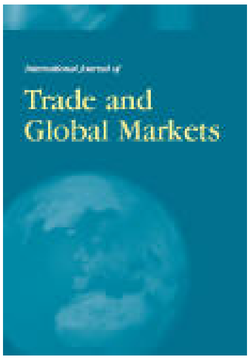

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Modelling price volatility in energy futures during Covid-19

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Abstract: Studies using various models have been undertaken to measure the impact of Covid-19 on energy futures but very few have focussed on identifying the best model. Therefore, this paper applied various models like GARCH, TGARCH, EGARCH and PGARCH with three error distribution terms to identify the best fit model that measures the volatility in Natural gas and Crude oil futures traded on MCX, before and during the pandemic. Further, it has tried to study volatility spillover effects of spot and futures prices for the entire duration by employing Bivariate BEKK GARCH Model. The results show the variation in leverage effect in both the futures and existence of bi-directional volatility spillover in long and short period. The findings of the study can help financial market players to have better understanding of the market dynamics of natural gas and crude oil volatility and help stakeholders deal with energy futures market volatility in a better way.

Keywords: Covid-19; volatility; energy futures; GARCH models; volatility spillover; crude oil; natural gas; forecasting.

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1 Introduction

Price volatility in a market-based economy brings in unavoidable consequences to the economy, indirectly affecting the economic growth, employment, GDP and other macro-economic variables. Covid-19 has brought volatility in the energy sector due to disruption in the demand and supply chains of energy, most importantly Crude oil and Natural gas. Volatility in Crude oil and Natural gas has impacted economies around the world. Covid-19 pandemic has brought in uncertainty and jolted the oil market like never before (Zhang and Hamori, 2021). Natural gas was also affected by Covid-19 because of loss of demand owing to industry shutdowns, lack of electricity usage in offices, buildings, movie theatres, restaurants, and malls (Smead, 2020). The unprecedented volatility in energy prices during Covid-19 pandemic has inspired researchers to conduct studies on the same. Volatility can be viewed as a tool for risk measurement. A higher volatility will result in higher risk and vice versa. It's because, volatility is one of the quintessential features of the financial markets and the forecast of volatility has numerous applications as well as implications in the field of finance. Volatility is a measure of quantum of change in market returns, and persistence is the duration it takes to go away (Yaya et al., 2020). Since 2007, excess volatility seems to be lasting longer, and, therefore, the persistence of volatility needs to be studied to figure out its causes and the manner in which shocks spread and affect the financial market (Fakhfekh et al., 2016). Three reasons for which the volatility is estimated are understanding risk, asset allocation and profit maximisation (Kumar and Patil, 2016). Crises can result in negative and positive market adjustments depending upon the impact of the news (Al-Rjoub and Azzam, 2012).

During crises, the nature of volatility purely depends upon the investor's expectations. The people worried about the future are less likely to invest, which will reduce volatility and the size of the trade. On the other hand, optimistic ones will invest more making the markets more volatile. Volatility was once considered to be constant, but ensuing research has shown that it varies with time (Kovačić, 2008). Volatility is 'bursty', and 'burstiness' is related to 'mean reversion' because a 'bursty' process is going back to its mean (Fouque et al., 2000). It is commonly believed that the price of the commodities displays a mean reversion tendency because of the relationship between demand and supply (Andersson, 2007) and researchers have found energy prices to be mean reverting (Figlewski et al., 2021; Geman, 2007). If there is even the slightest shift in volatility, it will not only affect the economy but also the investors (Rastogi, 2014). Therefore, it is pertinent to study the volatility. An econometric model named Autoregressive Conditional Heteroskedasticity (ARCH) was developed to predict the future volatility by studying past volatility (Engle, 1982). According to which the value of squared error terms does not remain constant over time. The concept behind ARCH is that today's volatility has some impact in the volatility of future periods. "If the pattern of volatility clusters is studied for longer duration, we observe that, once volatility reaches its highest point then it will continue for a longer duration" (Kumar and Patil, 2016). To overcome its limitations of dependence only on the lagged value of the squared errors while ignoring its own lagged value, Bolloerslev and Taylor (1986) propounded Generalised ARCH (GARCH) model. But this ignores the existence of leverage effect i.e., when change in price of asset is negatively correlated with change in volatility due to some shocks in the market. To overcome this limitation, various extensions of GARCH have been developed in later years that consider the leverage effect. Accordingly, different models have aimed to capture different features of volatility like 'volatility clustering', and "leverage impact". Usually, negative returns impact future volatility more than the positive returns, which causes the leverage effect (Almeida and Hotta, 2014). So, to catch the leverage effect more efficiently, many versions like Threshold GARCH (TGARCH), Exponential GARCH (EGARCH) and Power GARCH (PGARCH) have been added to the GARCH.

Myriad studies are conducted concerning volatility in energy market, but very scant literature is available with regard to the selection of the best-fitted model to study the volatility in futures market. Matringe and Guida (2004) tried to find the best-fitted model for studying volatility in futures traded in the French Major Stock Index. Kumar and Patil (2016) studied selection of best GARCH model with nine error distribution terms for forecasting variance in S&P 500 index. They found GARCH with generalised error distribution (GED) as the best model for forecasting the variance. Meher et al. (2020) investigated volatility in Crude oil and Natural gas futures during Covid-19 period by selecting an appropriate model for forecasting volatility with due consideration to EGARCH and three error distribution terms and opined EGARCH with SED (SED) to be the best model for analysing and forecasting volatility for both the futures. Though TGARCH could be superior to rest of the GARCH models (Ali, 2013), yet in finance literature, most of the researchers do not seem to consider any other variants of GARCH than the EGARCH as the best model. EGARCH has widely been used by different researchers to study the volatility in the market (Shihabudheen and Padhi, 2010; Shalini and Prasanna, 2016; Rout et al., 2019 and Meher et al., 2020).

Energy markets are highly volatile (Chebbi and Derbali, 2015) and Covid-19 has heightened the volatility in Crude oil and Natural gas prices (Balashova, 2021), resulting in the need for effective forecasting models (Almansour et al., 2021). Therefore, this paper not only studies the volatility but also focuses on the selection of appropriate model to study the volatility, through appropriate GARCH models along with different error distribution terms, in Crude oil and Natural gas during the study period (1st January, 2017 – 31st January, 2021) and two sub periods viz., Before Pandemic and During Pandemic.

Spot market shocks can also cause volatility in the futures market (Razmi et al., 2020). As a result, the volatility spillovers between spot and futures prices of Natural gas and Crude oil are also being investigated in this study. The reason behind considering energy futures in our study is that the prices of energy fell drastically due to pandemic and past studies advocated that "price instability in the spot market can be restored with the help of futures market" (Malhotra and Sharma, 2016) and the futures market reacts to innovations or shocks far more quickly than the spot market (Dey and Maitra, 2012). The pattern of volatility in commodity futures does not remain constant and varies with time. Same may be found in Crude oil and Natural gas futures, which makes it essential to study the volatility in futures market during Covid-19 crisis period.

We made several contributions to the literature on commodity futures volatility modelling. Unlike previous research, we did not consider only one GARCH model to study volatility, but instead compared many GARCH Family models and chose the best GARCH model to study volatility on the basis of Log Likelihood, Adjusted R^2 and lowest Schwarz Information Criteria. Secondly, for each of the selected GARCH models, we considered three error distribution terms. We performed a volatility comparison test between the pre-Covid period and the Covid period to determine whether an asymmetric effect exists in energy futures prices. Lastly, most of the studies related to the impact of covid on energy futures are conducted in developed markets and very few studies are undertaken in developing markets like India. The remainder of paper has four sections. Important literature related to performance of futures market during crisis, volatility in futures market and its association with the spot market have been discussed in Section 2. Data and analytical tools and modelling framework have been discussed in Section 3 and the analysis on empirical result are covered in Section 4. Conclusive explanations are covered in Section 5.

2 Literature review

Volatility in the commodity futures market and its association with the spot market has been explored by large pool of researchers. Literature having significant contribution in this area is discussed in this section.

Covid-19 cases and ensuing deaths resulted in 8–22% rise in daily oil price volatility (Devpura and Narayan, 2020). Volatility seems to persist for a longer period during financial/economic crises (Bhunia and Ganguly, 2020), which demonstrates that the volatility persistence is a significant feature during global economic and financial instability (Rastogi, 2014). As a result, studying volatility of the markets during the crisis and post-crisis period is essential to understand its behaviour, nature and the direction. During Asian and Global Financial Crisis (Zavadska et al., 2020) and Covid-19 (Gil-Alana and Monge, 2020), uncertainty and risk in Crude oil market lasted longer. Chhatwal et al. (2013) employed GARCH model to study volatility in Crude oil in Spot and Futures by considering the financial crisis of 2008 and found low and high volatility persistence before and during the crisis, respectively. In line with this, Shalini and Prasanna (2016) applied hybrid Wavelet EGARCH and fractional integration to study persistence and leverage effects in 18 commodities. Their findings were similar to the findings of Chhatwal et al. (2013), which states that during global financial crisis, volatility was high and systematic risk contributed more than idiosyncratic risk in increasing the volatility. Similarly, the findings of Roy and Roy (2017) also are in line with the findings of others which states the presence of high volatility and leverage effects during the crisis period. Go and Lau (2020) found positive correlation between the volatility in price and volume of Crude oil in post crisis period while negative correlation in pre-crisis and no volatility spillover during the crisis period. Stronger co-movement from one commodity exchange to another was observed during the period of stability which gradually weakened during the crisis period (Sehgal et al., 2013). The same held true for the energy and metal futures in emerging stock markets (Mandacı et al., 2020). Existence of asymmetric effects was observed in Crude oil and Natural gas futures during Covid-19 with Crude oil futures largely being impacted by the negative than the positive news, as compared to Natural gas, which was impacted more by the positive than the negative news (Meher et al., 2020). Borgards et al. (2021) found that base metals, precious metals and energy of 20 commodity futures had less overreaction except energy futures which had negative than the positive overreaction in pre and during Covid-19 period. They opined that extreme overreaction, can bring in profitable trading opportunities for the investors. Nissanke (2012) suggested that, during the period of crisis, futures markets can support the spot market by performing its two imperative functions i.e., price discovery and risk hedging.

Sometimes persistence in volatility can be due to the shocks from other markets which is termed as volatility spillover. Seth and Sidhu (2020), through a systematic review of literature, discovered substantial volatility transmissions from spot to futures. Understanding volatility transmissions across different markets would assist the decision makers in understanding the relationship between the markets with respect to volatility spillover. Chatrath and Song (1998) looked into the intraday behaviour of spot and futures markets after release of the information. They argued that the advent of new information in one market caused increased volatility in the other, and that the futures markets played major role in this. Thenmozhi and Priya (2008) tried to assess volatility interlinkage between both the markets of crude oil and found strong volatility spillovers between spot and futures of Crude oil. Maitra (2018) found volatility spillover between spot and futures price of agriculture commodities where, spot market dominated futures market in volatility spillover. It was also found that volatility spillover plays a prominent role in explaining and forecasting volatility in both the markets than seasonality and breaks. Malhotra and Sharma (2016) applied Bivariate GARCH to study the volatility dynamics in Oil and Oil seeds futures and spot markets in India. They found spot market taking lead over futures in deciding volatility spillover, which confirms spot market to be informational efficient than futures market. Sehgal et al. (2013) documented existence of bi-directional volatility spillover in Soyabean, Zinc and Natural gas with highest spillover from spot to futures. Rout et al. (2021) and Srinivasan (2011) reported existence of bi-directional spillover effect in agriculture futures and spot while the later takes lead in information transmission. Shihabudheen and Padhi (2010) analysed price discovery and volatility spillover in spot and futures market by taking 6 commodities viz., Gold, Silver, Crude oil, Castor seed, Jeera and Sugar. The study found price discovery and volatility spillover strongly transmitting from futures to spot in all commodities except sugar, in which spot plays a greater role. Lakshmi et al. (2015) explored connection between spot and futures returns for Crude oil. The study did not find sufficient evidence for futures forecasting spot. Similarly, Mathew et al. (2021) found strong spillover effect from futures to spot in case of energy commodities traded at MCX. Rastogi and Agarwal (2019) investigated impact of options and futures market on spot volatility and found no association between volatility in options market with spot and futures market but, found the association between volatility in both futures and spot markets. Manogna and Mishra (2021) used EGARCH model to examine volatility spillover effect in nine agriculture futures traded on NCDEX and spot market. The study discovered the presence of mutual spillover effects between spot and futures markets. Nakajima (2019) employed Realised Variance (RV) to analyse Japan's Crude oil futures with a purpose to investigate risk transmission between Crude oil and Petroleum product prices. Result of RV approach showed existence of bi-directional volatility spillover between Crude oil and Petroleum products. Wang and Wu (2012) used the GARCH model to determine factors leading to daily volatility for Natural gas and Crude oil futures traded on NYMEX. The study concluded that there is higher level of persistent volatility during winters and the existence of storage facilities and seasons to be the determinants of volatility for both the futures.

From the literature, it is evident that markets perform differently in before, after and during the crisis. So, therefore, it is imperative to study the volatility in crisis period, like Covid-19, to have an understanding of the nature and other nuances of volatility and to make investors, regulators, hedgers, etc. take informed decisions. Literature also throws light on the importance of studying volatility spillover between futures and spot market as both the markets are highly influenced by each other. Therefore, this study makes an attempt to have insights on volatility in Crude oil and Natural gas in pre, post and during the Covid-19 period along with volatility spillovers between futures and spot prices of both the energy commodities.

3 Data and methodology

3.1 Data extraction

The study has taken daily closing prices of Natural gas and Crude oil futures and spot, which are being extracted from Multi Commodity Exchange (MCX) website from 1st January, 2017 to 31st January, 2021. The study analysed the volatility in both the energy futures for full sample period and divided the whole period into two sub-periods. 1st January, 2017 – 31st December, 2019 is termed as Before Pandemic period and 1st January, 2020 – 31st January, 2021 as During Pandemic period. We have considered the data from 2017 because our main objective is to check volatility in two energy futures in before Covid-19 and during Covid-19 period, and taking a much longer period would not serve our purpose. The reason behind including Crude oil and Natural gas, in the study, is to analyse the massive impact of Covid-19 on these two commodities. Further, studying the volatility in futures price of these two commodities would help the policy makers and investors take informed decisions

3.2 Methodology

The methodology section contains six steps. In the first step, daily closing futures prices has been converted into daily log return series by using the following formula:

$$p = \log * \frac{p}{p_{t-1}} \tag{1}$$

where, p denotes the price, p_t is today's price and p_{t-1} is the price for preceding day.

Second step consists of checking unit root test. Nonexistence of unit root in futures price is confirmed by applying Augmented Dickey Fuller test (ADF) with intercept term and Schwarz Information Criteria for selecting optimum lag length. In the third step, some preliminary diagnostic tests have been performed which are essential to run GARCH models. In preliminary testing, volatility clustering and peakedness of the data were checked through graph and existence of ARCH effect were checked through ARCH LM test. After confirming the significance of all the three diagnostic tests, the standard GARCH, TGARCH, EGARCH and PGARCH, with three error distribution terms, viz., normal error distribution (NED), Student's *t* error distribution (SED) and GED were performed. In the fourth step, the best model was selected on the basis of highest value of Log Likelihood, Adjusted R^2 and lowest Schwarz Information Criteria. In the fifth step, diagnostic tests (Normality, Auto Correlation, Heteroskedasticity in the squared residuals) were performed on the formed model. Jarque-Bera Statistics was used to check normality, Ljung box test to check auto correlation and ARCH LM test has been used to check the heteroskedasticity in the squared residuals. Sixth step included the checking of volatility spillovers between Crude oil and Natural gas futures and spot prices by applying Bivariate BEKK GARCH (1, 1).

3.2.1 Modelling framework

The following models have been considered in the study to select the suitable model to analyse and forecast the volatility of Crude oil and Natural gas futures.

GARCH (1, 1)

The first model considered in the study is the standard GARCH. Volatility can be defined as discrepancy in returns, which assesses the risk inherent in financial assets. "Since a financial time-series does not have constant volatility" (Chhatwal et al., 2013), Auto Regressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982) can be used for its study. Before that there was no model to consider volatility in financial time series as non-constant. One of the limitations of ARCH model is that it depends only on the past values of the squared errors while ignoring its own lagged value. To overcome this limitation, Bollerslev and Taylor developed a Generalised Auto Regressive Conditional Heteroskedasticity (GARCH) in 1986.

The GARCH (1, 1) can be described with the following equation:

$$fr_t = \vartheta + \alpha_1 u^2_{t-1} + \beta_1 fr_{t-1} \tag{2}$$

where, fr_t is conditional variance of futures return series at time t, $\beta_1 fr_{t-1}$ is the GARCH term which represents past values of fr_{t-1}, and $\alpha_1 u^2_{t-1}$ is an ARCH term.

TGARCH (1, 1)

Standard GARCH model does not consider the impact of good and bad news differently or asymmetrically. TGARCH, is the abbreviation of Threshold GARCH, is an asymmetric version of Standard GARCH which takes into consideration the leverage effects. The model can be defined as:

$$fr_t = \vartheta + \alpha_1 u^2_{t-1} + \beta_1 fr_{t-1} + \Upsilon_1 u^2_{t-1} D_{t-1} \tag{3}$$

where

$D_t = 1$ if u_t is less than zero

$D_t = 0$ if u_t is more or equal to zero

Υ_1 is an asymmetric term.

If Υ_1 is identical to zero, it signifies good and bad news have symmetric impact. Υ_1 with positive value and statistically significant implies volatility is caused more by negative news than the positive news whereas, a negative and significant Υ_1 indicates the larger impact of positive news than negative news.

EGARCH (1, 1)

Exponential GARCH developed by Nelson (1991) also considers the asymmetric effect like TGARCH. EGARCH uses log of the variance to measure the asymmetric impact, which makes it different from the TGARCH. EGARCH (x, y) model is quantified as:

$$\text{Log}\ (fr_t) = \vartheta + \sum_{i=1}^{y} \alpha_1 \left[\frac{u_{t-1}}{fr_{t-1}} \right] + \sum_{i=1}^{y} \Upsilon_1 \ \frac{u_{t-1}}{fr_{t-1}} + \sum_{k=1}^{x} \beta_k \ \log\ (fr_{t\text{-k}}) \tag{4}$$

Where, Log (fr_t) is the log variance of futures return series, ϑ is the constant, α is ARCH effects, β is the GARCH effects, and Υ is asymmetric or leverage effects.

If Υ_1 is identical to zero, it signifies good and bad news does not have asymmetric impact. Υ_1 with positive value and statistically significant implies volatility impacted more by positive news than the negative news, and a negative and significant Υ_1 indicates larger impact of the negative news than the positive news.

PGARCH (1, 1)

Ding, Granger and Engle developed a model called Power GARCH (PGARCH) in 1993. "The power term is estimated within the model. It captures volatility clustering by changing the influence of the outliers" (Tully and Lucey, 2006). The model can be specified as:

$$(fr^{\delta}_t) = \vartheta + \sum_{i=1}^{q} \alpha_1 (\ |u_{t-1}| - \Upsilon_1 \ u_{t-1})^{\delta} + \sum_{k=1}^{p} \beta_k \ \log(fr^{\delta}_{t-k}) \tag{5}$$

where $\delta > 0$, and Υ_1 is asymmetric term.

3.2.2 Volatility spillover test

The interlinkage of one asset class upon another is termed as spillover effect. We tried to assess volatility spillover between futures and spot price of Crude oil and Natural gas. Bivariate BEKK GARCH (1, 1) has been applied to check the volatility spillover between Crude oil futures and spot price which is specified with the help of the following equation:

$$\begin{aligned} H_t = C_0' C_0 &+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{pmatrix} \varepsilon^2_{1,t-1} & \varepsilon^2_{1,t-1}\,\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon^2_{1,t-1} & \varepsilon^2_{2,t-1} \end{pmatrix} \begin{bmatrix} a_{11} a_{12} \\ a_{21} a_{22} \end{bmatrix} \\ &+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \end{aligned} \tag{6}$$

where a signifies ARCH term which is coefficient of square of one period error term (ε); *b* signifies GARCH term which is the coefficient of one period variance/covariance term (h); a_{11} and a_{22} denote short-term volatility within the market; b_{11} and b_{22} denote long-term volatility within the market; a_{12} and a_{21} symbolise volatility spillover between the markets in the short-term, b_{12} and b_{21} denote long-term volatility spillover between the markets.

4 Result and discussion

4.1 Result

4.1.1 Descriptive statistics

To analyse any time series data, the precondition is to check the stationary of the data. Table 1 shows the stationarity in the return series of Natural gas and Crude oil by applying Augmented Dickey Fuller Test for the entire period and sub periods along with descriptive statistics.

Table 1 Descriptive statistics

Indicators	*Before pandemic period*		*During pandemic period*		*Overall period*	
	Crude oil	*Natural gas*	*Crude oil*	*Natural gas*	*Crude oil*	*Natural gas*
Mean	0.022162	–0.000611	0.04597	–0.000854	0.004153	–0.000225
Standard Deviation	1.520862	0.020679	5.480049	0.035509	3.104304	0.025447
Skewness	–0.04318	0.166459	–1.55483	0.374725	–2.29872	0.377785
Kurtosis	6.393074	7.359951	25.36651	4.233	65.36747	6.634359
Jarque Bera Statistics	374.8933	622.1969	5991.687	24.46306	173380.5	610.8891
P-Value of Jarque Bera Statistics	0.0000	0.0000	0.0000	0.000005	0.0000	0.0000
Unit Root Test	–22.1724	–24.01699	–18.1359	–13.62405	–9.461116	–27.26951
P-Value of Unit Root Test	0.00000*	0.00000*	0.00000*	0.00000*	0.00000*	0.00000*

*Indicates significance at 5% level.

Source: Author's own estimation

In case of Natural gas, values of the standard deviations in all the periods were close to zero indicating low level of dispersion in the average log returns of Natural gas futures. Standard deviation was moderately low in overall period while it was relatively high during Pandemic period, indicating high dispersions in the average of log returns of Crude oil futures during Pandemic period as compared to the entire period. The skewness of the log of returns of Natural gas is positive with negative mean indicating the overall performance to be negative. Whereas, the mean of log returns of Crude oil in all the periods is positive with a negative mean which highlights the risk of left tail events which refers to "Black Swan Events". The Kurtosis of the log returns of both energy futures are more than three which indicates the log return series to be leptokurtic. The log return of Crude oil and Energy futures are not normally distributed which is evident from the P-Value of Jarque-Bera Statistics. Augmented Dickey Fuller Test found the return series of both the futures to be stationary at level which indicates that the return series can be used for further analysis.

4.1.2 Preliminary diagnostics before selecting models

Some preliminary tests, including volatility clustering, data peaking, and ARCH effects, must be run to check GARCH model volatility. Figure 1 shows the clustering of futures log returns which shows minor fluctuations are followed by minor fluctuations and major fluctuations by major fluctuations, indicating volatility clustering. Large fluctuations in Natural gas and Crude oil return series can be seen from March, when the pandemic's severity was widely known. Figure 2 shows peakedness of return series. Both energy futures data are highly peaked, or leptokurtic.

Figure 1 Volatility clustering (see online version for colours)

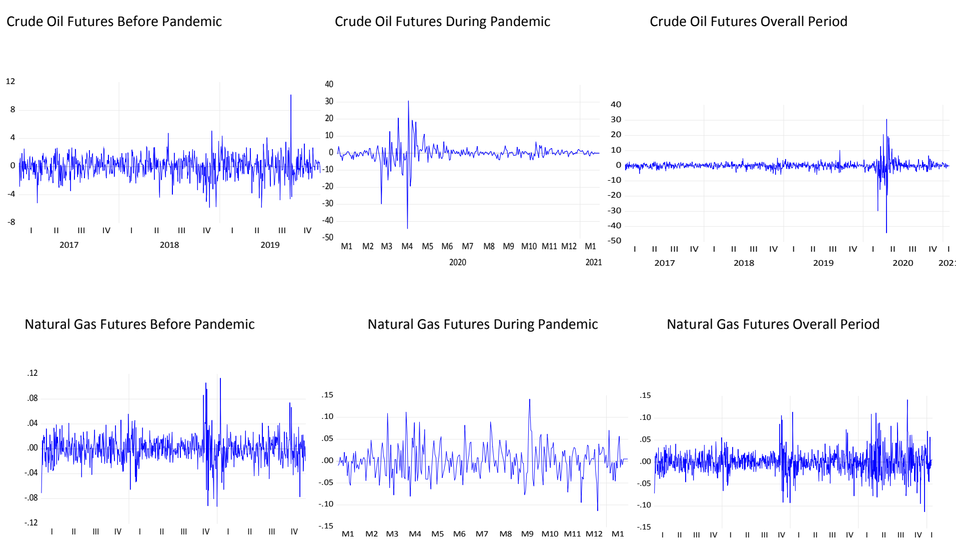
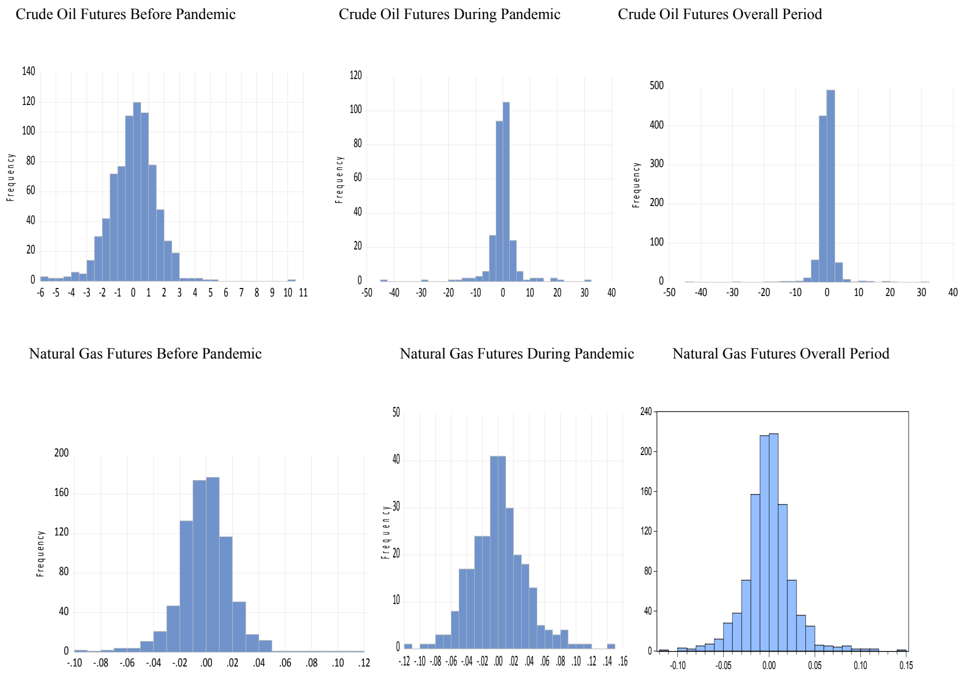


Figure 2 Peakedness (see online version for colours)



Source: Author's own estimation

Table 2 represents heteroskedastic test of futures return. The return series is heteroskedastic because its ARCH p-value is less than 0.05, indicating presence of ARCH effect in Energy futures return series for the entire period and sub periods. All diagnostic tests indicate using GARCH models to study the volatility in energy futures return series.

Table 2 ARCH test

	Before pandemic period		*During pandemic period*		*Overall period*	
	Crude oil	*Natural gas*	*Crude oil*	*Natural gas*	*Crude oil*	*Natural gas*
F-Statistic	5.242654	16.30364	25.07183	3.917509	131.4052	37.53919
P-Value	0.0001*	0.0001*	0.000*	0.0488*	0.0000*	0.0000*

*Indicates significance at 5% level.

Source: Author's own estimation

4.1.3 Criteria for selecting best model

We employed GARCH (1, 1), TGARCH (1, 1), EGARCH (1, 1), and PGARCH (1, 1) with Normal, Student's t, and GEDs. The best model has been selected on the basis of the highest Log Likelihood, Adjusted R2, and SIC. Table 3 compares all 3-error-term models. Table 3 shows the comparison among all the models with 3 error distribution terms. It is evident from the table that for Before Pandemic period, EGARCH (1, 1) model with SED and EGARCH (1, 1) with NED term is the best model for log return series of Natural gas and Crude oil futures, respectively. Whereas, EGARCH (1, 1) with NED for log return of Natural gas and EGARCH (1, 1) with SED error is found to be the best model to study the volatility for log return of Crude oil during Pandemic period. In case of overall period, EGARCH (1, 1) with student's t distribution and TGARCH (1, 1) with student's t distribution error terms are found to be the best fitted model for log return series of Crude oil and Natural gas, respectively.

Table 3 Decision table for selecting suitable model

Time period	*Commodity*	*Models*	*Error distribution*	*Log likelihood*	*Adj. R2*	*SIC*
Sub Period-1 Before Pandemic Period	Crude Oil	GARCH (1,1)	NED	–1382.817	0.047892	3.588372
			SED	–1372.299	0.047894	3.56994
			GED	–1376.438	0.047283	3.580554
		TGARCH (1,1)	NED	–1377.176	0.049139	3.582445
			SED	–1368.207	0.048821	3.567985
			GED	–1568.876	0.049155	4.082521
		EGARCH (1,1)	NED	–1376.931	0.04929	3.561817
			SED	–1367.732	0.049122	3.566768
			GED	–1371.629	0.048998	3.576759
		PGARCH (1,1)	NED	–1376.762	0.049273	3.589923
			SED	–1367.646	0.049102	3.575086
			GED	–1371.517	0.048893	3.58501
	Best Model	*EGARCH (1,1)*	*Normal Error Distribution*		*Highest Adj. R2*	*Lowest SIC*
	Natural Gas	GARCH (1,1)	NED	2015.342	0.021853	–5.12486
			SED	2038.783	0.020949	–5.17042
			GED	2030.893	0.021469	–5.15619
		TGARCH (1,1)	NED	2015.797	0.021495	–5.11748
			SED	2039.928	0.020713	–5.17082
			GED	2031.649	0.021135	–5.14959
		EGARCH (1,1)	NED	2016.416	0.021539	–5.11907
			SED	2040.302	0.02104	–5.17178
			GED	2032.146	0.02131	–5.15087
		PGARCH (1,1)	NED	2016.136	0.021467	–5.10982
			SED	2040.106	0.020825	–5.16274
			GED	2031.91	0.021167	–5.14173
	Best Model	*EGARCH (1,1)*	*Student's t Distribution*	*Highest Log Likelihood*		*Lowest SIC*

Table 3 Decision table for selecting suitable model (continued)

Time period	*Commodity*	*Models*	*Error distribution*	*Log likelihood*	*Adj. R2*	*SIC*
Sub Period-2 During Pandemic Period	Crude Oil	GARCH (1,1)	NED	–692.1734	–0.03735	5.026828
			SED	–656.1413	–0.05386	4.790437
			GED	–661.1481	–0.04687	4.826072
		TGARCH (1,1)	NED	–676.9262	–0.03178	4.938372
			SED	–654.3863	–0.05156	4.798011
			GED	–657.833	–0.04767	4.822543
		EGARCH (1,1)	NED	–779.8905	–0.53523	5.671214
			SED	–653.2258	–0.05667	4.789751
			GED	–656.5276	–0.0493	4.813252
		PGARCH (1,1)	NED	–668.7209	–0.06941	4.900036
			SED	–653.0143	–0.05209	4.808311
			GED	–655.3615	–0.06084	4.825018
	Best Model	*EGARCH (1,1)*	*Student's t Distribution*	*Highest Log Likelihood*		*Lowest SIC*
	Natural Gas	GARCH (1,1)	NED	553.6405	0.036949	–3.84018
			SED	560.2723	0.036338	–3.83731
			GED	561.2095	0.035057	–3.83398
		TGARCH (1,1)	NED	555.0882	0.036214	–3.83041
			SED	560.3828	0.036132	–3.84803
			GED	561.3901	0.035514	–3.8522
		EGARCH (1,1)	NED	556.5024	0.036567	–3.85448
			SED	559.8014	0.035937	–3.84389
			GED	561.1738	0.036385	–3.85366
		PGARCH (1,1)	NED	557.6595	0.034102	–3.82865
			SED	560.5579	0.035982	–3.82921
			GED	561.5004	0.036521	–3.83592
	Best Model	*EGARCH (1,1)*	*Normal Distribution*		*Highest Adj. R2*	*Lowest SIC*

Table 3 Decision table for selecting suitable model (continued)

Time period	*Commodity*	*Models*	*Error distribution*	*Log likelihood*	*Adj. R2*	*SIC*
Overall Period	Crude Oil	GARCH (1,1)	NED	–2100.18	–0.06188	3.984199
			SED	–2041.458	–0.057	3.880272
			GED	–2056.847	–0.05479	3.909226
		TGARCH (1,1)	NED	–2079.558	–0.05653	3.951956
			SED	–2039.448	–0.05515	3.877638
			GED	–2047.455	–0.05282	3.898111
		EGARCH (1,1)	NED	–2087.237	–0.06367	3.966405
			SED	–2036.007	–0.0559	3.876573
			GED	–2050.169	–0.0559	3.903218
		PGARCH (1,1)	NED	–2078.298	–0.05961	3.956141
			SED	–2037.549	–0.05456	3.878504
			GED	–2046.499	–0.05324	3.902867
	Best Model	*EGARCH (1,1)*	*Student's t Distribution*	*Highest Log Likelihood*		*Lowest SIC*
	Natural Gas	GARCH (1,1)	NED	2563.835	0.03132	–4.79099
			SED	2599.639	0.030792	–4.8518
			GED	2599.639	0.030792	–4.8518
		TGARCH (1,1)	NED	2564.533	0.031457	–4.78575
			SED	2599.739	0.030794	–4.87816
			GED	2591.209	0.030928	–4.82938
		EGARCH (1,1)	NED	2563.369	0.031523	–4.78356
			SED	2598.818	0.030884	–4.8437
			GED	2590.488	0.030999	–4.82803
		PGARCH (1,1)	NED	2564.532	0.031462	–4.77919
			SED	2599.733	0.030798	–4.83887
			GED	2591.225	0.030932	–4.82286
	Best Model	*TGARCH (1,1)*	*Student's t Distribution*	*Highest Log Likelihood*		*Lowest SIC*

Source: Author's own estimation

4.1.4 Diagnostic check for the selected models

Three Diagnostic tests viz., Normality, Heteroskedastic and Autocorrelation on the squared residuals of the return series are to be tested for the selected models. The residuals of the return series need to be normally distributed. Table 4 represents test for normality on the residuals and it can be confirmed from the p-value of Jarque-Bera Statistics that the residuals are not normally distributed in all the periods.

Table 4 Test for normality

	Before pandemic period		*During pandemic period*		*Overall period*	
	Crude oil	*Natural gas*	*Crude oil*	*Natural gas*	*Crude oil*	*Natural gas*
Jarque-Bera Statistics	44.8862	344.3019	1424.8	6.79833	2809	372.4073
P-Value	0.000	0.000	0.000	0.000	0.000	0.000

Source: Author's own estimation

Table 5 represents Autocorrelation test for the squared residuals of the log return of energy futures. We have applied Ljung-Box test for lag 1 to lag 18 for testing autocorrelation on the residuals. The p-value is more than 0.05 indicating non-existence of serial correlation in residuals return series of Natural gas and Crude oil futures for all the period.

Table 5 Test for autocorrelation

	Before pandemic period				*During pandemic period*				*Overall period*			
	Crude oil		*Natural gas*		*Crude oil*		*Natural gas*		*Crude oil*		*Natural gas*	
Lags	*Q-Statistics*	*P. Value*	*Q-Statistics*	*P. Value*	*Q-Statistics*	*P. Value*	*Q-Statistics*	*P. Value*	*Q-Statistics*	*P. Value*	*Q-Statistics*	*P. Value*
1	0.2048	0.651	0.0519	0.82	0.1764	0.675	0.1219	0.727	0.4146	0.52	0.0927	0.761
2	3.727	0.155	4.0427	0.132	0.1985	0.906	0.7591	0.684	1.5543	0.46	5.0344	0.081
3	3.7763	0.287	4.7511	0.191	0.415	0.937	2.6521	0.448	1.7127	0.634	7.048	0.07
4	4.8794	0.3	7.0243	0.135	1.1972	0.879	7.4804	0.113	1.8702	0.76	7.1223	0.13
5	5.0781	0.406	7.8779	0.163	2.2964	0.807	7.5843	0.181	3.0375	0.694	8.1655	0.147
6	5.1994	0.519	9.056	0.17	2.3776	0.882	8.0779	0.232	3.0479	0.803	8.4563	0.207
7	5.4068	0.61	10.779	0.149	2.4277	0.932	8.7187	0.273	3.1529	0.871	11.555	0.116
8	5.5899	0.693	10.839	0.211	3.2466	0.918	8.8322	0.357	4.5145	0.808	11.85	0.158
9	5.8061	0.759	10.854	0.286	3.3325	0.95	9.2741	0.412	4.537	0.873	11.949	0.216
10	6.2076	0.798	12.457	0.256	4.1484	0.94	10.049	0.436	4.5694	0.918	13.774	0.184
11	6.2548	0.856	12.676	0.315	4.4716	0.954	11.417	0.409	4.7889	0.941	14.62	0.201
12	9.4049	0.668	12.708	0.391	4.7771	0.965	11.912	0.453	6.9605	0.86	14.938	0.245
13	10.155	0.681	15.871	0.256	5.3056	0.968	13.373	0.419	8.1335	0.835	15.073	0.303
14	10.666	0.712	15.904	0.319	6.5133	0.952	14.753	0.395	8.1337	0.882	15.358	0.354
15	11.564	0.712	15.956	0.385	7.898	0.928	17.068	0.315	10.673	0.775	16.114	0.374
16	11.577	0.773	16.713	0.404	8.2777	0.94	17.336	0.364	10.87	0.817	16.141	0.443
17	13.703	0.688	17.095	0.448	8.8703	0.944	17.348	0.431	11.141	0.849	16.841	0.465
18	13.953	0.732	17.547	0.486	9.9091	0.935	19.672	0.352	11.455	0.874	17.184	0.511

Source: Author's own estimation

Table 6 represents ARCH LM test for checking Heteroskedasticity for the squared residuals of the log return of energy futures. The residuals should be homoscedastic. This means that there is nonexistence of heteroskedasticity in the residuals. The p-value is more than 0.05 which indicates the absence of heteroskedastic in the residuals.

Table 6 ARCH LM test for residuals

	Before pandemic period		*During pandemic period*		*Overall period*	
	Crude oil	*Natural gas*	*Crude oil*	*Natural gas*	*Crude oil*	*Natural gas*
F-statistic	0.13444	0.403855	0.2997	0.302665	1.7379	0.031963
P-Value	0.714	0.5253	0.5845	0.5827	0.1877	0.8581

Source: Author's own estimation

4.1.5 *Analysis of the model*

Table 7 portrays volatility results of selected models and it can be evident constant is significant in all the periods for both the commodity futures. α and β of both the commodities in all the periods are significant indicating persistence volatility in the short-term as well as in the long-term. The combined value of α and β is more than one in all the periods except Natural gas in the overall period, which indicates the volatility is not going down soon. EGARCH and TGARCH helps in capturing the asymmetric effect. Asymmetric term is negative as well as significant in case of Crude oil in all the three periods. This reveals that Crude oil reacts differently to the positive and negative shocks. Negative Y reveals that volatility in Crude oil reacts asymmetrically to negative news than the positive news.

However, in the full sample period and Before Pandemic period, volatility of Natural gas was not asymmetric to positive and negative news as evident from insignificant Y. While in During Pandemic period, volatility of Natural gas was asymmetric to negative news as evident from negative and significant Y. It can be concluded that there is existence of Leverage effects in Crude oil for all the periods, as Crude oil reacts more to the negative news than the positive news, while it exists in Natural gas only during Pandemic period indicating that the Covid-19 has contributed significantly to the volatility in the Natural gas.

Table 7 Volatility results using the selected models

Coefficients	*Pre Covid 19 Period*		*During Covid 19 Period*		*Overall Period*	
	Crude oil	*Natural gas*	*Crude oil*	*Natural gas*	*Crude oil*	*Natural gas*
C	–0.08886*	–0.264585*	–0.109822*	–0.586636*	–0.103296*	7.68E-06*
α	0.150512*	0.177435*	2.19472*	0.12925*	0.1641*	0.088298*
Y	–0.076809*	0.033043	–0.207591*	–0.124588*	–0.099797*	–0.014859
β	0.956305*	0.983754*	0.51459*	0.926975*	0.976618*	0.907908*

[1]*Indicates significance at 5% level.

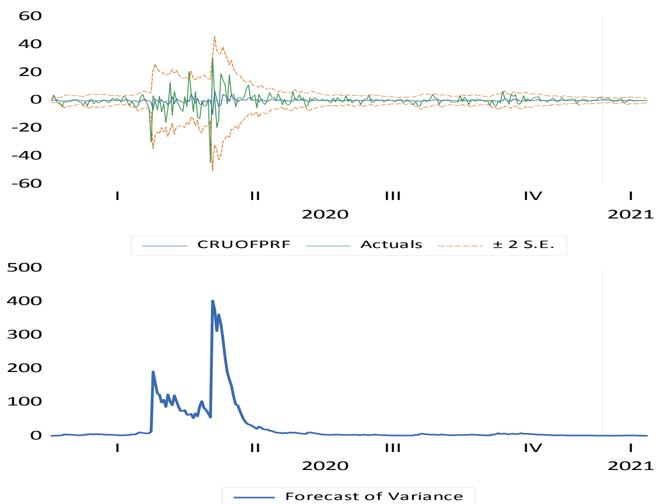
[2]*C* is the Constant, α is the coefficient of ARCH, Y is the co-efficient of asymmetric term and β is the co-efficient of GARCH.

Source: Author's own estimation

4.1.6 Forecasting volatility

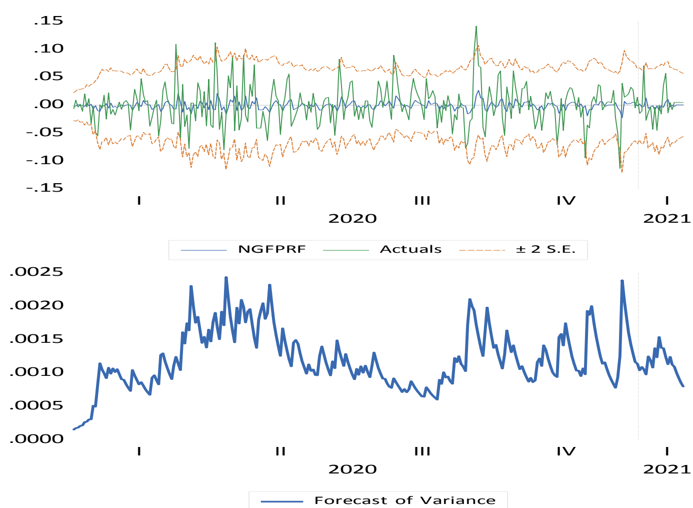
Figures 3 and 4 shows the forecasted return and variance for Crude oil and Natural gas from 1st January, 2020 to 31st January, 2021. The graph shows that forecasted returns of Crude oil were highly unpredictable between the first and second quarter of 2020, later returns remained stable after 2nd quarter of 2020. While the graph of the forecasted variance reveals the same that the volatility was high during 1st and 2nd quarter, which gradually slowed down towards the end of 2020, indicating the impact of Covid-19 on the Crude oil. Whereas, the return and variance forecast of Natural gas shows extremely unpredictable return and intense volatility for the said period.

Figure 3 Forecasting volatility for crude oil futures (see online version for colours)



Source: Author's own estimation

Figure 4 Forecasting volatility for natural gas futures (see online version for colours)



Source: Author's own estimation

Table 8 Volatility spillover result

Variables	*Crude oil*		*Natural gas*	
	Coefficients	*Z-Statistics*	*Coefficients*	*Z-Statistics*
μ_1	0.13395346	2.63298*	0.00005813	0.08793
μ_2	0.14782937	3.82849*	–0.0000038	0.000546
$c_{(1,1)}$	4.29E-01	5.93343*	–0.0091970	–8.62653*
$c_{(2,1)}$	–1.56E-01	–2.60425*	–0.0003786	–0.58063
$c_{(2,2)}$	–1.04E-06	–8.38E-06	4.20E-08	5.14E-05
$a_{(1,1)}$	0.291936	7.17333*	0.45642235	11.62277*
$a_{(1,2)}$	0.182457	5.99518*	0.2016513	7.15873*
$a_{(2,1)}$	–0.8586	–16.9818*	–1.0866799	–19.76089*
$a_{(2,2)}$	–0.108667	–2.45565*	–0.1774012	–4.14086*
$b_{(1,1)}$	0.466281	13.72857*	0.42492207	7.55292*
$b_{(1,2)}$	–0.3079	–9.20336*	–0.2070169	–6.5991*
$b_{(2,1)}$	0.440715	16.41811*	0.3134187	12.28691*
$b_{(2,2)}$	1.110865	71.42994*	1.06676806	90.90323*
Log Likelihood	–4110.3817		5126.0469	

'μ_1' represents mean equation coefficient of spot price. 'μ_2' represents mean equation coefficient of futures price. 1 refers to spot price and 2 refers to futures price. $a_{1,1}$ denotes volatility within the spot market in short-term and $a_{2,2}$ denotes volatility within the futures market in short-term $b_{1,1}$ denotes volatility within the spot market in the long-term while $a_{2,2}$ denotes volatility within the futures market in the long-term. $a_{1,2}$ and $a_{2,1}$ denotes short-term volatility spillover between the two market, $b_{1,2}$, and $b_{2,1}$ denote long-term volatility spillover between the two market.

Source: Author's own estimation

4.1.7 Volatility spillover

When shocks in one market led to volatility in another market, the interlinkage can be termed as spillover effects between the markets. When volatility in spot (futures) market leads to volatility in futures (spot) market then it refers to existence of volatility spillover between the markets. We have applied Bivariate BEKK GARCH (1, 1) model to check the volatility spillover between spot and futures price of Crude oil and Natural gas for the period from 1st January, 2017 to 31st January, 2021. Before conducting the test, we performed all the diagnostic tests in spot price as we conducted in futures price for analysing volatility in the futures prices. Table 8 represents volatility spillover result. ARCH term (a) represents short-term volatility or shock volatility spillover between the markets i.e., any bad news arrives in spot (futures) market then that news affects the price in futures (spot) market. GARCH term (b) refers to long-term volatility or price volatility spillover between the markets i.e., change in price in spot (futures) market affects the price in futures (spot) market (Rashtogi and Agarwal, 2020). The significance of a_{11}, a_{22}, b_{11}, and b_{12} indicates that the past shocks in the market have effect on itself for both short and long-term i.e., both the futures price and the spot price have been impacted by their own past volatility. Both the ARCH terms within the market i.e., a_{21} & a_{12} are significant indicating existence of short-term bidirectional volatility between spot and futures prices of Crude oil and Natural gas. This means, any shock in one market impacts the other market. Though the bidirectional volatility exists yet the volatility is usually stronger when it passes from the spot to futures in both the commodities. As evident from significance of b_{12} & b_{21}, there is existence of bidirectional long-term volatility spillover between the spot and futures. Thus, it means any price changes in both the market impact each other in a greater extent.

4.2 Discussion

Covid-19 has impacted the economy as well as the investors' psyche. Most investors are wary of their future returns, so consider energy futures to diversify their portfolio. Therefore, investors should have information not only on the effect of volatility in energy futures but also understand it's extent and the direction to take informed decisions. So, it is imperative to measure the quantum of predictability of the Crude oil and Natural gas price movement.

Further, the commodity price movement due to Covid-19 shock also vary over time owing to the fundamentals as well as behavioural and psychological factors. Heightened volatility coupled with the limited experience of the fearful investors can make them rush towards risky bets resulting in excess pay out on premium to protect themselves. This will negate the very objective of trading in the commodity futures. So, knowing and giving the right insights to predict the direction is essential for the success of the commodity futures markets and to serve the interests of the investors. We modelled the volatility in energy futures market by considering GARCH, TGARCH, EGARCH and PGARCH with three error distribution terms as one of the most important things is to consider error distribution terms while assessing volatility (Olayemi and Olubiyi, 2021). These models' fitness and forecasting performance were compared using Log Likelihood, Adjusted R^2 and Lowest Schwarz Information Criteria. As per the result of selected models, more volatility was found in Crude oil and Natural gas futures during Covid-19. Prior to any crisis, it is generally seen that the Crude oil prices are driven by the market forces and speculative factors (Joo et al., 2020). Besides psychological expectations altering the price mechanism by modifying the market participants, Covid-19 shocks have also increased the volatility of the oil market and disrupted the scale-invariant feature of Crude oil. One of the key reasons behind volatility in Crude oil and Natural gas is the nature of elasticity in supply and demand as the lower elasticity in oil supply or demand causes higher changes in price. The lockdown led to a drop in both commercial and non-commercial Crude oil and Natural gas trading activity. Although high Covid-19 cases have an effect on Natural gas demand prices, the effect is significantly smaller given that the Natural gas is primarily used as substitute for electricity (Ahmed and Sarkodie, 2021). As per the behavioural finance theorists, variations in energy commodity futures are linked to investor's expectations as investors, during the crisis, follow herd behaviour i.e., when investors make the similar decisions based on the same set of available information. "Since the efficient market should be free from any type of volatility asymmetry that results in predicting a certain market property in gaining profits, the volatility asymmetry is expected to induce some inefficiency" (Takaishi, 2021). Our study finds the existence of asymmetric leading to volatility which provides the speculators more scope for earning profit. This has also been confirmed by the unit root test which reveals that the energy prices are mean reverting, indicating that they do not follow a random walk. Therefore, it suggests that the speculators can take advantage of the mean reversion nature of energy prices to make profit. Indeed, during the crisis, speculators acting solely on financial rationality, anticipate price fluctuations in the futures market, which also caused substantial volatility in the energy futures prices during Covid-19 (Aloui et al., 2020). Higher fluctuations make investors risk averse, causing a decline in prices, which, as per the leverage effect, triggers further increase in volatility (Hillerbrand, 2003). Our study corroborates the findings of Shalini and Prasanna (2016), Chhatwal et al. (2013), and Roy and Roy (2017) who, in their study, also observed the persistence of high volatility and presence of asymmetric effect during the period of crisis (Meher et al., 2020).

Like Tsuji (2017) did a full analysis of BEKK model, we made a detailed study on the volatility spillover between spot and futures return of Crude oil and Natural gas. According to Tsuji, it is difficult to analyse the coefficients of $a(1,1)$ $a(2,1)$ and $a(1,2)a(2,2)$. When we multiply coefficients of $b(1,1)$ with $b(2,1)$ we get positive value for both Crude oil and Natural gas, which indicates positive return variances in both the prices that will lead to increase in the return variance of spot prices in the next period. Negative coefficient of $b(1,2)b(2,2)$ of both the commodities implies that increase in the spot and futures return covariance slightly decreases the futures return variance in the next period. Positive $a(1,1)a(1,2)$ indicates that shock in the spot market has a positive impact on futures and spot return variance in the next period. Similarly, negative value of $a(2,1)a(2,2)$ suggests that a shock to futures market has a negative effect on the spot market in the next day. It is indeed difficult to interpret $a(1,2)a(2,1)+a(1,1)a(2,2)$ because there are many other factors that influence the end result. We observed that negative value of $b(1,1)$ $b(1,2)$ of Crude oil and Natural gas, which indicates an increase in spot return variance has negative impact on the spot and futures return in the following day. Whereas, positive $b(2,1)b(2,2)$ shows that increase in futures return variance increases the spot return covariance in the next day. Therefore, $b(1,2)b(2,1)+b(1,1)b(2,2)$, with the value of 1.71 for Crude oil and 1.60 for Natural gas, indicate that there is an increase in the covariance of the spot and futures return which in turn increases both of the prices return covariance in the next day. These confirm that the shock and price changes in the spot market lead to positive changes in both the markets while shocks and price changes in futures market impact the markets in a negative way. Thus, it can be concluded that the spot market is more informational efficient than the futures market.

5 Conclusion

Covid-19 has had profound impact on all the sectors. Of all, its impact on the energy sector was the most detrimental and dreading. Energy was the most profitable sector of the pre pandemic times. With the human movement coming to a grinding halt, aviation and other transport systems had to bear the maximum brunt which was evident from the drastic fall of the prices of Natural gas and Crude oil during the pandemic. To ascertain the extent of its depth, substantial number of studies have been undertaken in developed markets by using various models, but very few studies have focussed on selecting the appropriate model for forecasting the volatility, understanding its behaviour, inferring the result and studying its future direction in the developing markets. As a result, despite humungous literature, forecasting future and studying the volatility has indeed been a herculean task for all the stakeholders to take suitable decisions. Therefore, the current study focussed on not finding the end result but on identifying the right model for analysis and forecasting the volatility in the energy sector i.e., Crude oil and Natural gas.

Popular models extensively used in the extant literature to forecast the volatility such as GARCH (1, 1), TGARCH (1, 1) EGARCH (1, 1), PGARCH (1, 1) with three distribution error terms viz., Normal, Student's t and GED were applied to identify the best model. It was found that the EGARCH 1, 1 with student's t distribution is the most suitable model for forecasting the future behaviour of Natural gas and Crude oil Before Pandemic period and for both During Pandemic and Overall period, respectively. Similarly, EGARCH (1, 1) with normal distribution error term was found to be the best model for studying volatility in Crude oil Before Pandemic and Natural gas During Pandemic period. With regard to forecasting the Overall period, TGARCH (1, 1) with student's t distribution error was found to be the best model for Natural gas. All these models satisfied the criteria of highest Log Likelihood and Adjusted R^2 and lowest SIC. Further, the results indicate the susceptibility of Crude oil to bad news than the good news for the entire period. But in stark contrast, it is discovered that the Natural gas is indifferent to both the good and bad news. Interestingly, despite its indifference, Natural gas has been badly affected by the pandemic. To the interest of the investors and policy makers, it was observed that the Crude oil stabilised gradually from its extreme volatility in initial period but the same went unabated for Natural gas during the same period. Besides identifying the best model to study the volatility, it was also observed that there were information linkages, through volatility spillovers, between futures and spot prices of Crude oil and Natural gas. This linkage was also found to be bidirectional between spot and futures for both Natural gas and Crude oil with spot prices taking the lead in information transmission process.

Presence of leverage effect in energy futures portend the possibility of increased price volatility in the future. So, it is of paramount importance and practically relevant to measure resultant directions of the markets. Various financial models have been developed to predict the volatility, study its interconnectedness and gauge the co-movement to provide actionable insights for the benefit of all the stakeholders. Identifying the best model, successful projection of the direction and knowledge about the factors causing the volatility and its extent is crucial for using the energy futures for absorbing the shocks and also deriving benefit by taking right decisions at the right time. Therefore, the findings of the study can be helpful to the financial market players in comprehending the dynamics of Natural gas and Crude oil volatility and help investors, traders, and Government agencies deal with energy futures market volatility better. This study can also be helpful to the researchers in selecting the appropriate GARCH models along with different error distribution terms for their study as different GARCH models provide different results and selecting best model by applying right criteria would help them in getting accurate results.

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