as those in Table 3, where WTIR is 1% significantly affected by past volatility of FUR and EIR. However, these estimations indicate that WTIR employed a marked structural conversion on our dummy variable at a specific time point.

4. Conclusion

The interest in oil markets, driven mainly by recent hikes of the oil price and the resultant volatility of oil prices, has intensified over the last few years. Several studies have examined the oil market from various perspectives, leading to several fresh insights into a market that has substantial significance for the global economic growth. The macroeconomic effects of oil shocks have been the subject of intense debate. Most studies have focused on the direct effects of shocks in the price of oil, emphasizing the relationship of the stock index market to financial and macroeconomic variables. In the present paper we studied the causal relationship with the Granger causality test, the impulse-response function analysis between variables, and the lead-lag relationship and volatility using the multivariate GARCH (1,1) of BEKK model. We used the daily data of the returns of the WTI oil spot returns (WTIR), Texas Light Sweet oil futures (FUR), of the US dollar/Euro exchange rate (ERR), and the S&P 500 energy index (EIR) for the period, January 4, 2000 to September 30, 2009.

The ADF results indicate that the variables are stationary. The results show a high power of the analysis for the unit root for WTIR, FUR, ERR, and EIR. The empirical results also show that there is a two-way Granger causality for the WTIR, FUR, and EIR. In particular, the variables show feedback relationships. However, the ERR only have a one-way Granger causality with the WTIR. In the impulse response for the WTIR, FUR, ERR and EIR, we found that the WTIR have a strong and medium impulse response by themselves, to the FUR, ERR and EIR.

Finally, the estimation results of the multivariate GARCH of the BEKK model show that, based on Eq. (7), the WTIR have truly significant impacts with a lag of one period by themselves and to the FUR, ERR, and EIR. Eq. (10) is divided into two forms: WTIR-FUR-ERR-D and WTIR-FUR-EIR-D. The WTIR-FUR-ERR-D shows that the WTIR are 1% and 5% significantly affected by past volatility from themselves, from FUR and ERR. In addition, the WTIR-FUR-EIR-D shows that the WTIR are also 1% significantly affected by past volatility from them, from FUR and from EIR. The WTIR on the regression show a structural conversion of our dummy variable at selected time points.

In terms of the regression of WTIR-FUR-ERR-D, the results show the same empirical analysis. The highest weight of the USD against major currencies (Euro: 65%) has a significant influence on the oil spot prices such as the USD nominal effective exchange rate which is a weighted average of the exchange value of the USD against the currencies of a large group of the USA's major trading partners. The results show that Europe is indeed a very important trading partner for the USA. Regarding the regression of WTIR-FUR-EIR-D, the general analysis adds to the larger range stock index, such as the S&P 500 stock index. However, in this study, we used the S&P 500 energy index, as it is sensitive to the oil price. Changing the stock index makes oil prices rise or fall; however, it is really affected. This finding is not consistent with earlier findings. Overall, our findings suggest that there are important links for the oil spot prices, futures markets, the exchange rate, and the stock index market for investors, allowing them to take advantage of the FUR, ERR, and EIR for WTIR purchases.

References

Ågren, M. (2006), *Does oil price uncertainty transmit to stock markets?* Department of Economics, Uppsala University, Working Paper 2006: 23.

Bollerslev, T. (1986), *Generalized autoregressive conditional heteroskedasticity,* Journal of Econometrics, 31, 307–327.

Cong, R.-G., Wei, Y.-M., Jiao, J.-L. (2008), *Relationships between oil price shocks and stock market: An empirical analysis from China*, Energy Policy, 361, 3544-3567.

Dickey, D.A., Fuller W.A. (1981), *Likelihood Ratio Statistic for Autoregressive Time Series with a Unit Root,* Econometrica, 49,143-159.

Engle, R. F. and Kroner, K. F., (1995), *Multivariate simultaneous GARCH*, Econometric Theory, 11, 122-150.

Engle, R. (1982), *Autoregressive conditional heteroskedasticity with estimates of the variance of the U.K. inflation*, Econometrica, 50, 987-1008.

Hammoudeh S., Eleisa L. (2004), *Dynamic relationships among GCC stock markets and NYMEX oil futures,* Contemporary Economic Policy, 22, 250-269.

Lee C.C., Chang C.P. (2007), *The impact of energy consumption on economic growth: evidence from linear and nonlinear models in Taiwan,* Energy, 32, 2282-2294.

Liao H.-C., Lee Y.-H., Suen Y.-B. (2008), *Electronic trading system and returns volatility in the oil futures market,* Energy Economics, 30, 2636–2644.

Lizardo R.A., Mollick A.V. (2010), *Oil price fluctuations and U.S. dollar exchange rates,* Energy Economics, 32, 399-408.

Nandha, M., Faff, R. (2008), *Does oil move equity prices? A Global view,* Energy Economics, 30, 986-997.

Narayan, P.K., Narayan, S. (2010), *Modelling the impact of oil prices on Vietnam's stock prices*, Applied Energy, 87, 356–361.

Narayan P.K., Narayan S., Prasad A. (2008), *Understanding the oil price-exchange rate nexus for the Fiji islands*, *Energy Economics,* 30, 2686–2696.

Park, J., Ratti, R.A. (2008), *Oil price shocks and stock markets in the U.S. and 13 European countries,* Energy Economics, 30, 2587-2608.

Wu T.W.J., Yang J., (2008), *Realized volatility and correlation in energy futures markets,* Journal of Futures Markets, 28, 993–1011.

Zhang Y.-J., Fan Y., Tsai H.-T., Wei Y.-M., (2008), *Spillover effect of us dollar exchange rate on oil prices,* Journal of Policy Modeling, 30, 973–991.