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# Implied volatility relationships between crude oil and the U.S. stock markets: Dynamic correlation and spillover effects

Zhenhua Liu[a,b], Hui-Kuan Tseng[c], Jy S. Wu[d,*], Zhihua Ding[a,b]

[a] School of Management, China University of Mining and Technology, Xuzhou, 221116, China
[b] Center for Big Data Marketing and Green Innovation Research, China University of Mining and Technology, Xuzhou, 221116, China
[c] Department of Economics, University of North Carolina at Charlotte, Charlotte, NC, 28223, USA
[d] Infrastructure and Environmental Systems, Department of Civil and Environmental Engineering, University of North Carolina at Charlotte, Charlotte, NC, 28223, USA

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ABSTRACT

This paper investigates the dynamic correlation and risk transmission between the oil market and the U.S. stock market, using the respective implied volatility indices published by the Chicago Board Options Exchange. The results indicate that, first, there is a significant positive time-varying correlation between oil and stock implied volatility returns. Second, during the global financial crisis, the correlation between oil and stock markets increases significantly. Third, there is a significant bidirectional implied volatility spillover between the oil and stock markets. Insights gleaned from the findings in this study could project energy and monetary policy implications. Monetary and/or energy policy changes could impact the predicted linkage mechanism between these two markets, which can be further leveraged to forecast the market's future volatility.

## 1. Introduction

Uncertainty in oil prices can hinder the global economy and pose a threat to energy security (Barsky and Kilian, 2004; Chen et al., 2014; Kun Sek et al., 2015; Liu et al., 2019b; Mork et al., 1994). Oil price fluctuations can be related to the current output, access to future supply, changes in demand, natural hazards and disasters, and geopolitical crises (Liu et al., 2019a). The U.S. Energy Independence and Security Act of 2007 was enacted to provide sustainable energy security for the nation, particularly by setting a goal to reduce the dependence on imported oil and develop new domestic oil production. As of 2018, the U.S. crude oil production has increased to 11.7 million barrels per day (mmb/d), which is a 120% increase compared to its production in 2008 and 13% higher than the previous peak production period of the 70s.[1] Following the fracking revolution of 2008, the U.S. has now added 6.2 mmb/d of new oil production, leading both Saudi Arabia and Russia.[2] The corresponding lowered oil prices attributed to an increase in oil production could subsequently benefit the manufacturing sector and stimulate the economy, but it may conversely hurt U.S. oil companies and affect domestic oil industry workers. On the contrary, high oil prices may help sustain the cost of operating hydraulically fractured wells[3]; however, a surge in oil prices can stifle the economic growth and depress the supply of other goods by increasing their production costs (International Energy Agency, 2004). Nonetheless, the S&P 500 index, a benchmark of the overall stock market to which all other investments are compared, showed a 178% increase relative to 2008 and reached 2, 507 points in 2018.[4] Without the U.S. oil boom in the past decade, the world could likely have paid much higher oil prices, and the U.S. stock market would have shown a gradual recovery. The change in crude oil prices has also played an influential role to impact returns of a variety of commodities in the financial market (Ding et al., 2017; Dutta et al., 2017).

The crude oil price benchmark of West Texas Intermediate (WTI) and the S&P 500 index have long been observed to exhibit a negative

* Corresponding author.
*E-mail address:* jwu@uncc.edu (J.S. Wu).

[1] Derived from https://www.macrotrends.net/2562/us-crude-oil-production-historical-chart. Accessed 13 August 2019.
[2] https://www.forbes.com/sites/rrapier/2018/07/22/how-the-fracking-revolution-broke-opecs-hold-on-oil-prices/#4604fc7a48ef. Accessed 13 August 2019.
[3] https://www.investopedia.com/articles/investing/032515/how-oil-prices-impact-us-economy.asp. Accessed 13 August 2019.
[4] Data retrieved from https://www.macrotrends.net/2324/sp-500-historical-chart-data. Accessed 13 August 2019.

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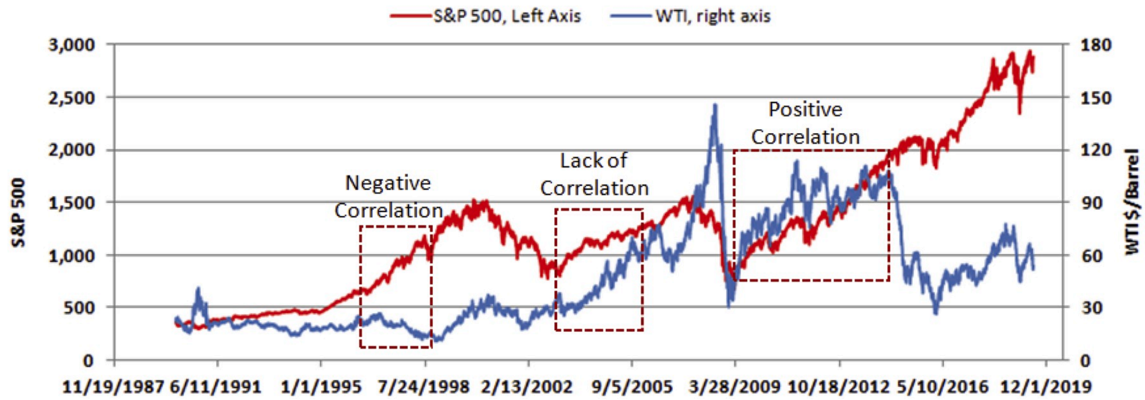


**Fig. 1.** S&P 500 and WTI crude oil prices (January 1990–June 2019).

correlation in the late 1990s, a lack of correlation in mid-2000s, and a positive correlation within 2000–2012 (see Fig. 1).[5] The oil-stock correlation may rise during demand-supply driven disruption and can be unstable during world crises and disasters. The relationships between oil prices and stock returns are generally time-varying and non-linear (Antonakakis et al., 2013; Broadstock and Filis, 2014; Chkili et al., 2014; Kang et al., 2015b; Reboredo and Rivera-Castro, 2014; Vo, 2011). Prior studies have mostly focused on the linkage between crude oil and stock markets at the price or return levels (Park and Ratti, 2008; Sadorsky, 1999; Tursoy and Faisal, 2018) for both oil importing and exporting countries (Khalfaoui et al., 2019; Sarwar et al., 2019; Wang et al., 2013), the interaction between oil price volatility and stock market returns (Alsalman, 2016; Angelidis et al., 2015; Caporale et al., 2015; Diaz et al., 2016; Joo and Park, 2017; Naifar and Al Dohaiman, 2013; Sadorsky, 1999), and the impact of oil price shocks on stock price volatility (Aloui and Jammazi, 2009; Kang et al., 2015a). Evidently, minimal attention has been given to studying the forward-looking volatility correlation between the crude oil and stock markets.

Examination of the correlation at the cross-market volatility perspectives could reflect more effectively on the dynamics of market interdependence than the market returns because the rate of change in market volatilities can be higher than market returns (Ding and Liu, 2019; Peng and Ng, 2012). Uncertainty in the oil market can delay investment decisions, which, in turn, increases the volatility of the stock market and the uncertainty of stock prices of oil-related companies (Bloom, 2009). The volatility of the oil market reflects the uncertainty of economic growth, leading to an increase in stock market volatility (Bašta and Molnár, 2018). Thus, a good understanding of the volatility relationship between oil and stock markets can help to maintaining a track of the information and risk transmission across markets, as well as determining the optimal weight and hedging ratio of the portfolio. Clearly, any attempt to combine oil-related assets with the stock market in a diversified portfolio could not effectively reduce risks in the context of a significant volatility correlation between these two markets (Jammazi et al., 2017).

In 1993, the Chicago Board Options Exchange (CBOE) for the first time created an implied volatility index (VIX), which shortly emerged as the world's barometer of market volatility. In contrast to the historical volatility or realized volatility that is based on past prices, VIX infers its value by options prices using a wider set of options derived from the broader S&P 500 index. VIX futures began trading in 2004. The implied index provides expectations of uncertainty in future markets, forward-looking for foreseeable risks, reflection of the fear from market participants as they trade, and alternatives to deal with shocks (Borovkova and Permana, 2009; Ji and Fan, 2016; Shaikh and Padhi, 2015; Whaley, 2000). Given the success and importance of VIX, other equity and commodity markets have subsequently developed their respective implied indices (Ji et al., 2018; Kocaarslan et al., 2017; Liu et al., 2013), such as the crude oil volatility index (OVX).

An analysis of the relationship between oil and stock markets based on implied volatility constitutes a relatively new area of research. The literature review highlights limited existing studies on implied volatility relationships between oil and stock markets, most of which mainly focuses on the impact of oil implied volatility on stock market returns. The implied volatility of crude oil was found to have a significant impact on China's stock market returns, while the impact of realized volatility of oil on stock market returns is negligible (Luo and Qin (2017). The U.S. clean energy stock market returns are noted to be sensitive to OVX shocks (Dutta, 2017) because OVX can effectively hedge the risk of clean energy stock market (Ahmad et al., 2018). In two recent studies: (a) researchers argue that OVX is co-integrated with Indian stock implied volatility and demonstrates a nonlinear and positive impact on stock implied volatility (Bouri et al., 2017), and (b) there is a long-term relationship and bi-directional Granger causality between the implied volatility of the oil market and the U.S. energy industry stock market (Dutta, 2018).

Oil price volatility is time-varying and can be affected by disparate and multiple factors such as the fundamentals, financial factors, and geopolitics (Chkili et al., 2014; Joo and Park, 2017; Zhang et al., 2019). Several studies have demonstrated the occurrence of a dynamic relationship between oil and stock markets (Broadstock and Filis, 2014; Chkili et al., 2014; Joo and Park, 2017; Liu et al., 2017; Nadal et al., 2017; Shahzad et al., 2018; Wang and Wang, 2019; Wen et al., 2019). The dynamic conditional correlation (DCC) can be affected by economic or political events (Chkili et al., 2014) and significant time-varying correlations have been established between different types of oil price shocks and stock market returns during 1995–2013 (Broadstock and Filis, 2014). In an analysis of data from 1973 to 2015, the direction of the relationship between oil returns and U.S. stock returns shows a varying construct over time (Foroni et al., 2017), exhibiting a positive relationship between markets since early 2007. However, historical information of volatility can only reflect the past market volatility with lags but fails to necessarily engage the current market conditions. The implied volatility derived from the options can accurately measure the market uncertainty (Borovkova and Permana, 2009) and improve the near-term OVX volatility forecasts (Haugom et al., 2014). In summary, all of the previous research has not attempted to reveal the dynamic correlation and risk transmission between oil and U.S. stock markets using implied volatility indices, particularly for the past 5–10 years. Our research effectively fills the knowledge gap and provides an understanding of the interaction between OVX and VIX in recent years.

Our work contributes to the existing literature in several ways. In

[5] Data retrieved from https://fred.stlouisfed.org/series/DCOILWTICO and https://finance.yahoo.com/quote/%5EGSPC/history/. Accessed 13 August 2019.

contrast to previous studies, we investigate the linkage of the oil-stock nexus at the implied volatility level rather than utilizing historical volatility information such as conditional, stochastic and realized volatilities. We explore the time-varying correlations between oil and stock implied volatility indices instead of unconditional correlations, in order to better understand the evolving volatility linkage in a time-varying environment.

From a methodological perspective, we carefully examine these correlation relationships using the traditional model of dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH), as well as advanced models of corrected dynamic conditional correlation GARCH (cDCC-GARCH) and the generalized orthogonal GARCH (GO-GARCH) model. The cDCC-GARCH model involves a reformulation of the correlation process (Aielli, 2013), while the GO-GARCH model has its ability to relax the conditions of model specificity along with its strength to overcome the estimation challenge on large datasets with multiple variable (van der Weide, 2002). Therefore, our study provides a critical assessment of the resulting correlations as estimated by different multivariate GARCH specifications.

The primary objective of this paper, thus, is to examine the dynamic correlation and risk spillover between the crude oil market and the U.S. stock market at the implied volatility level. Specifically, the study attempts to answer the following three questions:

- How would the correlation between OVX and VIX evolve over time as determined by different methods?
- In what way has the correlation between OVX and VIX responded to important events?
- What is the foreseeable spillover effect occurring between OVX and VIX?

The research period covers 10 May 2007 to 11 June 2018 in which the data series of OVX and VIX are both available. Employing the DCC-GARCH, cDCC-GARCH, GO-GARCH, and the full Baba-Engle-Kraft-Kroner GARCH (BEKK-GARCH) models, we find evidence of significant positive time-varying correlations between oil and stock implied volatilities. The results also reveal a significant bi-directional implied volatility spillover between the oil market and the U.S. stock market. Insights gleaned from the findings in this study help project energy and monetary policy implications. Monetary policy changes could further impact the predicted linkage mechanism between the two markets, thus further increasing their volatilities.

The remainder of this paper is organized as follows. Section 2 provides the data description and preliminary data analysis. Section 3 outlines the empirical methodology employed in this study. Section 4 presents the main empirical results and discussions. Section 5 addresses the implications of the findings for policy and risk management, whereas concluding remarks are given in Section 6.

## 2. Data

The OVX and VIX data were retrieved from CBOE.[6] These OVX and VIX indices measure the 30-day volatility implied by options provided by the United States Oil Fund and S&P 500 index, respectively. Our sample period includes a total of 2792 daily observations; Fig. 2 displays the level and returns of OVX and VIX, while Table 1 summarizes the descriptive statistics of these daily returns.

In general, a positive unconditional correlation coefficient of 0.42 exists between OVX and VIX returns, indicating a relatively close linkage between these two indices. Both indices tend to react similarly under the influence of several shocks, e.g. a spike in both OVX and VIX occurred during the global financial crisis in 2008. Fig. 2 depicts that the derived OVX and VIX returns have significant volatility agglomeration characteristics.

Based on the coefficient of variations (CV) calculated for both data series, a higher CV value for OVX indicates that OVX returns are generally more volatile than VIX returns. On a short-term basis, the volatility of the stock market may fluctuate more often than the oil market with decreased returns as the stock market runs up and down. Each return series appears to have a leptokurtic disturbance with an asymmetric tail because the skewness coefficients of both indices are significantly different from zero, and their Kurtosis coefficients are greater than 3. Both series do not satisfy the normality assumption as supported by the Jarque-Bera test (Jarque and Bera, 1987). According to the Ljung-Box Q-statistic with a lagging of the 20th order, there exists a serial correlation in each of the return series. The unit root test suggests that both return series exhibit stationary behavior at 1% significant level. The ARCH-LM test (Engle, 1982) provides evidence of the ARCH effects in both return series, which justifies the use of GARCH-type models to study the dynamic correlation and risk spillover between these two indices.

## 3. Methodology

The DCC-GARCH model (Engle, 2002), the cDCC-GARCH model (Aielli, 2013), and the GO-GARCH model (van der Weide, 2002) are used to simultaneously examine the dynamic correlations between OVX and VIX. The Vector Autoregressive (VAR) model (Sims, 1980) is employed to analyze the mean spillover, whereas the BEKK-GARCH model (Engle and Kroner, 1995) is applied to determine the volatility spillover between the indices.

### 3.1. Dynamic conditional correlations

In the present study, the DCC-GARCH model is taken as the basic approach to investigate the time-varying correlations between oil and stock implied volatilities. Results are compared with that derived from the cDCC-GARCH and the GO-GARCH models. The specification of these multivariate GARCH models is defined as follows.

Let $r_t$ be a vector of $n$ time series and $u_t$ be its conditional mean vector. Thus, given the information set $\Omega_{t-1}$:

$$r_t|\Omega_{t-1} = \mu_t + \varepsilon_t \tag{1}$$

Where $\varepsilon_t$ is a vector of residuals. The conditional mean, $\mu_t$, is modeled using a $AR(p)$ process (i.e. $\mu_t = \gamma_0 + \sum_{j=1}^{p} \gamma_j r_{t-j}$, where $\gamma_0$ is the constant and $\gamma_j$ is a coefficient matrix), The optimal lag p is selected according to the Akaike Information criteria. The vector of residuals, $\varepsilon_t$, is specified in the following sections.

#### 3.1.1. DCC-GARCH model

In the DCC-GARCH model, the exogenous variables affecting the implied volatilities are not included (Engle, 2002). The model involves a series of univariate estimates, followed by the calculation of the dynamic conditional correlations. Within this DCC model, the residuals $\varepsilon_t$ are modeled as:

$$\varepsilon_t = H_t^{1/2} z_t,\ z_t \sim iid(0,\quad I_n) \tag{2}$$

Where $z_t$ is a $n \times 1$ vector of standardized residuals and $I_n$ is an $n \times n$ identity matrix. $H_t$ is the $n \times n$ conditional covariance matrix of $r_t$, which can be decomposed as:

$$H_t = D_t R_t D_t \tag{3}$$

Where $D_t = diag(h_{11t}^{1/2}, \cdots, h_{nnt}^{1/2})$ is the matrix of conditional standard deviations. $R_t$ is the matrix of dynamic conditional correlations:

[6] http://www.cboe.com/vix. Accessed August 13, 2018.

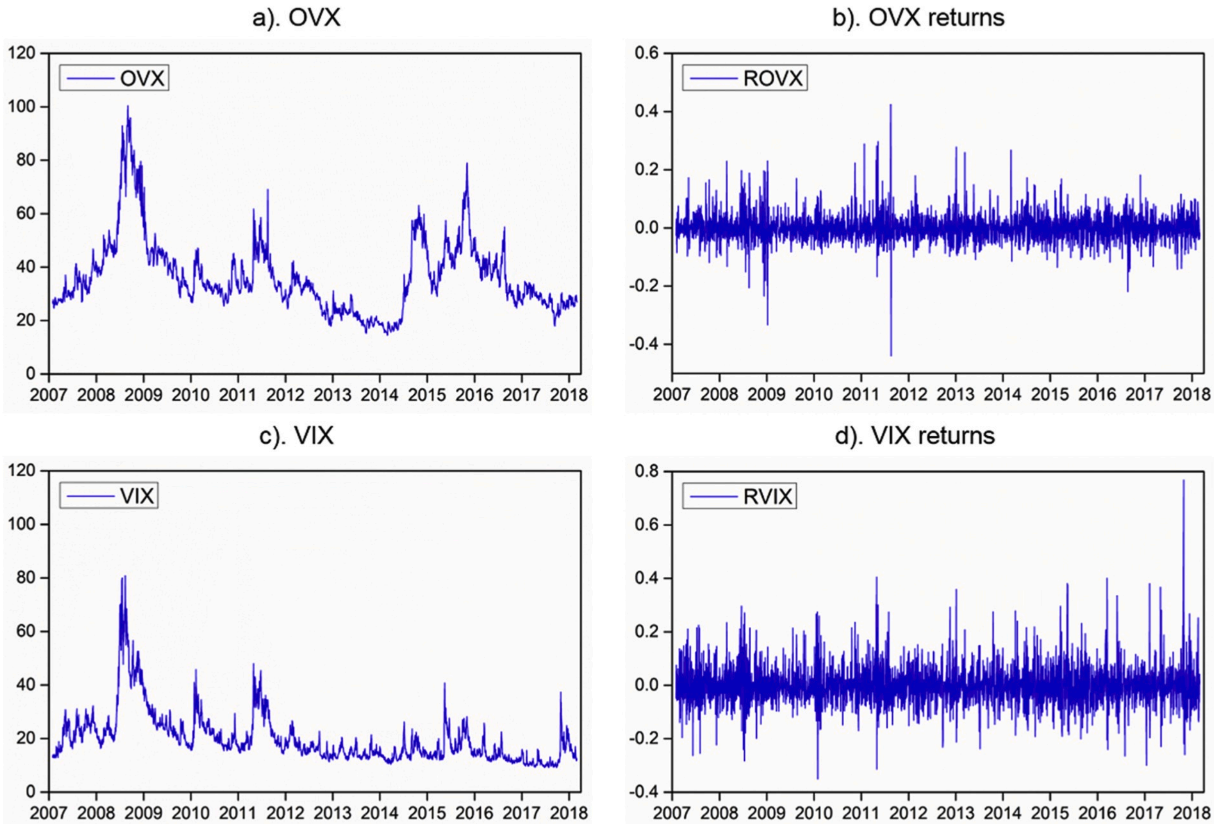


**Fig. 2.** Plots of daily implied volatility indices and returns.

**Table 1**
Descriptive statistics for the daily returns of OVX and VIX.

| | OVX returns | VIX returns |
|---|---|---|
| Panel A: Descriptive statistics | | |
| Mean | −3.05E-06 | −3.45E-05 |
| Maximum | 0.4250 | 0.7682 |
| Minimum | −0.4399 | −0.3506 |
| Standard deviation | 0.0480 | 0.0760 |
| Skewness | 0.6468 | 0.9705 |
| Kurtosis | 12.4954 | 9.5849 |
| Jarque-Bera | 10679.8500 | 5480.6430 |
| Probability | 0.0000 | 0.0000 |
| Q (10) | 75.4310*** | 50.6030*** |
| Q (20) | 91.7770*** | 60.9050*** |
| Panel B: Unit root tests | | |
| ADF | −33.7994*** | −41.5313*** |
| PP | −61.6997*** | −65.8604*** |
| KPSS | 0.0544*** | 0.0481*** |
| Panel C: Conditional heteroscedasticity test | | |
| ARCH-LM test | 262.5912*** | 63.1821*** |
| Panel D: Unconditional correlation | | |
| OVX returns | 1.0000 | |
| VIX returns | 0.4144*** | 1.0000 |

Notes: The Jarque-Bera test is for normal distribution. The Ljung-Box statistics, Q (n), test is for serial correlation of the return series up to the nth order. *** denotes the rejection of the null hypothesis at the 1% significance level.

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}} \tag{4}$$

Where $Q_t \equiv \{q_{ij,t}\}$ is a $n \times n$ conditional variance-covariance matrix. Under the DCC model, $h_{iit}(i = 1, \cdots, n)$ follows a univariate GARCH(1,1) process:

$$h_{iit} = \omega_i + \alpha_i \varepsilon_{it-1}^2 + \beta_i h_{it-1} \tag{5}$$

$Q_t$ is given by:

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q_t} + \theta_1 \left(z_{t-1} z_{t-1}^{'}\right) + \theta_2 Q_{t-1} \tag{6}$$

Where $\overline{Q_t}$ is the unconditional variance matrix of $z_t$. $\theta_1$ and $\theta_2$ denote the short-term and long-term persistence of shocks to the DCC, respectively. $\theta_1$ and $\theta_2$ are both non-negative and satisfying $\theta_1 + \theta_2 < 1$.

### 3.1.2. cDCC-GARCH model

In the cDCC-GARCH model, Aielli (2013) reformulates the specification of the correlation $Q_t$ that was originally defined in the DCC-GARCH model of Engle (2002). The specification of cDCC-GARCH model is the same as that of DCC-GARCH model. However, the correlation process is reformulated as shown in Eq. (7).

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q_t} + \theta_1 \left(z_{t-1}^{*} z_{t-1}^{*'}\right) + \theta_2 Q_{t-1} \tag{7}$$

Where $z_t^{*} = diag\{Q_t\}^{1/2} z_t$ and $z_t$ is the standardized residuals. The parameters $\theta_1$ and $\theta_2$ are nonnegative scalar coefficients with a sum less than unity $(a + b < 1)$. The conditional correlation coefficient between OVX and VIX is given as follows:

$$\rho_{OVX,\ VIX,\ t} = \frac{q_{OVX,\ VIX,\ t}}{\sqrt{q_{OVX,\ OVX,\ t} q_{VIX,\ VIX,\ t}}} \tag{8}$$

### 3.1.3. GO-GARCH model

The GO-GARCH model of van der Weide (2002) specifies the return $r_t$ as a function of the conditional mean $(u_t)$ and an error term $(\varepsilon_t)$ where the conditional mean can include an AR (1) term.

$$r_t = u_t + \varepsilon_t \tag{9}$$

The GO-GARCH model maps $r_t - u_t$ onto a set of unobservable independent factors, $f_t$, such that:

$$\varepsilon_t = A f_t \tag{10}$$

The mixing matrix A can be decomposed into an unconditional covariance matrix Σ and an orthogonal (rotational) matrix U.

$$A = \Sigma^{1/2} U \quad (11)$$

In the mixing matrix A, the rows are the assets and the columns are the factors that can be specified as:

$$f_t = H_t^{1/2} z_t \quad (12)$$

The random variable $z_t$ has characteristics $E(z_{it}) = 0$ and $E(z_{it}^2) = 1$. The factor conditional variances $h_{it}$ can be modeled as a GARCH process. The conditional distribution of factors $f$ satisfies $E(f_t) = 0$ and $E(f_t f_t^{'}) = I$. Combining Eqs. (9), (10) and (12) yields:

$$r_t = u_t + A H_t^{1/2} z_t \quad (13)$$

The conditional covariance matrix of the returns $r_t - u_t$ is then:

$$\Sigma_t = A H_t A^{'} \quad (14)$$

As discussed by Basher and Sadorsky (2016) and Ahmad et al. (2018), the multivariate t-distribution is not an option for the GO-GARCH model, while a multivariate affine negative inverse Gaussian (MANIG) distribution can be applied to the GO-GARCH model in order to address volatility clustering, fat tails, and autocorrelation issues. Following Broda and Paolella (2009) and Zhang and Chan (2009), we estimate the GO-GARCH model using the independent component analysis approach (Hyvärinen et al., 2001).

### 3.2. Spillover effects

#### 3.2.1. VAR model

The VAR model has been used to capture the linear interdependencies among multiple time series (Zhang and Sun, 2016). In the current study, the VAR model is used to capture the mean spillover between oil and stock implied volatilities, this bivariate VAR model for OVX and VIX is written as follows:

$$r_t^o = u_t^o + \sum_{m=1}^{M} a_m^o r_{t-m}^o + \sum_{n=1}^{N} b_n^o r_{t-m}^v + \varepsilon_t^o \quad (15)$$

$$r_t^v = u_t^v + \sum_{m=1}^{M} a_m^v r_{t-m}^v + \sum_{n=1}^{N} b_n^v r_{t-m}^o + \varepsilon_t^v \quad (16)$$

Where $r_t^o$ and $r_t^v$ are the logarithmic returns of OVX and VIX, respectively, while $\mu^o$ and $\mu^v$ are their respective conditional mean series. The superscripts $o$ and $v$ denote the oil and stock markets, respectively. Lag orders are $m$ and $n$ with maximum lag values being $M$ and $N$, respectively. Mean spillover coefficients $a^o$ and $a^v$ are for their own market and $b^o$ and $b^v$ are for across markets. The residual series are $\varepsilon_t^o$ and $\varepsilon_t^v$ for this VAR model. The VAR model provides the foundation for further volatility spillover calculations.

#### 3.2.2. BEKK-GARCH model

Next, the BEKK-GARCH model is employed to investigate the volatility spillover effects between OVX and VIX. In general, the BEKK-GARCH makes a specific representation of the positive definite covariance matrix (Engle and Kroner, 1995). The bivariate full BEKK-GARCH for OVX and VIX takes the following form.

$$H_t = CC^{'} + A^{'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} A + B^{'} H_{t-1} B \quad (17)$$

$$C = \begin{bmatrix} c^{oo} & 0 \\ c^{vo} & c^{vv} \end{bmatrix}, A = \begin{bmatrix} a^{oo} & a^{ov} \\ a^{vo} & a^{vv} \end{bmatrix}, B = \begin{bmatrix} b^{oo} & b^{ov} \\ b^{vo} & b^{vv} \end{bmatrix} \quad (18)$$

Where $C$ is a $2 \times 2$ lower triangular matrix of constants and $C^{'}$ is a transposed matrix of $C$. $a^{ov}$ and $b^{ov}$ capture shocks and volatility spillover from OVX to VIX, respectively; $a^{vo}$ and $b^{vo}$ capture shocks and volatility spillover from VIX to OVX, respectively. $a^{oo}$ and $a^{vv}$ capture the impact of past shocks of OVX and VIX on their own current volatility, respectively; and $b^{oo}$ and $b^{vv}$ capture the impact of past volatility of OVX and VIX on their own current volatility, respectively. If a pair of parameters, e.g. $a^{vo}$ and $b^{vo}$, are both positive, it can be deduced that the volatility of VIX may aggravate that of OVX market. When both parameters are negative, the volatility of VIX may weaken that of the OVX market. As such, there exists a volatility spillover effect when both the parameters are positive.

The conditional variance-covariance matrix of residuals is specified as a positive covariance matrix in the bivariate full BEKK-GARCH model for OVX and VIX returns. In comparison to the DCC-GARCH and cDCC-GARCH models, a full BEKK-GARCH model can measure the volatility spillover effects of the OVX and VIX indices on their own market as well as across markets.

## 4. Empirical results and discussions

### 4.1. Dynamic correlations

Table 2 displays the estimated results of the DCC-GARCH and cDCC-GARCH models.[7] Several observations regarding our results are given below.

For both DCC and cDCC models, ARCH and GARCH coefficients (α and β) are positive and present significant values at 1% level (Panel A, Table 2). The sums of the lagged square error (α) and the lagged conditional variance (β) are close to unity, implying that shocks to conditional variance are highly persistent. Moreover, β is much larger than α, indicating that the past volatility is more important than the past shocks for forecasting future market volatility.

The short-term ($\theta_1$) and long-term ($\theta_2$) persistence of shocks on the dynamic conditional correlation provide significant values at 1% level (Panel B, Table 2). This suggests the presence of time-varying correlations between OVX and VIX indices. With $\theta_2$ close to unity (0.9883 and 0.9881, respectively, for DCC and cDCC model), the long-term persistence of the shock plays an important role in predicting the dynamic correlation coefficients.

Results of the diagnostic test (Panel C, Table 2) reveal that the residuals of the DCC and cDCC models estimates are free from serial correlation and the ARCH effect, indicating that these GARCH-type models are correctly specified. Each of these information criteria shows that the cDCC model is the best fitting model. This finding verifies the viewpoints of Aielli (2013) and Wang and Li (2016), who conclude that the DCC estimator of the correlation exhibits bias when the persistency of the correlation process (measured by $\theta_1 + \theta_2$) is strong and the impact of the innovations (measured by $\theta_1$) is large, compared with cDCC model. Thus, an application involving the data sets for which $\theta_1 + \theta_2$ is close to 1, the use of the cDCC version is warranted.

For the GO-GARCH model, it is a common practice to present the rotation matrix (U), the mixing matrix (A), and the parameter estimates (Table 3). Notice that the GO-GARCH model only estimates factors but not standard errors. For each factor, the estimated short-run persistence (α) is considerably less than the long-run persistence (β) which is consistent with the findings from the DCC and cDCC models.[8] The first factor displays more short-run variation and less long-run variation.

[7] To determine the lag order that best fits our data, we first estimate the DCC and cDCC models with different specifications of mean and variance equations under various distributional assumptions, specifically the multivariate normal and multivariate $t$ distributions. We find that the multivariate $t$ distribution with AR(0) term in the conditional mean equation best fit our data under the Akaike Information Criteria (AIC).

[8] Note that the magnitudes of the parameters $\alpha$ and $\beta$ are different in the GO-GARCH model compared to the DCC and cDCC models. This is because in the GO-GARCH model, the persistence parameters pertain to the factor $f_t$ rather than to the residuals $\varepsilon_t$ as in the DCC and cDCC models.

**Table 2**
Estimation results of DCC-GARCH and cDCC-GARCH models.

| | DCC | | | | cDCC | | | |
|---|---|---|---|---|---|---|---|---|
| | Coef. | Prob | S.E | t-value | Coef. | Prob | S.E | t-value |
| Panel A: Parameter estimates of multivariate GARCH model | | | | | | | | |
| $\mu_{OVX}$ | 4.02E-06 | 0.9964 | 0.0009 | 0.0045 | 4.00E-06 | 0.9962 | 0.0008 | 0.0048 |
| $\omega_{OVX}$ | 3.40E-04*** | 0.0000 | 3.48E-05 | 9.7802 | 3.40E-04** | 0.0452 | 1.6753 | 2.0300 |
| $\alpha_{OVX}$ | 0.1011*** | 0.0000 | 0.0104 | 9.7569 | 0.1011*** | 0.0005 | 0.0288 | 3.5110 |
| $\beta_{OVX}$ | 0.7480*** | 0.0000 | 0.0232 | 32.2284 | 0.7481*** | 0.0000 | 0.0931 | 8.0320 |
| $\mu_{VIX}$ | −0.0002 | 0.8728 | 0.0013 | −0.1601 | −0.0002 | 0.8667 | 0.0012 | −0.1679 |
| $\omega_{VIX}$ | 0.0009*** | 0.0000 | 8.89E-05 | 9.9863 | 0.0009*** | 0.0000 | 0.0002 | 5.4340 |
| $\alpha_{VIX}$ | 0.1616*** | 0.0000 | 0.0106 | 15.2689 | 0.1617*** | 0.0000 | 0.0362 | 4.4650 |
| $\beta_{VIX}$ | 0.6855*** | 0.0000 | 0.0234 | 29.1890 | 0.6854*** | 0.0000 | 0.0483 | 14.1900 |
| Panel B: Estimates of dynamic conditional correlations | | | | | | | | |
| $\theta_1$ | 0.0067*** | 0.0005 | 0.0019 | 3.4994 | 0.0117*** | 0.0000 | 0.0027 | 4.3470 |
| $\theta_2$ | 0.9883*** | 0.0000 | 0.0039 | 249.7383 | 0.9881*** | 0.0000 | 0.0027 | 366.0000 |
| Panel C: Diagnostic tests | | | | | | | | |
| $Q^2_{OVX}(10)$ | 5.4876 | 0.8563 | | | 5.1619 | 0.8801 | | |
| $Q^2_{VIX}(10)$ | 7.6711 | 0.6609 | | | 7.5977 | 0.6681 | | |
| $ARCH_{OVX}$ | 0.5507 | 0.8547 | | | 0.5201 | 0.8772 | | |
| $ARCH_{VIX}$ | 0.7712 | 0.6569 | | | 0.7624 | 0.6655 | | |
| AIC | −6.258 | | | | −6.259 | | | |
| SBC | −6.232 | | | | −6.233 | | | |
| Log L | 8745.126 | | | | 8746.116 | | | |

Notes: Ljung-Box Q statistics correspond to a test of the no autocorrelation in squared standardized residuals in order of 10 lags. Arch Lagrange multiplier statistics correspond to a test of the null of no arch effect. ***and ** denote rejection of null hypothesis at 1% and 5% significance level, respectively.

Table 4 summarizes the descriptive statistics of these dynamic correlation coefficients, while Fig. 3 presents a plot of dynamic conditional correlations between OVX and VIX indices. Two observations from the analysis are given below.

The correlation between OVX and VIX is highly time-varying both within the time-frame of one year (e.g. 2008, 2009 and 2012) and across the full sample period. The correlation coefficient oscillates at a low level in 2007, but the coefficient rises from the second half of 2008 to reach a peak of 0.65 in mid-2010 and maintains this spike throughout. The gradual recovery of the global economy in the post-crisis era is reflected in the decline of the correlation coefficient again at the beginning of 2012, and it hovers in the range of 0.2–0.4 from 2014 onwards. When comparing Figs. 1 and 3, we notice that the correlation between markets tends to increase as the market is more volatile. This finding is consistent with observations shared by other research (Vo, 2011).

There is a risk synergy effect between the oil and stock market when faced with uncertain information in the market. The dynamic correlation coefficients are positive during the whole sample period. This is an indication of consistency in the changes of time-varying variances between these two markets. Correspondingly, the risk synergy may also change based on the rise or decline of the dynamic correlation coefficient (Zhang and Sun, 2016).

Note that the dynamic correlations between the DCC and cDCC models are very similar, while the correlations estimated from the GO-GARCH model show a different pattern. One possible explanation is that the GO-GARCH model is associated with a set of independent univariate and conditionally uncorrelated GARCH processes, where a liner map uses marginal density parameters to relate these elements to the observed data that offers more flexibility in the estimation, as compared to DCC and cDCC models. This is consistent with the findings of Basher and Sadorsky (2016), Sarwar et al. (2019) and Jin et al. (2020).

**Table 3**
Estimation results of GO-GARCH model.

| | | |
|---|---|---|
| Panel A: The rotation matrix U | | |
| | U (1) | U (2) |
| U (1) | −0.9480 | −0.3170 |
| U (2) | −0.3170 | 0.9480 |
| Panel B: The mixing matrix A | | |
| | A (1) | A (2) |
| A (1) | −0.0144 | −0.0456 |
| A (2) | −0.0751 | −0.0097 |
| Panel C: GO-GARCH parameter estimates | | |
| | F1 | F2 |
| ω | 0.1015 | 0.1319 |
| α | 0.1718 | 0.1137 |
| β | 0.7316 | 0.7450 |
| Skew | −0.3248 | −0.2893 |
| Shape | 1.3603 | 1.1432 |
| Log L | 8770.3860 | |

### 4.2. Spillover effects

Spillover effect includes the mean spillover estimated by the VAR model and the volatility spillover estimated by the BEKK-GARCH model.

In the VAR model estimation, we employed the AIC test to obtain the optimal lag order of 8 to help determine the optimal trade-off between the best “model fit” versus “model complexity”. The maximum lag order of 8 has been taken for M and N (Eqs. (15) and (16)). Table 5 shows the estimation results of the VAR model, mean spillover coefficients present significant values at 1% interval. This implies that (i) both OVX and VIX returns are related to their own past returns and, therefore, are predictable in the short-term horizon, and (ii) there is a significant bi-

**Table 4**
Descriptive statistics of correlation coefficients between OVX and VIX returns.

| | Mean | Max | Min | Median | Std. Dev. |
|---|---|---|---|---|---|
| DCC-GARCH | 0.4099 | 0.7530 | 0.0025 | 0.4337 | 0.1572 |
| cDCC-GARCH | 0.4083 | 0.7849 | −0.0144 | 0.4327 | 0.1589 |
| GO-GARCH | 0.4322 | 0.8595 | 0.3881 | 0.4184 | 0.0471 |

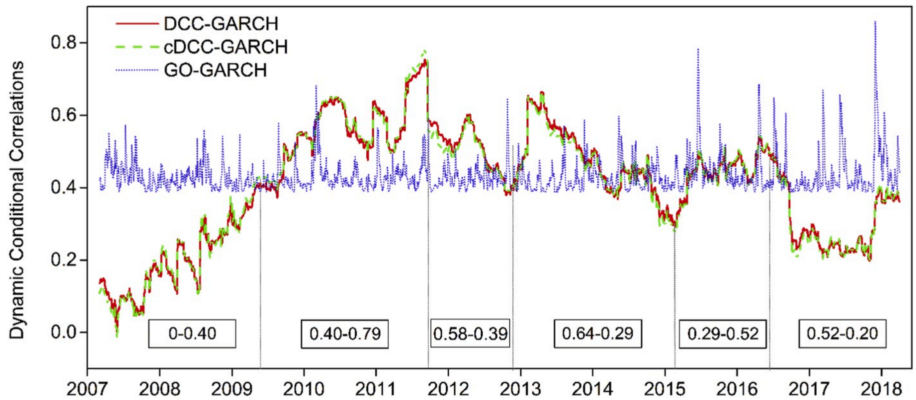


**Fig. 3.** Dynamic conditional correlations between OVX and VIX indices.

directional mean spillover between OVX and VIX, providing further verification of the ability for forecasting across the two implied volatility indices. In addition, the traditional Granger causality test has been employed to determine the relation between these indices. Results presented in Table 6 confirm the presence of a bi-directional Granger causality between OVX and VIX returns.

Table 7 provides the estimated results of the full BEKK-GARCH (1,1) model. All conditional variances have been found to be significant at the 1% confident interval (Panel A, Table 7). This indicates that the current volatility of OVX and VIX depend on past shocks ($a^{oo}$ and $a^{vv}$) and the past volatilities ($b^{oo}$ and $b^{vv}$). It implies that any unexpected events in the oil market or stock market can increase the implied volatility of their own markets. This is to say that current volatility in the oil market and/or the stock market has the potential to drive higher volatility in subsequent periods.

Review of volatility spillover across markets indicates a significant bi-directional volatility spillover between the two markets and these findings suggest an interdependent relationship between the volatility of the two markets. The significant parameters of $a^{ov}$ and $b^{ov}$ at the 5% or higher levels indicate a notable volatility spillover from the oil market to the stock market. Similarly, both $a^{vo}$ and $b^{vo}$ are significant at the 1% level; there is a significant volatility spillover from the stock market to the oil market.

## 5. Policy implications

This paper on implied volatility and the observations, as well as inferences, provide a progressive perspective for price fluctuation and insight on the probable volatility of the market in the future. Oil prices are controlled by traders who bid on oil future contracts, and as such, the dynamic conditional correlations between OVX and VIX provide useful guides for market participants to predict the interaction of oil price shocks on the macro-economy, and decision-makers to impose timely and informed policy changes.

To further expand these points, we examine the way DCCs respond to selected events relevant to the financial crisis, geopolitics, and policy changes. First, at the onset of the 2008 financial crisis, oil prices and stock markets fell sharply with the simultaneous increase in market uncertainty and volatility. This not only had a significant negative impact on the global economy but also rendered a closer intersect between OVX and VIX. The corresponding DCC coefficients jumped by 191% from 0.11 (22 September 2008) to 0.32 (30 November 2009) in one month. Correspondingly, in order to bring stability to global prices, to ease the stress on the oil market, and to prevent further spillover effects, the decision-makers decided to cut oil production by 16% in eight months. Concurrently, the U.S. oil production pulled back on drilling operations until prices began to improve and switched from conventional drilling to horizontal drilling following the 2008 crash. At the same time, the Fed responded with monetary policy change by adjusting the federal funds rates based on projections in unemployment and inflation rates. If such an increase in the dynamic interaction between OVX and VIX can be properly considered, policy makers could have arrived at an economic forecast with compromised and/or complementary monetary and energy policies, rather than acting on their own principles.

A second event involved the unrest in the Middle East that was initiated around the Arab Spring in late 2010 and continued with the civil war in Libya in 2011. During this period, the volatility of the oil market and the stock market increased significantly with the resulting DCC coefficients increasing by 48%, starting from 0.50 (23 May 2011) to 0.74 (16 November 2011). Considerations were once given to dismantle the nation's strategic petroleum in order to ease the oil supply uncertainty. This high correlation between OVX and VIX signals the likely impact of a policy change in oil supply onto the forecast of the near-term stock market recovery.

The third event was related to policy changes as the U.S. Federal Reserve sent out indications that it would slow down the large-scale

**Table 6**
Granger causality test.

| Null Hypothesis | F-Statistic | Prob. | Conclusions |
|---|---|---|---|
| RVIX does not Granger Cause ROVX | 10.2836 | 2.00E-05 | Reject |
| ROVX does not Granger Cause RVIX | 2.6650 | 6.98E-02 | Reject |

Notes: RVIX and ROVX denote returns of VIX and OVX, respectively.

**Table 5**
Estimation results of VAR model.

| | OVX returns | VIX returns |
|---|---|---|
| $u$ | −0.0008 (−1.0159) | −0.0021 (−1.6456) |
| $a_1$ | −0.0702*** (−3.1701) | −0.1158*** (−5.4105) |
| $a_2$ | −0.0495*** (−2.0822) | −0.0878*** (−3.8465) |
| $a_3$ | −0.0871 (−3.9523) | −0.0577*** (−2.6324) |
| $a_4$ | −0.0270 (−1.2484) | −0.0567*** (−2.6254) |
| $a_5$ | −0.0363 (−1.6323) | −0.0259 (−1.1827) |
| $a_6$ | −0.0558** (−2.5310) | −0.0354* (−1.6866) |
| $a_7$ | −0.0873*** (−4.1286) | −0.0438** (−2.1319) |
| $a_8$ | −0.0007 (−0.0345) | −0.0508** (−2.5730) |
| $b_1$ | 0.0440*** (3.4831) | 0.0477 (1.5619) |
| $b_2$ | 0.0085 (0.6640) | 0.0479 (1.5633) |
| $b_3$ | 0.0202 (1.6019) | −0.0207 (−0.7406) |
| $b_4$ | 0.0001 (0.0031) | −0.0234 (−0.7896) |
| $b_5$ | 0.0182 (1.3922) | −0.0897*** (−2.9306) |
| $b_6$ | 0.0337*** (2.5785) | −0.0236 (−0.7862) |
| $b_7$ | 0.0203 (1.6031) | −0.0374 (−1.2611) |
| $b_8$ | 0.0018 (0.1484) | 0.0094 (0.3175) |

Notes: values between parentheses are t-statistics, ***, ** and * denote rejection of null hypothesis at 1%, 5% and 10% significance level, respectively.

**Table 7**
Estimation results of BEKK-GARCH model.

| Panel A: BEKK-GARCH parameter estimates | | | | | |
|---|---|---|---|---|---|
| $C = \begin{bmatrix} c^{oo} & 0 \\ c^{vo} & c^{vv} \end{bmatrix}$ | | $A = \begin{bmatrix} a^{oo} & a^{ov} \\ a^{vo} & a^{vv} \end{bmatrix}$ | | $B = \begin{bmatrix} b^{oo} & b^{ov} \\ b^{vo} & b^{vv} \end{bmatrix}$ | |
| 0.2988*** (11.5289) | 0 (0.0000) | 0.3510*** (23.3885) | 0.0286** (2.1261) | 0.8971*** (141.1427) | −0.0289*** (−3.9493) |
| 0.1755*** (3.9610) | −0.4083*** (−20.6798) | −0.0735*** (−4.3916) | 0.5238*** (27.7962) | 0.0946*** (8.4032) | 0.8423*** (81.0298) |
| Panel B: Diagnostic tests | | | | | |
| | | OVX | | VIX | |
| $Q^2(10)$ | | 5.2800 (0.8717) | | 7.7426 (0.6539) | |
| ARCH | | 2.7270 (0.2557) | | 0.7780 (0.6777) | |
| Log L | | 8382.8194 | | | |

Notes: for BEKK-GARCH estimates between parentheses are t-statistics, for Ljung-Box test (Q) and ARCH effect test in parentheses are significance values. Ljung-Box Q statistics correspond to a test of the no autocorrelation in square standardized residuals in order of 10 lags. Arch Lagrange multiplier statistics correspond to a test of the null of no arch effect. *** and ** denote rejection of null hypothesis at 1% and 5% significance level, respectively.

purchase of assets in May 2013. By December 2013, U.S. officials announced the gradual withdrawal of quantitative easing monetary policy,[9] which significantly affected the liquidity of the U.S. stock market. The DCC coefficients tracked the news closely and decreased by 33% from 0.54 (11 December 2013) to 0.36 (16 July 2014).

The fourth event was caused by a change in the oil market policy. On 30 November 2016, the Organization of Petroleum Exporting Countries (OPEC) reached an agreement within its assembly of fourteen member countries to curtail oil production for the first time since 2008. Two weeks later OPEC and Non-OPEC producers jointly agreed to curtail oil output[10]. The DCC coefficients drop by 46% in less than two months (0.43 on 11 November 2016 to 0.23 on 4 January 2017).

These observations suggest the existence of an important interdependent and intersecting relationship between the implied volatility of the two markets. Interestingly, financial crises and geopolitical events appear to strengthen the linkages between the oil and stock markets, while policy changes in an individual market (oil or stock) decrease their correlations, e.g. at the imposition of quantitative easing. It can be inferred that the correlation between the oil and stock markets would be further strengthened by events that significantly impact the uncertainty of both markets. However, events that mainly cause an increase in the uncertainty of an individual market (oil or stock) may only weaken the correlation between the two markets. Events that cause changes in the market correlation can signal market participants to gauge the degree of uncertainty between the oil and the stock markets. In addition, the implied volatility not only reflects the uncertainty of the market but also the fears of market participants. Thus, the uncertainties and ambiguities plaguing the market participants regarding the shortage of oil supply will translate into increased oil preventive demand, and further affect the volatility of the stock market. Policy makers should, as such, carefully take into consideration the bi-directional volatility transmission between the oil market and the U.S. stock market.

## 6. Conclusions

Crude oil is a strategic energy resource for economic growth and national security. It is also a major commodity traded in financial markets. Future oil market uncertainty can intensely affect the nation's economy as well as stock investments.

Unlike previous studies that explore traditional returns series and volatility derived from the GARCH-type models, we employed the implied volatility index to study the dynamic correlation and risk spillover between the oil and the U.S. stock markets. As compared to the historical information volatility (GARCH volatility, stochastic volatility and/or realized volatility), implied volatility provides a more timely measurement of risks in the financial markets because it includes both market history information and future expectations. It further reveals the implied relationship between oil and stock options prices. Our work also reflects the era of the fracking revolution (since 2008) that is beyond the time period in which the peak oil theory fails to predict the U.S. oil production capacity.

We employed a series of multivariate GARCH models to capture the dynamic correlations and risk spillovers, including the DCC-GARCH, cDCC-GARCH, GO-GARCH, and BEKK-GARCH models. Overall, dynamic correlations calculated by DCC and cDCC models are similar but different from those computed by the GO-GARCH model. This is mainly attributed to the differences among GARCH estimation specifications that use different econometric properties (Basher and Sadorsky, 2016; Jin et al., 2020; Sarwar et al., 2019). However, we find that the cDCC-GARCH model outperforms the baseline DCC-GARCH model.

The major findings of this investigation are summarized as follows. Firstly, we discover a significant positive time-varying correlation between oil and stock implied volatilities with a positive unconditional correlation of 0.42, implying an interdependent relationship between the implied volatility of these two markets. Secondly, economic events, geopolitical events, and market policy changes are some of the high-level changes that can structurally alter the dynamic conditional correlation between oil and stock implied volatilities. In particular, the correlation between oil and stock markets showed a significant increase during the period from the global financial crisis to the early economic recovery period (2008–2011). However, changes of policies in the individual market (oil or stock) tend to decrease the correlation between the two markets, e.g. at the imposition of quantitative easing. Thirdly, a bi-directional Granger causality is observed between OVX and VIX returns and there exists a significant bi-directional implied volatility spillover between oil and stock markets.

These findings render important policy implications for investors, policymakers and regulators. For investors, such a positive correlation suggests a risk synergy effect between the oil and stock markets when encountering market uncertainty. Therefore, combining oil-related assets with the stock market in a diversified portfolio could not effectively reduce the foreseeable risks. Investors should dynamically adjust their portfolio strategies based on the dynamic correlations between oil and stock implied volatility to minimize risks and maximize profits. Policymakers should take extra caution to develop appropriate strategies in order to lessen the impacts of oil price uncertainty. Practically, it is important to incorporate the forward-looking market correlations when making changes in monetary and/or energy policies for stabilizing the economy and providing energy security to the nation. Governments can use past stock market volatility information to make appropriate and

[9] https://www.nytimes.com/2013/12/19/business/economy/fed-scales-back-stimulus-campaign.html. Accessed 13 August 2019.

[10] https://www.reuters.com/article/us-opec-meeting/opec-non-opec-agree-first-global-oil-pact-since-2001-idUSKBN13Z0J8. Accessed 13 August 2019.

informed energy purchase and storage decisions, especially for the large oil importing countries (Du and He, 2015).

In addition, implied volatility not only reflects market uncertainty but also the fears of market participants. As such, the spillover effect between oil and stock implied volatility also reflects the association of market investors' fears, which provides useful information for market regulation. Furthermore, our findings could also be useful for academics engaged in research involving energy risk management and asset pricing. For example, oil price uncertainty cannot be ignored as a major factor in building a valuation model of stock options, especially during the periods of economic turmoil. The uncertainty information contained in the market can be obtained from the volatility transmission between the oil and the stock markets, which can be further leveraged to forecast the market's future volatility (Maghyereh et al., 2016).

Our research contributes to the understanding of the relevancy and important aspects of the linkages between oil and stock markets at the implied volatility level. A natural extension of our work is to examine the connectedness between oil and stock implied volatility indices in the time-frequency domain (Baruník and Křehlík, 2018), as well as to investigate the implied volatility relationship in the oil-stock nexus for emerging aggregate stock markets and industry markets such as the renewable energy market.

## CRediT authorship contribution statement

**Zhenhua Liu:** Conceptualization, Writing - original draft, Data curation, Writing - review & editing, Methodology, Software. **Hui-Kuan Tseng:** Conceptualization, Writing - original draft, Supervision, Writing - review & editing. **Jy S. Wu:** Conceptualization, Writing - original draft, Supervision, Writing - review & editing. **Zhihua Ding:** Supervision.

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## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.resourpol.2020.101637.

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