On The Volatility of S&P CNX NIFTY

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INTRODUCTION

The financial system of a country is expected to work in a way that facilitates the channelisation of resources from the surplus sectors to the deficit sectors which have a pressing need for them. This is needed with a view to ensure growth in the economy. In order to do this, an economy needs a vibrant stock market which would ensure safety, integrity and liquidity to the investing community which makes investments in a wide range of financial instruments. Studies conducted by Singh (1997), Levine and Zervos (1998) reveal that being a part of the financial system, stock markets play a crucial role to the economic growth of a country.

However, investing activity is subject to various types of risk. Dispersion of returns of an asset from its mean return is called volatility. Stock Market Volatility is asymmetric, that is, low when prices rise and vice versa. Actually, volatility receives a great deal of concern because it can be used as a surrogate to risk. A rise in the volatility could be interpreted as a rise in risk of the concerned investment and investors may transfer funds to less risky assets. This move could result in rise in Cost of Capital of firms (Arestis et al (2001)). The study conducted by Bekaert (1995) observes that in segmented capital markets, volatility is a critical input in the cost of capital. Volatility can also be used as a decision making criterion. Evaluating more than one investment, it could be used as the comparison parameter. One would invest in those assets that yield the highest return per unit of risk (Wessels (2006).

According to Poon et al (2003), volatility has a very wide sphere of influence including investment, security valuation, risk management and policy making. They also put emphasis on the importance of volatility forecasting in various things such as options pricing, financial risk management etc.

Moreover, market volatility may also affect consumer spending. According to Garner (1988), stock market crash in 1987 reduced consumer spending in the USA. Furthermore, Gertler and Hubbard (1989) reveal that business investment spending is also influenced by stock return volatility.

Stock Market Volatility is a popular area of research due to the aforementioned facts. In the Indian context, Joshi and Pandya (2008) have successfully explored the movements of Stock Market Volatility of BSE. The present study therefore, seeks to analyse the volatility issue of another popular stock index S&P CNX NIFTY.

DATA

The present study is based on the daily closing time series data of S&P CNX NIFTY covering the period from 3rd January, 2000 to 28th November, 2008. The sample consists of 2232 observations. The data have been collected from the NSE website.

METHODOLOGY

CALCULATION OF DAILY MARKET RETURNS

Daily Market Returns (r_t) have been computed as follows:

$$\mathbf{r_t = \ln(I_t) - \ln(I_{t-1})}$$

Where, ln denotes natural logarithm

I_t is the closing index value at day 't'

I_{t-1} is the closing index value at day before 't'

DISTRIBUTION OF DATA

To observe the pattern of distribution of the time series, data skewness and kurtosis have been calculated. Zero

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skewness implies symmetry in the distribution, whereas, kurtosis indicates the extent to which probability is concentrated in the centre and especially at the tail of the distribution. Kurtosis measures the peakedness of a distribution relative to the normal distribution. A distribution with equal kurtosis as the normal distribution is called 'mesokurtic'; a distribution with small tails is called 'platykurtic' and a distribution with a large tail is called 'leptokurtic'.

Furthermore, to test normality of the time series data, the study applies Jarque-Bera Test in the following form:

$$JB = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right]$$

Where, n= number of observations,

S = Skewness

K= Kurtosis

For a normal distribution, the values of S and K should be 0 and 3 respectively so that JB becomes equal to 0. A high value of JB is an indicator of non-normality.

AUTO- CORRELATION TEST

To judge the auto correlation of the time series, data Box-Pierce Q statistic in the following form has been used.

$$Q = n \sum_{k=1}^{m} \hat{\rho}^2_k \sim \chi 2_m$$

Where, n=sample size and m= lag length. Since the present study uses daily data, a lag length up to 22 has been considered. The reason behind this is that there could be at most 22 trading days in a month that has 30 days.

If the computed Q statistic is significant, then it indicates the presence of autocorrelation.

UNIT ROOT TEST

The time series data used in the empirical study must be stationary. Mean, variance and co-variance of a stationary time series data does not change with the time shift. If the data is non stationary, then regression results using such data would be spurious, because the usual 't' test would not be applicable to test the significance of coefficients.

To test the stationarity, the unit root test is applied on the time series return data. In this regard, the Phillips-Perron Unit Root Test is used. In Phillips-Perron Test, non-parametric statistical methods are used to take care of the serial correlation in the error term (μt) of the following equation:

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \mu_t$$

Where, Yt is the time series data under consideration.

The test is based on the null hypothesis H_0 : Y_t is not I(0). If the PP statistics are less than the critical value , then Y_t is non-stationary.

MODELING VOLATILITY

McMillan et al (2000) evaluated the performance of ten alternative statistical models for predicting the UK FTA all shares and FTSE 100 stock index volatility. Their study reports that ranking of different forecasting models is dependent on the series, frequency of data such as monthly, weekly and daily and evaluation criteria.

To compute the conditional variance of sample return series, GARCH(1,1) model (Bollerslev(1986)) has been applied. This is a popular model in this subject. Brooks (1998) in his study finds that the GARCH models outperform other techniques while modeling volatility. Brailsford and Faff (1996) find that the GARCH models are superior to other models to forecast Australian monthly stock index volatility.

The estimation of the above model involves both the estimation of a mean and a conditional variance equation. The conditional mean equation is

$$Y_t = X_t \theta + \upsilon_t$$

Where, X_t is the vector of exogenous variables.

In the present case, since there is no exogenous variable, the above equation can be re-represented as:

$$Y_t = C + \varepsilon_t$$

The conditional variance σ_t^2 can be stated in the following equation

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \mu_t$$

Where, ω = mean

ε_{t-1}^2 = volatility from the previous period, measured as the lag of the squared residuals from the mean equation. It is also called the ARCH term.

σ_{t-1}^2 = last period's forecast variance. It is also called the GARCH term.

EMPIRICAL RESULTS

DESCRIPTIVE STATISTICS

Descriptive statistics of the daily NIFTY return have been reported in the Table 1.

It could be seen that the returns during the study period varies between -0.130551 to 0.079716. So a wide range of fluctuation in daily returns could be witnessed. The mean return during the whole study period is 0.000311 which is very near to zero. Therefore, a mean reverting process is a certain possibility.

Table 1: Descriptive Statistics of the Daily Return

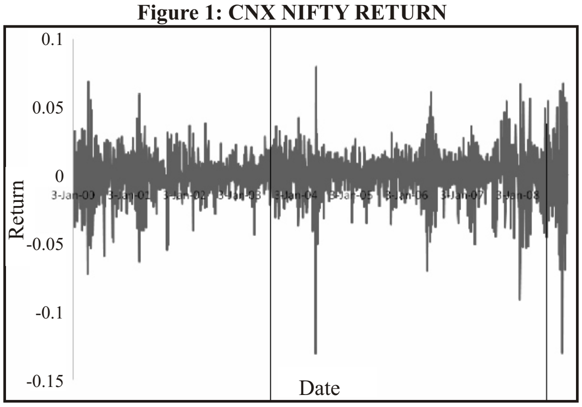
Mean	0.000311
Median	0.001439
Maximum	0.079716
Minimum	-0.130551
Skewness	-0.721216
Kurtosis	8.318526
JB	2822.896
Observations	2231

Skewness is negative indicating a relatively long left tail compared to the right one. Kurtosis in excess of 3 indicating heavy tails and the distribution is leptokurtic. These findings are similar to the existing literature. Mandelbrot et al (1963) observed volatility clustering and leptokurtosis are common observations in financial time series. Moreover, a highly significant large JB statistic confirms that the return series is not normally distributed.

According to Obaidullah (1991), time series return data in Indian Stock Markets are normally distributed. Present study begs to differ in this regard. Although his study was based on monthly data, daily observations have been used in the present one.

However, Harvey (1995b) points out that in many emerging markets, time series return data do not follow normal distribution. The graphical representation of the NIFTY daily returns for the selected sample period has been represented in the Figure 1.

Figure 1: CNX NIFTY RETURN



AUTO- CORRELATION TEST

The Q statistics of return time series data for lag 1 and lag 22 have been reported in Table 2.

Table 2: Box-Pierce Q Statistics of Return Time Series Data

Lag	Q statistic	Probability
1	16.492	0.000
22	64.107	0.000

From the above table, it is clear that Q statistics are highly significant. Hence, the return series is serially correlated.

UNIT ROOT TEST

The PP test result is reported in the Table3. The computed value of PP is -43.21 which is far greater than the critical value of -3.4363 at 1% significant level. Therefore, it appears that the variable used in this study is stationary at its level.

Table 3: Unit Root Test Results

Variable	Computed PP
Daily NIFTY Return Series	-43.21*

* Significant at 1% level

REGRESSION RESULTS OF GARCH (1,1) MODEL

Relevant regression results of fitted GARCH (1, 1) Model have been shown in Table 4.

Table 4: Regression Results of Variance Equation of GARCH (1,1) Model

	Coefficient	Standard Error	Z statistic	Probability
Constant	1.03E-05	3.07E-06	3.355511	0.0008
ARCH(1)	0.165417	0.030802	5.370368	0.0000
GARCH(1)	0.802422	0.034074	23.54953	0.0000

The above table shows that all the regression coefficients are highly significant at 1% level. To check whether the above model is a good fit or not, Q statistic for lag 22 as described earlier have been computed on squared residuals of above equation. The computed Q statistic is 21.495 with a corresponding p value of 0.490. Hence, Q statistic is not significant and the fitted equation is free from serial correlation.

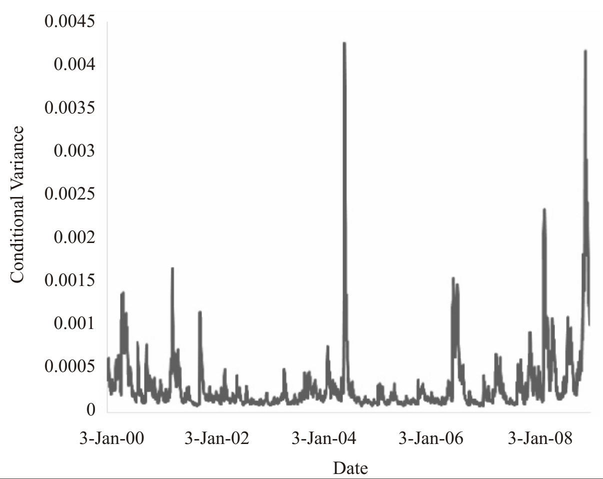
Secondly, the summation of the ARCH and GARCH terms is (0.165417+0.802422) or 0.9678 which is less than 1. This indicates that the data set is stationary. Hence, the model is a good fit.

The conditional variance equation can be represented as:

$$\sigma_t^2 = 0.0000103 + 0.165417\,\varepsilon_{t-1}^2 + 0.802422\,\sigma_{t-1}^2$$

The conditional variances have been shown in the Figure2.

Figure 2. Conditional Variance



CONCLUSIONS

Today, most of the trades in the Indian Stock Markets are conducted in BSE and NSE. Although, NSE was established only seventeen years ago, but growth in terms of value traded in NSE has increased by leaps and bounds.

In this paper, volatility of return series calculated from daily time series data of S&P CNX NIFTY have been analysed. The study reveals that the return series is mean reverting. Moreover, the return series is leptokurtic and returns are serially correlated. Furthermore, a modest attempt has also been made to fit the data into GARCH (1, 1) model to find conditional variances. The regression coefficients are highly significant and Q statistic indicates that the fitted equation is free from serial correlation. Therefore, GARCH (1, 1) model could be a good fit to explore the conditional variances. From the graphical representation (Fig.2) and large GARCH coefficient (0.8024), it appears that volatility persists over a long period of time in the said market. These findings are also at par with the existing literature. Joshi and Pandya (2008) report similar kind of results in their study conducted on BSE.

To conclude, while using GARCH model to explore the movements of volatility, no other variable except daily return has been applied. There may be some macroeconomic variables which could influence the market volatility. Hence, some macroeconomic variables could be used as exogenous variable in the model.

Finally, a scrip level analysis may be useful to capture the influence of company specific factors on scrip level volatility.

BIBLIOGRAPHY

1. Arestis, P, P.O. Demetriades and K.B. Luintel (2001), " Financial Development and Economic Growth: The Role of Stock Markets", *Journal of Money, Credit and Banking*, 33(2), 16-41.
2. Bekaert G. (1995), "Market Segmentation and Investment Barriers in Emerging Equity Markets". *TheWorld Bank Economic Review.* 43. 29-77.
3. Bollerslev, Tim, 1986. "Generalized Autoregressive Conditional Heteroskedasticity," *Journal of Econometrics*, 31 (April): 307-327.
4. Brailsford, T. J. and R. W. Faff (1996), "An Evaluation of Volatility Forecasting Techniques", Journal of Banking and Finance, 20, 419-438.
5. Brooks, C. (1998), "Predicting Stock Market Volatility: Can Market Volume Help?" , Journal of Forecasting, 17, 59-80.
6. Garner, A. (1988), "Has the Stock Market Crash Reduced Consumer Spending?" , *Federal Reserve Bank of Kansas City Economic Review* (April), 3-16
7. Gertler, M and R. G. Hubbard (1989), "Factors in Business Fluctuations, Financial Market Volatility", *Federal Reserve Bank of Kansas City* 33-72
8. Harvey, C.R. (1995b), "Predictable Risk and Returns in Emerging Stock Markets", Review of Financial Studies, 8(3), 773-816.
9. Joshi, P and Kiran Pandya (2008), "Exploring Movements of Stock Market Volatility in India", *The Icfai Journal of Applied Finance,* 14(3), 5-32.
10. Levine, R. and Zervos, S (1998), "Stock Market Development and Long-Run Growth", *World Bank Policy Research, WPS No. 1582.*
11. Mandelbrot, Benoit (1963), "The Variation of Certain Speculative Prices", *Journal of Business* 36, 394 419.
12. McMillan, D., A. Speight, and O. Gwilym (2000), "Forecasting UK Stock Market Volatility", Applied Financial Economics, 10, 435-448.
13. Obaidullah, M (1991), "The Distribution of Stock Returns" *Chartered Financial Analyst*
14. Poon, S. and C. Granger (2003), "Forecasting Volatility in Financial Markets: A Review", *Journal of Economic Literature*, 41, 478-539.
15. Singh, Ajit, (1997), "Financial Liberalisation, Stock Markets and Economic Development," *The Economic Journal* 107(May): 771-782.
16. Wessels, D.R., (2006), "The Characteristics of Stock Market Volatility", www.indexinvestor.co.za

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(Cont. from page 31)

BIBLIOGRAPHY

TEXT BOOKS

1. Donald E Ficher and Ronald J Jordan, Security analysis and portfolio Management, Prentice hall of india pvt ltd, new delhi ,6th edition 2002.
2. Preethi Singh Investment, Management Himalaya Publishing house, 14th Revised edition.
3. Punithavathy pandian, Security analysis and portfolio management, Vikas Publishing House Pvt. Ltd, new delhi-1100114, 2007.

WEBSITES

1) www.nseindia.com
2) www.bseindia.com
3) www.technicaltrends.com
4) www.stockcharts.com