ORIGINAL RESEARCH PAPER

Economics

A STUDY OF AUTOCORRELATION OF NIFTY ENERGY INDEX TO PREDICT MARKET SENTIMENT

KEY WORDS: NIFTY Energy Index, Autocorrelation, Unit Root Analysis, Stationarity, ADF test, ARMA Modelling, Variance analysis, GARCH Modelling

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ABSTRACT

The study is aimed at targeting one of the key sectors of Indian stock market i.e. Energy Sector. As NIFTY Energy Index defines the health of the sector and the sentiment of the investors, we have undergone detailed study of the index with an objective to assess various statistical parameters inbuilt in the data series of 3 years with 742 data points. As the sector is strategically important to the macroeconomic aspects of the country, the emphasis was more on the evaluation of trend of the sectoral index return and its dependence on its past data. As the Indian economy and its macroeconomic framework depends on import volume of Crude Oil, this analysis strongly poses the possible bi-directional causality between the Oil price and Energy Index based on the forecasted market sentiment. Establishment of positive outcome from the statistical modelling and analysis of the NIFTY Energy Index returns had guided us to predict the direction of the index and forecast investor sentiment in the sector.

1. INTRODUCTION

The health of any economy can be measured by analysing a multiple relevant parameters and indicators that are mostly macroeconomic in nature. The frequently used terms like bullish, sluggish, dovish, hawkish, though eponymous, are having its origin and implications both in the arena of macroeconomic fundamentals. While analysing the fundamentals and deriving some strong findings, it is very often assessed that many of the minor / insignificant variables come out to be supremely useful in analytics and its application.

While highlighting the growth prospects, we revolve around GDP growth, Gross Value Added (GVA), Gross Capital Formation calculations. In addition to this, the stock market health mostly depicts the investor sentiment which is primarily dependent on the VUCA (Volatility, Uncertainty, Complexity, Ambiguity) factors. The FDI and FPI inflows positively impact the economic health due to the formal acceptance of better economic prospects of any country by another. When FDI inflow is considered to be an indicator to ascertain the stability of an economy, it is a proven fact that it impacts the developed countries more than the developing ones. Similarly, the import dependent countries are essentially affected by the price movement of the key imported goods. This impact originates at trade deficit, traverses across current account deficit, foreign exchange depletion and ends at devaluation of home currency.

Hence the analysis of the imported goods contributing immensely to the macroeconomic parameters of the country is of pivotal importance. Crude Oil is contributing a whopping 25% of the approximate $450 Billion import bill of India. Despite various intermediate measures, India's oil dependence had jumped to an alarming 84% in 2018-19 where it was 77% in 2013-14. Oil consumption of the country increased from 185 million tonnes in 2015-16 to 195 million tonnes in the next year and 206 million tonnes in the following year. In 2018-19, the usage grew by 2.6 per cent to approximate 212million tonnes. India's Crude Oil import was reported as 4,341.414 Barrel/Day in Dec 2017 and subsequently jumped to 4,543.645 Barrel/Day in Dec 2018. This shows India's ever-increasing dependency on Crude Oil resulting in perennial pressure of fiscal indicators.

Energy Sector of the country is not only having direct relationship with the input cost of Crude Oil but also is significantly impacted by its price volatility. The market sentiment of this sector is reflected comprehensively by NIFTY Energy Index in India. NIFTY Energy Sector Index includes companies belonging to Petroleum, Gas and Power sectors. The Index comprises of 10companies listed on National Stock Exchange of India (NSE).NIFTY Energy Index is computed using free float market capitalization method, wherein the level of the index reflects the total freefloat market value of all the stocks in the index relative to particular base market capitalization value. NIFTY Energy Index can beused for a variety of purposes such as benchmarking fund portfolios, launching of index funds, ETFs and structured products. It consists of 10 companies that cater to 10% of the total NIFTY market cap of approximately $ 2.27 Trillion.

Constituents of the NIFTY Energy Index

Company's Name	Weight(%)
Reliance Industries Ltd.	33.96
NTPC Ltd.	13.70
Power Grid Corporation of India Ltd.	12.34
Oil & Natural Gas Corporation Ltd.	10.86
Indian Oil Corporation Ltd.	8.48
Bharat Petroleum Corporation Ltd.	6.89
GAIL (India) Ltd.	5.92
Hindustan Petroleum Corporation Ltd.	4.94
Tata Power Co. Ltd.	2.73
Reliance Infrastructure Ltd.	0.18

2. Literature Review

Zohra Bi, Abdullah Yousuf, Aatika Bi in their paper on the study of impact of power sector stock on nifty index had examined the causality between the daily returns of nifty stocks and the daily returns the power sector stocks in the nifty index. The authors did the Granger Causality test in which they found that there is a bidirectional causality between the selected Nifty Power Stock and market returns. They had concluded that market returns can explain the returns in the nifty power stock, but it cannot be the only explanatory factor explaining the total return of power stock.

Manna Majumder and Anwar Hussian had presented a computation approach using neural network to predict the nifty 50 index by using data from 1st January, 2000 to 31st December, 2009.They had validated the model of neural network across 4 years of trading days. The performance of neural network was reported with an average accuracy of 69.72% over a period of 4 years.

Dr. Jay Desai, Nisarg A Joshi had presented a computational approach for predicting the S&P CNX Nifty 50 Index. A neural network based model has been used in predicting the direction of the movement of the closing value trend of the index by predicting the seven day simple moving average value change after seven days.

Mulukalapally Susruth, in his paper on Financial Forecasting:

An Empirical Study on Box –Jenkins Methodologywith reference to the Indian Stock Market, had developed stock price predictive model with ARIMA where he outlined that actual and predicted values of the developed stock pricepredictive model are slightly close So far very less has been evaluated and analysed pertaining to NIFTY Energy index and we have tried to model the autocorrelation of the data series with the help of ARMA model and the variance with GARCH and EGARCH.

3. Initial Theoretical framework and Methodology

As the objective of the study and analysis is to find out the relationship of the NIFTY Energy index with its past value, it is also equally relevant to forecast its future value. The NIFTY Energy index, comprising of 10 major energy sector stocks, also guides us on the sentiment of investors on this import dependent sector. Although the objectivity of this research is being restricted to analyse core day-wise data of NIFTY Energy Index to find out the autocorrelation, it may also throw some light on the future trend of this sector which plays a key role in total core sector of the economy, WPI / CPI inflation rate and Industrial Production Index. The day wise NIFTY Energy Index data has been obtained from official NIFTY website (www.niftyindices.com) and the analysis has been performed based on 3 years data from January 01, 2016 to January 01, 2019. Total 742 data points have been analysed for this purpose to obtain utmost precision and to make the conclusion more reliable. To normalise the dataset and to reduce variances, the log return of the day wise data series has been considered as the base of analysis. The log return of the NIFTY Energy index has been defined as ((log(Xt/Xt-1)) where Xt is the index value at time t and Xt-1 is the index value at its previous time period (t-1). All the analysis has been performed with the help of EViews software.

While performing the data analysis, various statistical tools have been used. The data has been analysed in a methodical manner. Firstly, the descriptive statistics of the data series has been observed to assess its normality and subsequently the spike graph has been plotted to understand the volatility. Then the autocorrelation has been tested with the help of Correlogram and Breusch-Godfrey Serial Correlation test. While establishing correlation, the presence of Unit Root has been tested with Augmented Dicky Fuller test – with constant and with both constant and trend. When the stationarity of the time series data has been established, the suitable Autoregressive Moving Average (ARMA) model has been established. Subsequently the variances of the modelled data series have been analysed resulting in a suitable GARCH model. While comparing, it has been found that the variance of the data series can be represented better by an EGARCH model.

4. Presentation of data and explanation

The three-year NIFTY Energy index data with 742 data points has been analysed step-wise and the descriptive statistics of the return of the raw data is depicted in Figure 1.

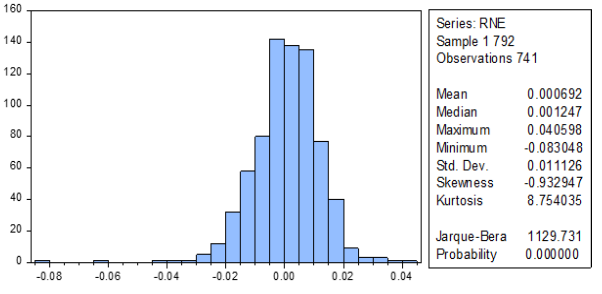

Figure 1

The skewness and Kurtosis values along with the Histogram plot reflect a tendency of normal distribution and the same is reiterated with a high but sub 2000 Jarque-Bera value. The index returns have been plotted (Figure 2) to ascertain the volatility and it has been observed that the returns are volatile in nature with limited shocks and evenly distributed volatility factors.

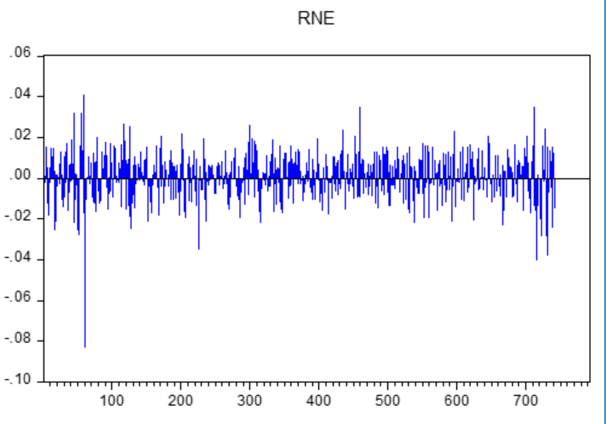

Figure 2

The index return data is then tested to assess any autocorrelation (AC) i.e. systemic relationship with its own lag. The autocorrelation of a series Y and lag k is estimated by:

$$\tau_k = \frac{\sum_{t=k+1}^{T} (Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^{T} (Y_t - \bar{Y})^2}$$

where Y bar is the sample mean of Y. This is the correlation coefficient for values of the series k periods apart. EViews estimates the partial autocorrelation (PAC) at lag k recursively by

$$\phi_k = \begin{cases} \tau_1 & \text{for } k = 1 \\ \dfrac{\tau_k - \sum_{j=1}^{k-1} \phi_{k-1,j}\tau_{k-j}}{1 - \sum_{j=1}^{k-1} \phi_{k-1,j}\tau_{k-j}} & \text{for } k > 1 \end{cases}$$

Where τ_k is the estimated autocorrelation at lag k and where:

$$\phi_{k,j} = \phi_{k-1,j} - \phi_k \phi_{k-1,k-j}.$$

This is a consistent approximation of the partial auto correlation. The algorithm is described in Box and Jenkins (1976, Part V, Description of computer programs). To obtain a more precise estimate of Φ, the following regression can be used:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \dots + \beta_{k-1} Y_{t-(k-1)} + \phi_k Y_{t-k} + e_t$$

(Eviews user guide: www.eviews.com)

where et is a residual. If the partial autocorrelation is within these bounds, it is not significantly different from zero at (approximately) the 5% significance level. The correlogram for 18 lags has been depicted in Figure 3. It is observed form the correlogram that the test statistics is significant at 5% level post 3 lags. The Q-statistics are significant and the probability values are considerable at 5% level. The Breusch-Godfrey Serial Correlation LM test has been performed to assess the autocorrelation of the index return data with Null Hypothesis H0: There is no autocorrelation in the NIFTY Energy index return data and Alternate Hypothesis H1: There is autocorrelation in the NIFTY Energy index return data. The outcome of the Breusch-Godfrey Serial Correlation LM test up to 6 lags (Figure 4)shows significant probability of chi-square and F-statistics to reject the null hypothesis and accept the alternate hypothesis that says there is serial correlation or autocorrelation in the index return data series.

Sample: 1 792
Included observations: 741

	AC	PAC	Q-Stat	Prob
1	0.068	0.068	3.4326	0.064
2	0.020	0.015	3.7319	0.155
3	0.009	0.007	3.7921	0.285
4	-0.090	-0.092	9.8275	0.043
5	-0.129	-0.119	22.267	0.000
6	-0.061	-0.044	25.071	0.000
7	-0.001	0.012	25.072	0.001
8	-0.010	-0.014	25.150	0.001
9	-0.007	-0.027	25.189	0.003
10	0.084	0.063	30.445	0.001
11	0.026	0.008	30.973	0.001
12	0.043	0.038	32.391	0.001
13	-0.007	-0.019	32.425	0.002
14	0.048	0.056	34.143	0.002
15	0.010	0.023	34.216	0.003
16	-0.032	-0.018	34.991	0.004
17	-0.067	-0.062	38.415	0.002
18	0.016	0.034	38.601	0.003

Figure 3

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 6 lags

F-statistic	3.665180	Prob. F(6,734)	0.0014
Obs*R-squared	21.55501	Prob. Chi-Square(6)	0.0015

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 08/21/19 Time: 22:15
Sample: 2 742
Included observations: 741
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.61E-06	0.000404	0.003969	0.9968
RESID(-1)	0.051369	0.036916	1.391498	0.1645
RESID(-2)	0.014046	0.036740	0.382308	0.7023
RESID(-3)	0.015646	0.036654	0.426845	0.6696
RESID(-4)	-0.082663	0.036806	-2.245884	0.0250
RESID(-5)	-0.117075	0.036969	-3.166799	0.0016
RESID(-6)	-0.043319	0.037165	-1.165588	0.2442

R-squared	0.029089	Mean dependent var	-5.24E-19
Adjusted R-squared	0.021152	S.D. dependent var	0.011126
S.E. of regression	0.011007	Akaike info criterion	-6.171086
Sum squared resid	0.088934	Schwarz criterion	-6.127556
Log likelihood	2293.387	Hannan-Quinn criter.	-6.154304
F-statistic	3.665180	Durbin-Watson stat	1.996802
Prob(F-statistic)	0.001357		

Figure 4

Unit Root Test:

Unit root tests are performed to assess stationarity in a time series. A time series can be termed as staionary if a shift in time doesn't result in a change in the shape of the distribution; unit roots are major cause for non-stationarity. The existence of unit roots can cause any analysis to have serious issues like errant behaviour and spurious regression. There are multiple tests to ascertain the presence of unit root namely Dickey Fuller Test, Elliott–Rothenberg–Stock Test, Schmidt–Phillips Test, Phillips–Perron (PP) Test, Zivot-Andrews test of which Augmented Dickey-Fuller (ADF) test handles lengthier and more complex models. It has the downside of a fairly high Type I error rate.

The data set has been tested here with Augmented Dickey Fuller Test. The Augmented Dickey Fuller Test (ADF) is unit root test for stationarity. Unit roots can cause unpredictable results in time series analysis. The Augmented Dickey-Fuller test can be used with serial correlation. The ADF test can handle more complex models than the Dickey-Fuller test, and it is also more powerful. That said, it should be used with caution because—like most unit root tests—it has a relatively high Type I error rate. The data has been tested with ADF test – both with only constant (Figure 5) and constant with linear trend (Figure 6). In both the tests, it has been observed that at 5% level of significance, t-statistic (calculated t-value) or tstat<tcritical obtained from the ADF table. This rejects the null hypothesis that the log return of NIFTY Energy index (RNE) data set has a unit root. This also emphasises the stationarity of the data set which can subsequently be modelled as an autoregressive moving average (ARMA) model as it will not traverse for a random walk.

Null Hypothesis: RNE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-25.34160	0.0000
Test critical values:	1% level	-3.438960	
	5% level	-2.865230	
	10% level	-2.568791	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RNE)
Method: Least Squares
Date: 08/21/19 Time: 09:43
Sample (adjusted): 3 742
Included observations: 740 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RNE(-1)	-0.931897	0.036773	-25.34160	0.0000
C	0.000643	0.000409	1.569865	0.1169

R-squared	0.465294	Mean dependent var	-2.12E-05
Adjusted R-squared	0.464569	S.D. dependent var	0.015190
S.E. of regression	0.011115	Akaike info criterion	-6.158340
Sum squared resid	0.091175	Schwarz criterion	-6.145890
Log likelihood	2280.586	Hannan-Quinn criter.	-6.153540
F-statistic	642.1969	Durbin-Watson stat	1.999123
Prob(F-statistic)	0.000000		

Figure 5

Null Hypothesis: RNE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=18)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-25.33309	0.0000
Test critical values:	1% level	-3.970502	
	5% level	-3.415901	
	10% level	-3.130218	

*MacKinnon (1996) one-sided p-values.

Sample (adjusted): 3 742
Included observations: 740 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RNE(-1)	-0.932306	0.036802	-25.33309	0.0000
C	0.000296	0.000820	0.360472	0.7186
@TREND("1")	9.35E-07	1.91E-06	0.488523	0.6253

R-squared	0.465467	Mean dependent var	-2.12E-05
Adjusted R-squared	0.464016	S.D. dependent var	0.015190
S.E. of regression	0.011121	Akaike info criterion	-6.155962
Sum squared resid	0.091146	Schwarz criterion	-6.137286
Log likelihood	2280.706	Hannan-Quinn criter.	-6.148761
F-statistic	320.8865	Durbin-Watson stat	1.998944
Prob(F-statistic)	0.000000		

Figure 6

Autoregressive Moving Average (ARMA) modelling:

The ARMA(p, q) discusses about a model with p autoregressive terms and q moving-average terms. This model consists of AR(p) and MA(q) models,

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

The general ARMA model was described in the 1951 thesis of Peter Whittle, who used Laurent series, Fourier analysis and its statistical inference. ARMA models were popularized later by George E. P. Box and Jenkins in a book in 1970, and they were proponents of an iterative (Box–Jenkins) method for selection and estimation. As the data series has been found as autocorrelated and stationary, autoregressive model will suit it the most. The data set has been modelled with only Autoregression AR (2) model, ARMA(1,1) and ARMA(2,2) model. Result of AR(2) model (Figure 7)highlights significant acceptability of AR(1) but no significance of AR(2) and constant terms at 5 % significant

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000690	0.000474	1.454386	0.1463
AR(1)	0.066936	0.022773	2.939285	0.0034
AR(2)	0.015396	0.033972	0.453207	0.6505
SIGMASQ	0.000123	3.45E-06	35.63319	0.0000

Figure 7

level. Subsequently the result of ARMA(1,1) model (Figure 8) rejects both AR(1) and MA(1) coefficients at 5% significant level. ARMA (2,2) model suited best for the given data set where the

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000690	0.000473	1.458313	0.1452
AR(1)	0.210621	0.472367	0.445884	0.6558
MA(1)	-0.142732	0.462184	-0.308821	0.7575
SIGMASQ	0.000123	3.45E-06	35.67211	0.0000

Figure 8

result (Figure 9) coefficients are significant for both AR(1), AR(2) and MA(1), MA(2) at 5% level. The lowest Akaike info criterion (AIC) for this reiterates the perfect suitability of the model. The values of both inverted AR roots and inverted MA roots signify that AR roots are stationary and MA roots are invertible. Hence the best fit ARMA(2,2) model for RNE can be

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written as: Equation 1:

$$\mathbf{RNE_t = 0.000687 + \varepsilon_t + 1.566553RNE_{t-1} - 0.820614RNE_{t-2} - 1.502940\varepsilon_{t-1} + 0.732694\,\varepsilon_{t-2}}$$

Dependent Variable: RNE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Sample: 2 742
Included observations: 741
Convergence achieved after 22 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000687	0.000394	1.743827	0.0816
AR(1)	1.566553	0.090579	17.29481	0.0000
AR(2)	-0.820614	0.089805	-9.137703	0.0000
MA(1)	-1.502940	0.101859	-14.75513	0.0000
MA(2)	0.732694	0.103205	7.099427	0.0000
SIGMASQ	0.000121	4.09E-06	29.43714	0.0000

R-squared	0.024849	Mean dependent var	0.000692
Adjusted R-squared	0.018216	S.D. dependent var	0.011126
S.E. of regression	0.011024	Akaike info criterion	-6.169271
Sum squared resid	0.089323	Schwarz criterion	-6.131959
Log likelihood	2291.715	Hannan-Quinn criter.	-6.154886
F-statistic	3.745943	Durbin-Watson stat	2.025392
Prob(F-statistic)	0.002348		

Inverted AR Roots	.78+.46i	.78-.46i
Inverted MA Roots	.75-.41i	.75+.41i

Figure 9

The data clearly implies the rejection of Null Hypothesis of no autocorrelation of Ljung-Box joint statistics as it is rejected at 5% level.

Variance modelling: Generalized Autoregressive Conditional Heteroskedasticity (GARCH) and Exponential GARCH (EGARCH) modelling:

If an autoregressive moving average model (ARMA) model is assumed for the error variance, the model is defined as a generalized autoregressive conditional heteroskedasticity (GARCH) model.

In that case, the GARCH (p, q) model (where p is the order of the GARCH terms σ^2 and q is the order of the ARCH terms ε^2), following the notation of the original paper, is given by

$$y_t = x_t'b + \epsilon_t$$

$$\epsilon_t | \psi_{t-1} \sim \mathcal{N}(0, \sigma_t^2)$$

$$\sigma_t^2 = \omega + \alpha_1\epsilon_{t-1}^2 + \cdots + \alpha_q\epsilon_{t-q}^2 + \beta_1\sigma_{t-1}^2 + \cdots + \beta_p\sigma_{t-p}^2 = \omega + \sum_{i=1}^{q}\alpha_i\epsilon_{t-i}^2 + \sum_{i=1}^{p}\beta_i\sigma_{t-i}^2$$

The NIFTY Energy Index data returns also showed heteroskedasticity in its variances and the variance has been modelled with both GARCH and EGARCH. While comparing the output of GARCH

Dependent Variable: RNE
Method: ML ARCH - Normal distribution (OPG - BHHH / Marquardt steps)
Sample (adjusted): 4 742
Included observations: 739 after adjustments
Failure to improve likelihood (non-zero gradients) after 432 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 2 3
Presample variance: backcast (parameter = 0.7)
GARCH = C(6) + C(7)*RESID(-1)^2 + C(8)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000908	0.000713	1.272498	0.2032
AR(1)	0.862129	0.238310	3.617671	0.0003
AR(2)	-0.771263	0.204244	-3.776193	0.0002
MA(1)	-0.813005	0.227902	-3.567348	0.0004
MA(2)	0.793508	0.189169	4.194704	0.0000
Variance Equation				
C	5.95E-05	3.39E-05	1.757352	0.0789
RESID(-1)^2	0.149979	0.040916	3.665569	0.0002
GARCH(-1)	0.599979	0.189231	3.170612	0.0015

R-squared	0.018152	Mean dependent var	0.000696
Adjusted R-squared	0.012801	S.D. dependent var	0.011140
S.E. of regression	0.011069	Akaike info criterion	-6.141157
Sum squared resid	0.089927	Schwarz criterion	-6.091302
Log likelihood	2277.157	Hannan-Quinn criter.	-6.121933
Durbin-Watson stat	1.977359		

Inverted AR Roots	.43-.77i	.43+.77i
Inverted MA Roots	.41-.79i	.41+.79i

Figure 10

(Figure 10) and EGARCH (Figure 11), lower Akaike Info Criterion (AIC) value establishes higher veracity of the EGARCH model. The probability of the AR and MA coefficients also reaffirms the fact. The probability of the coefficients of the model variables denotes better fitting probability of the EGARCH model which can be expressed as:

$$\sigma_t^2 = 5.9e^{-5} + 0.149979\ \varepsilon^2_{t-1} + 0.599979\ \sigma\ ^2_{t-1} \quad \text{..........................(Equation 2)}$$

Dependent Variable: RNE
Method: ML ARCH - Normal distribution (OPG - BHHH / Marquardt steps)
Sample (adjusted): 4 742
Included observations: 739 after adjustments
Convergence achieved after 40 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 2 3
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(6) + C(7)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(8)
*RESID(-1)/@SQRT(GARCH(-1)) + C(9)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001247	0.000391	3.186352	0.0014
AR(1)	1.204777	0.147839	8.149241	0.0000
AR(2)	-0.760358	0.102515	-7.417007	0.0000
MA(1)	-1.128786	0.156469	-7.214122	0.0000
MA(2)	0.713141	0.110344	6.462890	0.0000
Variance Equation				
C(6)	-1.178865	0.423053	-2.786562	0.0053
C(7)	0.289110	0.052216	5.536771	0.0000
C(8)	0.112601	0.035799	3.145404	0.0017
C(9)	0.895534	0.043301	20.68159	0.0000

R-squared	0.017862	Mean dependent var	0.000696
Adjusted R-squared	0.012510	S.D. dependent var	0.011140
S.E. of regression	0.011070	Akaike info criterion	-6.292283
Sum squared resid	0.089953	Schwarz criterion	-6.236197
Log likelihood	2333.998	Hannan-Quinn criter.	-6.270657
Durbin-Watson stat	2.032702		

Inverted AR Roots	.60+.63i	.60-.63i
Inverted MA Roots	.56-.63i	.56+.63i

Figure 11

As stated earlier, the variance of the same data series has been analysed with EGARCH (Figure 11) to obtain further outcome.

As described in the model definition, the variances can be represented as:

$$\mathbf{\log(\sigma_t^2) = -1.178865 + 0.895534\log(\sigma^2_{t-1}) + 0.112601\ \varepsilon_{t-1} / (\sqrt{\sigma^2_{t-1}}) + 0.289110\ [\ (|\varepsilon_{t-1}| /\ \sigma\ ^2_{t-1}) - \sqrt{\frac{2}{\pi}}\ ]} \quad \text{.................... (Equation 3)}$$

5. DISCUSSION

The NIFTY Energy Index has been analysed in the paper and the outcome is very much interesting. The index return data is highly autocorrelated and most of the lags have significant autocorrelation. The stationarity of the data set has been established with the absence of Unit Root and subsequently the data has been modelled optimally in ARMA (2,2) model (Equation 1). The variances have been normalised with the resultant equation in both GARCH (Equation 2) and EGARCH (Equation 3) model. The data series, with the help of the modelled equation, can be easily forecasted. The causality effect implies the dependence of Energy Index on Crude Oil price and Energy Index can be considered as dependent variable. However, when the Energy Index is having serial autocorrelation without unit root and with stationarity feature, it signifies its future predictability with its past data. The forecast of NIFTY Energy index not only states the health expectation of the sector but it also emphasises the market sentiment of the investors on crude oil price resulting in a reverse bi-directional causality effect on the index return. The crude oil price can subsequently be foreseen with the movement of this Energy Sector index return. With this in can be concluded that the NIFTY Energy index log return data is autocorrelated, stationary without significant impact of unit roots and can be modelled as ARMA (2,2) whereas its variance can be modelled as EGARCH. Both the models can be significantly represented to forecast the future outcome of the index.

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