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Nature of Volatility in Indian Stock Market – An Empirical Analysis

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Abstract—*The plots of market volatility can act as an electrocardiogram, reflecting the pulse of capital markets. It has been identified that stock indices in many developed as well as developing economies exhibit volatility clustering, which in finance literature is called "time varying conditional volatility". The purpose of the study is to characterize the time varying volatility of the Indian capital market in the long run. The study focus on aspects like time varying volatility, predictability of volatility, the symmetric nature of volatility towards positive and negative shocks, and the explanation for high volatility ofIndian capital marketfor a period of 20 years. This study has analyzed the price data as well as return data of NSE CNX Nifty. We have used GARCH (1, 1) Model to estimate time varying volatility and TARCH (1, 1) Model, to measure asymmetric volatility effect. The magnitude of volatility was found to fluctuate between periods and showed a repeating trend over time. It validates theasymmetric nature of volatility in Indian capital market and volatility clustering in the long run and give insights on the predictability of volatility.*

Keywords: *volatility, volatility clustering, predictability of volatility, asymmetry, stock market, TARCH model, GARCH model.*

1. INTRODUCTION

Investors are always worried about the current and forthcoming value of their investments. A highly volatile capital market makes it a playground for speculators and insider traders rather than a secure investment avenue for the real investors. This is attributed to the lack of confidence and the perception of greater risk among the investors in investing in such markets. If this view becomes universal, investors maysimply withdraw from the market.

The effectiveness of portfolio diversification and risk hedging strategies,to a larger extend, depends on the abilityto forecast variance and covariance, as well as volatility. This will also be a major determinantwhile pricing derivative instruments. Considerable efforts have been made recently in order to estimate and predict the aggregate stockmarket volatility. It has been identified that stock indices in many developed as well as developing economies exhibit volatility clustering, (i.e. higher volatilities followed by periods of higher volatility and lower volatilities followed by periods of lower volatility). In financial literature this phenomenon is termed as 'time varying conditional volatility'.

2. OBJECTIVE

The objective of this study is to characterize the long term volatility of Indian capital market by concentrating on the aspects of 1)time varying volatility, 2)predictability of volatility, 3)asymmetric nature of volatility towards negative and positive shocks, and finally 4)the explanations for higher volatility for a period of 20 years spanning from 1994 to 2014.

This paper is arranged in the following manner. Next section deals with a brief discussion about the data used and its properties. The subsequent section describes the measurement tools used for the study,followed by the discussion of empirical findings and finally ends with a summary and conclusion.

3. DATA AND ITS PROPERTIES

The data used in this empirical study are 5-day week daily time series data on closing price of S&P CNX nifty for the period from October 1994 to September 2014. The stock market index data was obtained from the database of NSE website.

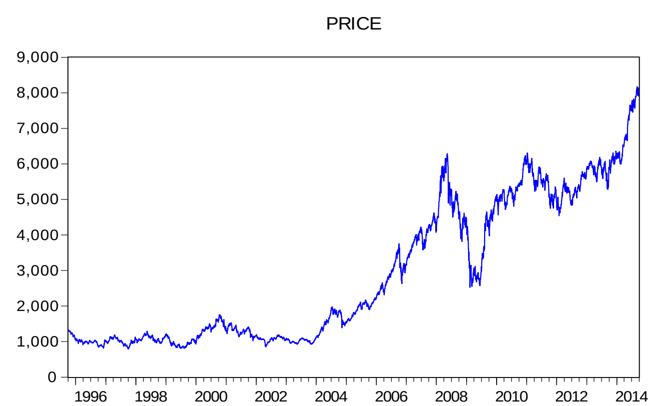

Fig. 1: Market index from 1994-2014

The time series data is pictorially presented in *FIg. 1* and *FIg. 2*. It is easy to identify that the price movements were more or less stableup to the beginning of the year 2004. Thereafter, the trend began to change. There was a higher rate of increase in returnfrom 2004 onwards and it prevailed in the Indian stock market till the beginning of 2008. Thiscan be characterized as the result of the economic boom that prevailed in the global economy till it was affected severely by the financial crisis of 2008. The price history clearly indicates that the Indian stock markets had brutally suffered from the financial crisis, where the Nifty index fell more than 3000 points within few months in 2008, and the trend continued till the beginning of 2009.By then the stock marketsslowly started its recovery from the crisis and again reached new heights by the middle of the year 2010. Again it faced a downfall in 2011 mainly attributed to stock market bubbles leading to mass entry and exit of investors. However,since 2012 the Indian capital market exhibits an upward trend in a continuous fashion. This trend is fuelled by many factors such as entry of more Foreign Institutional Investors, setting up of trading terminals abroad, demataccount trading facilityetc.

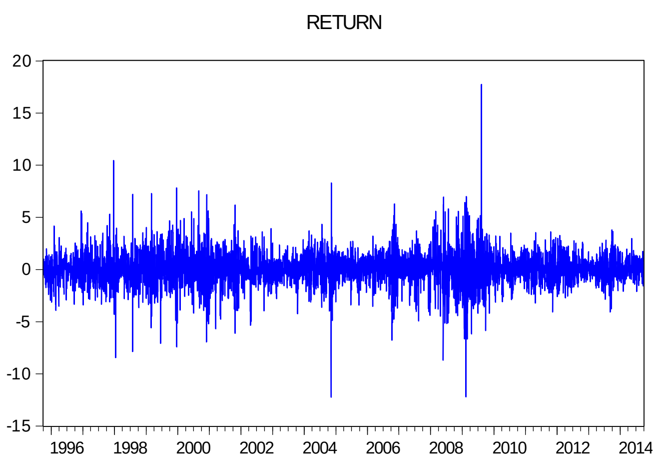

Fig. 2: Market return from 1994-2014

The daily return series (computed as the logarithm of the price today divided by the price yesterday) is pictured in the *FIg. 2*. It is very clear from the FIg. that the size of variation is occasionally higher compared to the normal trend. Another important feature that is to be highlighted is the higher volatility when returns are falling and the least volatility when the returns are increasing.

Table 1: Return characteristics

Mean	**0.049251**
Median	0.074331
Maximum	17.74407
Minimum	-12.23774
StdDev	1.596167
Skewness	0.062731
Kurtosis	10.12113
Jarque-Bera	10472.84
Probability	0.000000
Sum	244.0390
Sum SqDev	12621.55
Observations	4955

*Table 1*shows the descriptive statistics of the return time series data under our study.It summarizes the important characteristics of return data. The data has its mean closeto zero (0.049) and the standard deviation equal to 1.59.Jarque-Bera is a statistical test that determines whether the series is normally distributedor not. This statistic measures the difference of the skewness and the kurtosis of the series with those from the normal distribution. The null hypothesis is that the series is normally distributed against the alternative that it is not. Evidently, the Jarque-Bera statistic confirmed the rejection of the null hypothesis of normal distribution with a significant statistic for the period.

Kurtosis measures the peakedness or flatness of the distribution of the series.If the returns are normally distributed, kurtosis should be three. But kurtosis of our data is very high (10.113), indicating a leptokurtic curve which is sharper than a normal distribution, with the values concentrated around the mean and having thicker tails. This means high probability for extreme values.Lastly, skewness is a measure of asymmetry of the distribution of the series around its mean. The statistic for skewnessis greater than zero implying that the stock market returns are positively skewed implying a right skewed distribution where most values are concentrated on left of the mean, with extreme values to the right.

4. METHODOLOGY

In finance, volatility is a measure for variation of price of a financial instrument over time. Historic volatility is derived from time series of past market prices. The standard deviation essentially reports a fund's volatility, which indicates the tendency of returns to rise or fall drastically in a short period of time. The security that is volatile is also considered higher risk because its performance may change quickly in either direction at any moment.A number of alternative methods are used in finance literature to measure volatility, which ranges from the simple standard deviation method to the well advanced econometric models like Autoregressive Conditionally Heteroscedastic (ARCH) class of models. Simple Standard deviation is the most commonly used measure of volatility in financial analyses. Even though it is widely used, it may not be the appropriate estimate. In this method, the volatility can be estimated for a fixed period. But the major limitation attached with this method is that if the time period is too long, then it will not be relevant for current volatility and if it is too short, it will be very noisy. An alternative way to measure volatility is Rolling Standard Deviation method, which is calculated using a fixed number of observations. The start and end dates of the sample period is then rolled forward for each observation.

The assumption of equal weights in the above mentioned methods seems unattractive. More recent events should be more relevant and therefore it must have higher weights. The ARCH class of models proposed by Engle (1982) facilitates these weights to be estimated and thus it allows the data to forecast the variance by using best weights.Moreover, since the volatility cannot remain constant over a period of time a theory of dynamic volatility is needed, and this gap is filled by Auto Regressive Conditional Heteroskedasticity (ARCH) models and their different variants (Engle 2003). In fact these variants of ARCH/GARCH models have become common tools for volatility related studies.Currently, the most used generalization of this model is GARCH parameterization of Bollerslev (1986), which facilitate the weights on past squared residuals todecline at a rate, which is estimated from the sample data. Exponential GARCH or EGARCH model is another important generalization, introduced by Nelson (1991). This model recognizes that negative returns are better predictors of volatility than positive returns. So, large price declines forecast greater volatility than large price increases. The simple GARCH model fails to capture the negative asymmetry, because its conditional variance depends upon the magnitude of disturbance term, but not the sign. But the EGARCH model can capture the tendency of higher volatility associated with negative shocks. Subsequently a number of modified models were derived from EGARCH model. Threshold ARCH or TARCH, GJR GARCH etc. are examples for such modified models. There are still many others in the GARCH family such as AARCH, NARCH, PARCH, PNP-PARCH,STARCH and Component ARCH etc. which are used according to the nature and desirability of the data.

We can see from the *FIg. 2*, thatthe periods of high volatility tends to be followed by periods of high volatility and periods of lower volatility tends tobe followed by periods of lower volatility. This shows that our data is conditionally Heteroscedastic. If such a phenomenon exists in the data, it shows that conditional heteroscedasticty phenomenon prevail in the data. This result suggest that we can introduce ARCH or GARCH class of models to match and analyze it.

5. EMPIRICAL FINDINGS

Here we are estimating the volatility by using the ARCH class of models. The basic model to estimate is the GARCH (1, 1) model. In this model, the effect of a return shock on current volatility declines geometrically over time by way of giving proper weights. We have already observed in the data that the volatility will be more while prices are declining than that when price are increasing. So, we will use an asymmetric volatility model called threshold ARCH/TARCH (1, 1) model. In this model good news and bad news will have different impact on conditional variance.

Table 2: Statistical results of TARCH model

Variables	Coefficient	Std Error	z-Statistics	Probability
Constant	0.055689	0.005416	10.28195	0.0000
Positive Return	0.063680	0.005733	11.10775	0.0000
Negative Return	0.103985	0.009512	10.93153	0.0000
Previous Volatility	0.870097	0.006257	139.0596	0.0000

The statistical results of TARCH (1, 1) model is given in *Table 2*. As mentioned, there are two types of news, good and bad. It clearly shows that negative returns have a higher impact (0.103985) on the current volatility than the impactof positive returns (0.063680). This observation directs towards concluding on the existence of asymmetric volatility towards bad news and good news. The 'previous volatility' also has a relevant role (0.870097) in current volatility. More than 87% of current volatility is determined by the previous level of volatility. So, if a trend of higher volatility happened in the market, it will be continued for a period of time. It is directing towards the evidence of having volatility clustering phenomena.

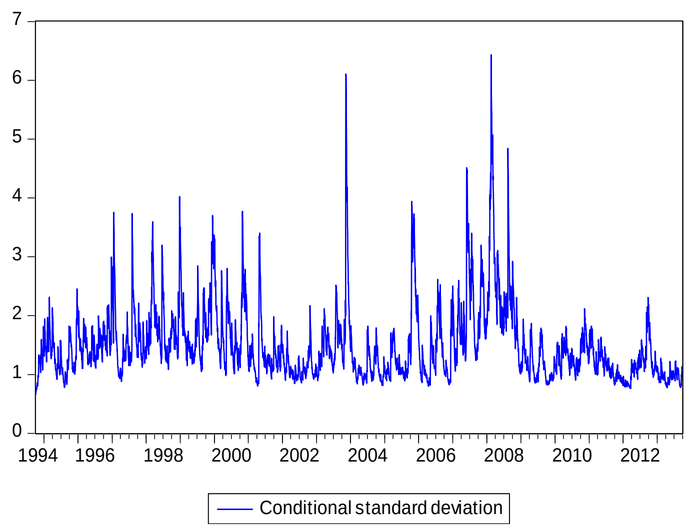

FIg. 3: Conditional Standard Deviation of S&P CNX Nifty from 1994 to 2014 estimated on the conditional variance equation of TARCH (1,1)

Conditional Volatility for the return series formulated by the TARCH (1, 1) model is depicted in *FIg. 3*. It clearly shows a transparent proof for volatility shifting over a period of 20 years. The level of volatility was comparatively lesser from 1994 to 1996. Afterwards it became more violent but more or less the same pattern was repeating and it continued till the beginning of 2001.During this period a series of security scams were revealed in Indian capital Market. Subsequently another pattern started with less volatility and it continued till the end of 2002.2003 was another high volatile period to the market. Volatility clustering again started in 2004 and gradually the most volatile period in history started by the end of 2005 and continued till the economy was hit by the repercussions of the great depression of 2008. Global financial crisis fueled the record levels of volatility in the period of 2006 to 2009. Indian capital market exhibit an almost tranquil nature in terms of volatility from 2010 onwards. Thus, from the FIg. of conditional volatility, we can draw a conclusion of existence of volatility clustering in the Indian capital market as well as its predictability. It is also supported by the coefficient value (0.8700) of 'Previous Volatility' in the *Table 2*.

One of the major reasons for higher volatility inIndian stock market is the domination of market by speculators and noisy traders. They manipulate the prices at the cost of general investors and drive the prices away from the fundamental level, causing excessive fluctuations in share prices. The cost associated with high volatility is huge. Investors may view the market as the province of speculators and insider traders and they will shift towards other investment avenues. It will seriously affect the fund mobilization through capital market. The bulk investment and withdrawal of Foreign Institutional Investors is yet another important factor for violent stock return fluctuations in the Indian capital market.

6. SUMMARY AND CONCLUSION

This study characterizes the volatility of daily stock return in the Indian capital market for a period of 20 years started from 1994 to 2014. Data used for the analysis is daily price return of S&P CNX Nifty. While analyzing the daily return series, it was found that market is sometimes tranquil and sometimes volatile, with the trend repeating itself over time. It is termed as volatility clustering. It gave a rough idea about the predictability of volatility. By using TARCH (1, 1) model we found that the periods of high as well as low volatility tend to cluster together and also that the volatility shows high persistence and is predictable. Another characteristic tested with the help of TARCH (1, 1) model is the asymmetric volatility effect and the results validates the asymmetry in volatility.

Conditional volatility generated by TARCH (1, 1) model also shows clearly a strong evidence for volatility shifting over a period of last 20 years in the Indian capital market. Levels of volatility were comparatively lower from 1994 to 1996 followed by high volatility for a period of next five years. 2002 and 2003 were periods of low volatility. But afterwards it had more complicated and the most volatile situation in the market. 2010 onwards Indian capital market was found to be tranquil and growing. The social cost associated with high volatility is huge. Real investors may lose their confidence and they may simply withdraw from the market. The most important reasons behindhigh volatility of Indian capital market includes domination of speculators and the bulk investments and withdrawals by FIIs. Like that of an electrocardiogram, the plots of volatility reflect the pulse of financial market by measuring the rate of price changes over the period of study.

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