An Empirical Study in Volatility between Spot and of NIFTY using GARCH (1.1) Model

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Abstract: With the implementation of liberalization, privatization and globalization in the Indian economy and also with the introduction of derivative instrument in the Indian Stock Exchange has resulted in huge trading in Indian stock market. This paper measures and compares volatility in stock market through use of certain descriptive statistical measures first and then through measures of conditional variance modeled in different ARCH family of frameworks for NIFTY index of 8 Global 500 rank holding companies of India as per 2013 data. Analysis of stock market for the evaluation of risk has received lot of attention both from policy makers and researchers. The quality of risk measures very largely depends on how well the econometric model captures the behavior of underlying asset. We employed GARCH i.e., General Autoregressive Conditional Heteroskedastic (GARCH), models to study the behavior of volatility. Our study shows that GARCH (1, 1) model fairly explains volatility clustering and its high persistence among the selected companies.

Key Words: Stock Price, Volatility, Heteroscedasticity, GARCH Model

Introduction

The Indian capital market especially the stock market has undergone several structural changes over the last 2 decades. The advent of new financial instruments such as Index futures, stock options, and stock futures started in a phased manner from mid 2000. These changes apparently changed the rule of trading and movement in the prices of the stock markets. Theoretical disagreements about coherence in future trading volume and spot trading volume has offset been a matter of consistent argument between practitioners and the theoreticians. Apparently the magnitude of fluctuation in the returns of an asset is directly proportional to the volume of trade and inversely proportional amongst the underlying and derived instrument. Anderson et al 2004 concluded this sampling interday return with sufficient frequency. It must be noted here that the significance of movement of the assets price is called its volatility. The prediction of volatility in financial market has been rekindled by Bollerslev et al 1994. when they established that financial assets returns volatility are highly predictable. Observably, they realized volatility i.e. measured by simply summing interday squared returns can be treated as "observed volatility". This has profound implication to financial researchers as it provides better measurement of total risk and can lead to better price prediction of various traded assets.

Survey of Literature

Popular models of volatility clustering where developed by Engle 1982 and Bollerslev 1986. The autoregressive conditional heteroscedastic (ARCH) models was developed by Engle 1982 and generalized ARCH(GARCH) models was developed by Bollerslev 1986 and has been extensively used in capturing volatility clustering in financial time series through the last 2 decades.

The advantage of GARCH model is that it can replicate the fat tails observed in many high frequency financial assets return series, where large changes occur more often than a normal distribution could imply.

Several studies earlier try to observe and compose the volatility clustering between derivatives prices and the NIFTY. Foremost amongst them are Karmakar (2005) used GARCH (1.1) model to understand volatility and predictability of NIFTY individual stocks. Rohit Krishnan (2010) observing the large and small error clustering in a GARCH (1.1) model using restricted stock prices and Index during study period, Dutta (2013) used five minute interval tick prices to compare the volatility clustering in very small period by using asymmetric GARCH and compared the threshold values of GARCH (p, q) and GARCH (1,1), TGARCH and EGARCH respectively to understand the steadiness of their models in prediction of volatility cluster.

Thenmozhi (2002) had examined the impact of NIFTY futures on the volatility of underlying NIFTY spot index. Gupta (2003) had tried to examine the impact of index futures on the underlying cash market volatility in India and ten compared the futures market volatility with that of spot market. Kumar and Mukhopadhya (2003) have tried to investigate the presence along with the extent of impact of index futures introduction on the volatility structure of the underlying NSE Nifty index.

Patra and Mohaptra (2013) studied the compared the volatility between spot and futures market using NSE data base and concluded that the returns in the futures market exhibit lesser volatility than returns in underlying spot market considering GARCH class models which process volatility.

Scope of the Paper

This paper is directed at studying the volatility clustering in Spot and Index of Nifty (S& P CNX Nifty) In order to understand the pattern of clustering in spot market as against the clustering in index.

Data and Methodology

High frequency data are direct information from the market and are a recent entrant to the world of statistics.

High-frequency data have now become a popular experimental bench for analyzing financial markets (Dacorogna et al., 2001). It cannot be denied that very high frequency data have microstructure effect (e.g., how the data are transmitted and recorded in the data base). In order to avoid serious microstructure biases and at the same time reduce the measurement error due to data generation at low frequency; we have used data at regularly spaced five-minute intervals (Andersen et al., 2001). The present study uses 8 companies listed on NSE over a period of August 2008 to February 2014 days. The closing prices of the day for the companies have become the pointer for study in this paper. The daily return has been calculated using this pointer. The daily closing index of the S&P CNN Nifty has been taken to calculate the return on the index for the same period of time. A large part of the data has been used to model volatility by using the GARCH (1,1) specification. The data consist of 1401600 data points.

Volatility forecasting

The volatility forecasting represent the accuracy with which one can predict the movement of the stock price/index changes with degree of certainty. For this we go through the following process:

Let,

$$r_{\pi}, i = 1,\ldots, m_t$$

denote log of price relatives at an intra-day time-point *i* on day *t*, where *mt* is the number of return observations obtained by using prices *m* times per day. Then daily return on day *t* is calculated as

$$r_t = \sum_{i-1}^{m_1} r_i$$

Following Andersen et al,

(2001), we define the daily *realized volatility* ($V_t^2 = \sum_{i=1}^{m_t} r_i^2$)as the sum of squares of returns collected at 5-minute intervals:

$$V_t^2 = \sum_{i=1}^{m_t} r_i^2$$

Let δ_t^2 denote volatility forecast. One can assess the accuracy of the daily volatility forecasts under a model by considering the simple linear regressions (Andersen et al., 2005) of y_t on δ_t^2:

$$y_t = a + b\delta_t^2 + \varepsilon_t$$

Where $y_t = V_t^2$ or r_t^2 and then computing the coefficient of determination R^2. The model with the highest R^2 value may be treated as the best model for predicting y_t. On the other hand, if the y_t Value turns out to be generally higher for one choice of y_t, then that choice $(V_t^2$ or $r_t^2,)$ may be considered to be a better measure of observed volatility.

VOLATILITY MODELS

Random walk: The random walk model is the simplest of the models considered and it is given by $\delta_r^2 = \delta_{t-1}^2 + \varepsilon_t$, where ε_t is a white noise series.

Historical Average: The historical average model (Yu, 2002) is given by:

$$\delta_r^2 = \frac{1}{t-1}\sum_{i=1}^{t-1}\delta_t^2$$

GARCH: The volatility model for the r_r or a_t is said to follow a GARCH (m, s) model (Bollerslev, 1986, Bollerslev et al., 1994) if;

$$a_t = \delta_t\varepsilon_t, \delta_t^2 = \alpha_0 + \sum_{i-1}^{m}\alpha_i\alpha_{t-i}^2 + \sum_{j=1}^{s}\beta_j\delta_{t-j}^2 \quad (5)$$

Where $\alpha_0 > 0, \alpha_j \geq 0, \beta_j \geq 0,$

$\sum_{i=1}^{\max(m,s)}(\alpha_i + \beta_i) < 1$, with $\alpha_i = 0$ for $i > m$ and $B_j = 0$ for $j > s$,

And $\{\varepsilon_t\}$ is a sequence of random variables

Table 1.1 GARCH (1,1) for the Spot market

Dependent Variable: PT				
Method: ML – ARCH				
Date: 06/02/14 Time: 15:26				
Sample: 1 800				
Included observations: 800				
Convergence achieved after 100 iterations				
	Coefficient	Std. Error	z-Statistic	Prob.
C	334.9536	5.289649	63.32246	0.0000
	Variance Equation			
C	7263.162	954.1529	7.612157	0.0000
ARCH(1)	1.493027	0.788965	1.892386	0.0584
GARCH(1)	-0.900798	0.032808	-27.45658	0.0000
R-squared	-0.374115	Mean dependent var		269.4260
Adjusted R-squared	-0.379293	S.D. dependent var		107.1997
S.E. of regression	125.8989	Akaike info criterion		1.71722
Sum squared resid	12617023	Schwarz criterion		1.74065
Log likelihood	-4682.890	Durbin-Watson stat		0.005057
Date: 06/02/14 Time: 15:37				

with mean 0 and variance 1, which is often assumed to have a standard normal or standardized student-t distribution.

An exogenous explanatory variable X_k may be included in the GARCH *model*. For example, the GARCH(1,1) model can be augmented as

$$a_t = \delta_t \varepsilon_t, \delta_t^2 = a_0 + a_1 a_{t-1}^2 + \beta_1 \delta_{t-1}^2 + \eta_1 X_k \quad (6)$$

GARCH (1,1) process $\delta_t^2 = a_0 + a_1 a_{t-1}^2 + \beta_1$ is done as follows. For this model the mean-reverting form is given by

$$(a_t^2 - \delta^2) = (a_1 + \beta_1)(a_{t-1}^2 - \delta^2) + u_t - \beta_1 u_{t-1}.$$

Where $\delta^2 = a_0 (1 - \alpha_1 - \beta_1)$ the unconditional long-run is level of volatility and $u_t = (a_t^2 - \delta_t^2)$ is the volatility shock.

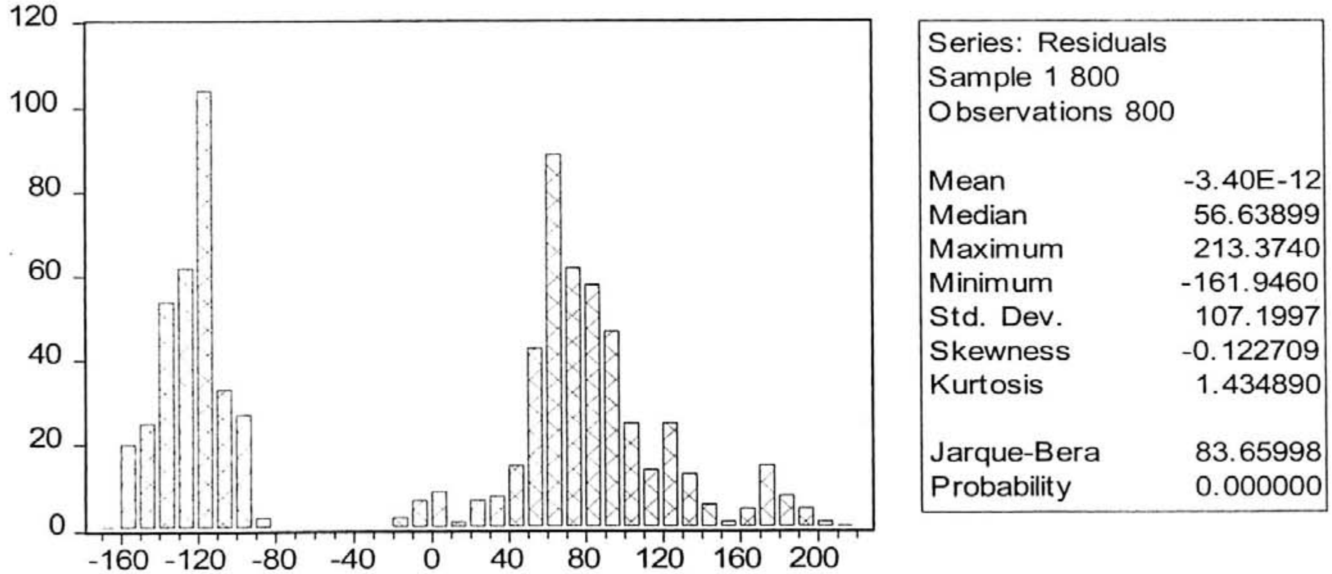

Fig 1.1 Histogram of the Spot Market

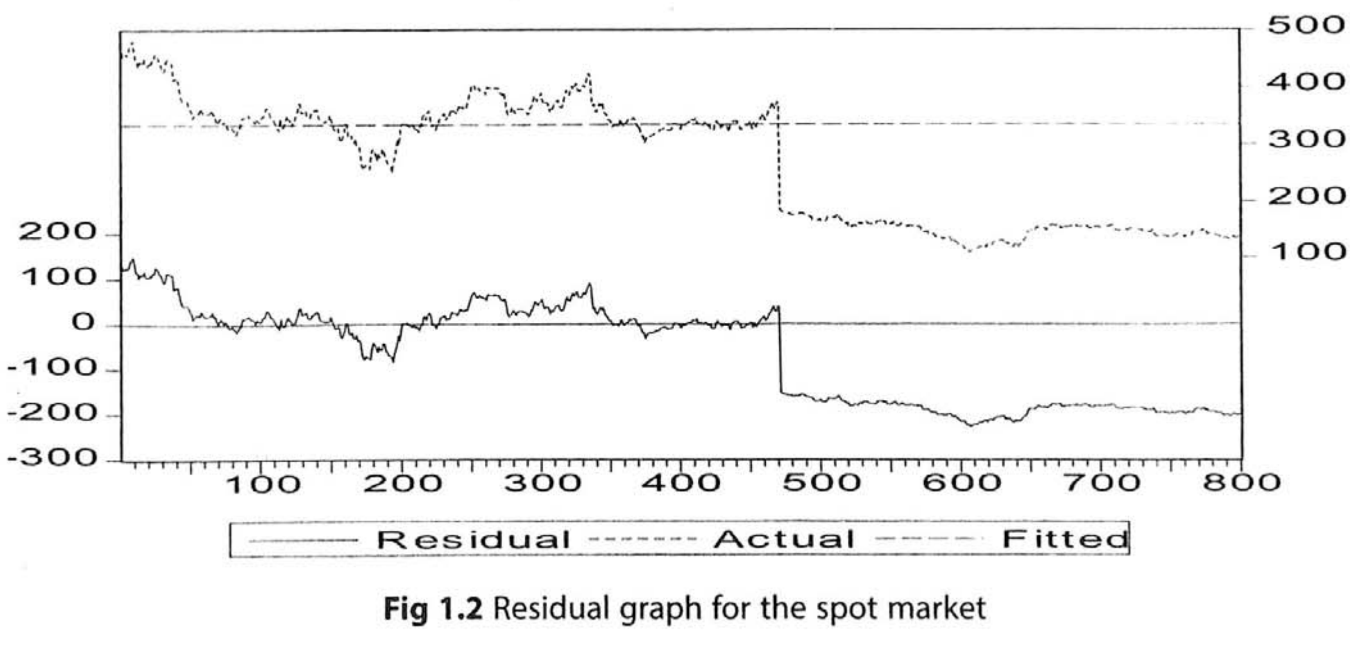

Fig 1.2 Residual graph for the spot market

Results and Analysis

SPOT Market Volatility test

The spot market shows that the AIC and SIC criterion are sufficiently low indicating that there is a good case of the fit for the GARCH (1,1) model. Since the DW value is less than zero, there is autocorrelation in the series. The residual graph indicate that there is a GARCH path where we see upto about 500 days there is high volatility which has gone into a low volatility period after 500 days. The Histograms show a low kurtosis indicating that data are log normal and shows two distinct period of flow of volatility.

The data has a skewness coefficient of zero and kurtosis coefficient of 1.44, hence the null hypothesis that the error are normally distributed is rejected and works in favour of the data. We observe that the GARCH(1,1) series in negatively correlated. Since the p<5%, the null hypothesis is accepted and there is no serial correlation in the series.

The NIFTY Volatility test

The volatility clustering for the NIFTY during the period is almost with a low SIC and AIC criterion. The DW value is less then zero indicate that there is positive autocorrelation in the data. The low kurtosis

Table 1.2 GARCH (1,1) for NIFTY

Dependent Variable: PT				
Method: ML – ARCH				
Date: 06/05/14 Time: 11:26				
Sample(adjusted): 2 800				
Included observations: 799 after adjusting endpoints				
Convergence not achieved after 100 iterations				
	Coefficient	Std. Error	z-Statistic	Prob.
C	5634.991	16.25209	346.7241	0.0000
	Variance Equation			
C	128855.6	21332.76	6.040271	0.0000
ARCH(1)	1.073639	0.327271	3.280585	0.0010
GARCH(1)	-0.774049	0.055760	-13.88175	0.0000
R-squared	-0.001769	Mean dependent var		5615.256
Adjusted R-squared	-0.005549	S.D. dependent var		469.4759
S.E. of regression	470.7768	Akaike info criterion		1.63888
Sum squared resid	1.76E+08	Schwarz criterion		1.66233
Log likelihood	-5844.233	Durbin-Watson stat		0.016232
Dependent Variable: PT				

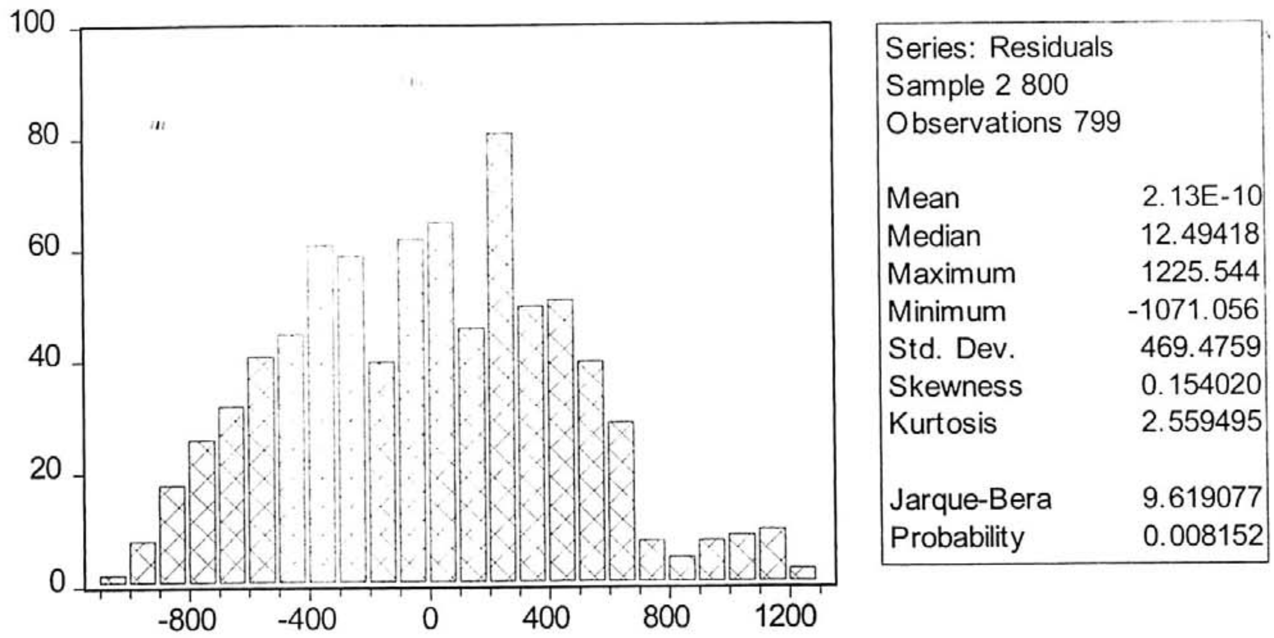

Fig. 1.3 Histogram of NIFTY

Table 1.3 Comparative analysis of volatility clustering of the SPOT and NIFT during the period under study.

Spot				NIFTY			
Sl. No.	Criterion	Interpretation	Effect	Sl. No.	Criterion	Interpretation	Effect
1	Is there a presence of GARCH (1,1)	Yes, low SIC and AIC indicative	There is high volatility followed by a low volatility after 500 days	1.	Is there a presence of GARCH (1,1)	Yes, low AIC and SIC indicative	There is presence of high volatility till 200 days followed by a period of low volatility
2.	Are the data normally distributed	Yes data is normally distributed as indicated by JB statistics	The error is not normally distributed	2.	Are the data normally distributed	Yes the data is normally distributed	The error is Not normally distributed
3.	Is there autocorrelation in the series?	Yes as the DW is less than zero.	The error covary with the series data giving a good prediction about the link of the error to the data series	3.	Is there autocorrelation in the series?	Yes as the DW is less than zero.	The error covary with the series data giving a good prediction About the link of the error to the data series
4.	Is there serial correlation?	Q statistics is low P>5% Hence the H0 is accepted	There is no serial correlation meaning adjacent error terms are related and does not spill to the next period	4.	Is there serial correlation?	Q statistics is low P>5% Hence the H0 is accepted	There is no serial correlation meaning adjacent error terms are related and does not spill to the next period

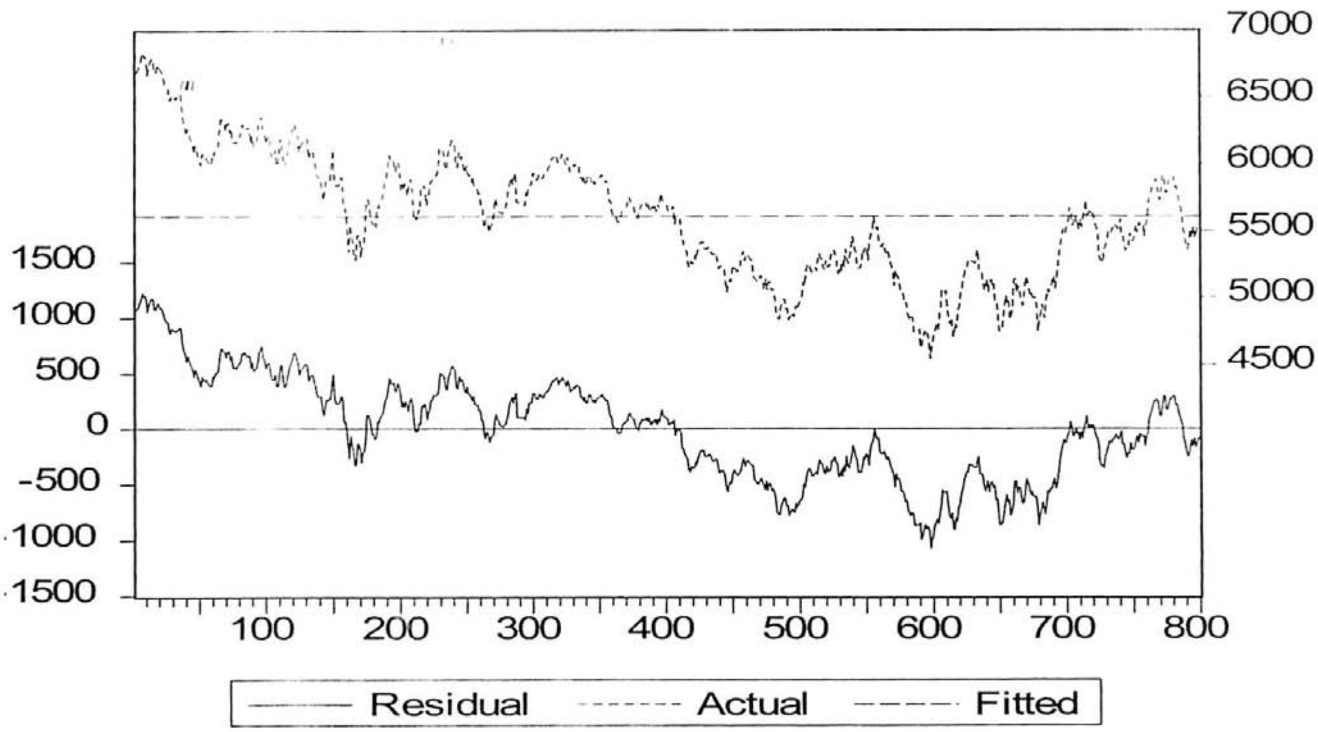

Fig. 1.4 Residual graph of NIFTY

being low the data is not necessarily normally distributed. The residual graph indicate a high volatility period upto 200 hundred days followed by a consistent period of low volatility.

The J B statistics is low indicating the error are not normally distributed and hence there is chance occurrence of the fit which could have been fat tailed. We observe that GARCH (1,1) model is negatively related with a fit due to low AIC and SIC criterion.

We therefore conclude the following from the above two time series which can be written compared as follows.

Conclusion

There has been an effort made in the paper to map volatility in stock market by comparing the volatility of the spot and the NIFTY in the same period. The paper uses eight distinct companies during the study period and uses GARCH (1,1) model to understand the clustering patterns. The results shows that there are distinct ARCH and GARCH patterns in the series and the periods are almost similar. The prolonged high volatility period is followed by a long low volatility period. There series are normally distributed and there is autocorrelation in the series. The absence of the serial correlation indicates that the adjacent error terms are related and does not spill into the next period. It is interesting to conclude that the volatility pattern of the spot and index are similar, showing the maturity of the Indian stock market. Despite the similarity, the index is better fitted by the model then the spot price.

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