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ABSTRACT

This study examines how crude oil price volatility affected the stock returns of major global oil and gas corporations during three major oil-price wars that took place between October 1991 and June 2020. Episodes considered include the 1998 Saudi Arabia—Venezuela war, the 2014-16 conflict and the 2020 Saudi Arabia—Russia war in a time of unprecedented crisis caused by the COVID-19 pandemic. Our findings reveal a significant evidence for volatility persistence and leverage effects in oil price during the three oil-price wars. These findings are consistent for WTI as well as Brent crude oil specifications. Though the persistence of volatility is similar to that of the previous two oil-price wars, the 2020 Saudi Arabia—Russia oil-price war has higher volatility spikes than the previous two wars. Besides, oil price shocks have a significant and positive effect on the returns of oil and gas companies. These findings provide information on how volatility in global oil prices is also sensitive to irregular events such as price wars between oil producers. This information can be important for economic agents contemplating shorter hedges by managing risks during times of high volatility.

JEL Classifications: C32; G12; Q40; Q43

Keywords: Crude Oil; Oil and Gas Corporations; Oil-price Wars; Stock Returns; Volatility

1. INTRODUCTION

Studies in energy economics have extensively documented the extreme volatility in the crude oil prices over the past decades as a result of extreme and irregular events. These include, on the one hand, extreme events such as geopolitical tensions and wars (e.g. Gulf War, 1990), economic crises (e.g. Mexico 1994; the East Asia crisis 1997; Argentina 2001), financial crises (e.g. Long Term Capital Management (LTCM) Russia 1998; Mortgage-backed-securities US 2008) or major terrorist attacks (e.g. 9/11), and on the other hand, irregular events such as hurricanes, OPEC production policy changes, disruption in oil production or supply due to worker strikes etc. Literature suggests a strong association between oil price volatility and stock market returns.

However, the debate is still ongoing and empirical evidence so far on the strength and direction of association is inconclusive. Some studies (e.g. Jones and Kaul 1996; Sadorsky 1999; Driesprong et al. 2008; Diaz et al. 2016; Joo and Park 2017; Xiao et al. 2018; Westerlund and Sharma 2019) pointed to a negative relationship, whereas others reported a positive association (Narayan and Narayan, 2010; Gupta, 2016; Diaz and Perez de Gracia, 2017; Luo and Qin, 2017; Wen et al. 2019) or even evidence for no significant relationship (e.g. Chen et al. 1986; Huang et al. 1996; Sukcharoen et al. 2014). To the best of our knowledge, no study so far has investigated the relationship between oil-price shocks and returns of oil and gas corporations during oil-price wars. Oil-price wars that take place among major oil producers cause sudden oil-price shocks which may significantly affect stock returns. Sudden drastic increases in oil supply during these wars lead to a market glut which results in falling oil prices and energy stocks.

We can identify three major oil wars during the past 25 years: The first war lasted for 17 months from November 1997 to March 1999. The feud between two Organisation of the Petroleum Exporting Countries (OPEC) members Saudi Arabia and Venezuela over violations of agreed production quota led to Saudi Arabia flooding the market, which caused prices to fall from \$20 per barrel to below \$10 within a month. Average prices plummeted to lowest levels since the 1970s.

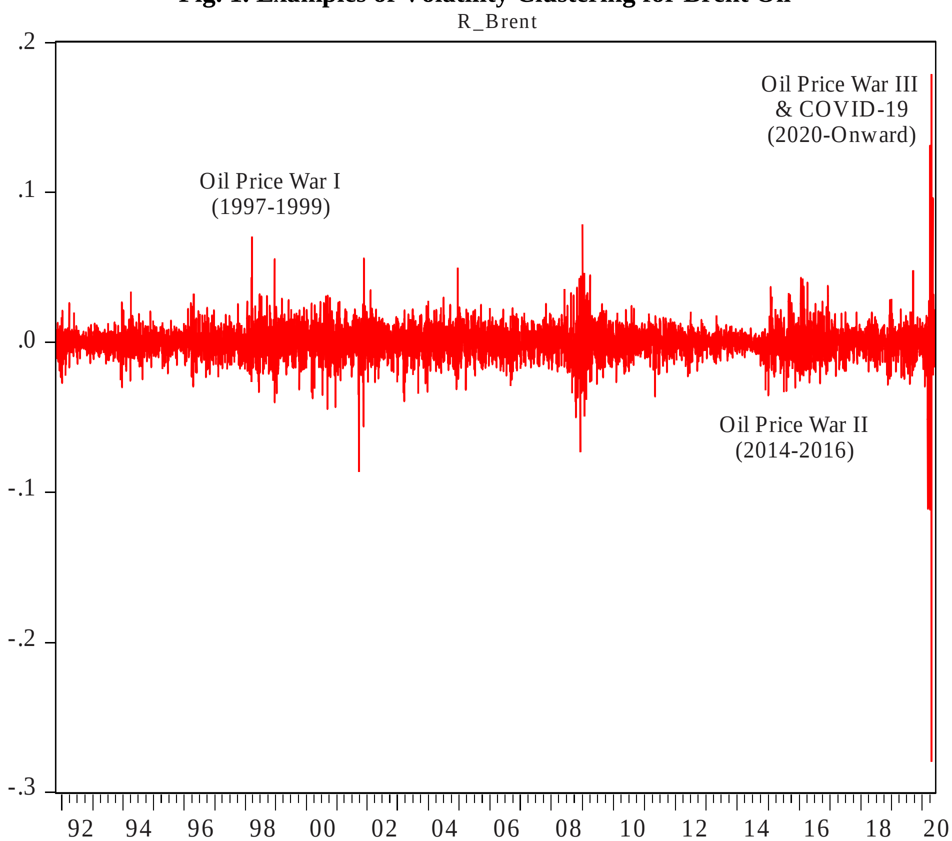
The second war lasted for 22 months from November 2014 to August 2016. It started in November 2014 with an OPEC meeting in Vienna. Tired of non-OPEC countries freeloading on the cartel’s production cuts, and worried about the impact of the United States (U.S.) shale revolution, Saudi Arabia adopted a policy of pump-at-will in spite of weak demand. Crude oil price collapsed from about \$100 per barrel to \$27 during the war period.

The latest and shortest oil war took place in March 2020 between the top OPEC exporter Saudi Arabia and the top non-OPEC exporter Russia. The war lasted only two months from March 2020 to June 2020. In response to Russia’s refusal to abide by the

OPEC decision to affect a total production cut of 3.6 million barrels per day (bpd), Saudi Arabia announced to massively increase its oil production. The brief price war added almost 100 million barrels of additional supply into an already oversupplied market, according to Bloomberg calculations. This came at a time when the world was facing an unprecedented economic slowdown resulting from the Covid-19 pandemic and the preventive lockdowns. Demand for non-essential goods and services had collapsed, industrial production had stopped, and transportation had come to a halt. As a result of the oil war, the price of oil dropped heavily. On Monday 9 March, prices fell by 30 percent, the biggest one-day drop since January 17, 1991 when oil prices fell by one-third at the outset of the 1991 Persian Gulf War.

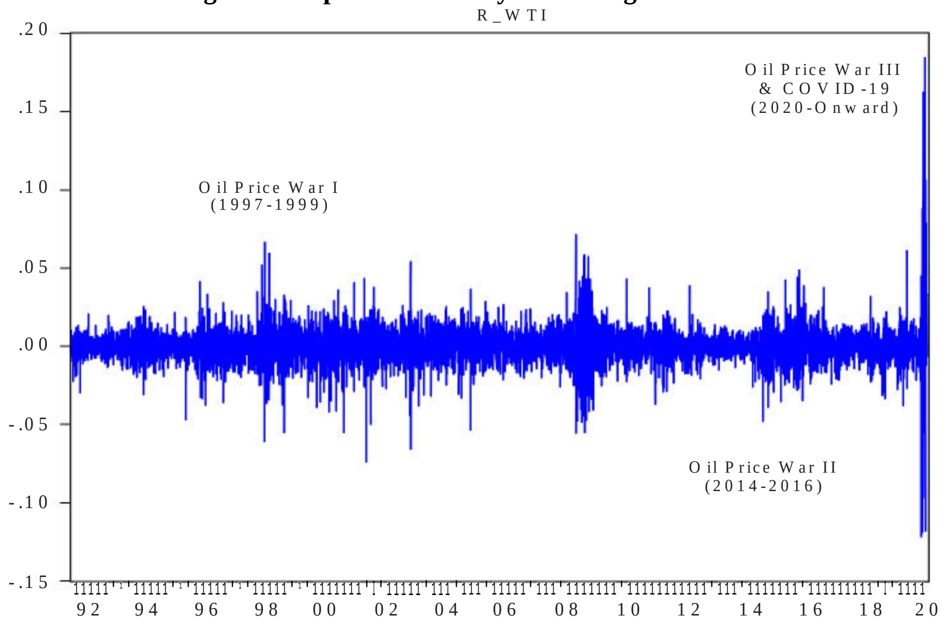
During times of high uncertainty derived from conflict or trade wars such as the above-discussed oil wars, commodity markets such as oil experience a surge in price fluctuations (Orbaneja et al. 2018). Figures 1 and 2 show volatility clustering of the Brent and the West Texas Intermediate (WTI) crude oil prices over the 1991–2020 period. Both figures clearly indicate high volatility in crude oil prices during the three oil wars. The stocks of major oil and gas corporations also show higher volatility due to oil-supply shocks, as shown in figures A1-3 in appendix A.

Fig. 1. Examples of Volatility Clustering for Brent Oil



Source: Authors' calculations using U.S. Energy Information Administration (EIA) online data.

Fig. 2. Examples of Volatility Clustering for WTI Oil



Source: Authors' calculations using U.S. Energy Information Administration (EIA) online data.

In this study, we considered 7,116 daily observations on ten largest oil and gas corporations listed on the New York Stock Exchange (NYSE) for the period from October 25, 1991 to June 8, 2020. This study is the first to consider the association between oil price shocks and returns of oil and gas corporations during the specific oil-price wars.

The contribution of our study to the extant literature is three-fold. First, this study contributes to the literature on volatility persistence in oil prices (see, Narayan and Narayan, 2007; Salisu and Fasanya, 2013; Zavadska et al., 2018). We analyse the three oil-price wars by focusing on the behaviour of the series for the whole period as well as the periods before, during and after each war episode. We rely on Generalised Autoregressive Conditional Heteroskedasticity (GARCH) and Threshold Generalised Autoregressive Conditional Heteroskedasticity (T-GARCH) models. The latter is used to test for asymmetries in the conditional variance due to deferential effect of positive and negative shocks. Furthermore, we explicitly consider structural breaks when modelling oil volatility by applying multiple break points to analyse all three oil-price war periods, as presented in Figure 1 and Figure 2. We analysed corresponding structural breaks by using the Bai and Perron structural break points test. The results of full sample period are compared with those obtained for four sub-periods: *whole* period, *pre-war* period, *oil price-crisis* period and *post-war* period. The presence of structural break points confirms abnormal behaviour in the series, which indicates higher uncertainty and elevated risk level. We find evidence for persistence and leverage effects in the oil price volatility during the three oil-price wars.

Second, the study extends recent literature on the impact of oil prices shocks on stock returns of oil and gas companies (see, Sadorsky, 2001; Lanza et al., 2005;

Giovannini et al., 2006; Chang et al., 2009; Sanusi and Ahmad, 2016; Diaz et al., 2017; Antonakakis et al., 2018). To this end, the study brings new empirical evidence on the impact of oil price shocks arising from oil-price wars on the stock returns of oil and gas corporations using a Vector Auto-Regressive (VAR) model. We find that oil price shocks have significant and positive effect on the stock returns of oil and gas companies. Third, the study sheds light on the behaviour of the latest oil-price war in comparison with the previous episodes in the recent past. The fact that this conflict occurred at a time the world economy was collapsing due to the Covid-19 pandemic meant that both the oil and stock markets experienced some of the worst volatility ever recorded. In light of our analysis, we are able to confirm that, despite the short period, the Saudi Arabia–Russia oil-price war has higher volatility spikes than the previous two wars. We find that the impact of oil-price shocks on oil and gas stocks has been the strongest during the most recent war (March 2020).

The rest of the paper is organised as follows. Section 2 provides the review of related literature. Section 3 presents the data and methodology. Section 4 discusses the empirical results followed by concluding remarks in Section 5.

2. RELATED LITERATURE

Since the seminal works by Jones and Kaul (1996) and Sadorsky (1999) on the oil price-stock price nexus, various strands of literature have emerged exploring different dimensions of the relationship between oil price shocks and stock market returns. One set of studies examined oil price changes in relation to sectoral stock returns (see for instance Sadorsky, 2001; El-Sharif et al., 2005; Boyer and Filion, 2007; Nandha and Faff, 2008; Nandha and Brooks, 2009; Phan et al., 2015; Gupta, 2016; Diaz and Perez de Gracia, 2017; Tiwari et al., 2018; Kocaarslan and Soytas, 2019; Pham, 2019; Yun and Yoon, 2019). The conclusion of most of these studies is that supply-side oil price shocks have a negative effect on the stocks of industries such as transportation and aviation which have high oil input costs, while positive effects on the stock prices of oil and gas firms which are net beneficiaries of higher oil prices. Zhu et al. (2016) and Narayan and Sharma (2011) reported heterogeneous effects across firms in different industries and of different sizes.

A second set of studies focused on the type of oil price shock (supply or demand). The pioneer work of Kilian (2009) suggested that “not all oil price shocks are alike”. Specifically, he proposed three types of oil price shocks: oil supply, oil demand and aggregate demand. Their study was followed by number of subsequent works including Apergis and Miller (2009), Filis et al. (2011), Broadstock and Filis (2014), Güntner (2014), Le and Chang (2015), Kang et al. (2017), Huang and Mollick (2020) and Otero (2020). These studies highlighted differential impact of demand and supply shocks in the oil market on various financial variables. For instance, Kang et al. (2017) found that oil demand-side shock has a positive effect on the return of oil and gas corporations, while Güntner (2014) noted that oil supply shocks have no significant effect on international stock markets.

A third strand of literature is based on the nature of the country as producer (oil exporting) or consumer (oil importing) (see for instance Park and Ratti, 2008; Wang et al., 2013; Bouri, 2015; Tchatoka et al., 2019; Cheema and Scrimgeour, 2019; Hamdi et al., 2019). Studies pertaining to oil-importing countries generally reported a negative relationship between oil price increase and stock prices (Sadorsky, 1999; Jones and Kaul, 1996; Kilian and Park, 2009; Cunado and de Gracia, 2014). Studies on oil-exporting countries, in contrast, noted an increase in stock prices as a result of increase in oil prices (Park and Ratti, 2008; Bjørnland, 2009; Gil-Alana and Yaya, 2014; Demirer et al., 2015).

As seen in this brief literature review, the body of literature on various aspects of oil price—stock linkage is substantial. However, to the best of our knowledge, no study examines the relationship by specifically focusing on the oil-price wars that take place between major oil producers. The significance of this topic lies in the fact oil-price wars are periods of sharp variations in oil prices which creates an environment of economic uncertainty. This in turn affects investors' future expectations of stock returns. The topic is of particular relevance these days as the unprecedented shock the world economy suffered as a result of the Covid-19 pandemic and the accompanying preventive lockdowns have accentuated the state of uncertainty prevailing in the commodity and stock markets.

Global oil markets have to contend, not only with the supply glut caused by the oil-price war between Saudi Arabia and Russian Federation, but also with the freeze of demand and supply chain-disruptions resulting from the coronavirus outbreak-related lockdowns. This provides an exceptional setting to study how oil-price volatility interacts with stock returns of oil and gas firms.

3. DATA AND METHODOLOGY

3.1. Data

The dataset for this study consists of 7,116 daily observations for crude oil prices and stock prices for the period from October 25, 1991 to June 8, 2020. The choice of using daily data for volatility analysis is relevant in this case as higher frequency data are required in order to accurately capture market changes (Zavadska et al., 2018). Data on Brent and West Texas Intermediate (hereafter, WTI) crude oil spot prices in the US dollars per barrel are taken from the U.S. Energy Information Administration (Thomson Reuters File). Data on stock prices come from Yahoo Finance and Datastream.[1] We use the longest series available for the closing stock prices of ten largest oil and gas corporations listed on NYSE. The selected oil and gas corporations are the following: British Petroleum P.L.C. (BP), Chevron Corporation (CVX), ConocoPhillips (COP), Exxon Mobil (XOM), Hess Corporation (HES), Hollyfrontier Corporation (HFC), Royal Dutch Shell (SHELL), Suncor Energy Inc. (SU), Total SA (TOTAL), and Valero Energy Corporation (VLO). Following Bouri et al. (2016), all variables are expressed in percentages using the first differences of the natural logarithms of the price multiplied by 100.

Table 1 identifies the summary statistics for crude oil and stocks. Following standard unit root procedures, the time series are found to be non-stationary. Consequently, first differences of logarithms are used to obtain returns. Most of the variables are negatively skewed and depicted a leptokurtic behaviour. The values for

[1] https://finance.yahoo.com/ , http://product.datastream.com/dsws/1.0/DSLogon.aspx

Table 1

Summary Statistics

	Observations	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF
WTI	7,116	0.0171	42.5832	-28.1382	2.6399	0.5904	30.6082	226,314.00 (0.000)	-89.85***
BRENT	7,116	0.0189	41.2023	-25.6389	2.4093	0.5593	28.4739	192,693.90 (0.000)	-83.73***
BP	7,116	0.0374	19.5610	-21.2006	1.7860	-0.5282	16.9772	58,231.31 (0.000)	-82.19***
COP	7,116	0.0471	22.4853	-28.5552	1.9588	-0.5022	17.7996	65,213.07 (0.000)	-88.08***
CVX	7,116	0.0498	20.4904	-25.0062	1.6621	-0.4325	23.7158	127,409.90 (0.000)	-34.13***
HES	7,116	0.0277	18.4946	-41.0506	2.3746	-1.0678	23.3036	123,527.80 (0.000)	-86.26***
HFC	7,116	0.1191	37.0400	-31.3984	2.7364	0.7646	21.0578	97,336.18 (0.000)	-84.97***
SHELL	7,116	0.0283	19.4767	-19.5932	1.7459	-0.4885	18.5469	71,918.60 (0.000)	-81.24***
SU	7,116	0.1141	358.9021	-24.1451	4.8791	5.8478	90.2120	5,100,000.00 (0.000)	-80.76***
TOTAL	7,116	0.0408	13.6408	-19.6269	1.8099	-0.4170	11.6608	22,436.91 (0.000)	-86.30***
VLO	7,116	0.0492	16.5329	-22.3144	2.4627	-0.3787	9.9477	14,476.10 (0.000)	-44.62***
XOM	7,116	0.0429	15.8631	-15.0271	1.5410	-0.0693	12.7112	27,956.07 (0.000)	-66.62***

Notes: This table presents the summary statistics for returns of ten oil and gas corporations listed on NYSE and crude oil market (Brent and WTI Oils) based on daily data over the period of October 1991 to June 2020. Jarque and Berra (1980) is the normality statistics test for the null hypothesis of a Gaussian distribution. Furthermore, ADF is the unit root test Augmented Dickey-Fuller test (1981). ***, **, * show that the null hypothesis of a unit root is rejected at 1%, 5% and 10% significance levels, respectively. All variables are expressed in percentages using the first differences of the natural logarithms of the price multiplied by 100.

kurtosis show that the data are associated with simultaneously sharp peaked and fat tail. Thus, preliminary econometric analysis confirmed well-known stylised facts of crude oil and financial markets including significant autocorrelations, asymmetry, and heteroskedasticity. The high levels of kurtosis justify the use of a VAR type model as a tool to appropriately take into account non-normal co-variations between oil and stock returns of oil and gas corporations.

3.2. Estimation Strategy

The empirical analysis begins with a standard test for stationarity analysis, the Augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1981) and the Kwiatkowski et al. (1992) KPSS test. The null hypothesis is tested for the presence of non-stationarity (a unit root) in the variables while the alternative hypothesis is tested for stationarity of the variables. As an alternative, we use the KPSS test in place of ADF test and find similar results.[2]

Next, we perform the Bai–Perron (1998, 2003) structural break test to examine the possibility of breaks caused by the major oil-price wars that occurred during the period under consideration. We divide each oil-price war episode into four sub-periods in order to better observe the fluctuations in oil prices that took place during the period. The first period is the *whole* period, the second is the *pre-war* period, the third is the *oil price-crisis* period, and the fourth is the *post-war* period. The results of the structural break tests are shown in Table 2.

Table 2

Structural Break Points—Bai–Perron Test

		Oil Price-war I		
	Whole-period	Pre-war	Oil price crisis	Post-war
Break-dates	30/5/1995 to 5/6/2002	30/5/1995 to 26/11/1997	1/12/1997 to 25/3/1999	29/3/1999 to 5/6/2002
		Oil Price-war II		
	Whole-period	Pre-war	Oil price crisis	Post-war
Break-dates	31/12/2013 to 18/9/2018	31/12/2013 to 20/11/2014	26/11/2014 to 29/8/2016	30/8/2016 to 18/9/2018
		Oil Price-war III		
	Whole-period	Pre-war	Oil price crisis	
Break-dates	30/12/2019 to 5/6/2020	30/12/2019 to 5/3/2020	6/3/2020 to 21/4/2020	

Notes: This table presents the computation of structural breaks. Bai-Perron tests of L+1 vs. L sequentially are employed to identify the number and timing of breaks. The break test options include significance at 5 percent level, trimming 0.15, and maximum breaks 5. Test statistics employ HAC covariance (Prewhitening with lags from AIC, Bartlett kernel, Newey-West automatic bandwidth). The error distributions are allowed to differ across breaks.

In the next step, we model volatility in oil prices during the three oil-price wars using GARCH model presented by Bollerslev (1986) and the Threshold GARCH (T-GARCH) model proposed by Zakoian (1994). Engle (1982) suggests that the variance of the residuals at the time t depends on the squared error terms from past periods. The

[2] The results are not reported here for the sake of brevity.

econometric specification for the mean and variance equations of ARCH (q) model can be given as follows:

$$Oil_t = \propto + \beta' x_t + \mu_t \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (1)$$

Where $\mu_t|\Omega_t \sim iid\ N(0, \sigma^2{}_t)$, and

$$\sigma^2{}_t = \gamma_0 + \sum_{j=1}^{q} \gamma_{j\mu^2{}_{t-j}} \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (2)$$

The generalised ARCH model by Bollerslev (1986) also termed as GARCH (p, q) is specified as:

$$Oil_t = \propto + \beta' x_t + \mu_t \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (3)$$

Where $\mu_t|\Omega_t \sim iid\ N(0, \sigma^2{}_t)$, and

$$\sigma^2{}_t = \omega + \sum_{i=1}^{p} \alpha_{i\sigma^2{}_{t-i}} + \sum_{j=1}^{q} \gamma_{j\mu^2{}_{t-j}} \quad \dots \quad \dots \quad \dots \quad \dots \quad (4)$$

The simplest form of GARCH (p, q) model is the GARCH (1, 1), which is extensively used in energy market research as it generally performs better than higher order GARCH models (Narayan and Narayan, 2007; Salisu and Fasanya, 2013). The variance equation for GARCH (1, 1) is given as:

$$\sigma^2{}_t = \omega + \alpha\mu^2{}_{t-1} + \beta\sigma^2{}_{t-1} \quad \dots \quad \dots \quad \dots \quad \dots \quad \dots \quad (5)$$

Equation (5) captures volatility of the previous period, measured as the lag of the squared residual term, ($\alpha\mu^2{}_{t-1}$, the ARCH effect) and the persistence of the volatility ($\beta\sigma^2{}_{t-1}$, the GARCH effect).

The ARCH and the GARCH models are symmetric; however, it has been observed that negative shocks have larger impact on volatility than positive shocks in most financial time series such as stocks and commodities (Zavadska et al., 2018). The T-GARCH model is considered more appropriate to test for asymmetries in the conditional variance and is therefore preferred in this analysis. The specification of the conditional variance equation for T-GARCH (1, 1) is as follows:

$$\sigma^2{}_t = \omega + \alpha\mu^2{}_{t-1} + \theta\mu^2{}_{t-1}D_{t-1} + \beta\sigma^2{}_{t-1} \quad \dots \quad \dots \quad \dots \quad (6)$$

Where D_t takes the value of 1 for μ_t<0, and 0 otherwise, suggesting that positive and negative shocks have different impacts. α captures the impact of positive news, whereas $\alpha + \theta$ measures negative shocks. Simply, the significant and positive T-GARCH result indicates that bad (negative) news have greater impact on volatility than good (positive) news and vice versa.

In the final step, linkage between crude oil prices volatility and stock returns of oil and gas corporations is examined through VAR based methodology proposed by Sims (1980). Before estimating the VAR model, we perform preliminary tests for time series properties including the unit root test for stationarity and the test for co-integration. We assume that all the variables are integrated of order one, i.e. the variables contain a unit root. We test for cointegration (Johansen and Juselius, 1990) using both the trace and the maximum Eigenvalue tests. As shown in Tables 3 and 4, we failed to reject the null hypothesis of no cointegration among the variables of interest. In other words, the results

Table 3

Johansen and Joselius Cointegration Tests: Trace Statistics (Full Sample)

WTI Crude Oil									
	Models with an Intercept					Models with an Intercept and a Linear Trend			
	Hypothesis	Eigen value	Tr. statistics	Prob		Hypothesis	Eigen value	Tr. statistics	Prob
BP – WTI	r = 0	0.00092	11.7241	0.475	BP – WTI	r = 0	0.0009	11.1620	0.205
	r ≤1	0.00074	5.07014	0.274		r ≤1	0.0006	4.9541	0.026
COP – WTI	r = 0	0.00085	9.60818	0.671	COP – WTI	r = 0	0.00071	9.02239	0.367
	r ≤1	0.00049	3.47941	0.493		r ≤1	0.00046	3.47649	0.061
CVX – WTI	r = 0	0.00045	5.66441	0.963	CVX – WTI	r = 0	0.00042	3.94817	0.905
	r ≤1	0.00035	2.47198	0.683		r ≤1	0.00016	1.01115	0.315
HES – WTI	r = 0	0.001254	11.8102	0.465	HES – WTI	r = 0	0.001240	11.57616	0.178
	r ≤1	0.000392	2.77160	0.624		r ≤1	0.00037	2.757633	0.096
HFC – WTI	r = 0	0.000586	7.09217	0.891	HFC – WTI	r = 0	0.000544	6.787624	0.602
	r ≤1	0.000417	2.94822	0.590		r ≤1	0.000416	2.940007	0.086
SHELL – WTI	r = 0	0.000573	6.84067	0.907	SHELL – WTI	r = 0	0.000485	6.215734	0.67
	r ≤1	0.000394	2.78999	0.620		r ≤1	0.000394	2.787056	0.095
SU – WTI	r = 0	0.000967	10.60615	0.580	SU – WTI	r = 0	0.000941	10.33117	0.256
	r ≤1	0.000532	3.766233	0.448		r ≤1	0.000519	3.673405	0.055
TOTAL – WTI	r = 0	0.000439	5.792709	0.958	TOTAL – WTI	r = 0	0.000421	4.718254	0.838
	r ≤1	0.00038	2.68459	0.641		r ≤1	0.000246	1.74094	0.187
VLO – WTI	r = 0	0.000435	4.630929	0.988	VLO – WTI	r = 0	0.000426	4.080497	0.896
	r ≤1	0.00022	1.557551	0.863		r ≤1	0.000151	1.067893	0.301
XOM – WTI	r = 0	0.000772	8.018681	0.822	XOM – WTI	r = 0	0.000696	7.199292	0.554
	r ≤1	0.000361	2.554351	0.666		r ≤1	0.000321	2.270858	0.131

Notes: Tr. statistics = trace statistic, r = number of cointegrating vectors. The lag length in all the tests has been selected according to the Akaike Information Criteria (AIC). No cointegrating equation is traced for all oil and gas corporations with WTI crude oil. The results Brent crude oil are qualitatively consistent with the findings of WTI crude oil. The result for Brent crude oil is available with the authors and can be provided on request.

Table 4

Johansen and Joselius Cointegration Tests: Max-Eigen Value Statistics (Full Sample)

	WTI Crude Oil								
	Models with an Intercept					Models with an Intercept and a Linear Trend			
	Hypothesis	Eigen value	m.λ.	Prob		Hypothesis	Eigen value	m.λ.	Prob
BP – WTI	r = 0	0.0009	6.6554	0.711	BP – WTI	r = 0	0.0008	6.2059	0.587
	r ≤1	0.0007	5.0707	0.276		r ≤1	0.0007	4.9555	0.026
COP – WTI	r = 0	0.00087	6.12901	0.773	COP – WTI	r = 0	0.00078	5.54592	0.672
	r ≤1	0.00049	3.47922	0.495		r ≤1	0.00049	3.47652	0.062
CVX – WTI	r = 0	0.00045	3.19243	0.987	CVX – WTI	r = 0	0.00042	2.93640	0.951
	r ≤1	0.00035	2.47198	0.683		r ≤1	0.00014	1.01175	0.315
HES – WTI	r = 0	0.001277	9.03861	0.429	HES – WTI	r = 0	0.001246	8.81853	0.301
	r ≤1	0.000392	2.77160	0.624		r ≤1	0.00039	2.75763	0.096
HFC – WTI	r = 0	0.000586	4.14394	0.949	HFC – WTI	r = 0	0.000544	3.84761	0.875
	r ≤1	0.000417	2.94822	0.590		r ≤1	0.000416	2.94000	0.086
SHELL – WTI	r = 0	0.000573	4.05068	0.954	SHELL – WTI	r = 0	0.000485	3.42867	0.914
	r ≤1	0.000394	2.78999	0.620		r ≤1	0.000394	2.78705	0.095
SU – WTI	r = 0	0.000967	6.83991	0.689	SU – WTI	r = 0	0.000941	6.65776	0.530
	r ≤1	0.000532	3.76623	0.448		r ≤1	0.000519	3.67340	0.055
TOTAL – WTI	r = 0	0.000439	3.10811	0.988	TOTAL – WTI	r = 0	0.000421	2.97731	0.948
	r ≤1	0.00038	2.6845	0.641		r ≤1	0.000246	1.74094	0.187
VLO – WTI	r = 0	0.000435	3.07337	0.989	VLO – WTI	r = 0	0.000426	3.01260	0.945
	r ≤1	0.00022	1.55755	0.863		r ≤1	0.000151	1.06789	0.301
XOM – WTI	r = 0	0.000772	5.46433	0.844	XOM – WTI	r = 0	0.000696	4.92843	0.750
	r ≤1	0.000361	2.55435	0.666		r ≤1	0.000321	2.27085	0.131

Notes: m.λ. = Max-Eigen statistics, r = number of cointegrating vectors. The lag length in all the tests has been selected according to the Akaike Information Criteria (AIC). No cointegrating equation is found for all oil and gas corporations with WTI crude oil. The results Brent crude oil are qualitatively consistent with the findings of WTI crude oil. The result for Brent crude oil is available with the authors and can be provided on request.

suggest non-existence of a long-run relationship between oil price changes and stock returns of oil and gas corporations. Consequently, we proceed to estimate VAR models for all ten oil and gas corporations.

In order to analyse the impact of oil price changes on returns of oil and gas corporations, we obtain Generalised Impulse Response Functions (GIRF) by estimating the VAR model. Moreover, unidirectional causality between oil prices changes and stock returns is captured through the Granger-causality test of the VAR system. The VAR model has been used for investigating the effect of oil price shocks on stock market returns by studies such as Park and Ratti (2008), Cunado and Perez de Gracia (2014) and Diaz and Perez de Gracia (2017). A VAR model of order p that includes k variables can be written as:

$$y_t = A_0 + \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \qquad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \qquad \ldots \qquad (7)$$

Where p is the number of lags, $y_t = [y_{1t} \ldots y_{kt}]'$ is a column vector of all the variables in the model; namely, Brent oil, WTI oil and returns of oil and gas corporations. A_0 is the constant term, A_i is a $k \times k$ matrix of unknown coefficients, and ε_t is the residual term with the following properties:

$E(\varepsilon_t) = 0 \qquad \forall_t,$

$E(\varepsilon_s \varepsilon'_t) = \Omega \qquad if\ s = t$, and

$E(\varepsilon_s \varepsilon'_t) = 0 \qquad if\ s \neq t$

Ω is the variance-covariance matrix with non-zero off-diagonal elements. The lag length is selected based on the Akaike information criterion (AIC).

4. FINDINGS

4.1. Volatility Models

We begin by discussing the volatility of oil prices and their persistence during the three oil-price wars. Table 5 presents the results of GARCH and T-GARCH models. Panels A – C show results for the first, second and third oil-price wars, respectively. With respect to the outcomes of GARCH models, oil-price wars I and II both depict positive and significant volatility levels during the four sub-periods.

For example, the price war I period shows positive and significant volatility levels during the four sub-periods for WTI oil price. Higher volatility spikes were found for the crisis and post-war periods, but persistence for long period was the main feature during the whole and pre-crisis periods. For example, the sum of ARCH and GARCH ($\alpha + \beta$) effects in the case GARCH (1,1) model for whole and pre-crisis was 0.9771 and 0.9785 respectively which is close to one. This indicates that the volatility shocks are quite persistent. Likewise, the combine effect of ARCH and GARCH for the crisis period was 0.7797 which is significantly lower than the other periods. This suggests that notable spikes are evidence of significant unsteady patterns of oil price returns particularly during the oil-price crisis period.

This finding is consistent with Figure 2 illustrate the dynamics of the WTI oil market. The behaviour of oil prices returns follows an unsteady pattern and suggests

Table 5

Volatility Models

Panel A: Volatility Models for the Oil Price-war I

		WTI Crude Oil				Brent Crude Oil			
		Whole-period	Pre-war	Oil price crisis	Post-war	Whole-period	Pre-war	Oil price crisis	Post-war
GARCH	ω	0.0380***	0.0244***	0.4296***	0.2363***	0.0340***	0.0081	0.2770*	0.1717**
(1, 1)		(0.0069)	(0.0079)	(0.1226)	(0.0797)	(0.0081)	(0.0051)	(0.1443)	(0.0670)
	α	0.0869***	0.0965***	0.1768***	0.1098***	0.1042***	0.0409***	0.1333**	0.1181***
		(0.0089)	(0.0186)	(0.0495)	(0.0226)	(0.0080)	(0.0123)	(0.0548)	(0.0221)
	β	0.8902***	0.8820***	0.6029***	0.7270***	0.8750***	0.9479***	0.7037***	0.7649***
		(0.0105)	(0.0177)	(0.0924)	(0.0629)	(0.0116)	(0.0162)	(0.1281)	(0.0613)
T-GARCH	ω	0.0364***	0.0200***	0.0595***	0.6209***	0.0391***	0.0051	0.2620	0.2440***
(1, 1)		(0.0066)	(0.0053)	(0.0234)	(0.2066)	(0.0085)	(0.0032)	(0.1573)	(0.0641)
	α	0.0975***	0.1349***	-0.0176	0.0383	0.0813***	0.0558***	0.1236*	-0.0034
		(0.0134)	(0.0220)	(0.0129)	(0.0427)	(0.0127)	(0.0161)	(0.0646)	(0.0293)
	θ	-0.0188	0.1559***	0.1246***	0.1801***	0.0448***	0.0481**	0.0116	0.2337***
		(0.0151)	(0.0217)	(0.0311)	(0.0568)	(0.0139)	(0.0186)	(0.0724)	(0.0492)
	β	0.8909***	0.9276***	0.9288***	0.4280***	0.8706***	0.9619***	0.7170***	0.7132***
		(0.0102)	(0.0131)	(0.0214)	(0.1624)	(0.0126)	(0.0113)	(0.1352)	(0.0574)

Panel B: Volatility Models for the Oil Price-war II

		WTI Crude Oil				Brent Crude Oil			
		Whole-period	Pre-war	Oil price crisis	Post-war	Whole-period	Pre-war	Oil price crisis	Post-war
GARCH	ω	0.0061***	0.0039	0.1012*	0.0145**	0.0018**	0.0023	0.0964*	0.0265**
(1, 1)		(0.0017)	(0.0036)	(0.0534)	(0.0061)	(0.0008)	(0.0096)	(0.0536)	(0.0121)
	α	0.0532***	0.0345	0.1066***	0.0220**	0.0427***	0.0323	0.0381*	0.0440***
		(0.0086)	(0.0219)	(0.0394)	(0.0088)	(0.0071)	(0.0310)	(0.0200)	(0.0132)
	β	0.9423***	0.9580***	0.8353***	0.9502***	0.9572***	0.9581***	0.8937***	0.9079***
		(0.0082)	(0.0297)	(0.0576)	(0.0148)	(0.0069)	(0.0865)	(0.0517)	(0.0270)
T-GARCH	ω	0.0049***	0.6272***	0.0072	0.0146**	0.0006	0.0010	-0.0056	0.1487**
(1, 1)		(0.0012)	(0.0479)	(0.0131)	(0.0063)	(0.0005)	(0.0017)	(0.0038)	(0.0605)
	α	0.0090	-0.0845***	-0.0200	0.0214**	-0.0070	-0.0386**	-0.0301***	0.0255
		(0.0058)	(0.0325)	(0.0142)	(0.0104)	(0.0047)	(0.0162)	(0.0072)	(0.0232)
	θ	0.0570***	0.0783**	0.1224***	0.0028	0.0586***	0.0393***	0.0882***	0.1521**
		(0.0116)	(0.0325)	(0.0320)	(0.0201)	(0.0081)	(0.0130)	(0.0193)	(0.0642)
	β	0.9575***	-0.9535***	0.9625***	0.9491***	0.9791***	1.0168***	0.9977***	0.6465***
		(0.0069)	(0.0354)	(0.0231)	(0.0162)	(0.0047)	(0.0190)	(0.0079)	(0.1141)

Continued—

Table 5—(*Continued*)

Panel C: Volatility Models for the Oil Price-war III

		WTI Crude Oil			Brent Crude Oil		
		Whole-period	Pre-war	Oil price crisis	Whole-period	Pre-war	Oil price crisis
GARCH	ω	-0.1572***	0.0802***	0.8624	-0.0984**	1.4975*	2.5741
(1, 1)		(0.0410)	(0.0167)	(1.0959)	(0.0454)	(0.8407)	(5.5322)
	α	-0.0642**	-0.3250***	-0.2995**	-0.06571	-0.1346	0.1438
		(0.0255)	(0.1021)	(0.1420)	(0.0533)	(0.2071)	(0.3814)
	β	0.79541***	0.8045***	0.7801***	0.6626***	-0.4968	0.5797
		(0.0787)	(0.1082)	(0.0581)	(0.0956)	(0.8759)	(0.6851)
T-GARCH	ω	0.2579***	0.1895**	0.4015	0.0829**	0.6078	-0.7268
(1, 1)		(0.0558)	(0.0749)	(0.7421)	(0.0359)	(0.5091)	(0.7463)
	α	-0.2771***	-0.3568***	-0.2969**	-0.3056***	-0.2788	-0.2679
		(0.0630)	(0.0660)	(0.1442)	(0.0672)	(0.1995)	(0.2756)
	θ	1.9142***	0.2269**	0.5468***	0.3788***	0.1304	2.0585
		(0.2508)	(0.0994)	(0.1787)	(0.0511)	(0.2288)	(1.6230)
	β	0.7427***	0.7993***	1.1692***	1.1611***	0.5104	1.1390***
		(0.0497)	(0.1178)	(0.1038)	(0.0802)	(0.5502)	(0.1173)

Notes: ***, **, * shows statistical significance at 1%, 5% and 10% levels, respectively. Standard-errors are reported in parentheses.

evidence of volatility clustering, i.e., periods of high volatility are followed by periods of relatively low volatility. The notable spikes seen in the figure are evidence of significant unsteady patterns of oil price returns particularly during the oil price crisis. These findings are consistent for WTI as well as Brent crude oil specifications.

We restrict our analysis of the third oil-price war to only the first three sub-periods (excluding the post-war period) given lack of sufficient hindsight at the time of analysis. Though the persistence of volatility is similar to that of oil-price wars I and II, oil-price war III has higher volatility spikes than the previous two wars. Since the start of the year 2020, oil prices have faced higher volatility spikes, pointing to the compounding impacts of the Covid-19 pandemic and the breakdown in the original OPEC+ agreement.

This finding of high volatility persistence in the crude oil price is consistent with the findings of Narayan and Narayan, 2007, Salisu and Fasanya (2013) and Zavadska et al. 2018) which point to variations of Brent and WTI prices.

The results for leverage effects during the three oil-price wars obtained using T-GARCH models confirm the existence of asymmetries in our series for most of the same sub-periods. A significant and positive result indicates that bad (negative) news have greater impact on volatility than good (positive) news. These results are in line with findings of Wang and Wu (2012), Salisu and Fasanya (2013) and Zavadska et al. (2018). The WTI and Brent oil markets are characterised by volatility with occasional occurrence of large shocks due to geopolitical, economic or financial factors, as studied in extent literature. The GARCH (1, 1) model shows higher spikes and lower persistency in the Brent oil market during the most recent oil-price war. This is a direct result of the oil supply shocks of war between the two top oil producers, Saudi Arabia and Russia concomitant with the Covid-19 pandemic demand shock arising in oil importing countries, particularly China, the biggest oil importer.

4.2. VAR Models

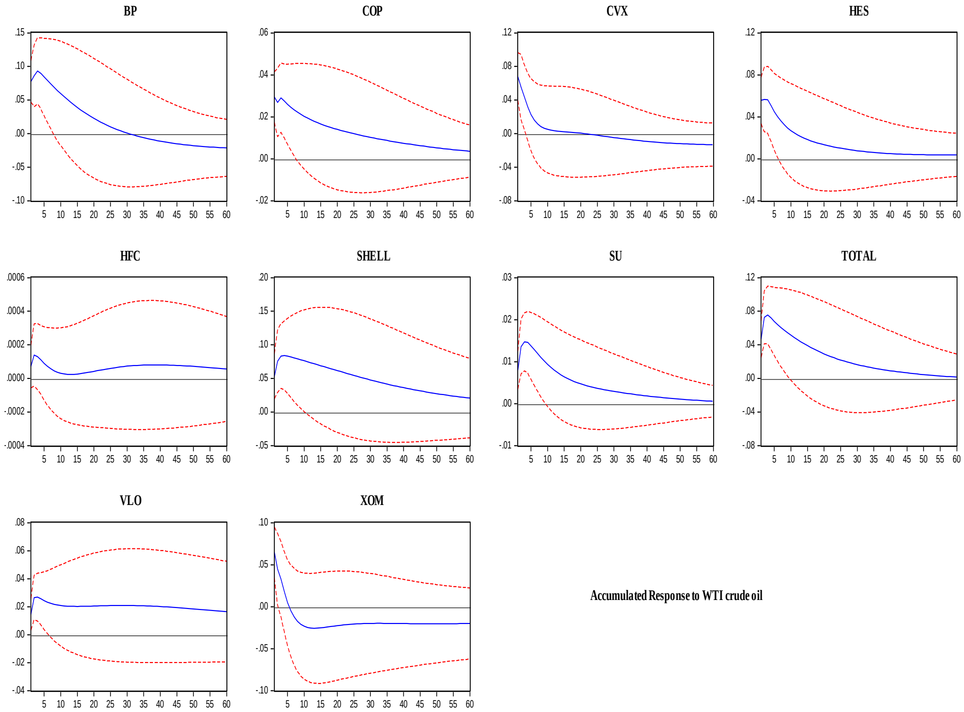
Figures 3-5 show generalised impulse-response functions for response of returns on oil and gas stocks to oil price shocks during the three oil-price wars. The dotted lines show the 95 percent confidence bounds for the response of stock returns to the shocks. The shocks have the largest positive impact on stock returns during the latest oil-price war while none of the impulse response functions are significant during the second oil-price war.

Figure 3 presents the generalised impulse-response functions of oil and gas stock returns to oil price shocks during oil-price war I (1997-1999). The graph shows that volatility shock to oil prices causes a positive immediate response of the returns of oil and gas stocks. This positive impact dies out within 10 days for Shell (SHELL), Suncor Energy Inc. (SU) and Total SA (TOTAL), however, the impact persists for 3 to 5 days for other companies.

Figure 4 exhibits the generalised impulse-response functions of oil and gas stock returns to oil price shocks during oil-price war II (2014-2016). The results indicate that none of the impulse response functions are significant, suggesting that the shock to crude oil price did not affect returns on oil and gas companies in the short-run.

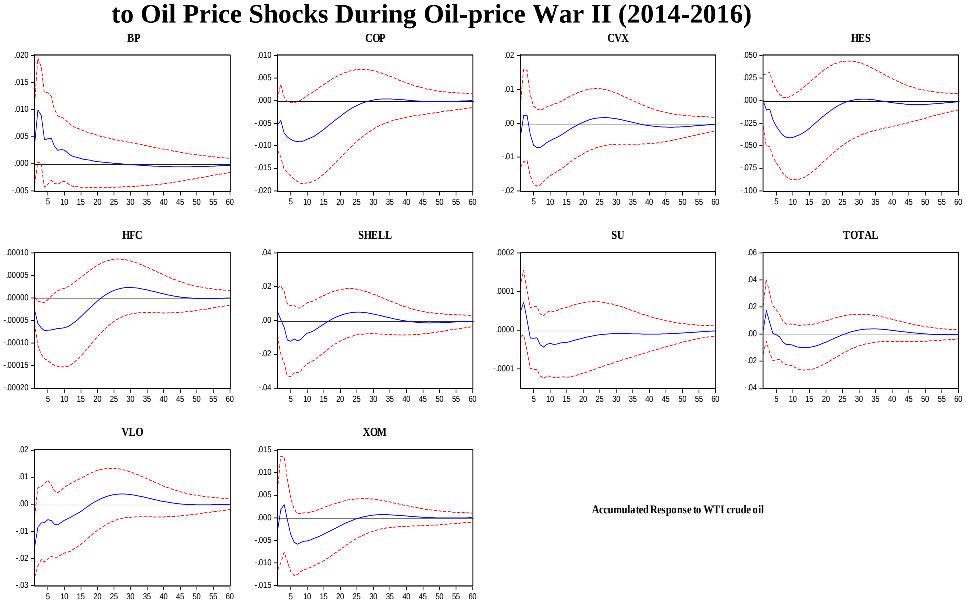
Finally, Figure 5 presents the generalised impulse-response functions of oil and gas stock returns to oil price shocks during oil-price war III (2020). A volatility shock to

Fig. 3. Generalised Impulse-response Functions of Oil and Gas Stock Returns to Oil Price Shocks During Oil-price War I (1997-1999)



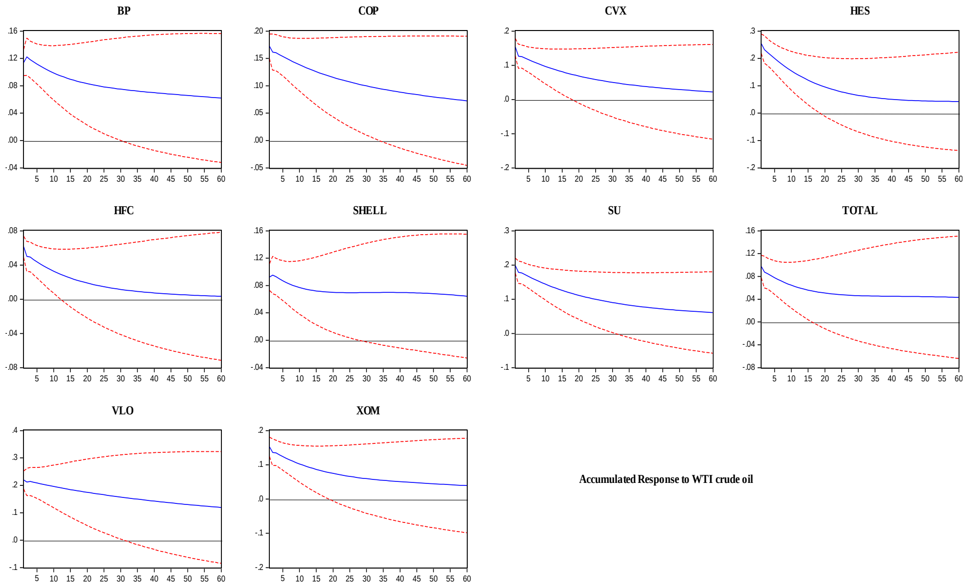
Notes: Solid line represents the generalised response function of stock returns to a shock in oil price change. Dotted lines are 95 percent confidence bounds.

Fig. 4. Generalised Impulse-response Functions of Oil and Gas Stock Returns to Oil Price Shocks During Oil-price War II (2014-2016)



Notes: Solid line represents the generalised response function of stock returns to a shock in oil price change. Dotted lines are 95 percent confidence bounds.

Fig. 5. Generalised Impulse-response Functions of Oil and Gas Stock Returns to Oil Price Shocks During Oil-price War III (2020-Onward)



Notes: Solid line represents the generalised response function of stock returns to a shock in oil price change. Dotted lines are 95 percent confidence bounds.

oil prices during this war causes a positive effect on the returns of oil and gas companies within the week of the shock. The impulse responses mostly last 30 to 35 days for British Petroleum P.L.C. (BP), ConocoPhillips (COP), Suncor Energy Inc. (SU), and Valero Energy Corporation (VOL). Overall, the positive impact seems to be persistent in the short term but the risk transmission is more significant in case of the third oil price war.

The impulse-response functions computed for Brent oil prices show a similar pattern of response to shocks to oil and gas stocks as those for WTI.[3]

Earlier studies on the impact of oil supply and demand shocks on stock market returns in the US (Kilian and Park, 2009; Apergis and Miller, 2009) and European countries (Cunado and de Gracia, 2014) reported a significantly negative effect of oil price shocks on stock market returns. However, recent studies by Gupta (2016), Diaz and Perez de Gracia (2017), Luo and Qin (2017) and Wen et al. (2019) report opposite results. In line with these recent studies, we also find a significantly positive effect of oil price shocks on oil and gas corporations listed on NYSE in the short-run. We find that stock returns of oil and gas corporations are sensitive to price shocks that arise from oil-price wars among oil producers.

Finally, we look for Granger causality between our oil-price and stock returns variables. Table 6 reports the results for Granger-causality test. We reject the null hypothesis of no Granger-causality for most of the oil and gas corporations with both WTI and Brent crude oil prices. Therefore, a unidirectional granger causality exists between crude oil and the stock returns of oil and gas corporations listed on NYSE. This is consistent with the findings of Diaz and Perez de Gracia (2017).

[3]The results are not reported for brevity purpose.

Table 6

Granger Causality Test

(Oil-price war-I)				(Oil-price war-II)				(Oil-price war-III)			
	WTI		Brent		WTI		Brent		WTI		Brent
BP→WTI	0.4537	BP→Brent	1.3348	BP→WTI	1.6629	BP→Brent	0.5559	BP→WTI	1.7220	BP→Brent	1.7558
WTI→BP	5.2621***	Brent→BP	5.7128***	WTI→BP	1.6507	Brent→BP	11.4788***	WTI→BP	7.2098***	Brent→BP	1.5601
COP→WTI	0.0404	COP→Brent	0.0648	COP→WTI	1.1165	COP→Brent	1.0985	COP→WTI	1.4526	COP→Brent	1.5827
WTI→COP	2.9271*	Brent→COP	2.6196*	WTI→COP	4.0206**	Brent→COP	14.7991***	WTI→COP	4.1240**	Brent→COP	0.4231
CVX→WTI	0.6169	CVX→Brent	1.4947	CVX→WTI	0.7458	CVX→Brent	0.6025	CVX→WTI	1.9529	CVX→Brent	1.5059
WTI→CVX	2.1932	Brent→CVX	0.1811	WTI→CVX	3.6250**	Brent→CVX	0.3336	WTI→CVX	4.0709**	Brent→CVX	0.8947
HES→WTI	2.7913	HES→Brent	0.3344	HES→WTI	1.4758	HES→Brent	0.9128	HES→WTI	1.2996	HES→Brent	1.1336
WTI→HES	3.9146**	Brent→HES	5.9017***	WTI→HES	3.0081*	Brent→HES	1.8471***	WTI→HES	5.1981***	Brent→HES	0.2052
HFC→WTI	0.2688	HFC→Brent	1.5348	HFC→WTI	0.2074	HFC→Brent	1.1797	HFC→WTI	1.5205	HFC→Brent	0.7864
WTI→HFC	1.7982	Brent→HFC	0.2533	WTI→HFC	2.8863*	Brent→HFC	4.3770**	WTI→HFC	2.8248*	Brent→HFC	1.6412
SHELL→WTI	2.0259	SHELL→Brent	4.5034	SHELL→WTI	2.0518	SHELL→Brent	0.0087	SHELL→WTI	2.0690	SHELL→Brent	2.9656*
WTI→SHELL	5.9021***	Brent→SHELL	3.0937**	WTI→SHELL	0.4942	Brent→SHELL	12.4930***	WTI→SHELL	8.2302***	Brent→SHELL	2.3596
SU→WTI	0.1211	SU→Brent	0.9857	SU→WTI	1.8273	SU→Brent	0.2614	SU→WTI	0.7438	SU→Brent	1.2084
WTI→SU	5.3780***	Brent→SU	1.3136	WTI→SU	3.0703**	Brent→SU	12.6091***	WTI→SU	2.6752*	Brent→SU	1.0430
TOTAL→WTI	1.9758	TOTAL→Brent	4.7679	TOTAL→WTI	2.0782	TOTAL→Brent	0.2036	TOTAL→WTI	1.3760	TOTAL→Brent	0.3935
WTI→TOTAL	8.1919***	Brent→TOTAL	3.4981**	WTI→TOTAL	1.0236	Brent→TOTAL	8.5198***	WTI→TOTAL	1.1493	Brent→TOTAL	1.2131**
VLO→WTI	3.3014	VLO→Brent	0.9423	VLO→WTI	0.1599	VLO→Brent	0.4286	VLO→WTI	0.7545	VLO→Brent	0.7427
WTI→ VLO	5.9948***	Brent→VLO	0.6530	WTI→ VLO	4.6952***	Brent→VLO	6.3424***	WTI→ VLO	4.1347**	Brent→VLO	3.1160**
XOM→WTI	0.8223	XOM→Brent	1.3436	XOM→WTI	0.9927	XOM→Brent	0.5965	XOM→WTI	2.1642	XOM→Brent	1.4334
WTI→XOM	2.6140*	Brent→XOM	0.8290**	WTI→XOM	0.1007	Brent→XOM	1.6561***	WTI→XOM	6.4695***	Brent→XOM	0.7695**

Note: *, **, and *** denotes rejection of null hypothesis the at 1%, 5% and 10% significance level.

5. CONCLUSIONS AND POLICY IMPLICATIONS

The uncertainties involved in high spikes of oil prices and related volatility arising due to supply or demand disruptions influence the decision-making process of investors, speculators and policy makers. In this study, we examined the effects of crude oil price supply-shocks on the returns to stocks of ten largest oil and gas corporations listed on NYSE during three oil-price wars that took place among major oil producers during the past thirty years. Our sample comprised of daily observations for crude oil prices and stock prices for the period from October 25, 1991 to June 8, 2020 with a total of 7,116 observations. We computed the persistence of volatility in oil prices during times of specific oil-price wars through GARCH (Generalised Autoregressive Conditional Heteroskedasticity) model and tested for the presence of leverage effects using T-GARCH (Threshold Generalised Autoregressive Conditional Heteroskedasticity) model. The period of estimation was divided into four sub-periods for each oil-price war: the whole period. pre-war period, oil price-crisis period, and post-war period. We tested for structural breaks that might occur due to the irregular nature of oil-price wars by using the Bai and Perron (1998, 2003) model. Furthermore, we investigated the linkage between oil price shocks and stock returns using a VAR (vector autoregressive) model.

Our results provide evidence for persistence in oil price volatility as well as for leverage effects during three oil-price wars. The persistence is the highest in case of the latest war, highlighting the twin impact of supply shock and demand shocks that have arisen due to the co-occurrence of the oil-price war and the global economic slowdown caused by the Covid-19 pandemic. We also found that oil-price shocks have significant and positive effect on the returns of major oil and gas companies. The impact has been the most potent during the 2020 oil-price war.

The positive impact of the oil-price shock on returns on stocks of oil and gas firms listed on the NYSE is in line with previous findings in the literature (see, for example, Gupta, 2016; Diaz and Perez de Gracia, 2017; Kang et al., 2017; Huang and Mollick, 2020). This supports the view that on average, the world economy benefits from higher oil prices. This was not the case when the U.S. was a net petroleum importer. Foroni et al. (2017) show that the sign of the relation between oil prices and the U.S. stock returns had changed over time, having turned positive since early 2007.

These findings provide an important insight that oil price volatility driven by wars among oil exporters has significant impact on stock returns. These findings provide investors information on how volatility in global oil prices is also sensitive to irregular events such as price wars between oil producers. This information can be important for economic agents contemplating shorter hedges by managing risks during times of high volatility.

This work can be extended by employing data mining and machine learning techniques using extensive datasets, especially for the third war period, given that data from this latest war period are still in infancy.

Appendix-A

Fig. A1. This Figure Shows the Volatility Clustering for Crude Oils and Oil and Gas Corporations During Oil-price War I (November 1997 to March 1999)

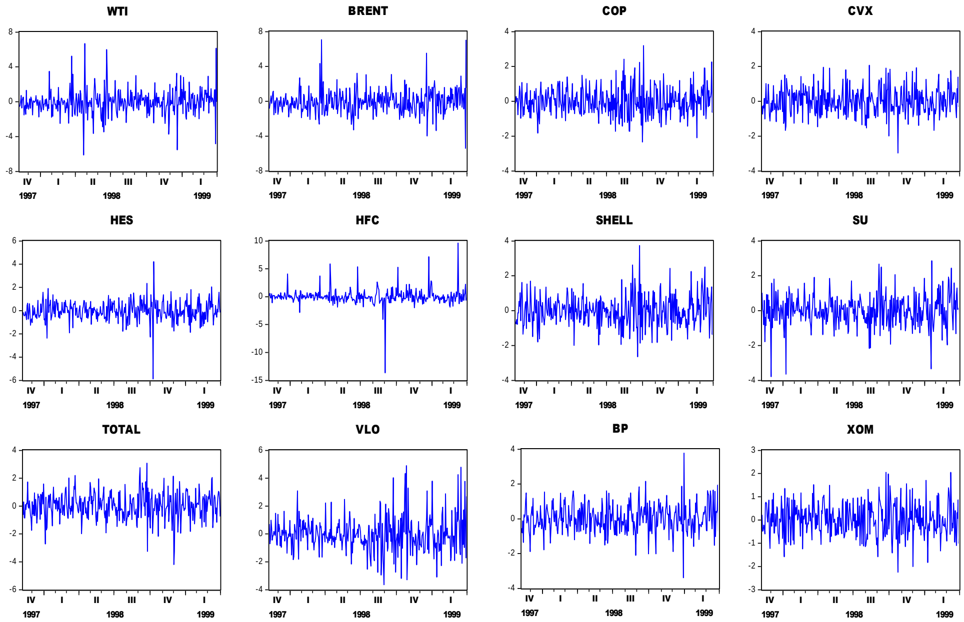


Fig. A2. This Figure Exhibits the Volatility Clustering for Crude Oils and Oil and Gas Corporations During Oil-price War II (November 2014 to August 2016)

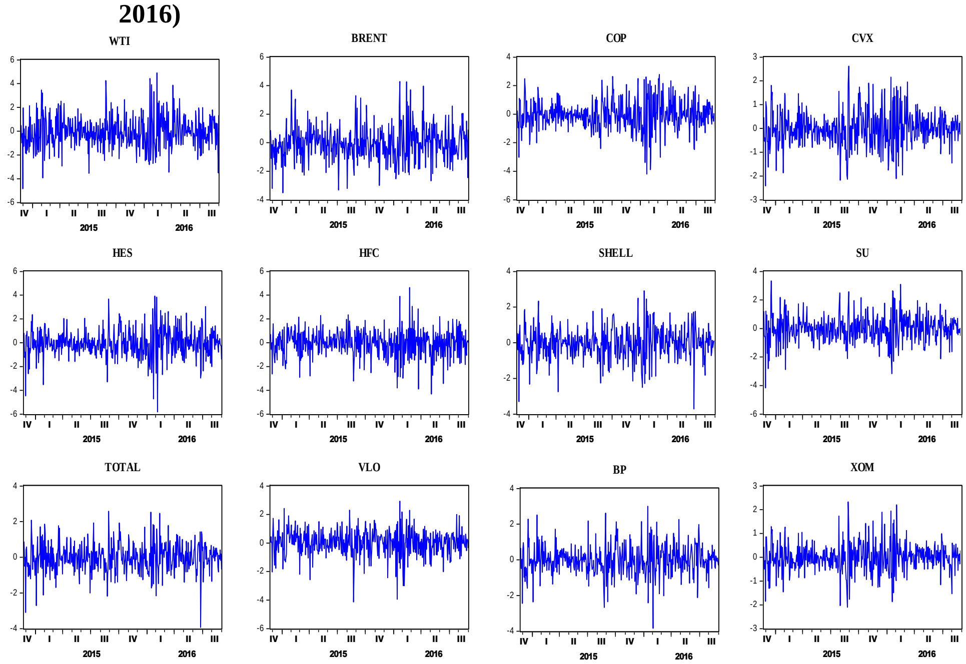
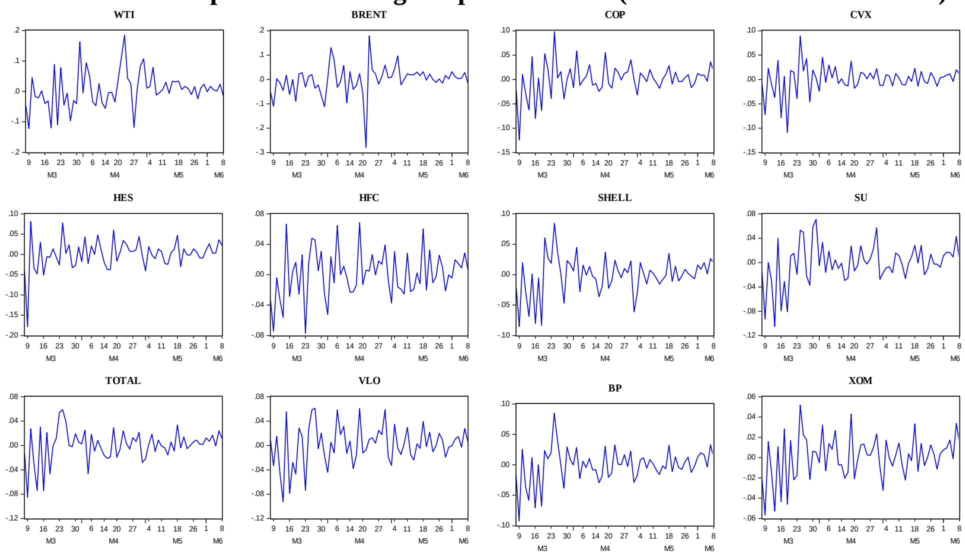


Fig. A3. This Figure Presents the Volatility Clustering for Crude Oils and Oil and Gas Corporations During Oil-price War III (9 March 2020 and onwards)



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