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Measuring the Time Varying Volatility of Futures and Options

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ABSTRACT

In industrialized countries, apart from money market and capital market securities, a variety of other securities like derivatives are available for investment and trading. There is a demand in India to introduce these securities, derivatives are highly speculative, risky and increase volatility. Volatility is the measure of how far the current price of an asset deviates from its average past prices. Pricing of securities is supposed to be dependent on the volatility of each asset. Matured market/developed markets continue to provide over long period of time high returns with low volatility. ARCH, Engle's ARCH, GARCH, GARCH (1, 1) are the methods which are deployed in this study for modeling financial time series that exhibits time-varying volatility of futures and options. The study finds an evidence of time varying volatility, which exhibits clustering, high persistence and predictability of futures and options in Indian market.

Key words: Time varying volatility, risk and return, derivatives, futures and options

INTRODUCTION

The security exchanges and regulators around the world face many challenges. Given the current trend towards liberalisation and globalisation of capital markets, the democratization of information technology, the development of new lower-cost trading mechanisms led to the advert of derivatives in developed and emerging markets like India. Equity derivatives in India were started in 1997 as part of capital market reforms to hedge price risk. Accordingly, the stock index futures were introduced first in BSE Sensex in June 9, 2000. NSE also commenced its trading on June 12, 2000 based on S and P Nifty. In India trading in options on Indices began in June 2001 and option as an individual stock began in July 2001 on the BSE and the NSE (Selvam and Raja, 2007).

Futures are standardised contracts between the buyers and sellers, which fix the terms of the exchange that will take place between them at some fixed future date. In practice they traded mostly for hedging, speculation and realising the money difference. They are similar to forward contracts in some concepts and differ from the latter in many aspects.

Options are contract between the contract writers and buyers which obligate the former and entitle the latter to sell/buy stated assets as per the provision of the contract. The major types of the options are stock options, bond options, currency options etc.

Volatility most frequently refers to the standard deviation of the change in value of a financial instrument with a specific time horizon. It is often used to quantify the risk of the instrument over that time period. Volatility is an important indicator of dynamic fluctuations of stock market prices. The term volatility is simply synonymous with risk. The high volatility is the reflection of high risk, because the security values are not dependable and the capital markets are not regarded as efficient.

In the literature, time varying conditional volatility is modeled through the Seminal Autoregressive Conditional Heteroskedasticity (ARCH) mode of Engle (1982) and its subsequent parsimonious representation through the Generalized ARCH (GARCH) of Bollerslev (1986). But these two models do not capture the asymmetric nature of volatility. Hence (GARCH (1, 1)) is used in this study for forecasting future volatility. This GARCH (1, 1) model incorporates the asymmetric volatility of the component exactly.

Theoretical background: The growth in the derivatives markets raised the question that, Have the derivatives market (Futures and options) become more volatile? In order to answer this question, one has to examine the partial volatility in the derivative markets especially in future and options. Hence the present study is an attempt to forecast the time varying volatility of futures and options with the help of GARCH (1, 1) model. There are many empirical studies evidencing the factors which have caused the markets to become more volatile. They are (1) The low P/E effect (2) Low-priced stock (3) The small firm and neglected firm effects (4) Market over reaction (5) Computerized tools have made it easier to trade large amounts of stocks continuously (6) Increasing political uncertainty is unnerving the market (7) Round the clock trading has reduced wait and watch reflex on the part of investors (8) The existance of asymmetric information problem (9) Runs of financial intermediaries (10) Herd behaviour on the part of investors (11) Excessive speculation (12) Fluctuation in the prices of real assets (13) Changes in exchange rate more than justified by changes in economic fundamentals (14) Instability of commodity prices (15) The January effect (16) The weekend effect and (17) The persistence of technical analysis.

A study Forecasting the Time Volatility of Emerging Asian Stock Market Index by Selvam and Raja (2007) finds an evidence that volatility is the measure of how for the current price of an asset deviates from its average past prices. Greater the deviation, greater the volatility. It indicates the strength or conviction behind a price movement of time varying volatility, which exhibits clustering, high persistence and predictability for almost all the Asian market indices in the sample. Selvam and Indhumathi (2009) in their study entitled Index Futures and Options Introduction - A case of Spot Market Volatility in BSE (Bombay Stock Exchange). This study examined the empirical relationship between financial derivatives products and the BSE spot market volatility. The analysis is done using the GARCH models to study volatility between June 1997 and December 2007. The empirical evidence is mixed and the results suggest that there has been an enhancement in the volatility of spot market index in the post-derivative period. Index Futures and Options Introduction on the Spot Market Volatility in NSE by Selvam and Indhumathi (2008) explain that the trading in derivatives is expected to affects the spot market for the underlying assets. Thus the introduction of index futures and options should not have any direct effect on the underlying spot market. However, in practice financial markets are never perfect and hence some effects of derivative markets are bound to exist on the underlying spot market.

Testing the Indian Capital Market Volatility with respect to Buyback Announcement by Raja et al. (2009) pointed out that the efficient and integrated capital market is an important

infrastructure that facilitates capital formation. A capital market is said to be volatile with respect to corporate event announcement (stock split, buyback, right issue, bonus announcement, mergers and acquisition, dividend announcement etc.) contained information's and it disseminations.

Najand (2002) examined whether the stock index future price is volatile or not. The researcher concluded that nonlinear GARCH models dominated linear models utilizing the rise and MAPE error statistics and EGARCH appears to be the best model for forecasting stock index futures price volatility. Tong and Maurice (2002) pointed out that there was no consensus about the cause for higher volatility at the market opening than at the market closing in the US market. However, the autocorrelation of the open to open return series also indicates that the temporary price deviation at the market opening is not significant. Brzeszcznski (2000) estimates various types of ARCH process including GARCH and asymmetric ARCH/GARCH specifications. The empirical applications were based on the data set to be composed of the major international stock market indices. The obtained result from this project was useful to verify the hypothesis about the stock market efficiency. Wei (2002) found that the GARCH model was best when the estimation sample did not contain extreme observations such as the stock markets crash and that the GJR models cannot be recommended for forecasting. Crawford and Fratantoni (2003) prescribed that while price changes on any particular home price changes were forecastable. The regime switching models were a compelling choice for real estate markets that have historically displayed boom and bust cycles. Brooks and Burke (2003) forecasted both the conditional mean and the conditional variance of two high frequency exchange rate series. The analysis indicated that the use of this model did lead to significantly improved forecasting accuracies for the conditional variance. In some cases, these improvements were by no means universal. Shenbagaraman (2003) assessed the impact of introducing index Futures and Options contracts on the volatility of the underlying stock index in India. The author found that the introduction of derivatives contracts improved liquidity and reduced informational asymmetries in the market. Further, the author suggested that Futures and Options trading have not led to a change in the volatility of the underlying stock index but the nature of volatility seems to have changed past futures.

From the literature cited above, it is clear that most of the studies measured the time variance volatility of various market indices. It is understood that almost all the market indices have the volatility. Majority of the studies were undertaken with individual markets indices but only few studies were undertaken in derivatives. Hence the present study makes an attempt to test the time varying volatility of futures and options of Indian market.

Statement of problem: Due to uncertainty in the share market movements, individual as well as institutional investors bear the risk of heavy loss. The share prices may fall or rise in the future especially in derivatives market and this volatility of the market presents a greater risk to the investor. Hence the volatility estimation in derivatives market is important for several reasons. The pricing of securities is supposed to be dependent on volatility of the markets. Indian derivative markets have started becoming more efficient contrary to the popular perception in the recent past. Volatility has not gone up. Intra-day volatility is also very much under control and has come down as compared to past years. Peripatetic stock prices and their volatility have now become endemic features of securities markets. The growing linkage of derivative market in currency, commodity and stock with world markets and existence of common players have spread volatility across the markets.

The dynamic behavior of stock index returns (Futures and Options) and its volatility have been investigated extensively. As a result, several stylized facts have emerged. First, at high frequencies, stock returns are positively correlated. The autocorrelation in index returns has been attributed to no synchronous trading. Second the unconditional distributions appear to be excessively leptokurtic when compared to the normal distribution. To deal with this problem, many researchers have used more general distributions (Mandelbrot, 1963; Fama, 1965; Nelson, 1991). Third short term returns invariably exhibits volatility clustering where tranquil periods of small returns are interspersed with volatility periods of large returns. The technical term given to this is Autoregressive Conditional Heteroskedasticity (ARCH). This type of behavior has been modeled very successfully with ARCH and GARCH models (Engle, 1982; Bollerslev,1990). Fourth, changes in stock prices tend to be negatively related to changes in volatility (Black, 1976; Christie, 1982). With this background the present study investigate the time varying volatility of futures and options of Indian stock market. More specifically, the study indicates whether volatility is time varying and predictable in the market with the help of GARCH (1,1) model.

To measure the time varying volatality of futures and options is important to investors to make the appropriate investment decision in derivatives markets. It helps investors, fund managers and financial analysts to predict the volatality in the nifty futures and options indices. GARCH is one of the suitable models to measure the volatality in the derivatives market.

Objectives:

- To analyse the varying perceptions about the volatility
- To measure the time varying volatility of Nifty futures index
- To predict the time varying volatility of Nifty option index
- To compare the degrees of volatility between Nifty futures and Nifty Options

Hypotheses:

- H₁: Ljung-Box-Pierce Q-Test proves Nifty Future index does not have hetroskedasticity
- H₂: Ljung-Box-Pierce Q-Test proves Nifty option index does not have hetroskedasticity
- H₃: Engle's ARCH Test proves Nifty Future index does not have hetroskedasticity
- H₄: Engle's ARCH Test proves Nifty option index does not have hetroskedasticity

Period of study: The study undertakes the analysis of monthly series of data for a period of seven years from June 2000 to December 2009. The study covers the entire period since inception of future and option till 2009.

Sources of data: The present study mainly uses secondary data. The information about share price and sample indices was obtained from the websites www.yahoofinance.com and www.indiainfoline.com. The information regarding growth of Futures and Options are obtained from NSE website www.nseindia.com and NSE official directory. The extensive use of books, journals and magazines was made for collecting the required information.

Tools used in the study

GARCH (1, 1) model: GARCH stands for Generalized Autoregressive Conditional Hetroskedasticity. It takes into account excess kurtosis (i.e., fat tail behavior) and volatility clustering, two important characteristics of financial time series. It provides accurate forecasts of

variances and co-variances of asset returns through its ability to model time - varying conditional variances. Bollerslev (1987) later proposed a more generalised form of the ARCH (m) model appropriately termed the GARCH (p, q) (General-ARCH) model. The GARCH (p, q) model has two equations which can be written as:

$$\sigma_{n}^{2} = w + a_{1}\sigma_{t-1}^{2} + b_{1}\varepsilon_{t-1}^{2} \tag{1}$$

This model is often sufficient to describe the conditional mean in a financial returns series. In the conditional variance mode (σ_{t-1}^2), the variance forecast consists of a constant plus a weighted average of last period's forecast ($a_1\sigma_{t-1}^2$) and last period's squared disturbance ($b_1\epsilon_{t-1}^2$).

Autocorrelation: Autocorrelation is a reliable measure for testing the independence of random variables in return series. The serial correlation coefficient measures the relationship between the values of a random variable at time t and its value in the previous period. The autocorrelation can be quantified by the preceding qualitative checks for correlation using formal hypothesis tests, such as the Ljung-Box-Pierce Q-test, Ljung-Box-Pierce Q-squared test and Engle's ARCH test.

Ljung - box - Pierce Q-test: Ljung-Box-Pierce Q-test is implemented to test the departure from randomness based on the ACF of the data. The Q-test is most often used as a post-estimation lack-of-fit test applied to the fitted innovations (i.e., residuals) and can also be used as pre-fit analysis because the default model assumes that returns are just a simple constant plus a pure innovation process:

$$LB = n(n+2)\sum_{k=1}^{m} \left\lceil \frac{pk^2}{n-k} \right\rceil \approx x^2 m \tag{2}$$

Where:

P^K = Autocorrelation coefficient at k and

N = No. of observations

Engle's ARCH test: Engle's test is implemented to test the presence of ARCH effects. Under the null hypothesis, a time series is a random sequence of Gaussian disturbances (i.e., no ARCH effects exist). This test statistics is also asymptomatically Chi-Square distributed. We can also show significant evidence in support of GARCH effects (i.e., hetroskedasticity).

Returns: To apply GARCH model, monthly closing values are converted into returns. The following model is used to find the yield of spot rates. Periodic compounding defines the transformation as:

$$y_{t} = \frac{P_{t+1} - P_{t}}{P_{t}} \tag{3}$$

Limitation of the study: This study, like any other descriptive research, is not devoid of limitations. To list out a few:

- The analysis is confined to only secondary data
- All the limitations of the models (GARCH (1,1)) deployed are applicable to this study also
- This study is restricted to only a set of indices of India

RESULTS AND DISCUSSION

Time-varying risk: This study focuses on the Nifty Index Futures and Nifty Option Index by analyzing the closing values measured at monthly intervals. As stated earlier, monthly closing values for the period of nine years and six months are taken into account for analysis.

Figure 1 displays the movement in the closing values of Nifty Future Index. It is understood from the above figure that Nifty Future Index falls on bullish trend. The prices of the indices in the market are going upward trend. Figure 2 shows the movement in the closing values of Nifty Option Index. This figure clearly reveals the fact that both the indices are in bullish trend.

Figure 3 exhibits the returns chart of Nifty Future Index while, where prices of indices moving up and down through out the period, but during the initial period it was high, it shows that prices of the indices traded in the market are not uniform, there was high volatile. It is very difficult to investor to take appropriate investment decision. Figure 4 displays the returns chart of Nifty Option Index. These figures clearly reveal the fact that both indices are volatile from the beginning of the study period.

Figure 5 shows the curve of autocorrelation of the returns of Nifty Future Index, it very clear from the figure that the calculated value is less than the table value which clearly indicates that there is significant correlation between the values. Hence Nifty Future index does not have hetroskedasticity.

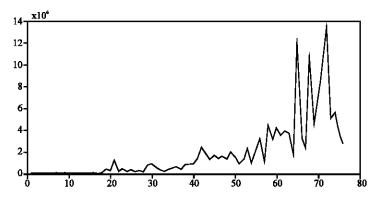


Fig. 1: Movement of nifty future index

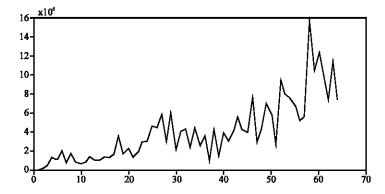


Fig. 2: Movement of nifty option index

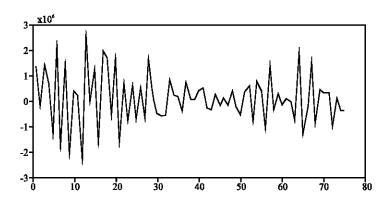


Fig. 3: Returns for nifty future index

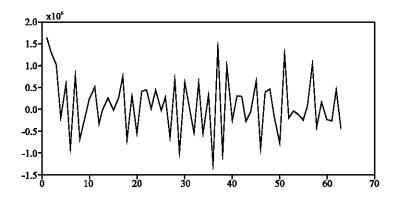


Fig. 4: Returns for nifty option index

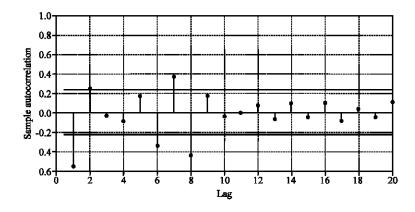


Fig. 5: Autocorrelation function of nifty future index

Figure 6 displays the curve of autocorrelation of the returns of Nifty Option Index. It displays the sample autocorrelation of the returns, along with the upper and lower standard deviation. This is based on the assumption that all autocorrelations are zero beyond lag zero.

Measuring correlation: According to Ljung-Box-Pierce Q-test and Engle's ARCH test when the statistical value is higher than the critical value, the auto correlation does exist, which denotes that

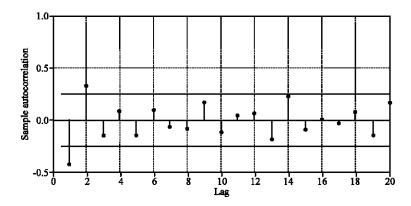


Fig. 6: Autocorrelation function of nifty option index

Table 1: Ljung-box-pierce Q-test for nifty future index

Hypothesis	Parameters	Statistical value	Critical value
1.0000	0.0000	26.8986	18.3070
1.0000	0.0000	26.8686	24.9958
1.0000	0.0000	34.1654	31.4104

Table 2: Ljung-box-pierce Q-test for nifty option index

Hypothesis	Parameters	Statistical value	Critical value
1.0000	0.0000	18.8079	18.3070
1.0000	0.0000	30.8058	24.9958
1.0000	0.0000	39.4216	31.4104

there exists hetroskedasticity. Thus both the tests are used in this study to examine the auto correlation of futures and options.

Table 1 shows the Ljung-Box-Pierce Q-Test for Nifty Future Index. It is understood from the table that the calculated statistical values (26.8986, 26.8686, 34.1654) are higher than the critical table values (18.3070, 24.9958, 31.4104) which clearly proves that there is significant correlation between the values when tested upto 10,15 and 20 lags in both Nifty Future and Option Index at 0.005 level of significance. Thus the null hypothesis (H1: Ljung-Box-Pierce Q-Test proves Nifty Future index does not have hetroskedasticity) is rejected.

Table 2 depicts the Ljung-Box-Pierce Q-Test for Nifty Option Index. It is understood from the table that the calculated statistical values (18.8079, 30.8058, 39.4216) are higher than the critical table values (18.3070, 24.9958, 31.4104) which prove that there is significant correlation between the values when tested upto10,15 and 20 lags in both Nifty Future and Option Index at 0.005 level of significance. Thus the null hypothesis (H1: Ljung-Box-Pierce Q-Test proves Nifty Future index does not have hetroskedasticity) is rejected.

Table 3 displays the Ljung-Box-Pierce Q squared-Test for Nifty Future Index. It is clear from the table that critical table values (18.3070, 24.9958, 31.4104) are lesser than the calculated statistical values (32.2419, 32.3834, 32.8650) which clearly proves that there is significant correlation between the values when tested upto10,15 and 20 lags in both Nifty Future and Option Index at 0.005 level significance. Thus the null hypothesis (H2: Ljung-Box-Pierce Q-Test proves Nifty option index does not have hetroskedasticity) is rejected.

Table 3: Ljung-box-Pierce Q-test (squared) for nifty future index

Hypothesis	Parameters	Statistical value	Critical value
1.0000	0.0004	32.2419	18.3070
1.0000	0.0057	32.3834	24.9958
1.0000	0.0349	32.8650	31.4104

Table 4: Ljung-Box-Pierce Q-test (squared) for nifty option index

Hypothesis	Parameters	Statistical value	Critical value
1.0000	0.0027	26.9321	18.3070
1.0000	0.0272	27.1993	24.9958
1.0000	0.0969	28.5543	31.4104

Table 5: Engle's ARCH test for nifty future index

Hypothesis	Parameters	Statistical value	Critical value
1.0000	0.0000	51.1407	18.3070
1.0000	0.0000	48.0206	24.9958
1.0000	0.0012	44.6019	31.4104

Table 6: Engle's ARCH test for nifty option index

Hypothesis	Parameters	Statistical value	Critical value
1.0000	0.0464	18.5494	18.3070
1.0000	0.0376	26.0440	24.9958
0	0.1155	27.7468	31.4104

Table 4 exhibits the Ljung-Box-Pierce Q squared-Test of Nifty Option Index. It is clearly understood from the table that the critical table values (18.3070, 24.9958, 31.4104) are lesser than the calculated statistical values (26.9321, 27.1993, 28.5543). This proves that there is significant correlation between the values when it is tested at 0,15 and 20 lags in both Nifty Future and Option Index at 0.005 level of significance. Thus the null hypothesis (H2: Ljung-Box-Pierce Q-Test proves Nifty option index does not have hetroskedasticity) is rejected.

Table 5 gives the Engle's ARCH Test for Nifty Future Index. It is proved from the table that the calculated statistical values (51.1407, 48.0206, 44.6019) are lesser than the critical table values (18.3070, 24.9958, 31.4104) which clearly indicates that there is significant correlation between the values when it is tested at 10,15 and 20 lags in Nifty Future Index at 0.005 level of significance. Thus the null hypothesis (H3: Engle's ARCH Test proves Nifty Future index does not have hetroskedasticity) is rejected.

Table 6 displays the Engle's ARCH Test for Nifty Option Index. It is clearly understood from the table that calculated statistical values (18.5494, 26.0440) are lesser than the critical table values (18.3070, 24.9958) which prove that there is significant correlation between the values when tested upto 10 and 15 lags in Nifty Option Index at 0.005 level significance. Therefore the hypothesis (H 4 = Engle's ARCH Test proves Nifty option index does not have hetroskedasticity) cannot be accepted. On the contrary, if Nifty Option Index is tested at 20 lag, the statistical value (27.7468) is lesser than the critical value (31.4104) which proves that there is no significant correlation and homoskedasticity does exist. Thus the null hypothesis (H4: Engle's ARCH Test proves Nifty option index does not have hetroskedasticity) is accepted.

Parameter estimation for conditional variance: Four parameters are now estimated with the help of GARCH model. They are given in the Table 7. The GARCH equation is formed as follows:

Table 7: Parameter estimation of nifty future index

Parameter	Value	Standard error	T statistic
C	1.8932e+006	2.4728e+005	7.6561
K	7.6137e+011	0	0.0000
GARCH(1)	0.61733	0.10822	5.7044
ARCH(1)	0.35804	0.24221	1.4783

Table 8: Parameter estimation of nifty option index

Parameter	Value	Standard error	t statistic
C	4.1036e+006	3.862e+005	10.6254
K	1.0517e+012	1.6521	63657.9211
GARCH(1)	0.70803	0.18395	3.8490
ARCH(1)	0.22237	0.31031	0.7166

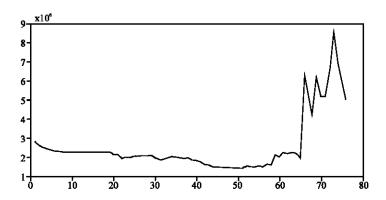


Fig. 7: Conditional variability of nifty future index

$$Y_t = 1.8932e + 006 + E_t$$
 (4)

$$\sigma_{\rm p}^2 = 1.2517e + 0.12 + 0.61733\sigma_{\rm t-1}^2 + 0.35804\varepsilon_{\rm t-1}^2$$
 (5)

Table 8 depicts the parameter estimation of Nifty Option Index, The GARCH equation for the Nifty Option Index is formed as under:

$$Y_{t} = 4.1036e + 006 + E_{t} \tag{6}$$

$$\sigma_{\rm p}^2 = 1.0517e + 0.12 + 0.70803\sigma_{\rm t-1}^2 + 0.22237\varepsilon_{\rm t-1}^2$$
 (7)

The conditional standard deviation for futures is estimated at 2.75. The conditional standard deviations, sigma, derived from the fitted yield are plotted in the Fig. 7. The plot clearly shows that the most recent values were above 2.75 in the long run which indicate asymptotic value.

Then the conditional standard deviation for options is estimated at 3.25. The conditional standard deviations, sigma, derived from the fitted yield are plotted in Fig. 8. The plot clearly reveals that the most recent values were above 3.25 in the long run.

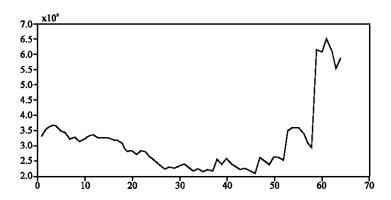


Fig. 8: Conditional variability of nifty option index

CONCLUSION

The present study thus sought to unearth whether volatility is time varying and predictable. Most popular pricing models such as Blacks hole Model assume that volatility of the underlying asset is constant. This assumption is far from perfect and real. In practice the volatility is a stochastic variable. Thus it is understood from this study that there is an evidence of time varying volatility which exhibits clustering, high persistance and predictability to some extent. The Futures and Options have hetroskedasticity nature of volatility.

REFERENCES

Black, F., 1976. Studies of stock market volatility changes. Proceedings of the 1976 Meeting of the Business and Economics Statistics Section (MBESS'76), American Statistical Association, pp: 177-181.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. J. Econ., 31: 307-327.

Bollerslev, T., 1987. A conditionality heteroskedastic time series model for speculative prices and rates of returns. Rev. Econ. Stat., 69: 542-547.

Bollerslev, T., 1990. Modeling the coherence in short-run nominal exchange rates: A multivariate generalised ARCH model. Rev. Econ. Stat., 72: 498-505.

Brooks, C. and S. Burke, 2003. Information criteria for GARCH model selection. Eur. J. Finance, 9: 557-580.

Brzeszcznski, J., 2000. Modeling stock prices using the ARCH and GARCH models. HWU School of Management and Languages.

Christie, A., 1982. The stochastic behaviour of common stock variance value, leverage and interest rate effects. J. Fin. Econ., 10: 407-432.

Crawford, G.W. and M.C. Fratantoni, 2003. Assessing the forecasting performance of regime-switching ARIMA and GARCH models of house prices. Real Estate Econ., 31: 223-243.

Engle, R.F., 1982. Auto regressive conditional hetroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50: 987-1008.

Fama, E.F., 1965. The behaviour of stock market prices. J. Bus., 38: 34-105.

Mandelbrot, B., 1963. The variation of certain speculative prices. J. Bus., 36: 394-419.

Najand, M., 2002. Forecasting stock index futures price volatility: Linear Vs nonlinear models with the help of three nonlinear models. Fin. Rev., 37: 93-104.

- Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica, 59: 347-370.
- Raja, M., J.C. Sudhahar and M. Selvam, 2009. Testing Indian stock market volatility with respect to buyback announcement. Int. J. Manage. Res. Technol., 3: 39-53.
- Selvam, M. and M. Raja, 2007. For casting the time volatility of emerging asian stock market index. Asia-Pacific Bus. Rev., 38-51.
- Selvam, M. and G. Indhumathi, 2008. Index futures and options introduction-A case of spot market volatility in BSE. Asia-Pacific Business Review, 28-36.
- Selvam, M. and G. Indhumathi, 2009. Index futures and options introduction on the spot market volatility in NSE. J. Contemporary Res., 25-33.
- Shenbagaraman, P., 2003. Do futures and options trading increase stock market volatility. NSE Research Initiative Paper, National Stock Exchange, India.
- Tong, W.H.S. and T.K.S. Maurice, 2002. Market structure and return volatility: Evidence from the Hong Kong stock market. Fin. Rev., 37: 589-612.
- Wei, W., 2002. Forecasting stock market volatility with non-linear GARCH models: A case for china. Applied Econ. Lett., 9: 163-166.