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Measuring Leverage Effect of Covid-19 on Stock Price Volatility of Energy Companies Using High Frequency Data

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ABSTRACT

The uprising of the pandemic COVID-19 has paralysed the whole Indian economy, and as a result the Indian stock market is severely affected too. The widely inclusive lockdown articulated on 24th March 2020 by the Prime Minister as a careful step against COVID-19, trailed by ensuing augmentations, has brought about a halt of all financial movement in the country. The objective of the study is to frame different asymmetric price volatility models for Selected Companies under Energy Sector using 1-min closing price from 15th October 2019 to 15th May 2020 to captivate the leverage effect of the pandemic. The asymmetric terms in the selected asymmetric models are providing sufficient proof that the stock price volatility of three companies out of six under NIFTY Energy i.e., BPCL, Power grid and Indian Oil Corporation are unfavourably influenced by the pandemic. The forecasting graphs for volatility of four companies have been plotted, reveals that there is consistency in the stock price returns of all these four companies but the graph of predicted variance of Indian Oil Corporation reveals that the volatility has been fluctuating drastically with many high peak variances or fluctuations during the 2 days of forecasted period.

Keywords: Asymmetric Volatility, EGARCH, GJR-GARCH, TGARCH, High Frequency Data
JEL Classifications: C40, C530, C550, C580, G110, G120, G170

1. INTRODUCTION

The pandemic, COVID-19, has jostled the global economy into a recession, which means the economy starts dwindling and growth trammels (Meher et al., 2021); (Pinto et al., 2020). If the coronavirus is infectious and migrations exist, the virus can affect many economies of the world and their stock markets simultaneously (Okorie and Lin, 2020). The uprising of the pandemic COVID-19 has paralysed the whole Indian economy, and as a result the Indian stock market is severely affected too. Indian Financial Market in India is witnessing sharp volatility at present because of the aftermath in worldwide global markets. The fall is in accordance with the worldwide benchmark indices as the domestic market usually tracks the major global indices and the high volatility is likely to exist soon (Raja Ram, 2020). The widely inclusive lockdown articulated on 24th March 2020 by the Prime Minister as a careful step against COVID-19, trailed by ensuing augmentations, has brought about a halt of all financial movement in the country (Meher et al., 2020).

Future economic effect of COVID is still highly unstable and thus it would be interesting to study the impact of such COVID-19 pandemic on the volatility of stock prices of selected companies under energy sector. Though many studies are there related to asymmetric volatility (Abounoori and Zabol, 2020); (Chang et al., 2012); (Manera et al., 2013); (Onali, 2020), high-frequency data, some studies on effect of COVID-19 on stock markets mentioned in the review of literature and an existing study is also there on effect of COVID-19 on the price volatility of Crude Oil and Natural Gas of MCX India using EGARCH (Meher et al., 2020) but this study could open a new dimension while examining the impact of COVID-19 pandemic on the price volatility of shares of companies of energy sector of India using the high-frequency data. Stock market in India underwent many reforms and changes in regulations to make it efficient and transparent (Kumar et al., 2018; Hawaldar, 2016; Iqbal, 2014)

Objectives of the Study:

- To frame different asymmetric price volatility models for Selected Companies under Energy Sector using 1 min closing price from 15th October 2019 to 15th May 2020 to capture the leverage effect of the pandemic COVID-19
- To select a reliable volatility model for each company that could consider the leverage effect of COVID-19
- To forecast volatility of those companies using the asymmetric models selected after analysis.

The awareness, regarding impact of COVID-19 on the stock market of India especially the Energy Sector are much needed in this current scenario. The results of the study can provide an appropriate volatility model for each selected company that could help the investors, having basic knowledge on algorithms, to run the developed models to forecast and study the volatility of stock prices of these companies during pandemic. This will also enable in minimizing the risk in investment. From this study the price volatility of selected companies can be predicted taking into consideration the leverage effect of pandemic which could also assist the future researchers to go for further study to develop appropriate volatility predicted models in future as well. Moreover, the research could depict the impact of pandemic on the price volatility of companies under energy sector, to the policy makers and companies as well, which may assist them to formulate important counter policies to avoid instability in prices of stocks.

2. REVIEW OF LITERATURE

Any significant events or incidence affects economic and financial systems of the world and particular country (Bolar et al., 2017; Kumar et al., 2020; Hawaldar et al., Empirical Testing of Month of the Year Effect on Selected Commercial Banks and Services Sector Companies Listed on Bahrain Bourse, 2017; Hawaldar et al., 2017). Many studies in India and abroad conducted to study the effect of an event on stock prices and volatility (Hawaldar, 2018, 2016; 2015; 2014; Mallikarjunappa and Hawaldar, 2003; Dum and Essi, 2017; Hailemariam and Smyth, 2019; Pindyck, 2004). Some studies on asymmetric volatility where a study on modelling the asymmetric or leverage effect in conditional variance of EGARCH (Exponential Generalized Autoregressive Conditional Heteroscedasticity) with (CWN) Combine White Noise model to derive suitable results using the quarterly data of U.K. Real Gross Domestic Product (GDP) from 1960-2014 and proved that CWN estimation is more efficient (Agboluaje et al., 2016).

Similarly, a study based on modelling three parametric asymmetric volatility models namely EGARCH, GJR-GARCH and PGARCH by employing the daily high frequency data related to the Stock Exchange of Thailand from 4th January, 2005 to 27th December, 2013, to test the leverage and volatility feedback effects and also constitutes the subprime crisis period in US that may affect the volatility of market return in emerging stock markets (Thakolsria et al., 2015). Again, a paper highlights an innovative explanation for asymmetric volatility based on the anchoring behavioural pattern using the fluctuations of large price in S&P 500 and found that effect of asymmetricity of price jumps and falls is less significant on realized volatility than their effect on implied volatility (Ormos and Timotity, 2016). Furthermore, a study with an objective to reveal the distinction between this connection and similar ones specific to developed economies (Albu et al., 2015). A study estimated Asymmetric GARCH models with endogenous break dummy on two novel assumptions using all share index on daily basis of Kenya, Germany, United States, China and South Africa ranging from 14th February 2000 to 14th February 2013. The results suggested the absence of asymmetric effect in Kenya and Nigeria stock returns but existed in others (Uyaebo et al., 2015).

Similarly, a paper used GARCH, Normal APARCH, Student APARCH, Risk Metrics and Skewed Student APARCH to examine the intraday price volatility procedure in few Australian wholesale electricity markets i.e. Queensland, New South Wales, Victoria and South Australia of half-hourly electricity prices and demand volumes over the period 1 January 2002 to 1 June 2003 where skewed Student APARCH model produces the best results in first three markets and the Student APARCH model in the Victoria market (Higgs and Worthington, 2005). Few papers on volatility with high-frequency data, where a paper attempts to show that the relationship between volatility and price processes can be assessed more precisely and correctly using high frequency data along the ability of definite stochastic volatility models to analyse the pattern observed in high frequency data (Litvinova, 2003). A paper suggested a methodology to refine modelling volatility by inculcating information that exists on latent volatility processes when the markets are closed and no transactions occur with high-frequency data (Matei et al., 2019).

On the other hand, some of the literature can also be found related to effect of COVID-19 on the elements of stock market which are done recently (Ashraf, 2020); (Choudhary, 2020); (World Bank, 2020). A study examines the impact of the COVID-19 on six different stock markets i.e., DJI, FMIB, IBEX, SHC, UKX, and XU100 from the Spain, United States, China, Italy, Turkey and the United Kingdom, respectively, for four different time intervals. The modified test of Iterative cumulative sum of squares algorithm (ICSS) reveals that the pandemic has led to structural breaks in the volatility of stock indexes (Gunay, 2020). An Event-study to test stock market reactions to pandemic based on returns on the world, Italian, German, French, U.K., Spanish, Philippine, U.S., Thai, and Chinese stocks (Khanthavit, 2020). Similar to that, an event study on the short-term effect of the pandemic on twenty one leading stock market indices in major affected countries i.e. UK, Korea, Japan, USA, Germany, Italy and Singapore etc. and found that Asian countries faced more abnormal negative returns as compared to other countries (Liu et al., 2020). A study focussed on the effect of COVID crisis on stocks with comparison to 2008 crisis and market downturn of 2018 with the help of OLS regression and Bayesian regression approach using S&P500 composite index (Pavlyshenko, 2020). A paper examines the link between the dynamics of implied volatility indices in thirteen countries across the globe and attention of investors as assessed by Google search probability during Covid-19 (Papadamou et al., 2020).

Similarly, a study attempted to forecast the short-term confirmed cases of COVID and IBEX in Spain using Sutte ARIMA method (Ahmar and Val, 2020). A paper concerned with the correlation between the spread of COVID, volatility of oil price, the stock market, economic policy uncertainty and geopolitical risk in the US and found that the effect of the pandemic on the geopolitical risk substantially is higher than on the US economic uncertainty (Sharif et al., 2020). A study surveyed the volatility return of selected commodities i.e., mentha oil, potato, crude oil, and gold traded under MCX (Multi Commodity Exchange), India from the year 2004 to 2012 using GARCH Model (Mukherjee and Goswami, 2017). Again, a study involved in prediction capacity of GARCH, EGARCH, GJR-GARCH and APARCH models with different error constructs by taking two major indices of Tel-Aviv Stock Exchange (TASE) i.e., TA25 and TA100 (Alberg et al., 2008). A paper on analysing the causal relationship between the market returns and crude oil price anomalies in the Indian stock market by taking 10 companies of oil exploration and drilling sectors listed in the CNX NIFTY indexes and BSE Sensex from 2009 to 2018 (Hawaldar et al., 2020). So measuring leverage effect on stock price volatility is one of the important areas of study in finance (Hawaldar and Mallikarjunappa, 2011; 2010; 2009; 2007).

The recent studies related to the pandemic, have not yet thrown any light on using the high-frequency data to frame asymmetric price volatility models for companies of energy sector to capture the leverage effect of COVID-19. This research gap is a most feasible one as using the minute wise to frame asymmetric volatility models could also provide a microscopic observation of effect of the pandemic on the price volatility of selected stocks.

3. RESEARCH METHODOLOGY

The study is Empirical in nature and based on high-frequency secondary data. The secondary data involves the 1 min closing prices of six selected companies based on market capitalisation, which are listed under NIFTY Energy. The 1 min data is ranging from 15th October 2019 to 15th May 2020 that have been downloaded from kaggle.com. Wherever required, attempt has been made to make the unbalanced data into balanced data. Six companies have been selected from the NIFTY Energy based on the highest value of market capitalization for the purpose of modelling and analysing. The sample size is 346,500 i.e., 6 companies of 57,750 observations each (Hwang and Pereira, 2004). Two renowned asymmetric volatility models have been used EGARCH and TGARCH. For the application of EGARCH and TGARCH, Log Daily Returns have been ascertained to convert the non-stationary data into stationary and ADF (augmented Dickey Fuller test) has been employed to examine whether the data is stationarity in nature. After formulating the models with different distribution, the results of the models have been analysed using various criteria to select the best suitable asymmetric volatility model for each company during the pandemic. To the formulation of models of selected commodities, E-Views 10 has been used.

4. ANALYSIS, RESULTS AND DISCUSSION

For formulating the two asymmetric GARCH Models i.e., EGARCH and TGARCH, log returns have been ascertained for all the six companies i.e., Bharat Petroleum Corporation Limited (BPCL), National Thermal Power Corporation Limited (NTPC), Indian Oil Corporation Limited (IOC), Oil and Natural Gas Corporation Limited (ONGC), Power grid Corporation of India and Reliance Industries Ltd (RIL). This has made all the data of selected six companies under Energy Sector, stationary. Again, the stationarity of the data has been checked with the help of unit root test i.e., Augmented Dickey Fuller Test with the inclusion of test equation as Intercept, Trend, and Intercept and None and found that all the data of six companies are stationary as the probability values in all the cases are significant even at 1% level of significance. in data of the results. The succeeding sections are based on the testing the appropriate hypothesis required to formulate EGARCH and TGARCH model along with the results and model for each company. The log returns of all the selected six companies are plotted on the graphs to visualize the existence of volatility clustering which are given in Figure 1.

After visualising the graphs of log returns of six companies in Figure 1, it can be said that there is existence of volatility clustering in the data of all companies i.e., huge variations in log returns followed huge variations in log returns and small variations in log returns followed small variations in log returns. Moreover, it is can also be observed during the month of March 2020, there were huge variations in the returns of the stocks of the selected companies. These large variations during the month of March 2020 are a clear indication that there is an existence of leverage effect of the pandemic on the stock prices of selected Energy Companies and asymmetric GARCH models would be appropriate in modelling the volatility of stock prices of these companies. Moreover, the data of all selected companies are leptokurtic or highly peaked which have been checked with the values of the coefficients of Skewness, Kurtosis and Jarque-Bera Statistics.

Besides existence of volatility clustering and peakedness, it is also necessary to check the presence of ARCH effect in the data of the selected companies to apply GARCH models. The results of ARCH effect of the six companies are given in Table 1.

The Table 1 depicts the results of Heteroscedasticity Test of stock returns of six companies which would reveal the existence of ARCH effect in the data of those companies. The presence of ARCH effect can be examined from Lagrange Multiplier (LM) statistics which is shown in the form of Observed R Squared. The values of Observed R Squared of BPCL, IOC, NTPC, ONGC, Power grid and RIL are 1436.4350, 6.3045, 487.8834, 704.0124, 918.5828 and 8.9267 respectively and the Probability Values of these Observed R Squared of BPCL, NTPC, ONGC, Power grid and RIL are significant even at 1% level of significance and that of IOC is significant at 5% level of significance. Moreover, the F statistics of all these six companies are also significant as its

Figure 1: Line graphs of log returns of selected six companies

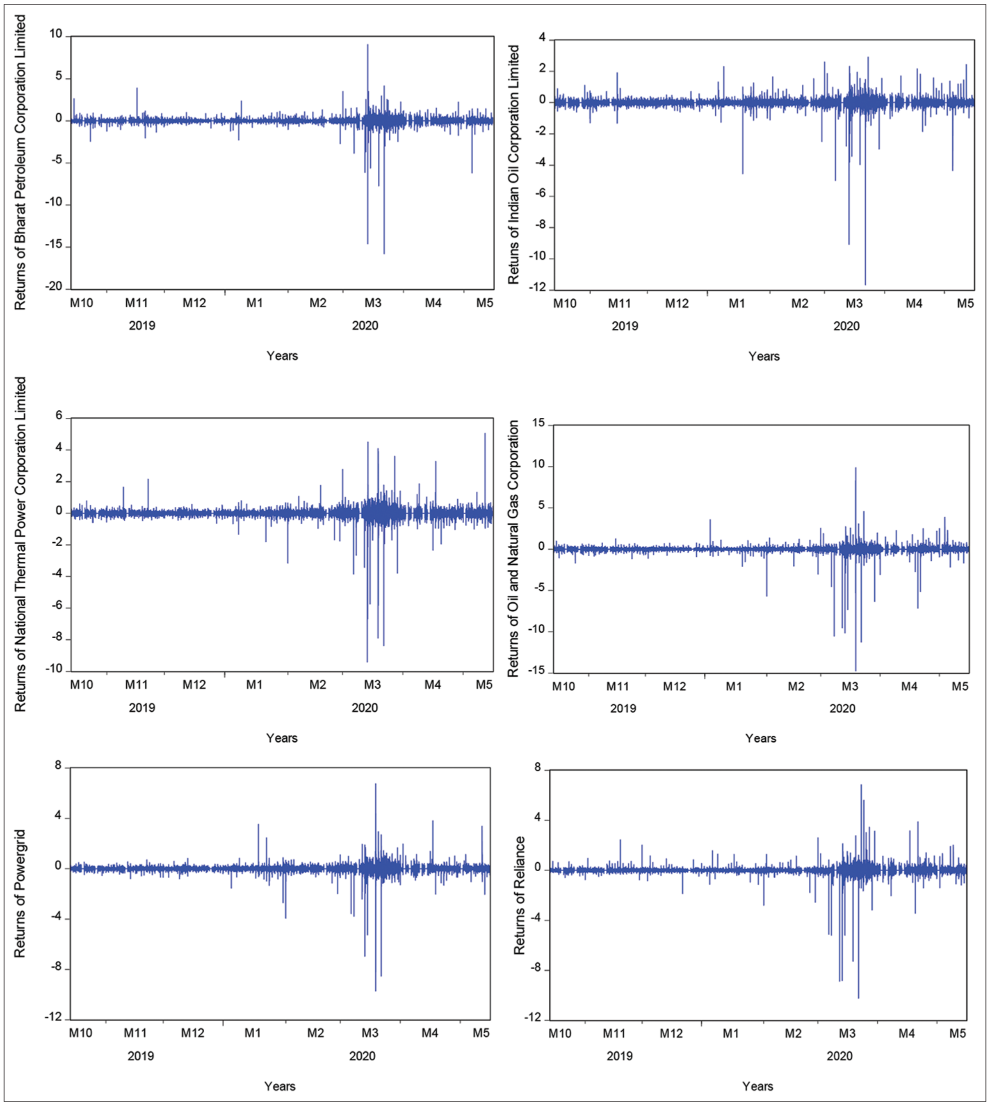


Table 1: Results of ARCH effect testing of selected six companies

Sl. No.	Name of the Company	Observed R Squared	Probability Value of Observed R Squared or Chi-Square	F-Statistics	Probability Value of F-Statistic
1.	Bharat Petroleum Corporation Limiteds	1436.4350	0.0000	1473.0270	0.0000
2.	Indian Oil Corporation Limited	6.3045	0.0120	6.3050	0.0120
3.	National Thermal Power Corporation Limited	487.8834	0.0000	492.0234	0.0000
4.	Oil and Natural Gas Corporation Limited	704.0124	0.0000	712.6764	0.0000
5.	Power grid Corporation of India	918.5828	0.0000	933.3986	0.0000
6.	Reliance Industries Ltd	8.9267	0.0028	8.9277	0.0028

Source: Authors' Computation through EVIEWS 10

significance value is less than 0.05. This turns out that there is presence of ARCH effect in the 1 min log returns data of all the six companies ranging from 15th October 2019 to 15th May 2020 which implies that GARCH Models can be applied.

The standard GARCH model is incapable to captive the asymmetric nature caused by the negative correlation between returns and volatility which is referred to as the leverage effect. The speciality of the two asymmetric volatility models i.e., EGARCH and TGARCH model are, these can captive the leverage effect of shocks like policies, information, news, incidents, and events on the financial market. Hence, EGARCH and TGARCH model has been selected to captive the leverage effect of COVID-19 on the price volatility of stocks of six selected energy companies.

"The EGARCH model is distinct from the GARCH variance structure because of the log of the variance" (Dhamija and Bhalla, 2010). 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 (ht) = log of variance or log returns
φ = Constant
η_i = ARCH Effects
λ_i = Asymmetric effects
θ = GARCH effects

"The threshold GARCH (TGARCH) is similar to the GJR model, different only because of the standard deviation, instead of the variance, in the specification" (Ali, 2013). The following formula is for TGARCH (1,1) model.

$$h_t = \varphi + \theta_1 h_{t-1} + b_1 u_{t-1}^2 + \gamma_1 u_{t-1}^2 D_{t-1}$$

Where:-
h_t = variance or returns
φ = Constant
θ = GARCH effects
D_t = value of 1 (bad news) for $u_t < 0$
γ = Asymmetric effects or leverage term
b_1 = good news (positive shock) has an impact of b_1
$b_1 + \gamma_1$ = Impact of Bad news

To choose an appropriate model, the results of the formulated models with three different distributions need to be analysed. "The standard way to select a model is, the coefficients, ARCH and GARCH should be significant and there should not be 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 squared and Adjusted R Squared is better" (Meher et al., 2020).

4.1. Formulation of EGARCH and TGARCH Models for Reliance Industries Limited (RIL)

Reliance Industries Limited (RIL) is an Indian multinational conglomerate company headquartered in Mumbai, Maharashtra, India. There is high possibility that the pandemic might have been affecting the stock price volatility of this company. This is the reason that different asymmetric volatility models have been framed to measure the price volatility capturing the leverage effect of the pandemic using 1 min closing stock price data. The statistical elements related to both asymmetric models are mentioned in Table 2 for taking decision in selecting a suitable model.

The Table 2 reveals that Coefficients, ARCH Effect and GARCH are significant in all the three EGARCH (1,1) and all the three TGARCH (1,1) models with Normal Distribution Error Construct, with Student t's Distribution Error Construct and with Generalised Error Distribution Construct. The result of the selected TGARCH (1,1) Model for Reliance Industries Limited is mentioned in the Table 3.

The Table 3 shows the results of TGARCH (1,1) model with Student t's Distribution Construct for Reliance Industries Limited. The results classified in two parts. The upper part shows the mean equation, and the lower part represents the variance equation. In the mean equation the constant (C) is significant as the probability value is less than 0.05 and even the co-efficient of first lag Reliance (-1)] is also significant as its probability value is also less than 0.05.

In case of variance equation, C is the Constant, RESID $(-1)^2$ is the ARCH co-efficient, RESID (-1) ^2*(RESID (-1) <0) is the asymmetric co-efficient and GARCH(–1) is the GARCH co-efficient. Only the ARCH and GARCH coefficients are significant in the variance equation as their probability values are less than 0.05. The coefficient of asymmetric term is negative i.e., –0.0082 and it is not statistically significant even at 5% level which indicates that for this stock there is no asymmetries due to the pandemic COVID-19. Hence, any of the asymmetric volatility model would not be suitable for forecasting stock price volatility of this company.

4.2. Formulation of EGARCH and TGARCH Models for ONGC

ONGC is the largest crude oil and natural gas Company in India, contributing around 75 per cent to Indian domestic production.

Table 2: Decision table for selecting suitable EGARCH (1,1) or TGARCH (1,1) model for RIL

Statistics	EGARCH			TGARCH		
	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution
Significant coefficients	Yes	Yes	Yes	Yes	Yes	Yes
ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	50288.75	78270.99	77379.39	51505.89	80527.55	75857.32
R squared	–0.004698	–0.000640	–0.000197	–0.000753	–0.001115	–0.001695
Adjusted R-squared	–0.004716	–0.000657	–0.000215	–0.000771	–0.001133	–0.001713
AIC	–1.741454	–2.710535	–2.679656	–1.783608	–2.788687	–2.626942
Schwartz IC	–1.740523	–2.709448	–2.678570	–1.782676	–2.787600	–2.625855
Heteroscedasticity (ARCH LM-Test)	No	No	No	No	No	No
Autocorrelation (Correlogram of Residuals)	No	No	No	No	No	No

Source: Authors' Computation through EVIEWS 10

Crude oil is the raw material used by downstream companies like IOC, BPCL, and HPCL (subsidiary of ONGC) to produce petroleum products like Petrol, Diesel, Kerosene, Naphtha, and Cooking Gas-LPG. The statistical elements related to both asymmetric models are mentioned in Table 4 for taking decision in selecting a suitable model.

The above table reveals that Coefficients, ARCH Effect and GARCH are significant in all the above six models except the TGARCH with generalised error distribution construct. While comparing the AIC and SIC of all the above six models, it has been found that TGARCH with Student t's Distribution has the lowest AIC (–2.28) and SIC (–2.28) as compared to other five models. This model also has highest Log Likelihood (65984.22), but slightly less R and Adjusted R squared value as compared to other models. Hence, TGARCH with Student t's Distribution is considered as most suitable model. The result of the selected TGARCH (1,1) Model for ONGC is mentioned in Table 5.

Table 5 shows the results of TGARCH (1,1) model with Student t's Distribution Construct for Reliance Industries Limited. The results classified in two parts. The upper part shows the mean equation, and the lower part represents the variance equation. In the mean equation the constant (C) is significant as the probability value is less than 0.05 and even the co-efficient of first lag [ONGC (-1)] considered as b_1 and is also significant as its probability value is also less than 0.05.

In case of variance equation, C is the Constant, RESID $(-1)^2$ is the ARCH co-efficient, RESID $(-1)^2$*(RESID (–1)<0) is the asymmetric co-efficient (γ) and GARCH(-1) is the GARCH co-efficient. All the coefficients except the coefficient of constant are significant in the variance equation as their probability values are less than 0.05. The coefficient of constant in variance equation (0.000000000000022) is close to zero. The coefficient of asymmetric term is negative i.e., –0.0210 but it is statistically significant at 5% level which indicates that the stock price volatility is not affected by the bad news related to pandemic COVID-19

Table 3: Results of TGARCH (1,1) with t's distribution error construct

Dependent Variable: Returns of Reliance Industries Limited				
Method: ML ARCH - Student's t distribution (BHHH/EViews legacy)				
Sample (adjusted): 10/15/2019 09:17 5/15/2020 15:29				
Included observations: 57748 after adjustments				
Convergence achieved after 40 iterations				
Presample variance: backcast (parameter = 0.7)				
GARCH = C (3) + C (4) *RESID (-1) ^2 + C (5)*RESID(-1)^2*(RESID(-1)<0) + C (6)*GARCH(-1)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.001188	5.26E-06	225.8340	0.0000
RRELIANCE (-1)	0.025900	0.004312	6.005911	0.0000
Variance Equation				
C	6.76E-12	9.33E-12	0.724618	0.4687
RESID (-1) ^2	0.217754	0.005124	42.49414	0.0000
RESID (-1) ^2*(RESID (-1) <0)	–0.008230	0.006968	–1.181177	0.2375
GARCH (–1)	0.829549	0.001936	428.4113	0.0000
T-DIST. DOF	4.691591	0.043978	106.6796	0.0000
R-squared	–0.001115	Mean dependent var		0.000119
Adjusted R-squared	–0.001133	S.D. dependent var		0.157092
S.E. of regression	0.157181	Akaike info criterion		–2.788687
Sum squared resid	1426.657	Schwarz criterion		–2.787600
Log likelihood	80527.55	Hannan-Quinn criter		–2.788349
Durbin-Watson stat	2.066466			

Source: Authors' Computation through EVIEWS 10

Table 4: Decision table for selecting suitable EGARCH (1,1) or TGARCH (1,1) Model for ONGC

Statistics	EGARCH			TGARCH		
	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution
Significant Coefficients	Yes	Yes	Yes	Yes	Yes	No
ARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes
GARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	38671.37	63833.24	42132.15	41596.19	65984.22	65084.82
R squared	–0.022669	–0.019513	0.001133	–0.024795	–0.023570	–0.000600
Adjusted R Squared	–0.022687	–0.019530	0.001116	–0.024813	–0.023588	–0.000617
AIC	–1.339107	–2.210509	–1.458930	–1.440403	–2.285005	–2.253855
Schwartz IC	–1.338176	–2.209422	–1.457844	–1.439472	–2.283918	–2.252769
Heteroscedasticity (ARCH LM-Test)	No	No	No	No	No	No
Autocorrelation (Correlogram of Residuals)	No	No	No	No	No	No

Table 5: Results of TGARCH (1,1) with t's distribution error construct for ONGC

Dependent Variable: RETURNS OF ONGC				
Method: ML ARCH - Student's t distribution (Marquardt/EViews legacy)				
Sample (adjusted): 10/15/2019 09:17 5/15/2020 15:29				
Included observations: 57748 after adjustments				
Convergence achieved after 30 iterations				
Presample variance: backcast (parameter=0.7)				
GARCH=C (3)+C (4) *RESID (–1) ²+C (5)*RESID(–1) ²*(RESID(–1)<0)+C (6) *GARCH (–1)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	0.000181	1.16E-06	155.0712	0.0000
RONGaaC (–1)	–0.108794	0.004746	–22.92118	0.0000
Variance Equation				
C	2.22E-14	1.06E-11	0.002087	0.9983
RESID (–1) ²	0.273633	0.005051	54.16952	0.0000
RESID (–1) ²*(RESID (–1) <0)	–0.021063	0.006633	–3.175487	0.0015
GARCH (–1)	0.792879	0.001845	429.6562	0.0000
T-DIST. DOF	8.530336	0.062743	135.9564	0.0000
R-squared	–0.023570	Mean dependent var		–0.001023
Adjusted R-squared	–0.023588	S.D. dependent var		0.211304
S.E. of regression	0.213782	Akaike info criterion		–2.285005
Sum squared resid	2639.144	Schwarz criterion		–2.283918
Log likelihood	65984.22	Hannan-Quinn criter		–2.284666
Durbin-Watson stat	1.675580			

Source: Authors' Computation through EVIEWS 10

rather the stock price is affected by the positive shock.

$$h_t = 2.21549613777e-14 + 0.792878949179 h_{t-1} + 0.273633038848 u_{t-1}^2 - 0.0210633521364 \; u_{t-1}^2 D_{t-1}$$

4.3. Formulation of EGARCH and TGARCH Models for NTPC

NTPC is India's largest energy conglomerate with roots planted way back in 1975 to accelerate power development in India. Since then, it has established itself as the dominant power major with presence in the entire value chain of the power generation business. The statistical elements related to both asymmetric models are mentioned in Table 6 for taking decision in selecting a suitable model.

Table 6 reveals that Coefficients, ARCH Effect and GARCH are significant in all the above six models except the EGARCH and TGARCH with Generalised Error Distribution Construct. Hence, these two models are rejected in first instance even though they have higher log likelihood values. While comparing the AIC and SIC of remaining four models, it has been found that TGARCH with student t's distribution has the lowest AIC (–2.5026) and SIC (–2.5015) as compared to other five models. Among the four models, this model also has highest Log Likelihood (72267.07), but slightly less R and Adjusted R squared value as compared to other models. Hence, TGARCH with student t's distribution is considered as most suitable model. The result of the selected TGARCH (1,1) Model for NTPC is mentioned in Table 7.

Table 7 shows the results of TGARCH (1,1) model with Student t's Distribution Construct for Reliance Industries Limited. The results classified in two parts. The upper part shows the mean equation, and the lower part represents the variance equation. In the mean equation the constant (C) is significant as the probability value is less than 0.05 and even the co-efficient of first lag [NTPC (-1)] is also significant as its probability value is also less than 0.05.

In case of variance equation, C is the Constant, RESID (-1) ^2 is the ARCH co-efficient, RESID (-1)^2*(RESID (-1)<0) is the asymmetric co-efficient and GARCH(-1) is the GARCH co-efficient. All the coefficients except the coefficient of constant are significant in the variance equation as their probability values are less than 0.05. The coefficient of constant in variance equation (0.0000000000129) is close to zero. The coefficient of asymmetric term is negative i.e., -0.01287 and it is not statistically significant even at 5% level which indicates that for this stock there is no asymmetries due to the pandemic COVID-19. Hence, any of the asymmetric volatility model would not be suitable for forecasting stock price volatility of this company.

4.4. Formulation of EGARCH and TGARCH Models for Powergrid Corporation of India

The Power Grid Corporation of India Limited (POWERGRID), is an Indian state-owned Maharatna company headquartered in Gurugram, India and engaged mainly in Transmission of Power. The statistical elements related to both asymmetric models are mentioned in Table 8 for taking decision in selecting a suitable model.

Table 8 reveals that Coefficients, ARCH Effect and GARCH are significant in all the above six models except the TGARCH with Student t's Distribution and Generalised Error Distribution Construct. Hence, these two models are rejected in first instance even though they have higher log likelihood values. While comparing the AIC and SIC of remaining four models, it has been found that EGARCH with student t's distribution has the lowest AIC (–2.6508) and SIC (–2.6497) as compared to other 3 models.

Table 6: Decision table for selecting suitable EGARCH (1,1) or TGARCH (1,1) model for NTPC

Statistics	EGARCH			TGARCH		
	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution
Significant coefficients	Yes	Yes	No	Yes	Yes	No
ARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
GARCH significant	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	54866.14	70714.78	89224.39	56030.65	72267.07	74252.37
R squared	–0.004670	–0.001686	–0.000008	–0.002368	–0.005083	–0.000196
Adjusted R-squared	–0.004688	–0.001703	–0.000025	–0.002386	–0.005101	–0.000213
AIC	–1.899984	–2.448839	–3.089887	–1.940315	–2.502600	–2.571357
Schwartz IC	–1.899053	–2.447752	–3.088800	–1.939384	–2.501513	–2.570271
Heteroscedasticity (ARCH LM-Test)	No	No	No	No	No	No
Autocorrelation (Correlogram of Residuals)	No	No	No	No	No	No

Table 7: Results of TGARCH (1,1) with t's distribution error construct for NTPC

Dependent Variable: RETURNS OF NTPC				
Method: ML ARCH - Student's t distribution (Marquardt/EViews legacy)				
Date: 08/31/20 Time: 21:01				
Sample (adjusted): 10/15/2019 09:17 5/15/2020 15:29				
Included observations: 57748 after adjustments				
Convergence achieved after 22 iterations				
Presample variance: backcast (parameter=0.7)				
GARCH=C (3)+C (4) *RESID(–1) ^{2}+C (5)*RESID(–1) ^{2}*(RESID(–1)<0)+C (6) *GARCH (–1)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	–0.000539	2.32E-06	–232.8522	0.0000
RNTPC (–1)	–0.121364	0.004242	–28.60756	0.0000
	Variance Equation			
C	1.29E-11	2.59E-11	0.498950	0.6178
RESID (–1) ^{2}	0.315385	0.005579	56.53395	0.0000
RESID (–1) ^{2}*(RESID (–1)<0)	–0.012871	0.007254	–1.774471	0.0760
GARCH (–1)	0.729427	0.002082	350.3834	0.0000
T-DIST. DOF	5.851448	0.053170	110.0522	0.0000
R-squared	–0.005083	Mean dependent var		–0.000453
Adjusted R-squared	–0.005101	S.D. dependent var		0.164509
S.E. of regression	0.164928	Akaike info criterion		–2.502600
Sum squared resid	1570.755	Schwarz criterion		–2.501513
Log likelihood	72267.07	Hannan-Quinn criter		–2.502262
Durbin-Watson stat	1.842165			

Source: Authors' Computation through EVIEWS 10

Table 8: Decision table for selecting suitable EGARCH (1,1) or TGARCH (1,1) model for power grid

Statistics	EGARCH			TGARCH		
	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution
Significant Coefficients	Yes	Yes	Yes	Yes	NA	No
ARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes
GARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	58972.16	76546.74	63883.61	59168.30	81047.99	79977.50
R squared	–0.005839	–0.001827	0.000760	–0.002749	0.000616	–0.001733
Adjusted R Squared	–0.005857	–0.001845	0.000742	–0.002767	0.000599	–0.001751
AIC	–2.042189	–2.650819	–2.212253	–2.048982	–2.806712	–2.769637
Schwartz IC	–2.041257	–2.649732	–2.211167	–2.048051	–2.805625	–2.768551
Heteroscedasticity (ARCH LM-Test)	No	No	No	No	No	No
Autocorrelation (Correlogram of Residuals)	No	No	No	No	No	No

Source: Authors' Computation through EVIEWS 10

Among the remaining four models, this model also has highest Log Likelihood (76546.74), but slightly less R and Adjusted R squared value as compared to other models. Hence, EGARCH with student t's distribution is considered as most suitable model. The result of the selected EGARCH (1,1) Model for Power grid is mentioned in the Table 9.

Table 9 shows the results of EGARCH (1,1) model with Student t's distribution Construct for Power grid. 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) and the coefficient of first lag [RPOWERGRID (–1)] are significant as their probability values are less than 0.05.

In case of variance equation, C (3) is the Constant, C (4) is the ARCH coefficient, 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 less than 0.05. Moreover, the model has least AIC (–2.6508) and SIC (–2.6497) as compared to other relevant models. The value of Log Likelihood is 76546.74 and is higher as compared to the other relevant models. The important point to be focussed is the co-efficient of the asymmetric term (λ) is negative i.e., -0.076281 and statistically significant which implies that there is existence of leverage effect of COVID-19 on the stock price volatility of the company, and it also indicates that bad news i.e., spreading of COVID-19 has a larger effect on the volatility of stock price of the company. Hence the variance equation can be shown as given below.

$$log\left(h_t\right) = -0.207351 + \sum_{i=1}^{1} 0.217259 \left| \frac{u_t - i}{\sqrt{h_t - i}} \right| - \sum_{i=1}^{1} 0.076281 \frac{u_t - i}{\sqrt{h_t - i}} + \sum_{k=1}^{1} 0.982983 \log(h_{t-k})$$

4.5. Formulation of EGARCH and TGARCH Model for BPCL

Bharat petroleum corporation limited (BPCL) is an Indian government-controlled oil and gas company headquartered in Mumbai, Maharashtra. The statistical elements related to both asymmetric models are mentioned in Table 10 for taking decision in selecting a suitable model.

Table 10 depicts that Coefficients, ARCH Effect and GARCH are significant in all the three EGARCH (1,1) models and all the three TGARCH (1,1) models with normal distribution error construct, EGARCH with student t's distribution error construct and EGARCH with generalised error distribution construct. While comparing the AIC and SIC of all the above three models, it has been found that EGARCH with Student t's Distribution Construct has the lowest AIC (–2.187297) and SIC (–2.186210) as compared to other models. Similarly, while comparing the six models, the TGARCH with student t's distribution construct has highest Log Likelihood hence, this model is the most suitable model. The result of the selected TGARCH (1,1) Model for the company is mentioned in the Table 11.

Table 11 shows the results of TGARCH (1,1) model with Student t's Distribution Construct for BPCL. The results classified in two parts. The upper part shows the mean equation, and the lower part represents the variance equation. In the mean equation the constant (C) is significant as the probability value is less than 0.05 and even the co-efficient of first lag BPCL (-1)] is also significant as its probability value is also less than 0.05.

In case of variance equation, C is the Constant, RESID $(-1)^2$ is the ARCH co-efficient, RESID$(-1)^2$*(RESID(–1)<0) is the asymmetric co-efficient and GARCH(–1) is the GARCH co-efficient. All the coefficients are significant in the variance equation

Table 9: Results of EGARCH (1,1) with t's distribution error construct for power grid

Dependent variable: RPOWERGRID				
Method: ML ARCH - Student's t distribution (Marquardt/EViews legacy)				
Sample (adjusted): 10/15/2019 09:17 5/15/2020 15:29				
Included observations: 57748 after adjustments				
Convergence achieved after 24 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	–0.003050	1.47E-05	–208.0230	0.0000
RPOWERGRID (–1)	–0.077223	0.003341	–23.11428	0.0000
Variance Equation				
C (3)	–0.207351	0.003197	–64.85887	0.0000
C (4)	0.217259	0.004460	48.71532	0.0000
C (5)	–0.076281	0.002472	–30.85987	0.0000
C (6)	0.982983	0.000316	3109.732	0.0000
T-DIST. DOF	2.691868	0.035726	75.34845	0.0000
R-squared	–0.001827	Mean dependent var		–0.000381
Adjusted R-squared	–0.001845	S.D. dependent var		0.160703
S.E. of regression	0.160851	Akaike info criterion		–2.650819
Sum squared resid	1494.072	Schwarz criterion		–2.649732
Log likelihood	76546.74	Hannan-Quinn criter		–2.650481
Durbin-Watson stat	1.909856			

Source: Authors' Computation through EVIEWS 10

Table 10: Decision table for selecting suitable EGARCH (1,1) or TGARCH (1,1) model for BPCL

Statistics	EGARCH			TGARCH		
	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution
Significant coefficients	Yes	Yes	Yes	Yes	Yes	Yes
ARCH Effect	Yes	Yes	Yes	Yes	Yes	Yes
GARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	42089.87	61559.60	60297.90	42914.95	63163.00	60329.67
R squared	0.005222	0.004631	0.004013	0.003558	0.005276	0.001491
Adjusted R Squared	0.005204	0.004614	0.003996	0.003540	0.005259	0.001474
AIC	–1.457501	–2.131766	–2.088069	–1.486076	–2.187297	–2.089169
Schwartz IC	–1.456569	–2.130679	–2.086982	–1.485144	–2.186210	–2.088083
Heteroscedasticity (ARCH LM-Test)	No	No	No	No	No	No
Autocorrelation (Correlogram of Residuals)	No	No	No	No	No	No

Source: Authors' computation through EVIEWS 10

Table 11: Results of EGARCH (1,1) with student t's distribution error construct for Bharat Petroleum Corporation Limited

Dependent Variable: RBPCL				
Method: ML ARCH - Student's t distribution (BFGS/Marquardt steps)				
Sample (adjusted): 10/15/2019 09:17 5/15/2020 15:29				
Included observations: 57748 after adjustments				
Failure to improve likelihood (non-zero gradients) after 83 iterations				
Coefficient covariance computed using outer product of gradients				
Presample variance: backcast (parameter=0.7)				
GARCH=C (3)+C (4)*RESID (–1) ²+C (5)*RESID(–1) ²*(RESID(–1)<0)+C (6)*GARCH(–1)				
Variable	**Coefficient**	**Std. Error**	**z-Statistic**	**Prob.**
C	–0.001888	8.01E-06	–235.7892	0.0000
RBPCL (–1)	–0.076551	0.004563	–16.77703	0.0000
Variance Equation				
C	1.34E-12	5.01E-13	2.678501	0.0074
RESID (–1) ²	0.686218	0.026743	25.65993	0.0000
RESID (–1) ²*(RESID(–1)<0)	0.435893	0.030943	14.08705	0.0000
GARCH (–1)	0.667206	0.003605	185.0776	0.0000
T-DIST. DOF	2.731401	0.034050	80.21837	0.0000
R-squared	0.005276	Mean dependent var		–0.000750
Adjusted R-squared	0.005259	S.D. dependent var		0.201387
S.E. of regression	0.200856	Akaike info criterion		–2.187297
Sum squared resid	2329.663	Schwarz criterion		–2.186210
Log likelihood	63163.00	Hannan-Quinn criter		–2.186959
Durbin-Watson stat	1.997918			

Source: Authors' Computation through EVIEWS 10

as their probability values are less than 0.05. The coefficient of constant in variance equation (0.00000000000134) is close to zero. The coefficient of asymmetric term is positive i.e., 0.435893 and it is also statistically significant even at 1% level which indicates that for this stock there is existence of leverage effect due to the bad news related to pandemic COVID-19.

$$h_t = 1.34164097035\mathrm{e}-12 + 0.667205511022 h_{t-1}$$
$$+0.686217923487 u_{t-1}^2 + 0.435892872394 u_{t-1}^2 D_{t-1}$$

4.6. Formulation of EGARCH and TGARCH Models for IOC

Indian Oil Corporation Limited (IOCL) is an Indian public sector oil and gas company headquartered in New Delhi. The statistical elements related to both asymmetric models are mentioned in Table 12 for taking decision in selecting a suitable model.

Table 12 reveals that Coefficients, ARCH Effect and GARCH are significant in all the three EGARCH (1,1) models and all the three TGARCH (1,1) models with Normal Distribution Error Construct, EGARCH with Student t's Distribution Error Construct and EGARCH with Generalised Error Distribution Construct. 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 (–4.218038) and SIC (–4.216951) as compared to other models. Similarly, while comparing the six models, the EGARCH with Generalised Error Distribution Construct has highest Log Likelihood, R and Adjusted R Squared hence, this model is the most suitable model. The result of the selected EGARCH (1,1) Model for the company is mentioned in the Table 13.

Table 13 shows the results of EGARCH (1,1) model with Generalised Error distribution Construct for Indian Oil Corporation

Table 12: Decision table for selecting suitable EGARCH (1,1) or TGARCH (1,1) model for Indian Oil Corporation (IOC)

Statistics	EGARCH			TGARCH		
	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution
Significant Coefficients	Yes	Yes	Yes	Yes	Yes	Yes
ARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes
GARCH Significant	Yes	Yes	Yes	Yes	Yes	Yes
Log Likelihood	51237.97	70934.95	121798.6	51952.04	74511.71	74213.92
R squared	–0.015429	–0.009163	–0.000063	–0.009619	–0.001561	–0.000409
Adjusted R Squared	–0.015446	–0.009180	–0.000081	–0.009637	–0.001578	–0.000427
AIC	–1.774329	–2.456464	–4.218038	–1.799059	–2.580339	–2.570025
Schwartz IC	–1.773397	–2.455378	–4.216951	–1.798128	–2.579253	–2.568939
Heteroscedasticity (ARCH LM-Test)	No	No	No	No	No	No
Autocorrelation (Correlogram of Residuals)	No	No	No	No	No	No

Source: Authors' Computation through EVIEWS 10

Table 13: Results of EGARCH (1,1) with generalized error construct for IOC

Dependent Variable: RETURNS OF IOC				
Method: ML ARCH - Generalized error distribution (GED)				
Sample (adjusted): 10/15/2019 09:17 5/15/2020 15:29				
Included observations: 57748 after adjustments				
Convergence achieved after 424 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	6.87E-10	2.06E-10	3.336859	0.0008
RIOC (–1)	4.24E-08	1.16E-08	3.643836	0.0003
Variance Equation				
C (3)	–0.037947	0.001737	-21.85053	0.0000
C (4)	2.658836	0.253008	10.50888	0.0000
C (5)	0.274181	0.140011	1.958283	0.0402
C (6)	0.996585	0.000498	2000.515	0.0000
GED PARAMETER	0.125331	0.001250	100.2761	0.0000
R-squared	–0.000063	Mean dependent var		–0.001149
Adjusted R-squared	–0.000081	S.D. dependent var		0.144513
S.E. of regression	0.144518	Akaike info criterion		–4.218038
Sum squared resid	1206.058	Schwarz criterion		–4.216951
Log likelihood	121798.6	Hannan-Quinn criter		–4.217699
Durbin-Watson stat	2.025274			

Source: Authors' Computation through EVIEWS 10

(IOC). 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) and the coefficient of first lag [RIOC (-1)] are significant as their probability values are less than 0.05.

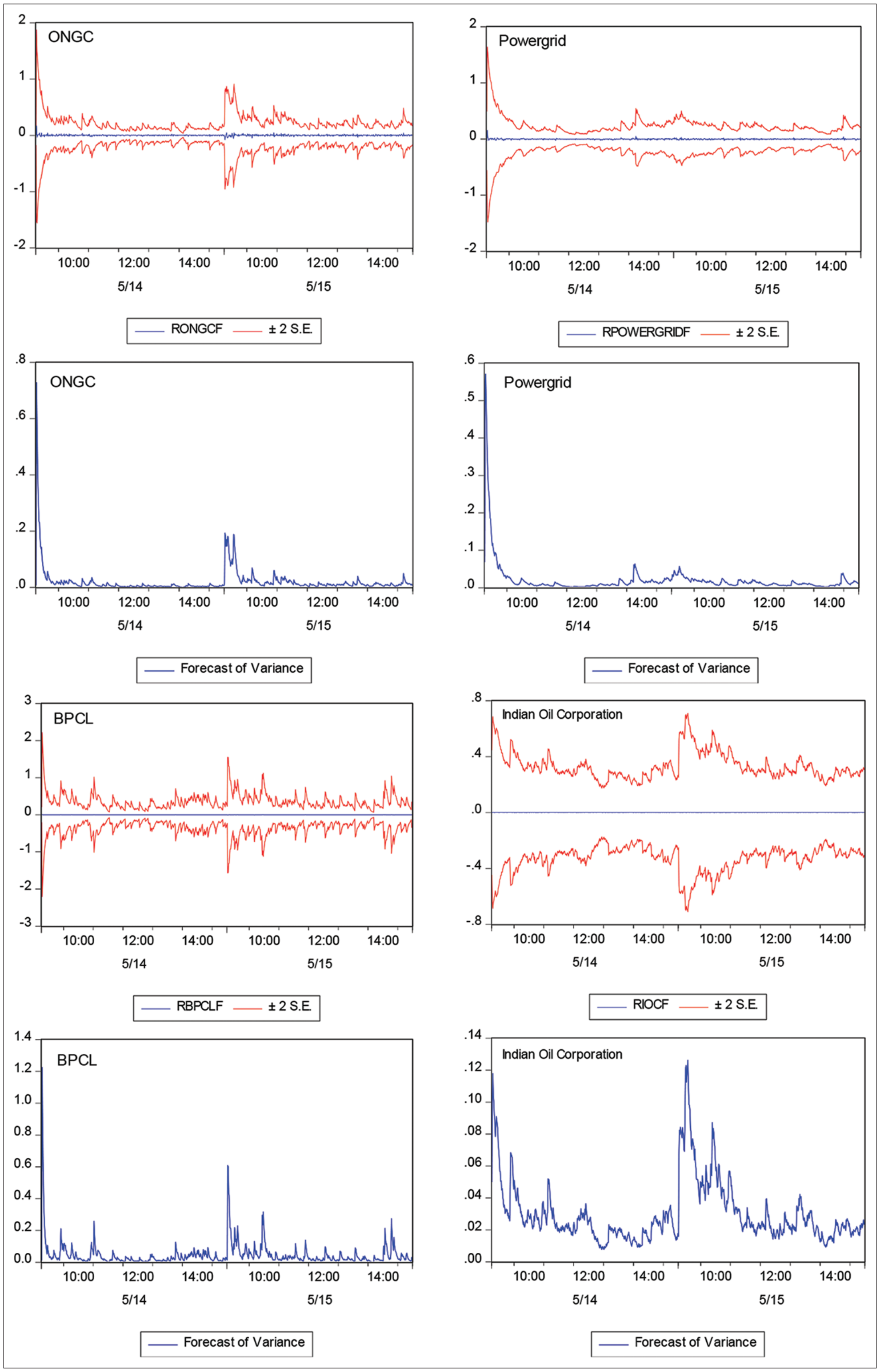
In case of variance equation, C (3) is the Constant, C (4) is the ARCH coefficient, C (5) is the asymmetric co-efficient and C(6) is the GARCH co-efficient. All the coefficients in the variance equation are significant accept the asymmetric term as their probability values are less than 0.05. Moreover, the model has least AIC (–4.218038) and SIC (–4.216951) as compared to other relevant models. The value of Log Likelihood is 121798.6 and is higher as compared to the other relevant models. The important point to be focussed is the co-efficient of the asymmetric term (λ) is positive i.e., 0.274181 and statistically significant implies that there is existence of asymmetric effect, but the stock price of the company is positively affected. Hence the variance equation can be shown as given below.

$$log\left(h_t\right) = -0.037947 + \sum_{i=1}^{1} 2.658836\left|\frac{u_t - i}{\sqrt{h_t - i}}\right| + \sum_{i=1}^{1} 0.274181\frac{u_t - i}{\sqrt{h_t - i}} + \sum_{k=1}^{1} 0.996585\log(h_{t-k})$$

4.7. Forecasting Volatility of ONGC, Powergrid, BPCL and Indian Oil Corporation on the for 2 Days Data i.e., 14th May 2020 and 15th May 2020 by Using the above Formulated Model

The graphs in Figure 2 are meant to understand the forecasted asymmetric stock price volatility of ONGC, Power grid, BPCL and Indian Oil Corporation caused by COVID-19. The reason for considering forecasting for 2 days i.e., 14th May 2020 &

Figure 2: Forecasted asymmetric stock price graphs using selected suitable models



15th May 2020 because the data used in formulating forecasting asymmetric volatility models are high frequency in nature. As the data are high frequency in nature it is better to have very small forecasting period so that accuracy could be attained (Alper et al., 2009)

The line graphs of ONGC in Figure 2 show the forecasted returns and forecasted variance for ONGC for 14th May 2020 and 15th May 2020. The first graph of forecasted returns depicts that there is a consistency in the stock price returns of ONGC during those 2 days while the graph of forecasted variance of ONGC depicts that the volatility has been fluctuating slightly but high variance can be seen on 15th May 2020 from 9:25 a.m. to 9:42 a.m. but after that again the variance shows the same trend as like on 14th May 2020. This shows that the volatility of stock price of ONGC has been affected slightly but in a positive way.

Furthermore, the line graphs of Power grid show the forecasted returns and forecasted variance for Power grid for 14th May 2020 & 15th May 2020. The first graph of forecasted returns depicts that there is a consistency in the stock price returns of power grid during that 2 days while the graph of forecasted variance of Power grid depicts that the volatility has been fluctuating slightly but high variances or fluctuations can be seen during 2:14 p.m. to 2:24 p.m. on 14th May 2020 and 9:15 a.m. to 9:44 a.m. on 15th May 2020 but after that again the variance shows the same trend as like on before.

Again, the line graphs of BPCL show the forecasted returns and forecasted variance for BPCL for 14th May 2020 & 15th May 2020. The first graph of forecasted returns depicts that there is more consistency in the stock price returns of BPCL during those 2 days while the graph of forecasted variance of IOC depicts that the volatility has been fluctuating drastically and high peak variances or fluctuations can be seen at 9:54 a.m. and 11:54 a.m. on 14th May. Again, high peaks can be seen at 9:17 a.m., 10:29 a.m., 2:34 a.m. and 2:47 p.m. on 15th May 2020. This shows that the volatility of stock price of BPCL has been largely affected by the COVID-19 pandemic.

Similarly, the line graphs of Indian Oil Corporation (IOC) show the forecasted returns and forecasted variance for IOC for 14th May 2020 & 15th May 2020. The first graph of forecasted returns depicts that there is more consistency in the stock price returns of IOC during that 2 days while the graph of forecasted variance of IOC depicts that the volatility has been fluctuating drastically with many high peak variances or fluctuations. This shows that though asymmetric model has been framed to capture the leverage effect of the pandemic, but the model is may does not depict appropriate volatility due to high variances in forecasted returns graph.

5. CONCLUSION

It has been found that out of top six companies under NIFTY Energy, the data related to the stock price of four companies i.e., ONGC, Power grid, BPCL and Indian Oil Corporation have the asymmetries and asymmetric models can be formed for these four companies. Among these companies two companies' data i.e., ONGC and BPCL have asymmetries which is properly reflected by TGARCH Model with student t's distribution and these TGARCH models have highest Log likelihood and lowest Schwarz criterion. It is also notable that in case of ONGC the volatility is affected by positive shock as the asymmetric term in TGARCH model has negative value whereas in case of BPCL the volatility of stock price is affected by the negative shock of the pandemic. On the other hand, two companies' data i.e., Power grid and Indian Oil Corporation have asymmetries which is properly reflected by EGARCH model as the models got highest Log likelihood and lowest Schwarz criterion. Whereas an optimum model for measuring asymmetric volatility of stock price of remaining two companies i.e., Reliance Industries Limited (RIL) and NTPC could not be framed though hikes in the stock price returns could be seen in their graphs. From the detailed analysis done above it is clear that though the presence of leverage affect has been proved in the price volatility of crude oil in India (Meher et al., 2020) but few of the companies like Reliance and NTPC might not be affected much.

In the forecasting section where the forecasting graphs for volatility of four companies have been plotted, reveals that there is stability in the stock price returns of all these four companies but the graphs of the forecasted variance of IOC reveals that the volatility has been varying drastically with many high peak variances or fluctuations during the 2 days of forecasted period. The asymmetric terms in the asymmetric models are providing sufficient proof that the volatility of the three of the companies out of six under NIFTY Energy i.e., BPCL, Power grid and Indian Oil Corporation are affected by the COVID-19 pandemic. The models framed in the paper can be used to forecast short-term volatility for four companies during the pandemic. It will also be interesting to use the high frequency data and to predict the stock prices of companies during the pandemic COVID-19 using the univariate time series models for future researchers.

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