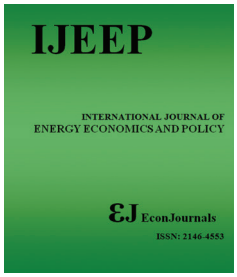


International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2020, 10(5), 422-431.

The Impact of COVID-19 on Price Volatility of Crude Oil and Natural Gas Listed on Multi Commodity Exchange of India

Bharat Kumar Meher[1], Iqbal Thonse Hawaldar[2]*, Latasha Mohapatra[3], Adel M. Sarea[4]

[1]Department of Commerce, D.S. College, Katihar, Under Purnea University, Purnia, Bihar, India, [2]Department of Accounting and Finance, College of Business Administration, Kingdom University, Sanad, Bahrain, [3]Department of Commerce, Manipal Academy of Higher Education, Manipal, Karnataka, India, [4]College of Business and Finance, Ahlia University, Manama, Bahrain. *Email: thiqbal34@gmail.com

Received: 07 May 2020 **Accepted:** 01 July 2020 **DOI:** https://doi.org/10.32479/ijeep.10047

ABSTRACT

The impact of COVID-19, due to the wide-spread demand and supply destruction and downward movement of crude oil prices is of concern for all those connected with the oil and gas industry. In this study, an attempt has been made to estimate the price volatility of crude oil and natural gas listed on multi commodity exchange of India (MCX). We measured the leverage effect of COVID-19 on price volatility of crude oil and natural gas by using the daily prices of crude oil and natural gas from May 01, 2017 to April 30, 2020. The findings of the study reveal that there is a presence of leverage effect of COVID-19 on the price volatility of crude oil. However, this leverage effect is not present on the price volatility of natural gas. The findings of the study will help investors to develop investment strategies and to the policymakers to formulate appropriate policies to overcome or minimise the impact of COVID-19. The forecasting graphs of crude oil prices indicate that there is a possibility that price volatility will be higher in the future. However, it is difficult to forecast the expected price volatility of natural gas for the future because the price volatility graph is extremely fluctuating.

Keywords: COVID-19, Asymmetric Volatility, Leverage Effect, Crude Oil, Natural Gas, MCX Limited
JEL Classifications: G15; G20; G21; G22; G23

1. INTRODUCTION

The outbreak of COVID–19, which was started in the Wuhan city of China during November 2019 has been declared as a global pandemic by the World Health Organisation (WHO) on March 11, 2020. Based on WHO worldometers website as of June 07, 2020, there are 6,467,333 confirmed cases, 3,078,403 recoveries and 382,766 deaths across the world. China and G7 countries account for the majority of COVID–19 confirmed cases and deaths (WHO, 2020). The outbreak of COVID–19 has shaken the global financial markets, commodity markets, economic activities, employment and GDP of the countries. If anyone can accurately predict the price volatility in the stock market or commodity market, then they have the chances to earn higher returns by developing appropriate investment strategies (Shakila et al., 2017; Hawaldar et al., 2017c). Measuring of volatility has various applications especially in trading, investment, and portfolio selection of stock and commodities market because it assists the investors in risk management, derivative pricing, hedging, and predicting price (Iqbal and Mallikarjunappa, 2010). Moreover, studying volatility enables to predict the direction of any market then anyone can have a good intent on what to expect from the economy, hence volatility has operations beyond the stock and commodities market (Iqbal and Mallikarjunappa, 2011). Various techniques are used in measuring volatility like historical volatility, Bollinger bands which are considered as traditional methods and such methods are easily understood by layman investors as well. The modern methods include many algorithmic functions for modelling volatility like ARCH, GARCH, EGARCH, TARCH etc. These volatility models are used to describe a changing, possibly volatile variance and to predict the volatility of a time series data (Iqbal and Mallikarjunappa, 2010).

"The ARCH (autoregressive conditional heteroscedasticity) model proposes that the variance of residuals regressed on the squared error terms from the periods of past. The residual terms should be conditionally normally distributed and serially uncorrelated." (Mukherjee and Goswami, 2017) One of the major limitations of this ARCH model is it "supposes that the variance or heteroscedastic of tomorrow's return is an equally-weighted average of the residuals' squared from the last 22 days. The assumption of equal weights looks ill-favoured, as one may think that the more recent events would be more significant and therefore should have more weights" (Engle, 2001). Hence an advancement has been done in ARCH model by Tim Bollerslev in 1986 and named it as GARCH. In contrary to ARCH Model, GARCH (generalised autoregressive conditional heteroscedasticity) has diminishing weights that nowise decline to zero. It provides parsimonious models that are soft to estimate and, even in its simplest form, has proven astonishingly successful in forecasting conditional variances (Bollerslev, 1986). Moreover, "The latest volatility process of asset returns is material for a wide variety of operations, such as risk management and option pricing whereas generalized autoregressive conditional heteroscedasticity (GARCH) models are extensively used to model the dynamic features of volatility" (Peter et al., 2012). Inverse correlation between the return and the shocks is a salient feature of the stock market (Ali, 2013) but it is not captured by simple GARCH, hence an advanced model proposed by Glosten et al. (GJR) propound GJR-GARCH also known as Threshold GARCH (TGARCH) with differing effects of positive and negative shocks taking into account the leverage portent (Glosten et al., 1993) The leverage portent is caused by the fact that adverse returns have more influence on future volatility than do favourable returns (Almeida and Hotta, 2014). To capture the above leverage portent or effect, the exponential GARCH (EGARCH) model has been developed in which the "conditional distribution is heavy-tailed and skewed is proposed. The characteristics of the model, including autocorrelations, unconditional moments and the asymptotic distribution of the maximum likelihood estimator, are portrayed" (Harvey and Sucarrat, 2014; Daly, 2008).

This study focuses on measuring the impact and the leverage effect of corona virus disease 2019 (COVID-19) on the price volatility crude oil and natural gas listed on MCX, India by using EGARCH model. The reason for taking the crude oil is it's a vital commodity and has significance in both financial markets and economic growth. First, oil price generally has a negative and non-linear effect on economic growth, and usually acts as a predictor variable in economic growth (Kilian, 2008), (Narayan et al., 2014; Apergis, Bowden, & Payne, 2015). The reason for taking natural gas because many latest studies even depict that consumption of natural gas plays a pivotal job in facilitating economic growth in both the long-run and short-run (Apergis et al., 2010) and that disruptions in its supply entail huge economic cost (Alcaraz and Villalvazo, 2017). The leverage effect of COVID-19 has been considered in the study as the novel coronavirus (COVID-19) pandemic has affected both demand and supply of commodities due to lockdowns, shutdowns and interruptions to supply chains which also lead to economic growth a standstill (Baker McKenzie, 2020). Even drastic effects can be seen particularly for commodities related to transportation. Oil prices have dropped, and demand is also expected to drop further by an unprecedented amount in 2020 (World Bank, 2020). Thus, the EGARCH Model is appropriate for capturing the leverage effect of COVID-19 on the price volatility of two most traded energy commodities i.e. crude oil and natural gas.

2. REVIEW OF LITERATURE

There are many research works have been done in the area of the commodities market, natural gas, crude oil and price volatility. Some of the important works are mentioned here. A paper investigates the behaviour of crude oil and natural gas price volatility in the United States since 1990 using GARCH model (Pindyck, 2004). Again, a study concerned with modelling of price volatility of crude oil market in Nigeria employing both symmetric and asymmetric models of GARCH family (Dum and Essi, 2017). Like that study, a paper inspected a long memory volatility model for sixteen agricultural commodity futures where the empirical results are attained using unit root tests i.e., GARCH, APARCH, EGARCH, FIGARCH, FIAPARCH, and FIEGARCH model (Chang et al., 2012). Similarly, a study examined the effect of different types of speculation on the volatility of commodity futures prices of selected four energy and seven non-energy commodity futures observed over the period 1986-2010 using GARCH models. (Manera et al., 2013) the study served the return volatility of selected commodity as financial assets i.e., gold, potato, Mentha oil and crude oil traded under MCX (multi commodity exchange), India covering the period from 2004 to 2012 by using GARCH Model. (Mukherjee and Goswami, 2017) investigated the prediction capability of GARCH, GJR-GARCH, EGARCH and APARCH models together with the different error constructs like Student's t-distribution, normal distribution and asymmetric Student's t-distribution with a comparison between asymmetric and symmetric distributions using these three different error constructs by taking two major indices of Tel-Aviv stock exchange (TASE) i.e., TA25 and TA100. The results suggest that overall estimation can be improved by employing the asymmetric GARCH model with fat-tailed densities for estimating conditional variance (Alberg et al., 2008). There was a study investigating the causal association between the stock market returns and crude oil price anomalies in the Indian stock market covering 10 companies of oil drilling and exploration sectors listed in the CNX NIFTY indexes and BSE Sensex from 2009 to 2018 (Hawaldar et al., 2020). Furthermore, the study focussed on comparing between realized GARCH model with some conventional GARCH models such as GARCH, GJR-GARCH and EGARCH by using the Gold 5 min intra-day data from April 2012 to April 2018. The comparison has been done in two ways. First, the fitness of data into the models and then, examining the accuracy of forecasting the conditional variance of the sample by using the rolling window approach and using a loss function to select the most accurate model (Abounoori and Zabol, 2020). Crude oil price crisis has an impact on the performance of firms (Hawaldar et al., 2017a; 2017b). Besides that, a study focussed on determining the primary drivers affecting U.S. natural gas price volatility by applying a structural heterogeneous autoregressive VAR (SHVAR) model, using time series monthly data of natural gas price, demand and supply ranging from January 1978 to July 2018 to dig outs several

structural changes in shock volatility and coefficients in the natural gas market (Hailemariam and Smyth, 2019).

The researches done earlier in India were oriented towards volatility of financial assets i.e., companies share and stocks and only a few studies on commodities traded on MCX, India. Moreover, no studies are focusing on the impact of COVID-19 pandemic on the price volatility of the commodities market. Therefore, there is a need to study the impact of COVID -19 pandemic on the price volatility of crude oil and natural gas.

The objectives of the study are as follow:

- To formulate the relevant type of GARCH model to estimate the price volatility of crude oil and natural gas listed on MCX, India
- To assess the impact and the leverage effect of COVID-19 on the price volatility of crude oil and natural gas listed on MCX, India.

3. RESEARCH METHODOLOGY

The study is based on daily prices of natural gas and crude oil listed on MCX, India. The daily prices of both the commodities for the period of May 01, 2017-April 30, 2020 have been downloaded from the website investing.com. The total observations are 1,568 i.e. 2 commodities of 784 observations each (Hwang and Pereira, 2004). For the application of EGARH, log daily returns have been calculated to make the data stationary and Augmented dickey-fuller test (ADF) has been used to check whether the data is stationarity in nature. EGARCH (exponential generalised autoregressive conditional heteroscedasticity) has been used to formulate the model for price volatility. The models have been used to predict the volatility for the period from February 01, 2020 to April 30, 2020. To formulate models and forecasting price volatility of crude oil and natural gas commodities, E-Views 10 has been used.

4. ANALYSIS OF THE RESULTS AND DISCUSSION

The standard or simple GARCH model is unable to capture the skewness or asymmetric nature caused by the negative correlation between returns and volatility which is referred to as the leverage effect. Therefore, the EGARCH model has been selected to measure the leverage effect of COVID-19 on the price volatility of the two selected commodities. In addition to that, "the advantage of using EGARCH is that the positivity of the parameters is assured as it will be working with the log of the variance" (Hassan, 2012). The following formula is for EGARCH model.

$$log\left(h_t\right)=\varphi+\sum_{i=1}^{q}\eta_i\left|\frac{u_t-i}{\sqrt{h_t-i}}\right|+\sum_{i=1}^{q}\lambda_i\frac{u_t-i}{\sqrt{h_t-i}}+\sum_{k=1}^{p}\theta_k\log(h_{t-k})$$

Where
log (h_t)=log of variance or log returns
φ=Constant
η_i=ARCH Effects
λ_i=Asymmetric effects
θ=GARCH effects

To formulate the EGARCH model the log returns have been calculated for both the commodities i.e., crude oil and natural gas. This has made both the data of crude oil and natural gas, stationary. Again, the stationarity of the data has been examined with the help of a unit root test i.e., Augmented dickey-fuller test with the inclusion of the test equation as intercept, trend and intercept and none. The following sections are based on the testing the relevant hypothesis required for formulating EGARCH model along with the results and model for each commodity.

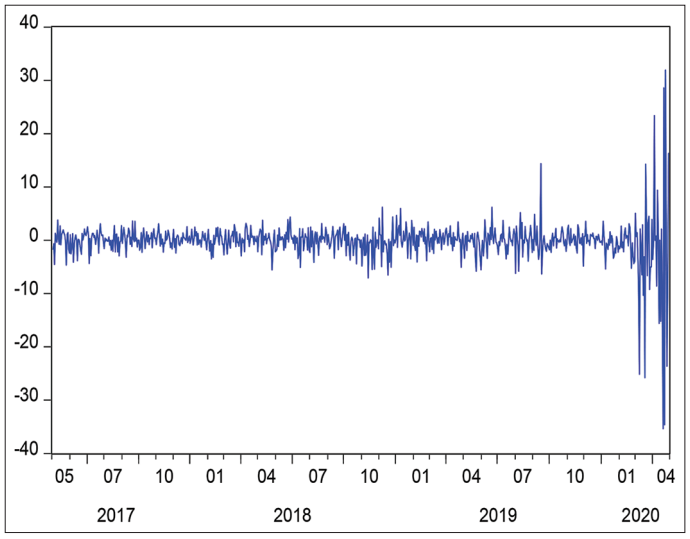
4.1. Formulation of EGARCH Model for Crude Oil

The pandemic COVID-19 severely hit the demand for crude oil due to lockdowns. "The coronavirus pandemic has almost induced the travel industry across the globe, to a standstill, reduction in the demand for the commodity which has fallen by almost a third this year. Analysts expect demand to remain subdued due to Covid-19 impact and this could see crude prices falling further" (IANS, 2020). In a few of the countries like the US, the price of the crude oil became negative during the last week of April 2020 due to running out of storage options. (Mudgill, 2020) In this way, this pandemic COVID-19 might bring a leverage effect on the price volatility of crude oil in India also which can be examined by formulating EGARCH model for the same.

To formulate the EGARCH model few more items need to be tested i.e. volatility clustering, peakedness of data and presence of ARCH effects. Figure 1 and represents the volatility clustering of crude oil data from May 01, 2017 to April 30, 2020.

The visualisation of above Figure 1 of price volatility or log-returns of crude oil depicts that there is the presence of volatility clustering i.e., small variations tracked by small variations and large variations tracked by large variations which imply that volatility models can be formulated. Moreover, large fluctuations in prices could be seen

Figure 1: Log returns of crude oil



Source: Authors' computation through E-views 10

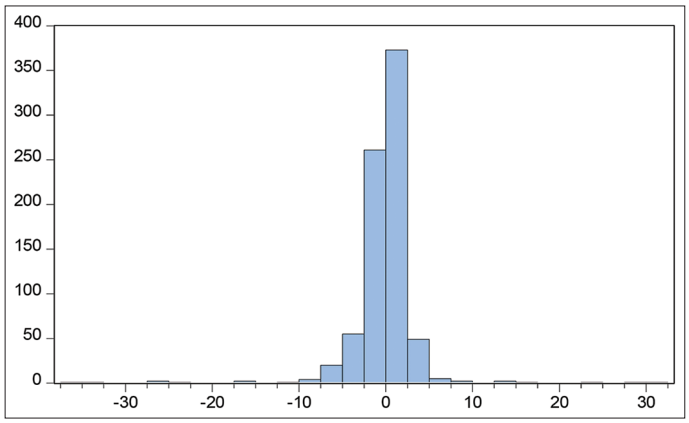
after March 12, 2020 which shows that there is an existence leverage effect of COVID-19 on the price of crude oil. Though the COVID-19 entered India during February 2020 its significant impact on crude oil price can be seen after March 12, 2020.

Figure 2 shows the peakedness of crude oil data.

The Graph No. 2 shows that the data of crude oil is highly peaked, or data is leptokurtic. Moreover, the coefficients of Skewness (−1.4396), Kurtosis (39.6709) and Jarque-Bera Statistics (44143.30) have also verified that the return series is leptokurtic or skewed. After examining the volatility clustering and peakedness the next step is to check the existence of ARCH effect in the data. To apply any GARCH model it is also mandatory to inspect the presence of ARCH effect within the data i.e. price volatility of crude oil in India. Table 1 is based on testing the presence of ARCH effects in data related to the price volatility of crude oil.

Table 1 reveals the results of heteroscedasticity test of crude oil which could show the presence of ARCH effect in the data.

Figure 2: Peakedness of crude oil data



Source: Authors' computation through E-views 10

Table 1: COVID-19 effects on crude oil returns

Heteroskedasticity test: ARCH			
F-statistic	114.6183	Prob. F (1,779)	0.0000
Obs*R-squared	100.1736	Prob. Chi-square (1)	0.0000
Test equation			
Dependent variable: RESID²			
Method: Least squares			
Sample (adjusted): 5/04/2017 4/30/2020			
Included observations: 781 after adjustments			
Variable	**Coefficient**	**Std. error**	**t-Statistic**	**Prob.**
C	8.759157	2.662063	3.290365	0.0010
RESID²(−1)	0.359094	0.033541	10.70600	0.0000
R-squared	0.128263	Mean dependent var		13.54286
Adjusted R-squared	0.127144	S.D. dependent var		78.49951
S.E. of regression	73.33954	Akaike info criterion		11.43063
Sum squared resid	4189998.	Schwarz criterion		11.44257
Log-likelihood	−4461.663	Hannan-Quinn criteria		11.43522
F-statistic	114.6183	Durbin-Watson stat		2.226111
Prob. (F-statistic)	0.000000			

Source: Authors' Computation through E-views 10

The ARCH effect can be judged from lag range multiplier (LM) statistics which is shown in the form of observed R square. The observed R square statistics is 100.1736 and it is considered significant as its probability value is <0.05. Moreover, the F statistics (114.6183) is also significant as its significant value is <0.05. This proves that there is an existence of ARCH effect in the crude oil data from May 1, 2017 to April 30, 2020.

After testing the existence of ARCH effects, three EGARCH (1,1) models have been formulated i.e., EGARCH with normal distribution error construct, EGARCH with student t's distribution error construct and EGARCH with generalised error distribution construct. To select the suitable model, the results of all the three models, need to be analysed. Table 2 shows the results of all these three models.

The standard way to select a model is, the coefficients, ARCH and GARCH should be significant and there should not be the existence of heteroscedasticity and autocorrelation after framing the model. In addition to that, the model with lesser AIC (Akaike information criterion) and SIC (Schwartz information criterion) is better and a model with higher log-likelihood statistics, R square and adjusted R square are better.

Table 2 depicts that Coefficients, ARCH Effect and GARCH are significant in all the three EGARCH (1,1) models i.e. EGARCH with normal distribution error construct, EGARCH with student t's distribution error construct and EGARCH with generalised error distribution construct. After framing the above models, there is no Heteroscedasticity (which has been checked with the help of ARCH LM test) and there is no Autocorrelation (which has been checked with the help of correlogram of residuals and squared residuals) in any of the three models. While comparing the AIC and SIC of all the above three models, it has been found that EGARCH with Generalised Error Distribution Construct has the lowest AIC (4.27) and SIC (4.31) as compared to other two models. Similarly, while comparing the three models, the EGARCH with generalised error distribution construct has highest log likelihood, R squared, and adjusted R squared. Hence, the model with the generalised error distribution construct is the most suitable. The result of the selected EGARCH (1,1) model for crude oil is presented in Table 3.

The above table shows the results of the EGARCH (1,1) model with generalised error distribution construct of crude oil. The results contain two parts. The upper part shows the main equation and the lower part represents the variance equation. In the main equation, the constant (C) is significant as the probability value is <0.05 but the co-efficient of first lag [OILR (−1)] is considered as weak as the probability value is more than 0.05.

In case of variance equation, C (3) is the Constant, C (4) is the ARCH co-efficient, C (5) is the asymmetric co-efficient and C (6) is the GARCH co-efficient. All the coefficients in the variance equation are significant as their probability values are <0.05. Moreover, the model has least AIC i.e., 4.2725 and SIC i.e., 4.3143 as compared to other models. The values of R squared i.e., 0.0159,

Table 2: Decision table for selecting suitable EGARCH (1,1) model for crude oil

Statistics	Normal distribution	Student t's distribution	Generalised error distribution
Significant coefficients	Yes	Yes	Yes
ARCH significant	Yes	Yes	Yes
GARCH significant	Yes	Yes	Yes
Log-likelihood	−1715.331	−1667.381	−1663.576
R squared	0.007096	0.011493	0.015981
Adjusted R squared	0.005823	0.010226	0.014720
AIC	4.402381	4.282304	4.272572
Schwartz IC	4.438149	4.324034	4.314302
Heteroscedasticity (ARCH LM-Test)	No	No	No
Autocorrelation (correlogram of residuals)	No	No	No

Source: Authors' computation through E-views 10

Table 3: Results of EGARCH (1,1) with generalised error distribution construct

Dependent variable: Log returns of crude oil				
Method: ML ARCH - generalized error distribution (GED)				
Sample (adjusted): 5/03/2017 4/30/2020				
Included observations: 782 after adjustments				
Convergence achieved after 25 iterations				
Presample variance: Backcast (parameter=0.7)				
LOG(GARCH) = C (3) + C (4) *ABS (RESID (−1)/@SQRT (GARCH (−1))) + C (5)				
*RESID (−1)/@SQRT (GARCH (−1)) + C (6) *LOG (GARCH (−1))				
Variable	**Coefficient**	**Std. error**	**z-statistic**	**Prob.**
C	0.135628	0.051178	2.650124	0.0080
OILR (−1)	−0.044223	0.029263	−1.511226	0.1307
Variance equation				
C (3)	−0.080584	0.029984	−2.687603	0.0072
C (4)	0.123858	0.042016	2.947833	0.0032
C (5)	−0.076757	0.029218	−2.627006	0.0086
C (6)	0.994131	0.007217	137.7538	0.0000
GED parameter	1.040783	0.063520	16.38507	0.0000
R-squared	0.015981	Mean dependent var		−0.111283
Adjusted R-squared	0.014720	S.D. dependent var		3.804363
S.E. of regression	3.776260	Akaike info criterion		4.272572
Sum squared resid	11122.91	Schwarz criterion		4.314302
Log-likelihood	−1663.576	Hannan-Quinn criteria.		4.288620
Durbin-Watson stat	2.402932			

Source: Authors' computation through E-views 10

Adjusted R squared i.e., 0.0147 and Log-Likelihood i.e., −1663.57 are higher as compared to the other models. The important point to be focussed is the co-efficient of the asymmetric term (λ) is negative i.e., −0.076757 and also statistically significant which implies that there is the existence of leverage effect of COVID-19 on the price volatility of crude oil and it also indicates that bad news i.e., spreading of COVID-19 has a larger effect on the volatility of crude oil. Hence the variance equation can be shown as given below.

$$log\left(h_t\right) = -0.0805 + \sum_{i=1}^{1} 0.1238 \left| \frac{u_t - i}{\sqrt{h_t - i}} \right|$$

$$-\sum_{i=1}^{1} 0.0767 \frac{u_t - i}{\sqrt{h_t - i}} + \sum_{k=1}^{1} 0.9941 \log(h_{t-k})$$

By using the above-formulated model, the volatility of crude oil has been forecasted in the forecasting volatility section.

4.2. Formulation of EGARCH Model for Natural Gas

"The impact of COVID-19, whether due to the wide-spread demand destruction or the downward spiral of crude prices, is of enormous concern for all of the Indian Oil and Gas industry participants" (Jacob and Nutula, 2020). As like crude oil and other sectors of commodities market of India, natural gas utilities, too, have been badly hit by the coronavirus spread. The lockdown for 21 days up to April 14 and again extension of it, has had a major impact on the sales volumes of gas utilities. The demand from key segments like compressed natural gas for vehicles and piped natural gas for businesses has been crashed due to shutting down of operations of many industries and non-running of vehicles on the roads. As per many reports say, in major city gas distribution (CGD) markets such as Delhi, Mumbai and Gujarat, CNG demand has fallen 70-80%, and many outlets have been shut down. Hence, there is a possibility that as like in the case of crude oil, the pandemic COVID-19 might have also created a leverage effect on the price volatility of natural gas.

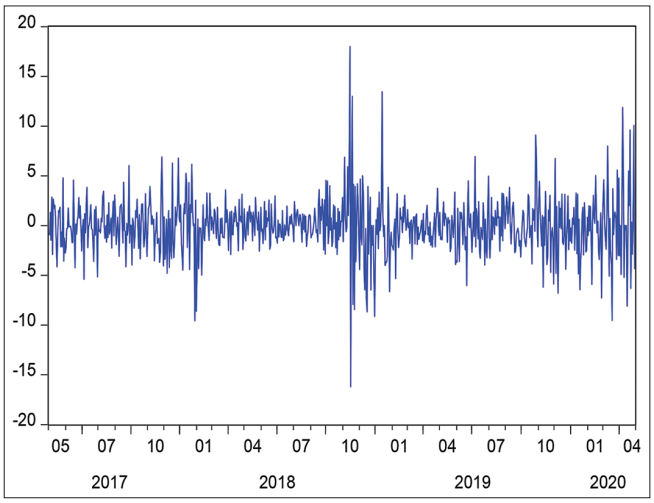
Figure 3 showing the price volatility (log returns) of natural gas indicates that there is the presence of volatility clustering i.e. small variations followed by small variations and large variations followed by large variations which imply that volatility models can be formulated. During October and November, 2018 large fluctuations in prices could be seen which shows that there is an existence of leverage effect of a factor other than COVID-19. Moreover, large and continuous fluctuations in prices could be seen after January 2020 which shows that could be the existence of leverage effect of COVID-19 on the price of Natural Gas. Though the COVID-19 entered India during February 2020 its significant impact on crude oil price can be seen after March 12, 2020. Hence, the EGARCH model may not only capture the leverage effect of COVID-19 on the price volatility of natural gas.

Figure 4 shows that like crude oil, the data of natural oil is also highly peaked i.e. leptokurtic. Moreover, the coefficient of skewness (0.3236), kurtosis (8.6991) and Jarque-Bera Statistics (1073.357) have also verified that the return series is skewed or leptokurtic. After examining the volatility clustering and peakedness the next step is to check the presence of ARCH effect in the data as it is also a basic condition need to examine before applying any GARCH model. The following table is based on the testing the presence of ARCH effect in data related to the price volatility of natural gas.

Table 4 shows the results of heteroscedasticity test of natural gas. The ARCH effect can be analysed by using lag range multiplier (LM) statistics which is shown in the form of observed R squared. The observed R squared statistics is 60.622 and it is considered significant as its probability value is <0.05 which proves that there is an existence of ARCH effect in the natural gas data ranging from May 01, 2017 to April 30, 2020.

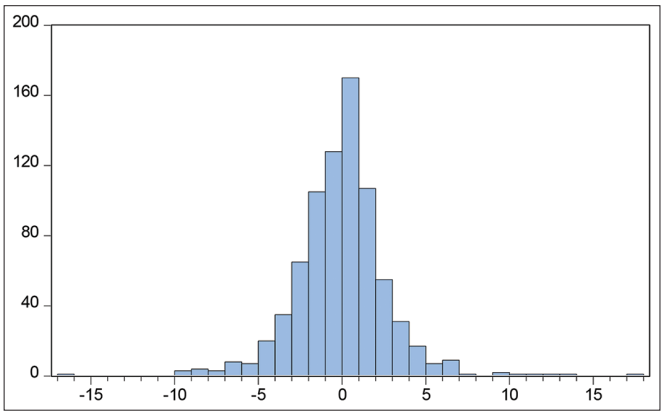
After testing the existence of ARCH effects, three EGARCH (1,1) models have been formulated i.e., EGARCH with normal distribution error construct, EGARCH with Student t's distribution error construct and EGARCH with generalised error distribution construct. To select the suitable model, the results of all the three models, need to be analysed. Table 5 shows the results of all these three models.

Figure 3: The log returns of natural gas



Source: Authors' computation through E-views 10

Figure 4: Peakedness of natural gas data



Source: Authors' computation through E-views 10

Table 4: Testing of ARCH effects in natural gas returns

Heteroskedasticity test: ARCH				
F-statistic	65.55569	Prob. F (1,779)		0.0000
Obs*R-squared	60.62240	Prob. Chi-square (1)		0.0000
Test equation:				
Dependent variable: RESID^2				
Method: Least squares				
Date: 05/04/20 Time: 20:18				
Sample (adjusted): 5/04/2017 4/30/2020				
Included observations: 781 after adjustments				
Variable	**Coefficient**	**Std. error**	**t-statistic**	**Prob.**
C	5.604131	0.786006	7.129888	0.0000
$RESID^2(-1)$	0.278615	0.034411	8.096647	0.0000
R-squared	0.077622	Mean dependent var		7.769390
Adjusted R-squared	0.076437	S.D. dependent var		21.49330
S.E. of regression	20.65553	Akaike info criterion		8.896400
Sum squared resid	332360.9	Schwarz criterion		8.908335
Log-likelihood	-3472.044	Hannan-Quinn criteria		8.900990
F-statistic	65.55569	Durbin-Watson stat		2.043854
Prob(F-statistic)	0.000000			

Source: Authors' computation through E-views 10

The standard way to select a model has already been discussed while analysing Table 5 for selecting suitable EGARCH (1,1) model for crude oil. Table 5 depicts that coefficients, ARCH effect and GARCH are significant in all the three EGARCH (1,1) models i.e., EGARCH with normal distribution error construct, EGARCH with Student t's distribution error construct and EGARCH with Generalised Error Distribution Construct. After framing the above models, as like the models for crude oil, there is no Heteroscedasticity (which has been checked with the help of ARCH LM Test) and there is no autocorrelation (which has been checked with the help of correlogram of residuals and squared residuals) in any of the three models for natural gas. The EGARCH Model with normal distribution error construct can be rejected initially as it has negative R squared and negative adjusted R squared. While comparing the AIC and SIC of all the reaming two models, it has been found that EGARCH with t's distribution error construct has the lowest AIC (4.59) and SIC (4.63) as compared to other two models. Similarly, while comparing the three models, the same EGARCH model with t's distribution error construct has highest log likelihood, R squared, and adjusted R squared. Hence, the model with t's distribution error construct is the most suitable model. The result of the selected EGARCH (1,1) model for natural gas is mentioned in Table 6.

Table 6 shows the results of the EGARCH (1,1) model with t's distribution error construct of natural gas. The results contain two parts. The upper part shows the main equation and the lower part represents the variance equation. In the main equation, both the constant (C) and the co-efficient of first lag [OILR (−1)] are considered as weak as the probability value is more than 0.05.

In case of variance equation, C (3) is the Constant, C (4) is the ARCH co-efficient, C (5) is the asymmetric co-efficient and C (6) is the GARCH co-efficient. All the coefficients in the variance equation are significant as their probability values are <0.05. Moreover, the model has least AIC i.e., 4.5921 and SIC i.e.,

Table 5: Decision table for selecting suitable EGARCH (1,1) model for natural gas

Statistics	Normal distribution	Student t's distribution	Generalised error distribution
Significant coefficients	Yes	Yes	Yes
ARCH significant	Yes	Yes	Yes
GARCH significant	Yes	Yes	Yes
Log-likelihood	−1806.487	−1788.547	−1790.621
R square	-0.000625	0.002143	0.001728
Adjusted R square	-0.001908	0.000863	0.000448
AIC	4.635517	4.592192	4.597496
Schwartz IC	4.671286	4.633922	4.639226
Heteroscedasticity (ARCH LM-Test)	No	No	No
Autocorrelation (correlogram of residuals)	No	No	No

Source: Authors' computation through E-views 10

Table 6: Results of EGARCH (1,1) with t's distribution error construct

Dependent variable: NGASR				
Method: ML ARCH – Student's t distribution				
Date: 05/05/20 Time: 20:29				
Sample (adjusted): 5/03/2017 4/30/2020				
Included observations: 782 after adjustments				
Convergence achieved after 32 iterations				
Resample variance: back cast (parameter=0.7)				
LOG(GARCH) = C (3) + C (4) *ABS (RESID (−1)/@SQRT (GARCH (−1))) + C (5)				
***RESID (−1)/@SQRT (GARCH (−1)) + C (6) * LOG (GARCH (−1))**				
Variable	**Coefficient**	**Std. error**	**z-statistic**	**Prob.**
C	0.013718	0.072918	0.188125	0.8508
NGASR (−1)	−0.029909	0.037048	−0.807305	0.4195
Variance equation				
C (3)	−0.102711	0.030552	−3.361814	0.0008
C (4)	0.167799	0.041201	4.072737	0.0000
C (5)	0.062356	0.025801	2.416848	0.0157
C (6)	0.987885	0.009092	108.6549	0.0000
T-DIST. DOF	6.405844	1.443034	4.439149	0.0000
R-squared	0.002143	Mean dependent var		−0.045005
Adjusted R-squared	0.000863	S.D. dependent var		2.792539
S.E. of regression	2.791333	Akaike info criterion		4.592192
Sum squared resid	6077.403	Schwarz criterion		4.633922
Log-likelihood	−1788.547	Hannan-Quinn criteria		4.608240
Durbin-Watson stat	2.059066			

Source: Authors' computation through E-views 10

4.6339 as compared to other models. The values of R squared i.e., 0.002143, Adjusted R squared i.e., 0.000863 and Log-Likelihood i.e. -1788.54 are higher as compared to the other models. The important point to be focussed is the co-efficient of the asymmetric term (λ) is positive i.e., 0.062356 and also statistically significant which implies that there is an absence of leverage effect of COVID-19 on the price volatility of natural gas and it indicates that COVID-19 has created any larger effect on the volatility of crude oil. Hence the variance equation can be shown as given below.

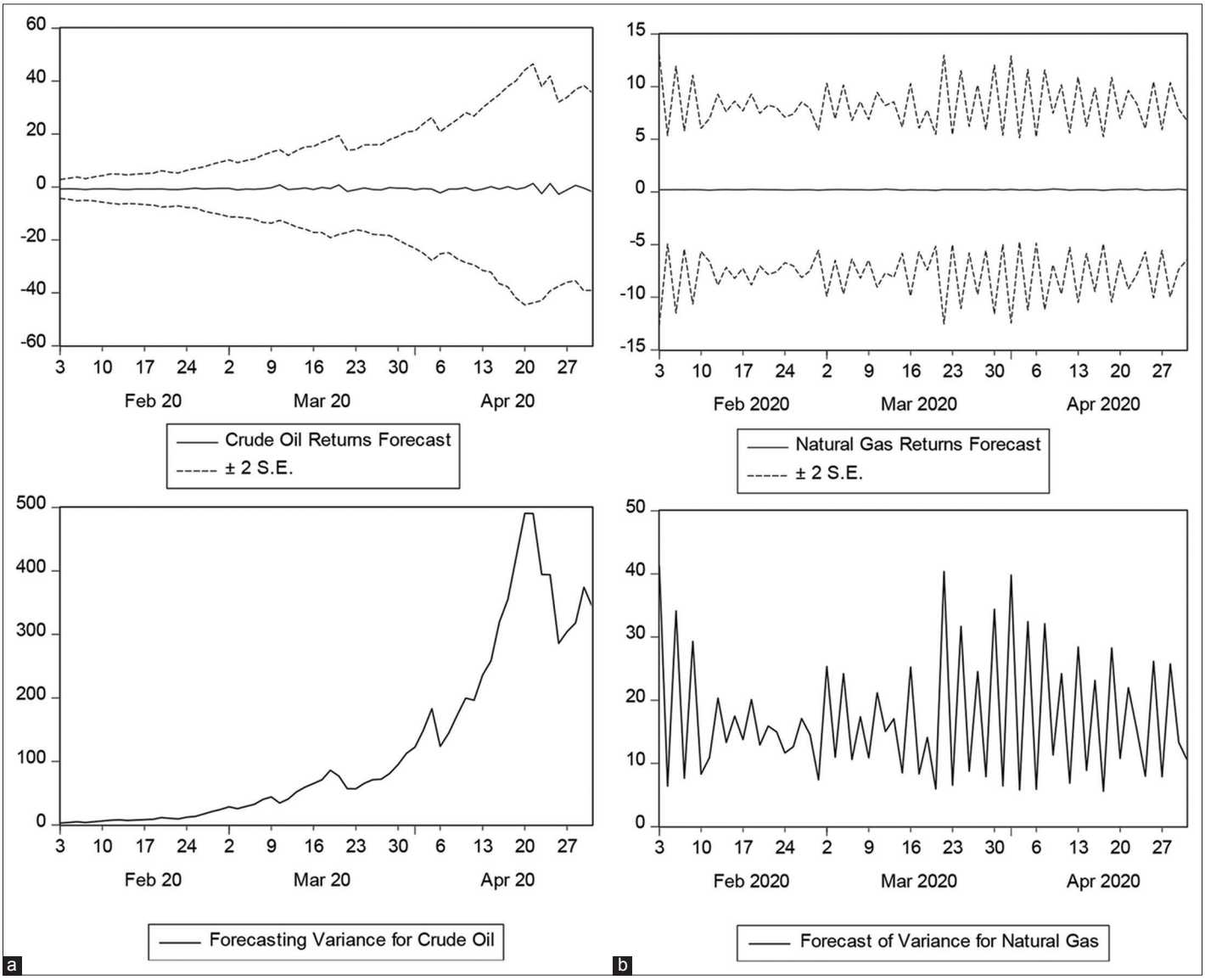
$$log(h_t) = -0.1027 + \sum_{i=1}^{1} 0.1677 \left| \frac{u_t - i}{\sqrt{h_t - i}} \right| + \sum_{i=1}^{1} 0.0623 \frac{u_t - i}{\sqrt{h_t - i}} + \sum_{k=1}^{1} 0.9878 \log(h_{t-k})$$

By using the above-formulated model, the volatility of natural gas has been forecasted in the forecasting volatility section.

Figure 5 shows the forecasted returns of crude oil and the forecasted variance for crude oil for the period from February 01, 2020 to April 30, 2020. The first graph of forecasted returns of crude oil depicts that there is a consistency in the returns of crude oil during that 3 months while the graph of the forecasted variance of crude oil depicts that the volatility has been increasing since from the mid of February 2020 and reached to a high peak on 19th April, stop a little on 25th April and again started rising. This shows that the pandemic COVID-19 has affected severely the volatility of crude oil.

Figure 5 reveals the forecasted returns of crude oil and the forecasted variance for crude oil for the period from February 01, 2020 to April 30, 2020. The first graph of forecasted returns of natural gas depicts that there is a consistency in the returns of crude oil during that 3 months while the graph of the forecasted variance of natural gas depicts that the volatility has been fluctuating tremendously for the last 3 months. This shows that the pandemic COVID-19 has impacted severely the price volatility of crude oil.

Figure 5: Forecasting volatility based on modified 3 months data i.e. from 1st February 2020 to 30th April 2020 by using the formulated model. (a) Forecasting for crude oil (b) Forecasting for natural gas



5. CONCLUSION

The results of the study indicate that there is a presence of asymmetric volatility in crude oil prices due to the spread of COVID-19. The news related to spreading of the pandemic COVID-19 has an impact on the price volatility of crude oil which is also statistically proven as an asymmetric term within the equation i.e., λ is negative (−0.076757) and statistically, significant i.e. $P < 0.05$. However, there is no leverage effect of the COVID-19 pandemic on the price volatility of natural gas as an asymmetric term within the equation i.e., λ is positive (0.062356) and statistically significant as the $P < 0.05$. The forecasting graphs of crude oil prices indicate that there is a possibility that volatility will be higher in the future. It is difficult to predict the expected volatility of prices of natural gas for the future as the volatility graph is extremely fluctuating. The investors in the commodities market focusing on investing in the crude oil and natural gas sector can use the formulated models to take investment decisions.

The results of the study will help the policymakers to assess the impact of the COVID -19 pandemic on the price volatility of crude oil and natural gas and to formulate appropriate policies and strategies to minimise the impact of COVID-19.

REFERENCES

Abounoori, E., Zabol, M.A. (2020), Modeling Gold Volatility: Realized GARCH Approach. Iranian Economic Review (IER), 24(1), 299-311.

Alberg, D., Shalit, H., Yosef, R. (2008), Estimating stock market volatility using asymmetric GARCH models. Applied Financial Economics, 18(15), 1201-1208.

Alcaraz, C., Villalvazo, S. (2017), The effect of natural gas shortages on the Mexican economy. Energy Economics, 66, 147-153.

Ali, G. (2013), EGARCH, GJR-GARCH, TGARCH, AVGARCH, NGARCH, IGARCH and APARCH models for pathogens at marine recreational sites. Journal of Statistical and Econometric Methods, 2(3), 57-73.

Almeida, D.D., Hotta, L.K. (2014), The leverage effect and the asymmetry of the error distribution in Garch-based models: The case of Brazilian market related series. Pesquisa Operacional, 34(2), 237-250.

Apergis, N., Bowden, N., Payne, J. (2015), Downstream integration of natural gas prices across US states: Evidence from deregulation regime shifts. Energy Economics, 49, 82-92.

Apergis, N., Loomis, D., Payne, J.E. (2010), Are shocks to natural gas consumption temporary or permanent? Evidence from a panel of US states. Energy Policy, 38(8), 4734-4736.

Baker McKenzie. (2020), International: The Impact of COVID-19 on the Oil and Gas Industry. Available from: https://www.bakermckenzie.com; https://www.bakermckenzie.com/en/insight/publications/2020/04/the-impact-of-covid19-on-the-oil-and-gas-industry.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31(3), 307-327.

Chang, C.L., McAleer, M., Tansuchat, R. (2012), Modelling long memory volatility. Annals of Financial Economics, 7(2), 1-27.

Daly, K. (2008), Financial volatility: Issues and measuring techniques. Physica A, 387(11), 2377-2393.

Dum, D.Z., Essi, I.D. (2017), Modeling price volatility of Nigerian crude oil markets using Garch model: 1987-2017. International Journal of Applied Science and Mathematical Theory, 3(4), 23-49.

Engle, R. (2001), GARCH 101: The use of ARCH/GARCH models in applied econometrics. Journal of Economic Perspectives, 15(4), 157-168.

Glosten, L.R., Jagannathan, R., Runkle, D.E. (1993), Relationship between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance, 48(5), 1779-1801.

Hailemariam, A., Smyth, R. (2019), What drives volatility in natural gas prices? Energy Economics, 80, 1-31.

Harvey, A., Sucarrat, G. (2014), EGARCH models with fat tails, Skewness and leverage. Computational Statistics and Data Analysis, 76(1), 320-338.

Hassan, E. (2012), The application of GARCH and EGARCH in modeling the volatility of daily stock returns during massive shocks: The empirical case of Egypt. International Research Journal of Finance and Economics, 96, 153-165.

Hawaldar, I.T., Rajesha, T.M., Lokesha, Kumar, A. (2017b), Impact of financial and oil price crisis on the financial performance of selected banks in Bahrain. International Journal of Economic Research, 14(18), 83-96.

Hawaldar, I.T., Rajesha, T.M., Sarea, A.M. (2020), Causal nexus between the anamolies in the crude oil price and stock market. International Journal of Energy Economics and Policy, 10(3), 233-238.

Hawaldar, I.T., Rohit, B., Pinto, P., Rajesha T.M. (2017a), The impact of oil price crisis on financial performance of commercial banks in Bahrain. Banks and Bank Systems, 12(4), 4-16.

Hawaldar, I.T., Shakila, B., Pinto, P. (2017c), Empirical testing of month of the year effect on selected commercial banks and services sector companies listed on bahrain bourse. International Journal of Economics and Financial Issues, 7(2), 426-436.

Hwang, S., Pereira, P.V. (2004), Small Sample Properties of GARCH Estimates and Persistence. CEA@Cass Working Paper Series No. WP-CEA-10-2004. p1-33.

IANS. (2020), Crude oil Price Worsens on Covid-19 Concerns, Poor Chinese Ecodata. Available from: https://www.auto.economictimes.indiatimes.com; https://www.auto.economictimes.indiatimes.com/news/oil-and-lubes/crude-oil-price-worsens-on-covid-19-concerns-poor-chinese-ecodata/75214677.

Iqbal, T.H., Mallikarjunappa, T. (2010), A study of efficiency of the Indian stock market. Indian Journal of Finance, 4(5), 32-38.

Iqbal, T.H., Mallikarjunappa, T. (2011), Efficiency of Stock Market: A Study of Stock Price Responses to Earnings Announcements. Germany: LAP Lambert Academic Publishing Company.

Jacob, A., Nutula, P. (2020), OPINION: COVID-19 Impact on the Oil and Gas Industry-a Perspective. Available from: https://www.energy.economictimes.indiatimes.com; https://www.energy.economictimes.indiatimes.com/news/oil-and-gas/opinion-covid-19-impact-on-the-oil-gas-industry-a-perspective/75726882.

Kilian, L. (2008), Exogenous oil supply shocks: How big are they and how much do they matter for the US economy? Review of Economics and Statistics, 90(2), 216-240.

Manera, M., Nicolini, M., Vignati, I. (2013), Futures Price Volatility in Commodities Markets: The Role of Short Term vs Long Term Speculation. DEM Working Paper Series.

Mudgill, A. (2020), Here's Why Crude Oil Prices Fell Below $0 a Barrel. Available from: https://www.economictimes.indiatimes.com; https://www.economictimes.indiatimes.com/markets/commodities/news/what-led-crude-oil-prices-fall-below-0-a-barrel/articleshow/75264813.cms?from=mdr.

Mukherjee, I., Goswami, B. (2017), The volatility of returns from commodity futures: Evidence from India. Financial Innovation, 3(15), 1-23.

Narayan, P., Sharma, S., Poon, W., Westerlund, J. (2014), Do oil prices predict economic growth? New global evidence. Energy Economics,

41, 137-146.
Peter, H.R., Huang, Z., Shek, H.H. (2012), Realized GARCH: A joint model for returns and realized measures of volatility. Journal of Applied Econometrics, 21(1), 1-21.
Pindyck, R.S. (2004), Volatility in natural gas and oil markets. The Journal of Energy and Development, 30(1), 1-20.
Shakila, Pinto, P., Hawaldar, I.T. (2017), Semi-monthly effect in stock returns: New evidence from Bombay. Investment Management and Financial Innovations, 14(3), 160-172.
WHO. (2020), Novel Coronavirus (2019-nCOV) Situation Report No. 92. Available from: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports.
World Bank. (2020), A Shock Like No Other: Coronavirus Rattles Commodity Markets. Available from: https://www.worldbank.org; https://www.worldbank.org/en/news/feature/2020/04/23/coronavirus-shakes-commodity-markets.