Digitized India Announcement volatile the Indian Stock Market with special reference to NIFTY 50 and BSE Sensex- A critical analysis

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Abstract: Firm's performances can be measured by its financial growth and a nation's growth or economic development can be measured by the demand and supply of finance. But in today's changing world development of any nation can be evaluated through the advancement of technology. Similarly a developing country like India announcement of "Digital India" put an impact on domestic as well as the international financial market. In the financial market, maintaining the pricing, portfolio, and risk management is the most important feature. This can only be possible through understanding the characters of volatility modeling.

Several researchers already proved the volatility existence in the stock market which helped many in pricing, portfolio and risk management. In India, the stock market plays a vital role as it is considered being one of the criteria for understanding the economic growth of the nation. Due to such a reason, the stock market is always found to be highly volatile.

Therefore, the study will satisfy the objective of examining the effect of Digitized India on Nifty 50 and BSE Sensex the paper will also state about volatility characteristics after the declaration of Digitized India i.e. on 1st July 2015. This analysis will highlight leverage effect, leptokurtosis, and volatility clustering. These objectives can be examined through symmetric and asymmetric models. For analysis, the tools used are ARCH, GARCH, and EGARCH that will provide a clear picture about the behavior of Indian stock market. For such examination, the performance of NSE-NIFTY-50 and BSE Sensex are considered for a period from 1st July 2013-30th June 2017. The result will help to predict the characteristic of NSE-NIFTY-50 and BSE Sensex through (symmetric model) ARCH/ GARCH models along with that the existence of volatility clustering platy kurtosis/ leptokurtosis will be identified, while EGARCH will be used to identify the effect of leverage on NSE-NIFTY-50 and BSE Sensex.

Index Terms- Digitized India, Stock Market, Volatility Clustering, Leverage Effects, GARCH models

I. INTRODUCTION

In the era of globalization, sustainability of a firm depends on better products and services to its ultimate users. Sustainability by satisfying both customer and the business firm can be possible through innovations. When we talk about innovation in India it states about "DIGITIZED INDIA". In the field of finance, the risk management and risk transfer, a non-banking financial institution in capital market played a major role all over the world as it is one of the reasons for the development of nation along with economic growth (Arya, 2018).

The economic condition of any nation is dependent on several factors, while one of the major factors is Financial Markets. Raja and Selvam, 2011 states to identify the volatility in the stock prices, the financial market has a major contribution. Volatility is considered as a chief reason to identify the risk as it leads to change in asset pricing (Markowitz, 1952).

(Gokbulut and Pekkaya, 2014; Ezzat, 2012; Goudarzi, 2011) identifying the real volatility help the management for measuring the risk, pricing the assets and manage the portfolio.

Identifying the model that best suit to identify any kind of fluctuation will help the academicians and practitioners to rely on any kind of deviation. (Emenike, 2010) This will support for assets pricing, investment decisions, capital rising by the policymakers, top-level management, investors.

Ezzat(2012), Emenike (2010), Lee(2009), Najand (2002), McMillan et.al (2000), Tse (1991), Poterba and Summer (1986), and some of the early researcher like Black (1976), Fama (1965), Mandelbrot (1963) had confirmed the presence of volatility in the time series .

Engle, 1982 opined a statistical model that can be considered for the evaluation of financial time series volatility, leptokurtosis or the leverage effect. The behavior can be measured through implementing ARCH (Autoregressive Conditional Heteroscedasticity) model.

Bollerselev (1986) opined a model as GARCH (Generalized AutoRegressive Conditional Heteroscedasticity) which consider various parameters for the measurement that was not in ARCH model.

To measure the volatility clustering and leptokurtosis, ARCH and GARCH models can be considered as the best tool. But the leverage effect i.e. effect of volatility due to bad or good news cannot be tested by any of the models. Neloson (1991) approached with a model EGARCH (Exponential GARCH) model which can identify this type of conditional asymmetric shocks. Later on, various researchers like [Suleyman Gokcan, 2000; Su, Chang 2010; Moustafa AbdEI Aal, 2011; Ezzat Hassan, 2012; Freedi et. al, 2012] supported it.

Basing on all the detailed study the paper will consider the model from GARCH family to study the characteristic of volatility clustering and EGARCH model for leverage effect on the NSE-Nifty 50 and BSE Sensex.

II. LITERATURE REVIEW

Benoit M. (1963), Fama E.F. (1965), and Black F. (1976), the three learned researchers approached first on the volatility clustering, leverage effect and leptokurtosis of stock return. This measurement supports the decision makers to understand the behavior of prices of stock in the financial market. Engle (1982), and Bollerslev (1986) were motivated to measure such volatility and they proposed ARCH and GARCH model for evaluation.

Engle et al. (1987) came up with an advanced model i.e. GARCH-M, that consider the mean for determining the conditional variance. This analysis helps to justify the risk premium but not the time-invariant.

Nelson (1991) proposed a new model EGARCH, as GARCH model had several limitations as it was unable to consider the inconsistency of return as positive or negative. The findings show an empirical result of both stock market variance and excess returns that are negatively correlated.

Glosten et al. (1993) proposed a model i.e. GJR GARCH which was an advanced tool to GARCH-M which helps to measure the un-uniform return due to the positive or negative shocks. Keeping in view of the limitation of GARCH models several models were developed like; APARGCH (Asymmetric Power GARCH) suggested by Ding et. Al (1993), TGARCH (threshold GARCH) by Zokoian (1994), during 2006, DAGARCH (Dynamic Asymmetric) stated by Caporin and McAleer, (QGARCH) Quadratic GARCH, CARR (Conditional Auto Regressive Range) and so on.

GARCH (1, 1) model can only be considered for the measurement of volatility stated by various researchers like [Hsieh D.A. (1989), Stephen J. Taylor (1994), Bekaert and Harvey (1997), Aggarwal et. al (1999), Brook and Burke (2003), Frimpong and Oteng (2006), and Olowe (2009)].

Gokan (2000), Awartani and Corradi (2005), Yalami and Sevil (2008), Miron and Tudor (2010), and Su (2010) compared the various model i.e. GARCH-M, EGARCH, TGARCH, and PGARCH and confirmed that all the models of GARCH identify the daily return volatility. However, amongst all the models EGARCH is founded to be the best for volatility measurement.

R. Gokbulut and M. Pekkaya (2014) in Turkey, Goudarzi, and Ramanarayanan (2011) of India, Rashid and Ahmad (2008) in Pakistan, Akgül and Sayyan (2005), Aydin (2002) few recent researchers analyzed the stock market volatility through ARCH and GARCH models. Their results state that leptokurtosis exists in the emerging economies along with non-normality and skewness as negative with volatility clustering. They also mention that GARCH (1, 1) fits the best. However, Gokbulut and Pekkaya (2014) state that CGARCH and TGARCH are more accurate to estimate the volatility.

Several research is conducted by Freedi et al. (2012) of Saudi Arabia, Ezzat Hassan (2012) of Egypt, Moustafa Abd el Aal (2011), Angabini and Wasiuzzaman (2011) in Malaysia, Su (2010) in China, Emenike (2010) and Floros (2008) in Nigeria on emerging economies. The comparison was made between ARCH and GARCH models and suggests that GARCH, EGARCH, and GJR GARCH are best fit for leverage effect, leptokurtosis volatility measurements and identifying the cluster

Many types of research are conducted by incorporating ARCH and GARCH family models. While few analysis is done in Jordan. The ASE (Amman Stock Exchange) data are considered for a period from (1992-2004). The result states that ARCH and GARCH model is best suit for volatility measurement said by Rousan and Al Khouri (2005).

III. OBJECTIVE:

- To analyze the effect of Digitized India on the return series of BSE Sensex and NSE Nifty 50
- To estimate the volatility in the return series of BSE Sensex and NSE Nifty 50 after digitized India
- To state the appropriate model for the return series of BSE Sensex and NSE Nifty 50 digitized India
- To examine the leverage effect in the return series of BSE Sensex and NSE Nifty 50 digitized India

Hypothesis:

H_{01}: The data series is dependent on previous data.
H_{02}: The distributions of series of return are not normal
H_{03}: The series of return series has stationary
H_{03}: The Data has ARCH effect
H_{04}: The return series has volatility clustering

Condition,

For Hypothesis 1;

If P < 0.05, then there will be a rejection of null hypothesis and acceptance of the alternative hypothesis.
If P > 0.05, then there will be acceptance of null hypothesis and rejection of the alternative hypothesis.

For Hypothesis 2to5;

If P < 0.01, then there will be a rejection of null hypothesis and acceptance of the alternative hypothesis.
If P > 0.01, then there will be acceptance of null hypothesis and rejection of the alternative hypothesis.

IV. RESEARCH METHODOLOGY:

4.1. Methods of Study:

This paper considers EGARCH as ARCH/GARCH models have several limitations to examine the leverage effect due to larger shocks. However, both ARCH and GARCH are taken into consideration to check the asymmetric and asymmetric distribution respectively. This will support the analysis of stock return characteristic of NIFTY 50 and BSE Sensex.

So for this analysis, the methodology that will be considered is ARCH/GARCH model to test the character of the volatility of NIFTY 50 and BSE Sensex. So as to test leptokurtosis, leverage effects, volatility clustering and long memory EGARCH will suit best.

4.2 Empirical Results and Discussion:

4.2.1. Data

For analysis, a sum total of 985 daily closing prices are considered of Indian stock market (NIFTY 50 and BSE Sensex) for a period from 1st July 2013 to 30th June 2017. The return of such is calculated as follows

Rt= Log (pt/pt-1)………………….. (4)

Figure 1&2. Log Return Distribution

From the plot, we get a clear picture of NIFTY 50 and BSE Sensex series that gives a satisfactory result. In general, it means the return lies close to the mean i.e. zero. Along with that, we can see a rising trend and a falling trend for certain period of time.

From the daily series of NIFTY 50 and BSE Sensex, a plot sketching gives us satisfactory results. It means the mean value and return is close to zero. And the result shows a continuous change for some period it is high while for some period it is low.

4.2.2. Results

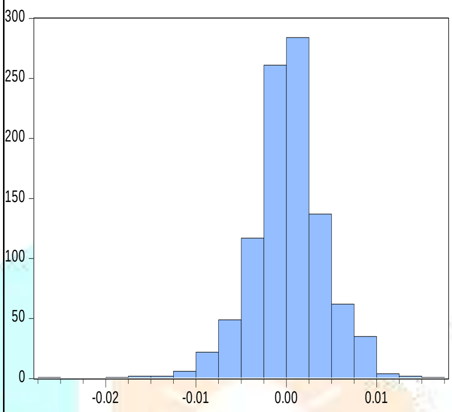
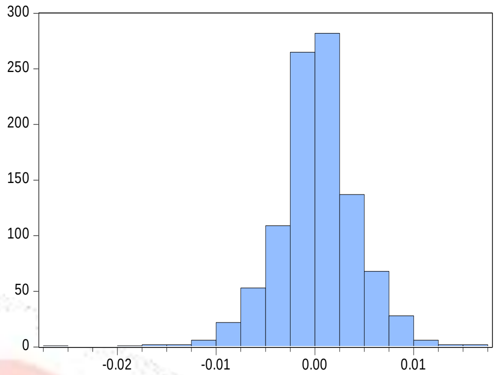
From below table-1, the results shows are mean, median, max, min, skewness, kurtosis and Jarque and Bera results for the period from 2013-2017 of NIFTY 50 and BSE Sensex.

V. RESULTS AND DISCUSSION

5.1 Results of Descriptive Statics of Study Variables

Table-1-Testing the Normality of data series Jarque Bera Test
Result output

Variables	**Sensex**	**Nifty-50**

Jarque- Bera	412.6725	408.1008
Probability	0.0000	0.00000
Observation	986	986
Skewness	-0.420201	-0.431081
Kurtosis	6.055895	6.031528
Minimum	-0.026578	-0.026480
Maximum	0.016084	0.016234
Average	0.000201	0.000211
Median	0.000227	0.00189
Std. Dev.	0.004049	0.004120
Graph		

The mean return value of NIFTY 50 and BSE Sensex as 0.000211 and 0.000201 resp. shows a value of positive throughout the period that confirms a nominal profit and the standard deviation shows 0.004120 and 0.004049.
The result of skewness should be 0 for normal distribution series and the 3 should be that value of kurtosis, while we get the result as -0.420201and -0.431081 resp. for skewness that implies a negatively skewed long left tail and far from normality. For leptokurtosis, we get a result as 6.055895 and 6.031528 which is too high than normal kurtosis value 3, which implies the return is tailed fat.
For JB (Jarque Bera) test of normality at 1% level of significance, that there is a rejection of null hypothesis and acceptance of alternative hypothesis that is the series of data i.e. the return is not normally distributed. So this result helps to implement the ARCH and GARCH model as it is not normally distributed, leptokurtic and fat-tailed.

5.2. An era of Digitized India in the stock market

The stock market, in general, is found to be highly volatile and observing Indian Stock market, it is completely dependent on sentiments. Any kind of shock whether positive or negative it makes the market volatile. To understand the effect of any such shock can be understood through the run test. It is a non-parametric statistical tool to identify the randomness of two sequence data.

Table-2 Descriptive Statistics and Run test of Sensex return and Nifty 50 return of Pre and Post Digitization

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
Sensex Return	986	.00020132	.004049251	-.0265776	.0160837
NSE Return	986	.00021086	.004120432	-.0264801	.0162338

	Sensex	NIFTY 50
Test Value[a]	.000201326	.000210863
Cases < Test Value	490	496
Cases >= Test Value	496	490
Total Cases	986	986
Number of Runs	466	462

Z	-1.783	-2.038
Asymp. Sig. (2-tailed)	.075	.042

Run-test (Mean)

From the above table- 2 we can find the impact of Digital India on Sensex and Nifty 50 return, the result shows the asymp. Sig. (2-tailed) mean as 0.075 respectively. And for Nifty 50 the result shows 0.042 for the mean. Here we can say that we reject our null hypothesis in case of NSE 50 return and accept the null hypothesis in case of Sensex return hence, we can say that the announcement of digital India has not affected Sensex return significantly statistically but it has affected the Nifty 50. Although it cannot be confirmed as their might be other factors that it produces a different result.

5.3. Stationary Test through ADF and PP test

Table- 3 (a) Stationary Test Sensex

	t-Statistic	Prob.*		Adj. t-Stat	Prob.*
Augmented Dickey-Fuller test statistic	-16.49613	0.0000	**Phillips-Perron test statistic**	-268.034	0.0001
1% level	-3.436844		1% level	-3.43677	
5% level	-2.864296		5% level	-2.86426	
10% level	-2.568290		10% level	-2.56827	

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

Table- 3 (b) Stationary Test Nifty-50

	t-Statistic	Prob.*		Adj. t-Stat	Prob.*
Augmented Dickey-Fuller test statistic	-12.02060	0.0000	**Phillips-Perron test statistic**	-275.228	0.0001
1% level	-3.436913		1% level	-3.43677	
5% level	-2.864326		5% level	-2.86426	
10% level	-2.568306		10% level	-2.56827	

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

Table-3 (a) and (b), states about a test of unit root or stationary of return series through ADF test and Phillips Perron test. The findings of ADF and PP test show significant at level 1%. This defines that the alternative hypothesis is accepted and reject the null hypothesis i.e. the return series is stationary in nature. Which conclude that there exists no autocorrelation.

5.4. Testing of Volatility Clustering using GARCH

Table-4(a) GARCH model for Sensex

Dependent Variable: BSE
Method: ML - ARCH (Marquardt) - Normal distribution
Included observations: 985 after adjustments
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0) +
C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000181	0.000130	1.391772	0.1640
AR(1)	-0.610297	0.125710	-4.854805	0.0000
MA(1)	0.733232	0.108990	6.727485	0.0000
Variance Equation				
C	6.05E-07	1.54E-07	3.930738	0.0001
RESID(-1)^2	-0.013057	0.010583	-1.233778	0.2173
RESID(-1)^2*(RESID(-1)<0)	0.129891	0.023515	5.523825	0.0000
GARCH(-1)	0.908811	0.018381	49.44288	0.0000

R-squared	0.021925	Mean dependent var	0.000204
Adjusted R-squared	0.019933	S.D. dependent var	0.004050
S.E. of regression	0.004010	Akaike info criterion	-8.288729
Sum squared resid	0.015789	Schwarz criterion	-8.253959
Log-likelihood	4089.199	Hannan-Quinn criteria.	-8.275505

Durbin-Watson stat	2.031512
Inverted AR Roots	-.61
Inverted MA Roots	-.73

Table-4(b) GARCH model for Nifty-50

Dependent Variable: NSE
Method: ML - ARCH (Marquardt) - Normal distribution
Included observations: 985 after adjustments
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0) + C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000195	0.000129	1.516605	0.1294
AR(1)	-0.633315	0.109829	-5.766364	0.0000
MA(1)	0.757435	0.093732	8.080817	0.0000
Variance Equation				
C	6.56E-07	1.48E-07	4.432110	0.0000
RESID(-1)^2	-0.017137	0.011041	-1.552135	0.1206
RESID(-1)^2*(RESID(-1)<0)	0.146866	0.022691	6.472518	0.0000
GARCH(-1)	0.902058	0.017230	52.35323	0.0000

R-squared	0.022723	Mean dependent var	0.000214
Adjusted R-squared	0.020733	S.D. dependent var	0.004121
S.E. of regression	0.004078	Akaike info criterion	-8.269555
Sum squared resid	0.016333	Schwarz criterion	-8.234785
Log-likelihood	4079.756	Hannan-Quinn criteria.	-8.256330
Durbin-Watson stat	2.026287		
Inverted AR Roots	-.63		
Inverted MA Roots	-.76		

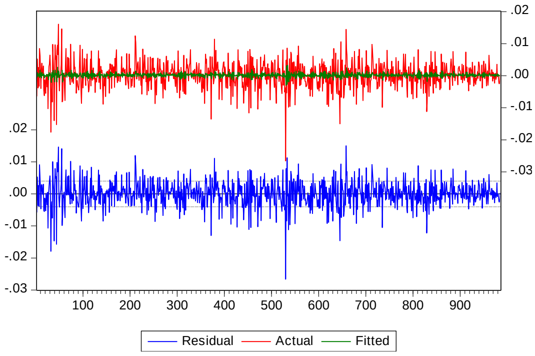
By testing ARMA model, we got a satisfactory result that the ARCH or GARCH model can be considered. From table 4 (a) and (b) we found a level of significance at 1% for ARCH model. This defines that our alternative hypothesis is accepted that is the series of return has ARCH effect and our null hypothesis is rejected. The model is found as ARCH (1, 1).

As we get the existence of ARCH, then the analysis is done with GARCH model to match the changing variance. The analysis states that GARCH (1, 1) is considered. From the analysis, we accept that there exists volatility clustering as we get a result as positive at 1% level of significance for the NIFTY 50 and BSE Sensex return from GARCH model. It means our alternative hypothesis is accepted i.e. the return series has volatility clustering and the null hypothesis is rejected.

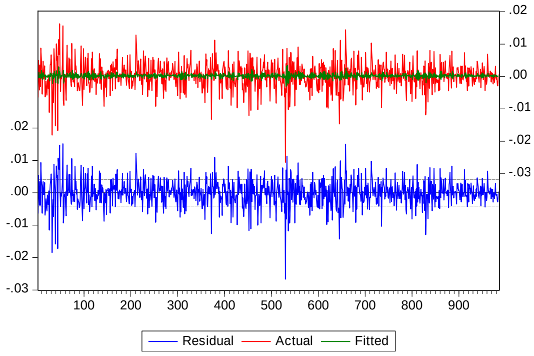
In general sense, the condition for volatility is dependent on previous periods. Which means if the GARCH result of α and β through addition shows a result close to one (i.e. unity) then there lies a persistence of stock to conditional variance. From the above output ($\alpha + \beta$) we get (0.895754) and (0.884921) resp. it means the both NIFTY 50 and BSE Sensex has persistence and volatility clustering.

Residual Graph

Graph-1 Sensex



Graph-2 Nifty-50



Note: From above graph 1 and 2 we can see the existence of volatility clustering in both BSE and NSE by observing the residuals i.e. low volatility is prolonged to low volatility and high volatility is prolonged to high volatility in long run.

5.5. Testing of Leverage Effect through EGARCH

Table-5(a) EGARCH for Sensex

Dependent Variable: BSE
Method: ML - ARCH (Marquardt) - Normal distribution
Included observations: 985 after adjustments
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000162	0.000126	1.284528	0.1990
AR(1)	-0.638385	0.123379	-5.174201	0.0000
MA(1)	0.750885	0.106471	7.052483	0.0000
Variance Equation				
C(4)	-0.430266	0.093559	-4.598850	0.0000
C(5) (α)	0.092407	0.024409	3.785717	0.0002
C(6) (β)	-0.115130	0.015282	-7.533797	0.0000
C(7) (γ)	0.967724	0.007738	125.0575	0.0000

R-squared	0.022063	Mean dependent var	0.000204
Adjusted R-squared	0.020071	S.D. dependent var	0.004050
S.E. of regression	0.004010	Akaike info criterion	-8.304601
Sum squared resid	0.015787	Schwarz criterion	-8.269831
Log-likelihood	4097.016	Hannan-Quinn criteria.	-8.291376
Durbin-Watson stat	2.010313		

Inverted AR Roots	-.64
Inverted MA Roots	-.75

Table-5(b) EGARCH for Nifty-50

Dependent Variable: NSE
Method: ML - ARCH (Marquardt) - Normal distribution
Included observations: 985 after adjustments
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000156	0.000126	1.240843	0.2147
AR(1)	-0.659928	0.108650	-6.073859	0.0000
MA(1)	0.774496	0.091924	8.425355	0.0000
Variance Equation				
C(4)	-0.418372	0.082059	-5.098418	0.0000
C(5) (α)	0.089778	0.024226	3.705877	0.0002
C(6) (β)	-0.119067	0.014344	-8.300909	0.0000
C(7) (γ)	0.968494	0.006753	143.4083	0.0000

R-squared	0.022748	Mean dependent var	0.000214
Adjusted R-squared	0.020758	S.D. dependent var	0.004121
S.E. of regression	0.004078	Akaike info criterion	-8.286057
Sum squared resid	0.016332	Schwarz criterion	-8.251287
Log-likelihood	4087.883	Hannan-Quinn criteria.	-8.272833
Durbin-Watson stat	2.006533		

Inverted AR Roots	-.66
Inverted MA Roots	-.77

From Table-5 (a) and (b), the asymmetric behavior of return series of NIFTY 50 and BSE Sensex is tested along with the leverage effect. The analysis is interpreted by using EGARCH model for leverage effect. The result of gamma (γ) in EGARCH model i.e. C(7) is expected to be negative and significant.

From the Table-5, EGARCH model results show a significant result of all parameters at 1% level except β at 10% level of significance. For asymmetric volatility, gamma parameter should be considered which significant at 1% level of significance and positive. It implies that the return of NIFTY 50 and BSE Sensex will be affected with any positive or negative shocks i.e. bad or good news.

VI. CONCLUSION AND POLICY IMPLICATIONS:

In special reference to emerging economies and frequent development of technology, the investors are surrounded by various risks in financial markets. So volatility measurements and modeling can help them to plan and take the right decision on time prior to that the effect of recent change of digital India is observed through run test on NIFTY 50 and BSE Sensex which shows a less impact on BSE Sensex and significant impact on NSE 50 however, there are other macroeconomic factors which are not taken into consideration for analysis.

The purpose of this paper was to find out the impact of Digital India and finding the best model fit for Indian stock market NIFTY 50 and BSE Sensex. To satisfy the objective run test is conducted and ARCH and GARCH models both are used to test NIFTY 50 and BSE Sensex for a period of 1st July 2013 to 30th June 2017. The analysis includes leverage effect, volatility clustering, and leptokurtosis.

So as to identify the symmetric of NIFTY 50 and BSE Sensex, ARCH and GARCH (1, 1) model is used. This shows that the return on the stock which is not normally distributed. This output shows the existence of conditional Heteroscedasticity which means volatility clustering. However, this analysis also helps to find out the existence of leptokurtosis, long memory, fat-tailed - left skewed and volatility persistence.

By the objective mentioned above regarding the effect of asymmetric in data, the paper inculcates EGARCH (1, 1) model. This analysis can answer the effect of any news i.e. bad or good in near future for NIFTY 50 and BSE Sensex. Through analysis, it is observed that there is no presence of leverage effect as the outcome has a gamma (γ) which is positive, while the result is supposed to be negative. Hence, it can be termed that the stock is highly volatile. It can conclude that whether the shock is good (positive) or bad (negative) there will be no effect for volatility in near future. So it can be interpreted that India is a developing country and Indian Stock Market may be affected by several reasons or events so there must be various other factors for the volatility.

The overall output can be interpreted as the NIFTY 50 and BSE Sensex has no leverage effect, but there exist leptokurtic and Volatility clustering since after the announcement of Digital India.

VII. LIMITATION OF STUDY

The study uses the data of Sensex and Nifty 50 return for a period of 4 years to identify the impact of Digitized India, the conclusion is drawn with a very few factors however stock market is dependent on several economic factors which are not taken into consideration like exchange rate, policy, interest rate and other macroeconomic factors. So this study cannot be confirmed that digitized India has affected the output as a whole.

Further Study

This type of analysis can be done on other exchanges, market (spot or derivative) or sectors or indices by considering any kind of recent news that is expected to affect the stock return.

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