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ON THE DAILY RETURNS & CONDITIONAL VOLATILITY OF S&P CNX NSE NIFTY: IMPACT OF RECENT GLOBAL RECESSION

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Abstract *The present study has tried to explore a few stylized facts regarding the volatility of daily returns of S&P CNX NSE NIFTY. Highly significant JB statistic confirms that the return series is not normally distributed. Moreover, clear evidence of volatility clustering could be observed during the study period. Furthermore EGARCH (1, 1) model has been used to compute conditional variance of the NIFTY daily returnsof the sample period. The empirical results confirm that above model is a good fit and it clearly indicates that volatility in NSE persists over a long period. The empirical results establish that news asymmetry and Leverage Effect are present in this market. Finally, it has been clearly established that the recent sub-prime crisis has significant effect on the daily returns and volatility of S&P CNX NSE NIFTY.*

Keyword: *NIFTY, EGARCH (1,1), Sub-prime Crisis*

INTRODUCTION

The global economy was crawling with the impact of recession which started with the sub-prime crisis in the USA and transmitted to other developed and emerging economies of the world. In USA, mortgage brokers trapped in the greed to earn big commissions made arrangement to provide loans to prospective buyers of house property with minimal down payment and without proper credit checks. The increase in demand of housing loan combined with low interest rates attracted large inflow of funds which helped banks to create easy credit conditions. Banks and other financial institutions in USA assumed that housing price would increase with the increase in demand for the same and loans created might be converted into profitable securities. Banks and other financial institutions then repackaged these loans and converted them to Collateralized Debt Obligations (CDOs) and sold them to investors. During the year 2006-07 with a hike in interest rates there was a decline in housing prices in the USA. Consequently, increased defaults in loan repayment and decline in the resale of mortgaged properties lead to a heavy downfall in CDOs. As a result many banks and financial institutions were severely affected. On 9th August, 2007 BNP Paribas froze three of their CDOs. It was the first major bank to acknowledge the risk of exposure to sub-prime mortgage markets. The crisis peaked in September 2008 when the Lehman Brothers collapsed and ultimately turned out to be a disaster that imposed great losses on other firms across the industries.

Though the epicenter of the crisis was the US sub-prime mortgage market, its shockwaves were expected to be felt in financial markets all over the world due to the globalisation of world economy. The shock was expected to have also been felt in India's stock market since we are exposed to international markets after our economic reforms of 1991. One of the ways to investigate the possible impact of the recession to Indian economy is to study the pattern of volatility of daily S&P CNX NIFTY(from now NIFTY) as it is one of the premier indices in the Indian stock markets.

In this back drop the present paper has sought to investigate whether there is any significant impact of recent global financial crisis on the return and volatility of S&P CNX NIFTY.

LITERATURE REVIEW

There is ample number of empirical research works on stock market volatility in the emerging economies. In the Indian context few attempts have been made to find appropriate models of measuring volatility and forecasting the same. Roy & Karmakar (1995) sought to measure the average level of volatility and investigated whether volatility had increased in the early 1990s or not. Goyal (1995) used conditional volatility estimates as suggested by Schwert (1989) to study the nature and trend of stock return volatility and the impact of carry forward system on the level of volatility. Reddy (1997-98) using standard deviation as the measure of volatility tried to explore the effects of establishment of the National Stock Exchange (NSE) and the introduction of

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Bombay Stock Exchange Online Trading (BOLT) system on the volatility. Pattanaik & Chatterjee (2000) used ARCH and GARCH models to model volatility in the Indian financial markets. On the other hand, Kumar & Mukhopadhyay (2002) applied a two-stage GARCH and ARMA-GARCH model to find how NASDAQ composite daytime returns and volatility have an impact on the conditional mean and the conditional volatility of NIFTY overnight returns during the period ranging between July 1999 to June 2001. Their study revealed that the previous day's day time returns of both NASDAQ composite and NIFTY had significant impact on the next day's overnight return of the NIFTY. However, they found that volatility spillover effects are significant only from NASDAQ composite index which implied that the conditional volatility of NIFTY overnight returns came from the US markets. Kaur (2004) in her study reported significant autocorrelation in daily returns SENSEX and NIFTY. Batra (2004) applied GARCH model to investigate the time varying pattern of volatility in Indian stock market. The study reported that liberalisation of the market did not have any direct affect on stock market volatility. Moreover, the study revealed that volatility declined in the post liberalisation phase for both the bull and bear phases of the market. Karmakar (2005) found strong evidence of time varying volatility and low volatility clustering in Indian capital market. Furthermore, a high persistence of volatility has also been reported. Banerjee & Sarkar (2006) reported long memory in conditional variance of returns in Indian market. They revealed that the FIGARCH was the best fitted model among the other GARCH class of models. However, their study did not find any leverage effect. Recently, Goudarzi & Ramanarayanan (2011) investigated whether the good and bad news had effects on the volatility of BSE 500 stock index during the global financial crisis of 2008-09 or not. They observed that the bad news in the Indian market increased volatility more than the good news.

Joshi & Pandya (2008) and Sen *et al.*(2012) successfully explored the movements of Stock Market Volatility of BSE in their respective studies.

Sen (2010) applied GARCH (1, 1) model to compute conditional variance of NIFTYcovering the period from 3rd January, 2000 to 28th November, 2008. The empirical results showed that above model is a good fit and it was established that volatility in this market persists over a long period.

The present study may be considered as the extension of the aforesaid study. More advanced model has been used in this study to capture the consequence of recent global economic crisis to model conditional volatility of NIFTY.

DATA

The present study is based on the daily closing time series data of daily CNX NSE NIFTY covering the period from 1st January, 2001 to 31st December, 2013. The sample consists of 3246 observations. Since one data point has been lost after calculating daily returns, ultimately 3245 observations are there. The source of the above data is the website www.nseindia.com. The reason behind selecting such a long period is that there should be enough observations representing pre-crisis period, crisis period, and post-crisis period.

Determination of Sub Periods

This is very difficult to determine the exact time span of recent global financial crisis. This paper has considered 9th August, 2007 as the beginning of the crisis period as on that very day BNP Paribas froze three of their CDOs. As the situation eased within the year 2009 the present study has considered the time period starting from 9th August, 2007 to 31st December, 2009 as the crisis period. Hence, period from 1st January, 2001 to 8thAugust, 2007 has been considered as the pre-crisis period and the period after 31st December, 2009 as the post- crisis period.

METHODOLOGY

Calculation of Daily Market Returns

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

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

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'

Volatility Clustering

Mandelbrot (1963) observed that "large changes in stock prices tend to be followed by large changes of either sign, whereas small changes tend to be followed by small changes of either sign". In case, if there is volatility clustering there would be a strong autocorrelation in squared return. To detect such clustering Box-Pierce Q statistic has been computed.

$$Q = n\sum_{k=1}^{m}\hat{\rho}_k^2 \sim \chi^2 \text{m} \quad (1)$$

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 30 days month.

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

Unit Root Test

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.

The MacKinnon (1996) critical value calculations have been used to compare the computed t value and if p value is significant then there is no unit root in the series.

The GARCH Model

One of the assumptions of the CLRM is that the variance of the errors is constant is known as homoscedasticity. If the variance of the errors is not constant, this would be known as heteroscedasticity. If the errors are heteroscedastic, but assumed homoscedastic, an implication would be that standard error estimates could be wrong. It is unlikely in the context of financial time series like the return data that the variance of the errors will be constant over time, and hence it makes sense to consider a model that does not assume that the variance is constant, and which describes how the variance of the errors evolves.It is well established now that the appropriate model in this case is GARCH(1,1) model of (Bollerslev, 1986). Bollerslev, Ray & Kenneth (1992) were of opinion that GARCH (1, 1) is often considered by most investigators as an excellent model for estimating conditional volatility for a wide range of financial data. Kim & Kon (1994) showed that GARCH models are able to model stock returns displaying volatility clustering in some international stock markets. Brailsford & Faff (1996) found that the GARCH models are superior to other models to forecast Australian monthly stock index volatility.

Brooks (1998) reported that GARCH models outperform other techniques while modeling volatility.

To estimate the above model both the mean and the conditional variance equation are to be estimated.

The conditional mean equation is

$$Y_t = X_t\theta + v_t \tag{2}$$

Where X_t is the vector of exogenous variables.

If there is no exogenous variable the above equation can be re-represented as

$$Y_t = C + \varepsilon_t \tag{3}$$

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

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{4}$$

where α_0 = 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.

For non negativity $\alpha_1 \geq 0, \beta \geq 0$ and $\alpha_1 + \beta \leq 1$

Regarding detail steps to fit GARCH models in sample data one could see Sen *et al.* (2012).

Estimation of EGARCH (1,1) Model

However, GARCH models enforce a symmetric response of volatility to positive and negative shocks. The conditional variancein equation (4) is a function of the magnitudes of the lagged residuals and not their signs (by squaring the lagged error in (4), the sign is lost). However, it has been observed that a negative shock to stock market return time series is likely to cause volatility to rise by more than a positive shock of the same magnitude, (Black, 1976). This is called the leverage effect.

The EGARCH or Exponential GARCH model was proposed by Nelson (1991). The estimation of the above model also involves the estimation of mean and conditional variance equations.

A Dummy Variable (DUM) has been included in the mean equation of this study as:

DUM=1 if the returns fall in crisis period and 0 otherwise.

Hence, the equation could be re-written as:

$$Y_t = C + DUM + \varepsilon_t \tag{5}$$

If the coefficient of DUM is found significant it can be concluded that crisis period has significant effect on Nifty returns and volatility. The specification for the conditional variance is:

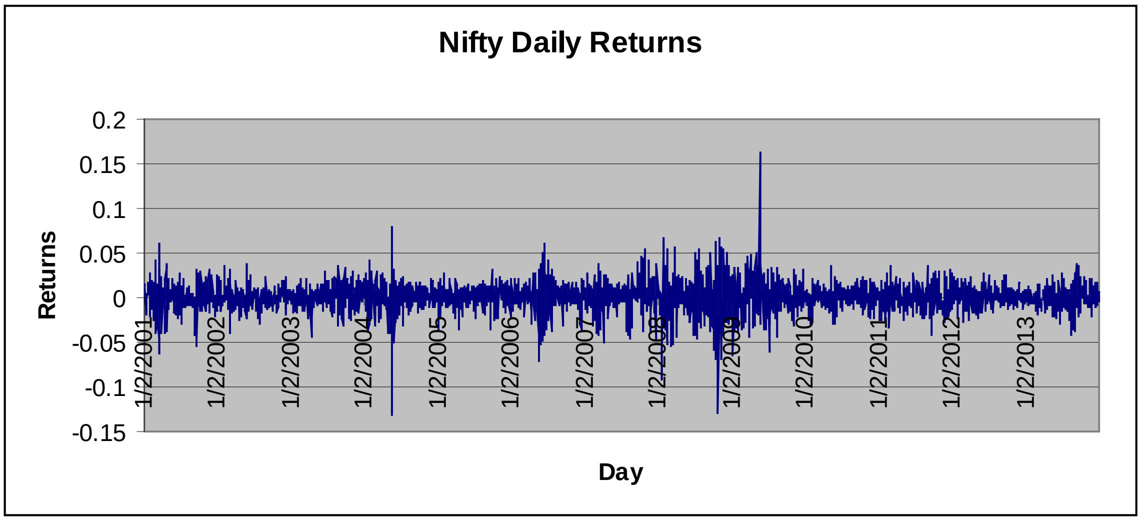
$$\ln\sigma_t^2 = \omega + a\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta\ln\sigma_{t-1}^2 \tag{6}$$

The logarithmic form of the conditional variance implies that the leverage effect is exponential, and that forecasts of the variance are non-negative. The asymmetry effect is highlighted by γ. This estimated parameter must be significant and lower than zero.

There is a difference between the Eviews specification of the EGARCH model and the original Nelson model. Estimating this model will yield identical estimates to those reported by Eviews except for the intercept term ω. For example if the error term is normally distributed the difference will be $\alpha_1\sqrt{2/\pi}$. In this study it has been assumed that error terms follow student t distribution.

All calculations have been done with the help of Eviews7 software.

Figure 1: Nifty Daily Returns



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 -0.13054 to 0.163343. So a wide range of fluctuation in daily returns could be witnessed. The mean return during the whole study period is 0.000498 which is very near to zero.

Table 1: Descriptive Statistics of the Daily Return

Mean	0.000498
Median	0.001061
Maximum	0.163343
Minimum	-0.13054
Std. Dev.	0.015783
Skewness	-0.263538
Kurtosis	11.60125
Jarque-Bera	10040.47
Probability	0.000000
Observations	3245

Distribution of Data

Since skewness is negative, there is 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. Moreover, from the highly significant large JB statistic it is clear that the daily NIFTY returns are not normally distributed.

Volatility Clustering

The graphical representation of the NIFTY daily returns for the selected sample period has been represented in the Fig. 1.

Figure 1 indicates apparent volatility clustering. Table2 reports the results of Q statistic. It could be seen that Q statistic at each lag is highly significant. Therefore, there is significant autocorrelation in daily squared returns. Hence volatility clustering is present during the study period. Fama's (1965) also observed that stock returns exhibit volatility clustering where large returns tend to be followed by large returns and small returns by small returns leading to contiguous periods of volatility and stability.

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

Lag	AC	PAC	Q-Stat	Prob
1	0.074	0.074	17.632	0.000
2	-0.048	-0.053	25.001	0.000
3	-0.009	-0.002	25.285	0.000
4	0.011	0.010	25.705	0.000
5	-0.009	-0.011	25.961	0.000
6	-0.046	-0.044	32.821	0.000
7	0.015	0.021	33.532	0.000
8	0.039	0.032	38.465	0.000
9	0.023	0.019	40.164	0.000
10	0.025	0.027	42.254	0.000
11	-0.014	-0.017	42.884	0.000
12	-0.010	-0.007	43.181	0.000
13	0.032	0.034	46.426	0.000
14	0.057	0.055	57.069	0.000

Lag	AC	PAC	Q-Stat	Prob
15	-0.005	-0.010	57.168	0.000
16	-0.006	0.001	57.285	0.000
17	0.038	0.034	61.952	0.000
18	-0.010	-0.019	62.254	0.000
19	-0.006	0.004	62.367	0.000
20	-0.059	-0.056	73.655	0.000
21	0.003	0.007	73.676	0.000
22	0.006	-0.004	73.801	0.000

Unit Root Test

The PP test result is reported in the Table3. The computed value of PP is -52.90* which is far greater (in absolute term) than the critical value of -3.43 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	-52.90*

* significant at 1% level

Estimated Results of EGARCH (1, 1) Model

The results of mean equation (5) and variance equation (6) have been reported in Table 4.

From Table 4 it appears that the coefficient of the dummy variable in the mean equation is highly significant. Hence, the effect of recent financial crisis has a significant effect on NIFTY returns and volatility.

The asymmetry effect is highlighted by γ. Because this parameter is significant and lower than zero (-0.107053), the daily volatilities of the NIFTY returns are characterized by asymmetry. The new negative information determines a higher volatility compared with the new positive information.

To see whether any ARCH effect is still present or not Q statistic on the squared residuals of estimated model has been calculated and the result has been reported in Table 5.

Table 5: Box-Pierce Q Statistics of Squared Residuals

Lag	AC	PAC	Q-Stat	Prob
1	-0.006	-0.006	0.1228	0.726
2	0.006	0.006	0.2446	0.885
3	0.013	0.013	0.8036	0.849
4	0.019	0.019	1.9885	0.738
5	-0.001	-0.001	1.9913	0.850
6	0.012	0.011	2.4354	0.876
7	0.006	0.005	2.5434	0.924
8	-0.008	-0.008	2.7426	0.949
9	-0.008	-0.008	2.9349	0.967
10	0.037	0.036	7.3756	0.690
11	-0.015	-0.014	8.0801	0.706
12	-0.007	-0.007	8.2334	0.767
13	0.031	0.031	11.444	0.574
14	0.012	0.012	11.949	0.610
15	0.023	0.024	13.683	0.550
16	0.017	0.016	14.680	0.548
17	-0.010	-0.012	15.000	0.596
18	-0.014	-0.015	15.649	0.617
19	0.005	0.004	15.744	0.674
20	0.026	0.024	18.005	0.587
21	-0.002	0.000	18.015	0.648
22	0.020	0.021	19.350	0.624

Table 4: Regression Results of Mean and Variance Equations

Variable	Coefficient	Std. Error	z-Statistic	Prob.
Mean Equation				
C	0.000656	0.000208	3.154859	0.0016*
DUM	0.001337	0.000607	2.204246	0.0275**
	Variance Equation			
ω	-0.508537	0.060245	-8.441113	0.0000
α	0.218968	0.022086	9.914454	0.0000
γ	-0.107053	0.012936	-8.275899	0.0000
β	0.960938	0.006195	155.1267	0.0000

* significant at 1% level; ** significant at 5% level

Since none of the Q statistic at any lag is significant, so no ARCH effect is left.

CONCLUSION

In this paper conditional volatility of return series calculated from daily time series data of CNX NSE NIFTY have been analyzed. The study reveals that the return series is leptokurtic and returns are serially correlated. Hence, strong evidence is there in favour of volatility clustering. Moreover, a modest attempt has also been made to fit the data into EGARCH (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, EGARCH (1, 1) model could be a good fit to explore the conditional variances. From the large β coefficient (0.96) it appears that volatility persists over a long period of time in the said market.

From the empirical result [γ<0] it is also clear that *Leverage Effect* is present in the market. Furthermore, as γ coefficient is not equal to zero there is news asymmetry in the market and the bad news has more effect on volatility than the good news.

Finally, since the coefficient of the dummy variable in the mean equation is highly significant, the effect of recent financial crisis has a significant effect on NIFTY returns and volatility.

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