IMPACT OF FUTURES INTRODUCTION ON UNDERLYING INDEX VOLATILITY EVIDENCE FROM INDIA

ABSTRACT

This paper addresses whether, and to what extent, the introduction of Index Futures contracts trading has changed the volatility structure of the underlying NSE Nifty Index. Using a CUSUM plot and Bayesian analysis it is first confirmed that there is indeed a shift in volatility around the time of Index Futures introduction. The classical F-Test (Variance-Ratio test) also indicates that the spot volatility has changed, since the inception of Index Futures trading. Next the GARCH family of techniques is employed to capture the time-varying nature of volatility and volatility clustering phenomena present in the data. The results obtained from the ARMA-GARCH model indicate that while the introduction of futures trading has no effect on the underlying mean level of the returns and marginal volatility, it has significantly altered the structure of spot market volatility. Specifically, it is found that new information is assimilated into prices more rapidly than before, and there is a decline in the persistence of volatility since the onset of futures trading. These results for NSE Nifty are obtained even after accounting for world market movements, asymmetric effects and sub-period analysis, and, contrasting the same with a control index, namely, NIFTY Junior which does not yet has a derivative segment. Thus it is concluded that such a change in the volatility structure appears to be the result of futures trading, which has expanded the routes over which information can be conveyed to the market.

JEL Classification: G15; G14
Keywords: GARCH; Index Futures; Information; Volatility;

Kotha Kiran Kumar[♣] **&** **Chiranjit Mukhopadhyay**

Research Scholar — **Asst. Professor**

kotha@mgmt.iisc.ernet.in — **cm@stats.mgmt.iisc.ernet.in**

Department of Management Studies
Indian Institute of Science,
Bangalore, INDIA.

[♣] Corresponding Author, Research Scholar, Dept of Management Studies, Indian Institute of Science, Bangalore, India – 560012. Ph: 91-80-22933269, Mobile: 0-0-9841111751, Fax: 91-044-28279208

IMPACT OF FUTURES INTRODUCTION ON UNDERLYING INDEX VOLATILITY
EVIDENCE FROM INDIA

ABSTRACT

This paper addresses whether, and to what extent, the introduction of Index Futures contracts trading has changed the volatility structure of the underlying NSE Nifty Index. Using a CUSUM plot and Bayesian analysis it is first confirmed that there is indeed a shift in volatility around the time of Index Futures introduction. The classical F-Test (Variance-Ratio test) also indicates that the spot volatility has changed, since the inception of Index Futures trading. Next the GARCH family of techniques is employed to capture the time-varying nature of volatility and volatility clustering phenomena present in the data. The results obtained from the ARMA-GARCH model indicate that while the introduction of futures trading has no effect on the underlying mean level of the returns and marginal volatility, it has significantly altered the structure of spot market volatility. Specifically, it is found that new information is assimilated into prices more rapidly than before, and there is a decline in the persistence of volatility since the onset of futures trading. These results for NSE Nifty are obtained even after accounting for world market movements, asymmetric effects and sub-period analysis, and, contrasting the same with a control index, namely, NIFTY Junior which does not yet has a derivative segment. Thus it is concluded that such a change in the volatility structure appears to be the result of futures trading, which has expanded the routes over which information can be conveyed to the market.

JEL Classification: G15; G14
Keywords: GARCH; Index Futures; Information; Volatility;

1. INTRODUCTION:

One of the most recurring themes in empirical financial research is studying the effect of Derivatives trading on the underlying asset. Special interest is devoted to studying whether Derivatives markets stabilize or destabilize the underlying markets. Many theories have been advanced on how the introduction of Derivatives market might impact the volatility of an underlying asset. The traditional view against the Derivatives markets is that, by encouraging or facilitating speculation, they give rise to price instability and thus amplify the spot volatility. This is called the Destabilization hypothesis. This has led to call for greater regulation to minimize any detrimental effect. An alternative explanation for the rise in volatility is that Derivatives markets provide an additional route by which information can be transmitted, and therefore, increase in spot volatility may simply be a consequence of the more frequent arrival, and more rapid processing of information. Thus Derivatives trading may be fully consistent with efficient functioning of the markets. This topic has been the focus of attention for both academicians and practitioners alike. In empirical terms, practitioners and regulators are both concerned with different experiences of how the introduction of trading new financial instruments are associated with price volatility.

Thus despite the long debate about the issue of stock market volatility, an agreement seems to be difficult to reach, when it concerns the identification of the sources of stock market volatility, including futures transactions. An increase in volatility of the stock market can simply reflect a change in the underlying economic context, and thus it must not be considered, ex-ante, a market-destabilizing factor. Stock index futures, because of operational and institutional properties, are traditionally more volatile than spot markets. The close relationship between the two markets induces the possibility of transferring volatility from futures markets to the underlying spot markets. There are numerous studies that have approached the effect of the introduction of Index Futures trading from an empirical perspective. Majority of the studies compare the volatility of the spot index or individual component stocks in an index before and after the introduction of the futures contract using different methodologies ranging from simple comparison of variances, to linear regression to more complex GARCH models with different underlying assumptions and parameters in the models.

Authors who report that inception of futures trading increases spot volatility are Figlewsky (1981), Harris (1989), Brorsen et al (1991), Lee and Ohk (1992), Kumara et.al., (1992) Antoniou and Holmes (1995) among others who have studied the issue in highly developed markets such as the United States, United Kingdom, and Japan. These authors support the Destabilization hypothesis based on the observation that futures markets are likely to attract uninformed traders because of their high degree of leverage. Authors who report decrease or no change in the spot market volatility after the start of index futures trading are Edwards (1988), Becketti and Roberts (1990), Hodgson and Nicholls (1991), Darrat et.al., (1995), Butterworth (2000) among others. These papers can't reject the non-Destabilization hypothesis and support the view that futures markets play an important role of price discovery, and have a beneficial effect on the underlying cash markets.

Most of these studies examined the impact of introduction of index futures in one market and thus were unable to compare across markets. Gulen and Mayhew (2000) examine stock market volatility before and after the introduction of index futures trading in twenty-five countries, using various GARCH models augmented with either additive or multiplicative dummy. Their statistical model takes care of asynchronous data, conditional heteroskedasticity, asymmetric volatility responses, and the joint dynamics of each country's index with the world market portfolio. They found that futures trading is related to an increase in conditional volatility in the U.S. and Japan, but in nearly every other country, no significant effect could be found.

In June 2000, Stock Index Futures contracts were introduced in India when both the Bombay and National stock exchanges started the BSE Sensex and NSE Nifty futures transactions. As mentioned before, the impact of the introduction of Stock Index Futures on the underlying spot market is a well-documented issue in the context of well-developed international markets like USA, UK or Japan. However to what extent their studies are applicable to less-developed markets remains unclear. There is a significant lack of empirical studies on this subject with respect to Indian market. The only studies so far with reference to Indian market are those of Thenmozhi (2002), Gupta and Muneesh Kumar (2002) who report a reduction in the volatility of spot index after the inception of Index Futures trading. These studies applied a simple Variance Ratio test and Ordinary Least Squares Multiple Regression technique to examine the shift in volatility of NSE Nifty and thus neglect the possible autocorrelation in returns and inherent 'time-varying' nature of volatility. Further, the Regression technique does not allow one to explicitly capture the connection between information and volatility.

The study in this article improves the earlier studies in five aspects, first two are in general context and the others are in Indian context. First, the paper examines closely whether there is any shift in the NSE Nifty volatility in the period under investigation through a change-point analysis and then confirms that indeed a change has occurred around the date of introduction of Index Futures trading. To the authors' knowledge no other study has thus objectively validated the event-study methodology, typically applied in studying problems of the kind discussed in this paper. Second, marginal volatilities of before and after series are compared apart from the well-documented comparison of conditional volatility of a series before and after occurrence of an event. The volatility comparison through GARCH model gives whether the conditional volatility of the series (which is same as that of residuals) has changed or not and does not comment on the volatility of the underlying series as such. Third, this study applies the GARCH model, which inherently incorporates endogenous information in the expression of conditional volatility as discussed in Ross (1989), apart from effectively controlling the temporal dependency phenomena. Following Antoniou & Holmes (1995), the GARCH model is augmented with individual dummies. The use of individual dummies is important as one can measure whether there is a change in the speed and persistence with which volatility shocks evolve after the futures trading[1]. Fourth, this paper deviates from the existing

[1] Though in the standard GARCH literature, persistence is understood as a condition like $\alpha_1 + \beta_1 < 1$ for GARCH (1,1) (see Bollerslev (1986) for instance), Antoniou & Holmes use the term persistence to indicate the effect of past conditional variance on the present conditional variance. In rest of the paper the term persistence refers in this later sense, as in Antoniou & Holmes.

literature on the studies of the Indian markets in using Nifty Junior index as a proxy for market-wide movements given that it contributes a mere 6% on average, of market capitalization. Instead, MSCI World Index has been used to control for market-wide movements. Fifth, the entire test procedure is implemented on Nifty Junior, which does not have corresponding futures contract and thus may be treated as a control index. This strengthens the analysis of impact of Index Futures trading on Nifty as its results differ from that of Nifty Junior.

The study reports that while there is no change in the mean returns and marginal volatility there is a substantial change in the dynamics by which the conditional variance evolves. Specifically, the results suggest that futures trading improves the quality and speed of information flow to spot market and this trend is not evident in the control index, NSE Nifty Junior. The remainder of this paper proceeds as follows: the next section presents the methodology used. Next the data and the empirical results are presented. The final section provides a summary and conclusions.

2. METHODOLOGY

Any test applied to measure the effects of an intervention, such as the introduction of futures trading, requires the knowledge of when the intervention took place, followed by an analysis of the behavior of the spot market before and after the event. The classic Event-study methodology is applied to study the impact of introduction of index futures trading on the volatility of NSE Nifty Index. However before blindly initiating the event-study methodology, one has to first check whether there is indeed any change in the series under study, around the event date without using its prior knowledge, through a Change-Point Analysis. For this purpose an informal descriptive statistical technique called CUSUM (Cumulative Sum) chart is employed, which has been widely used in Statistical Process Control literature for change-point detection, (vide., Ch 7 of Montgomery, 1991) and as well as a formal Bayesian analysis. If there is any shift in the spot volatility because of Futures introduction then the date obtained from CUSUM plot or the Bayesian analysis should approximately coincide with that of the actual starting date of Futures trading.

2.1. CUSUM Chart

Taylor (2000) suggested the use of Cumulative Sum plots (CUSUM) to detect the possible change point in time series data. CUSUM charts are constructed by calculating and plotting a cumulative sum based of the data as follows. If X_1, X_2, …, X_n represent the n consecutive observations of a time series, the cumulative sums S_0, S_1, …, S_n are calculated as follows:

1. First calculate the average $\overline{X} = \dfrac{X_1 + X_2 + ... + X_n}{n}$
2. Start the cumulative sum at zero by setting $S_0 = 0$.
3. Calculate the other cumulative sums by adding the difference between current value and the average to the previous sum, $S_i = S_{i-1} + (X_i - \overline{X})$ for i=1,2,..n.

A segment of the CUSUM chart with an upward slope indicates a period where the values tend to be above the overall average. Likewise a segment with a downward slope indicates a period of time where the values tend to be below the overall average. Thus a sudden change in direction of the CUSUM indicates a sudden shift or change in the average. Fig 1 shows the CUSUM chart with NSE Nifty daily squared returns, as a proxy for volatility, from June 1999 to June 2001. As is evident from the CUSUM chart, the NSE Nifty squared returns have taken a sudden turn on 6th June 2000. Incidentally, BSE Sensex Futures started on 5th June 2000 and NSE Nifty Futures started on 12th June 2000. So around the date of introduction of Futures there has been a sudden turn in NSE Nifty daily squared returns and needs further examination to conclusive evidence.

2.2. Bayesian Change Point Analysis

From the CUSUM chart one may suspect that there is an abrupt change in the volatility of the Nifty series around the futures introduction. However it may be argued that the spike found around the date of futures introduction may only be due to the natural variability of the Nifty series. Thus in this section the change point analysis is approached from a Bayesian viewpoint to see if one can statistically infer that there indeed exists a change in the volatility process of NSE Nifty without utilizing the knowledge of exact date of introduction of futures trading.

The simplest formulation of the change-point problem in Bayesian approach is as follows. The underlying time-varying GARCH model is specified as follows:

$$Y_t = \phi_0 + \sum_{i=1}^{l} \phi_i Y_{t-i} + \sum_{j=1}^{m} \lambda_j \varepsilon_{t-j} + \varepsilon_t$$

$$h_t = \alpha_0 + \sum_{i=1}^{p}\alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j h_{t-j} + \alpha_{0,d} D_t + \sum_{i=1}^{p}\alpha_{i,d} D_t \varepsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_{j,d} D_t h_{t-j} \ldots \quad (1)$$

where D_t takes the value 0 for t = 1,…..,κ and 1 for t = κ+1,…., T, where κ is the unknown change-point parameter, that is to be estimated from the data. It is assumed that κ can take any of the integral value between 1 and T-1. The likelihood function resulting from T observations y= (y_1, y_2,.,y_T) generated by model (1) is given by $L(\Theta,\kappa \mid D) \prec \prod_{t=1}^{\kappa} p_t(\varepsilon_t \mid \Theta) \prod_{t=\kappa+1}^{T} p_t(\varepsilon_t \mid \Theta)$ where D denotes the data set, p_t(. | Θ) is on appropriate Normal probability density function and Θ is the vector of ARMA-GARCH parameters. In the Bayesian approach, a joint prior distribution p(Θ,κ) is assumed for the parameters and then the Bayes theorem yields the joint posterior distribution p(Θ,κ|D) which is proportional to L(Θ,κ|D)p(Θ,κ). Interest is now focused on making inference about the change-point parameter κ through its marginal posterior probability mass function, which is given by

$$p(\kappa \mid D) \prec \int_{\Theta} p(\Theta,\kappa \mid D) d\Theta = \int_{\Theta} p(\Theta,\kappa \mid D) p(\Theta,\kappa) d\Theta \ldots \qquad \ldots(2).$$

That is to evaluate p(κ|D), Θ must be integrated out of p(Θ,κ|D). Assuming a uniform prior distribution for κ, an arbitrary "regular" prior for Θ, and independence between κ and Θ, the Laplace approximation of the second integral in (2) yields

$$p(\kappa \mid y) \propto \int_{\Theta} L(\Theta,\kappa \mid y) p(\Theta) d\Theta \propto L(\hat{\Theta}_k) \left| \hat{\Sigma}(\hat{\Theta}_\kappa \right|^{0.5} \ldots \qquad ..(3)$$

where $\hat{\Theta}_\kappa$ is the MLE of Θ for a fixed κ in model (1) and $\hat{\Sigma}(\hat{\Theta}_k)$ is the corresponding inverse of the observed information matrix (which is the same as the asymptotic variance-covariance matrix of $\hat{\Theta}_\kappa$). The marginal posterior probability mass function of κ as obtained in (3) is plotted in Fig 2. Like the CUSUM chart, Fig 2 also confirms the existence of a change-point on 6th June 2000. However there appears to be another significant change-point occurring on 15th May 2000. Thus for the event-study methodology, the event window is taken to be from 12th May 2000 to 14th June 2000 and the pre-Futures period is from 2nd June 1999 to 11th May 2000 and the post-Futures period from 15th June 2000 to 1st June 2001. Note that thus this change-point analysis not only allows one to confirm a change around the futures introduction date, it also allows an objective selection of the time periods for before or after study.

2.3. Controlling Other Factors:

The next step is the choice of the length of test period or the length of the estimation window. The choice of the length of the test period is a critical question where a balance needs to be struck between the length of the period for reliable estimation of model parameters, against the possibility of existence of other events that might affect the series and thus the parameter estimates. The later is because stock markets are usually affected by a number of other events over a period of time, which are distinct from the event in question. Thus there is a problem of confounding by other intervening variables. The effects of these events on volatility are uncertain and disentangling these intervening events and extracting a ‘normal’ model of expected volatility is not a simple task.

Indian Stock Market has experienced the introduction of a wide variety of Derivative contracts in the last three years *viz,* Index Futures in June 2000, Index Options in June 2001, Individual Stock Options in July 2001 and Individual Stock Futures in November 2001. We are mindful of these potential confounding events, and careful against erroneously attributing a change in volatility to the introduction of Index Futures trading. To control these confounding effects, an appropriate test period and a control procedure is implemented. As our study concentrates only on the impact of Index Futures, in order to avoid the effect of confounding events of introduction of other derivative contracts, a test period of one-year pre and post introduction of index futures trading is considered i.e. from 2nd June 1999 to 1st June 2001, which is free from the events of introduction of other Derivative instruments.

Two methods are used to guard against drawing erroneous conclusion about the shift in volatility due to introduction of index futures trading, which in reality might be attributed to other factors. First, the MSCI World index is used to control for market-wide movements. Second, a control procedure is undertaken by implementing the entire test procedure on a similar index that did not have any derivative trading. If the NSE Nifty exhibits a change while the control index does not, then the conclusions drawn with respect to the impact of the introduction of the index futures trading on the NSE Nifty are strengthened. Given that index futures contracts have been introduced on the most popular and broad measure of Indian stock market, the choice of control index should typically be the next largest index. Towards this end, NSE Nifty Junior is chosen as the control index, which does not have futures trading yet. The theoretical framework of analyzing the change in volatility is described in the next sub-section.

2.4. Using GARCH Model : Analyzing the structure of Volatility

The general approach adopted in the literature to examine the effect of onset of futures trading is to compare the spot price volatility prior to the event with that of post-futures. In analyzing the behavior of pre- and post-futures volatility, one should attempt to explicitly capture the temporal dependency phenomena and time-varying nature of volatility. In addressing these issues, following Chan and Karolyi (1991), Lee and Ohk (1992), Antoniou and Holmes (1995), within the framework of the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model is performed. By providing a detailed specification of volatility, this technique enables one to not only check whether the volatility has changed but also provides the endogenous sources of change in volatility.

Following Pagan and Schwert (1990) and Engle and Ng (1992), the first step in GARCH modeling of daily returns series, which does not possess a unit root, is to remove any predictability associated with lagged returns and holiday / week-end effects by accommodating sufficient number of (AR, MA) terms and holiday/weekend dummies in the mean equation respectively. To account for worldwide price movements on volatility, MSCI world market index return is included as an independent variable. It should be noted that because of differences in time zones, the lagged world market index is taken as independent variable against the level variable.

Thus for NSE Nifty logarithmic daily returns, the conditional mean equation is specified as:

$$R_t = \phi_0 + \sum_{i=1}^{l} \phi_i R_{t-i} + \sum_{j=1}^{m} \theta_j \varepsilon_{t-j} + \nu HOL_t + \sum_{k=1}^{n} \gamma_k RW_{t-k} + \varepsilon_t \qquad (3)$$

where R_t is the daily logarithmic return on the NSE Nifty index, RW_t is the daily logarithmic return on the MSCI World Market Index and HOL_t corresponds to week-end/ holiday dummy. Graphical analysis and the computation of some basic statistical measures like the kurtosis and Ljung-Box Q-statistics for squared returns provide evidence about the presence of volatility clustering phenomenon, which calls for GARCH modeling. To model the conditional variance, Bollerslev (1986) introduced GARCH models that relate conditional variance of returns as a linear function of lagged conditional variance and past squared error.

The standard GARCH (p, q) model can be expressed as follows:

$$\varepsilon_t / \Omega_{t-1} \sim N(0, h_t)$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \qquad (4)$$

where, ε_t is the same error term in equation (3), Ω_t is the information set till time t, α_i's are news coefficients measuring the impact of recent news on volatility and β_j's are the persistence coefficients measuring the impact of "less recent" or "old" news on volatility. These interpretations of α_i's & β_j's can be found, for instance, in Antoniou & Holmes (1995) and Butterworth (2000).

First separate models been fitted for the before and after Nifty time series using the ARMA-GARCH model of (3) & (4) and it is found that the ARMA-GARCH orders of the two models are same. This facilitates writing a single model for the entire series including both before and after components by introducing a dummy variable, D_t, taking value 0 for before period and 1 for after. Accordingly the conditional mean and variance equations (3) & (4) can be refined for the entire series as follows:

$$R_t = \varphi_0 + \sum_{i=1}^{l} \varphi_i R_{t-i} + \sum_{j=1}^{m} \theta_j \varepsilon_{t-j} + \nu HOL_t + \sum_{k=1}^{n} \gamma_k RW_{t-k} + \varphi_0' D_t + \sum_{i=1}^{l} \varphi_i' D_t R_{t-i} + \sum_{j=1}^{m} \theta_j' D_t \varepsilon_{t-j} + \sum_{k=1}^{n} \gamma_k' D_t RW_{t-k} + \varepsilon_t \quad (5)$$

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \alpha_{0,d} D_t + \sum_{i=1}^{p} \alpha_{i,d} D_t \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_{j,d} D_t h_{t-j} \quad (6)$$

By including individual dummies, instead of additive or multiplicative dummy, as suggested in Butterworth (2000) and Gulen & Mayhew (2000), the proposed ARMA-GARCH model in (3)-(4) allows one to identify and study the nature of potential impacts of introduction of the futures contracts on the structure of both mean level and volatility of the spot market in general terms. By examining the significance of dummy coefficients, one can test whether there is a change in both the speed and persistence with which the volatility shocks evolve. Following the onset of futures trading, a positive significant value of α_{id} would suggest that news is absorbed into prices more rapidly, while a negative and significant value of $\beta_{j,d}$ implies that "less recent news" have less impact on today's price changes. This means that the investors attach more importance to recent news leading to a fall in the persistence of information. Thus, the ARMA-GARCH framework enables one to model changes that might occur both in the mean level and structure of volatility, which can be detected by checking the sign and significance of the coefficients attached to dummy variables.

2.5. Marginal Volatility Comparison

Though the GARCH framework explicitly model how the conditional volatility evolves over time, it does not comment on change in volatility of the series as a whole, which is the primary objective of the study. Further the conditional volatility of the series or residuals by definition depends on the past information and hence unable to conclude on the overall volatility pattern of the series. This is accomplished by calculating the marginal volatility of the series, which is derived from the ARMA-GARCH model (eqn 5 & 6) as follows:

Marginal Variance of the return series: $$\sigma^2 = \frac{\alpha_0 + \alpha_d}{\left[1-\left(\sum_{i=1}^{p}\alpha_i + \sum_{i=1}^{p}\alpha_{i,d}\right)-\left(\sum_{j=1}^{q}\beta_j + \sum_{j=1}^{q}\beta_{j,d}\right)\right]\left[1-\sum_{i=1}^{l}\phi_i^2\right]} \quad ..(7)$$

The marginal variances of the return series before and after the index futures introduction say σ_B^2 and σ_A^2 respectively are calculated from the empirically fitted model using (7). Using the Wald test statistic, the null hypothesis of no change in the marginal volatility of the Nifty returns series before and after the introduction of the futures contracts, can be tested as follows:

$$H_0: \; g(\mathbf{\Psi}) = \frac{\sigma_A^2}{\sigma_B^2} = 1 \text{ against the alternative } H_a: \; g(\mathbf{\Psi}) \neq 1$$

where $\mathbf{\Psi}$ denotes the vector of parameters, which include the coefficients of the mean and variance equations, of both the "before" and "after" ARMA-GARCH models. The Wald statistic for testing these hypotheses is given by

$$Z = \frac{g(\hat{\mathbf{\Psi}}) - 1}{SE(g(\hat{\mathbf{\Psi}}))} \qquad \text{.... (8)}$$

where $\hat{\mathbf{\Psi}}$ is the MLE of $\mathbf{\Psi}$, $g(\hat{\mathbf{\Psi}})$ is the MLE of $\frac{\sigma_A^2}{\sigma_B^2}$, and $SE(g(\hat{\mathbf{\Psi}}))$ is the estimated asymptotic standard error of $g(\hat{\mathbf{\Psi}})$ and $SE^2(g(\hat{\mathbf{\Psi}})) \approx \left(\frac{\delta g}{\partial \mathbf{\Psi}}\right)' Cov(\hat{\mathbf{\Psi}}) \left(\frac{\delta g}{\partial \mathbf{\Psi}}\right)$, where $\left(\frac{\delta g}{\partial \hat{\mathbf{\Psi}}}\right)$ is the gradient vector of g (.), evaluated at $\hat{\mathbf{\Psi}}$ and $Cov(\hat{\mathbf{\Psi}})$ is the inverse of the observed information matrix of the full likelihood containing both the "before" and "after" terms, which are assumed to be independent. For large samples Z would follow a Standard Normal Distribution under H_0 and thus one can check for its significance.

3. DATA and PRELIMINARY ANALYSIS:

Daily closing prices for S & P CNX Nifty, CNX Nifty Junior and MSCI World Index were obtained respectively from www.nseindia.com and www.msci.com over the period 2nd June 1999 to 1st June 2001. The data comprises a total of 481 observations, of which 238 observations relate to the period prior to the introduction of futures trading and the remaining 244 observations to the period after the introduction of futures trading. Continuously compounded percentage returns are estimated as the log price relative. That is for an index with daily closing price P_t, its return R_t is defined as log (P_t/P_{t-1}). All the return series (before, after and full period) are subjected to Augmented Dickey Fuller test and the null hypothesis of unit root is rejected in all cases. Table I presents a set of basic descriptive statistics and Fig 3 plots the returns, correlogram of returns and squared returns. The most relevant figures in Table I for this study are the variances, which provide an initial view of volatility for NSE Nifty. The pre-futures NSE Nifty volatility is greater than that of post-futures and this reduction in variance is statistically significant through an F-Variance ratio test. This broadly suggests that the introduction of index futures has not destabilized the spot market. However, inferences cannot be drawn from these figures alone, as they do not consider market-wide movements, temporal dependence in returns and time-varying nature of volatility. Further, Table I reports the LB statistic of both returns and squared returns up to 20 lags. The presence of significant LB statistics clubbed with excess kurtosis is compatible with the temporal dependency and volatility clustering phenomena in the NSE Nifty returns. The NSE Nifty raw returns series plot in Fig 3.1 and the correlogram of returns and squared returns in Fig 3.2 and Fig 3.3 further supports this. The return series displays the volatility-clustering phenomenon, namely, large (small) shocks of either sign tend to follow large (small) shocks. These preliminary findings motivate and call for further investigation by GARCH modeling.

4. EMPIRICAL RESULTS:

The conditional mean equation as specified in (3) is estimated with appropriate lag structure for R_t and RW_t for both before and after periods separately. As the orders of both the models are same, the mean structure of the entire period is estimated using equation (5). The results indicate that the entire mean return process is AR(1) with a strong effect of $MSCI_{t-1.}$ The primed coefficients associated with the dummy variables turned out to be insignificant. This suggests that there is no change in the mean returns with the inception of Index Futures trading. The final estimation results after dropping these insignificant terms are reported in Table II together with the standard diagnostic statistics. The model diagnostic graphs namely the Residual Plot, Correlogram of residuals and residual squares are displayed in Fig 4.1, Fig 4.2 and Fig 4.3. Following Engle and Ng (1993), Ljung-Box test statistics reported for the 20^{th} order serial correlation both in the residuals and their squares. The Ljung-Box statistics reported for the residual levels tell us that the regression model possibly removes serial correlation in the stock return series suggesting the elimination of the predictable part of the return series. The Ljung-Box test statistics for the squared residuals however are highly significant, consistent with the existence of time varying volatility of index returns. This is further supported by the excess kurtosis of the residuals. These statistics support that some type of GARCH specification as specified in equation (6) is necessary to properly model returns.

Thus equations (5) and (6) are next jointly estimated using the BHHH algorithm and Table III reports the quasi-maximum likelihood estimates of the coefficients of (5) and (6). The model diagnostic graphs namely the Residual Plot, Correlogram of residuals and residual squares are displayed in ,Fig 5.1, Fig 5.2 & Fig 5.3. These diagnostics show that the residuals of the model are reasonably well behaved. The portmanteau (Box-Ljung) statistics in Table III evaluate the serial correlations in the raw and squared standardized residuals of the model up to lags 20 and show that the specified model has captured most of the conditional dependence in the returns and squared returns well. The insignificant

LM test statistics suggests the absence of any further ARCH effects. Finally, the sign and size bias test statistics also do not indicate any significant degree of asymmetry in the residuals supporting the correct model specification. As the joint bias statistic is marginally significant an asymmetric GARCH model also estimated. However the symmetric GARCH model is chosen against Asymmetric GARCH on the basis of AIC criterion.

In Table III, the estimates of $\alpha_{1,d}$ and $\beta_{1,d}$, among the GARCH parameters are of interest. There is a substantial increase in news incorporation coefficient $\alpha_{1,d}$, which is positive, implying increase in market efficiency, measured by its ability to quickly incorporate new information. This is followed by a decrease in the persistence coefficient $\beta_{1,d}$, which is negative, implying that the volatility shocks become less persistent and hence the spot market becomes more efficient. This finding is further strengthened by the fact that the pre-futures model is a candidate for I-GARCH, whereas the post-futures model is obviously not so. Pre-futures α_1 and β_1 sum to 0.9371, compared to 0.8143 of post-futures. Wald tests were carried out to test for I-GARCH and reveal that while the pre-futures sample is integrated, the post-futures model is not so at the 10% level. Thus the persistence of shocks decreased since the onset of index futures trading. Therefore, the introduction of the index futures trading led to a more rapid absorption of news into prices and a decrease in persistence. Further the marginal volatility of NSE Nifty before and after futures introduction is 4.029684 and 3.573364265 respectively and the Wald's test statistic for the significant difference between the volatilities turns out to be –0.2728 and the p-value is 0.3. This suggests that one cannot reject the null of index futures does not impact the underlying spot volatility. Hence on the whole, the volatility of the Nifty series has not changed but the structure of the volatility changed due to the introduction of index futures.

The entire test procedure is replicated by considering six-months and nine- months before and after futures introduction and the result is qualitatively same. Further the table shows that the results of NSE Nifty are in contrast with those of Nifty Junior, the control index. As the coefficients of the dummies in the variance equation of NSE Nifty Junior are not significant, the evidence strengthens the result that the introduction of Index Futures trading has indeed changed the dynamics by which the Nifty spot volatility evolves.

5. CONCLUSION:

This paper investigates whether and to what extent the introduction of Index Futures trading has had an impact on the mean level and volatility of the underlying NSE Nifty Index. The results reported for the NSE Nifty indicate that while the introduction of Index Futures trading has no effect on mean level of returns and marginal volatility, it has significantly altered the structure of spot market volatility. Specifically, there is evidence of new information getting assimilated and the effect of old information on volatility getting reduced at a faster rate in the period following the onset of futures trading. This result appears to be robust to the model specification, asymmetric effects, sub-period analysis and market-wide movements. These results are consistent with the theoretical arguments of Ross (1989).

References:

Antoniou & Holmes (1995). Futures trading, information and spot price volatility: Evidence for the FTSE -100 stock index futures contract using GARCH. Journal of Banking and Finance, 19, 117-129.

Becketti, Sean & Roberts, Dan J. (1990). Will Increased Regulation of Stock Index Futures Reduce Stock Market Volatility?. Economic Review, 75(6), 33-46.

Bollerslev, Tim (1986). Generalized Autoregressive Conditional Heteroscedasticity. Journal of Econometrics, 31(3), 307-327.

Butterworth, D. (2000). The impact of futures trading on underlying stock index volatility: The case of the FTSE Mid 250 contract. Department of Economics, University of Durham.

Brorsen, B. Wade (1991). Futures Trading, Transaction Costs, and Stock Market Volatility. Journal of Futures Markets, 11(2), 153-163.

Chan, K., Chan, K. C. & Andrew Karloyi (1991). Intraday volatility in the stock index and stock index futures market. Review of financial studies, 4, 657 – 684.

Darrat, A.F., & Rahman, S. (1995). Has futures trading activity caused stock price volatility?, Journal of Futures Markets, 15, 537 – 557.

Edwards, Franklin, R. (1988). Does Futures trading increase stock market volatility?. Financial Analysts Journal, Jan/Feb, 63-69.

Engle, R.F. & Ng, V. (1993). Measuring and Testing the Impact of News on Volatility. The Journal of Finance, 48, 1749-1778.

Figlewski, S. (1981). Futures trading and volatility in the GNMA market. Journal of Finance 36 (May), 445-56.

Gupta, O.P. & Muneesh Kumar (2002). Impact of Introduction of Index Futures on Stock Market Volatility: The Indian Experience. Pacific Basin Finance, Economics, and Accounting Conference 2002, Nanyang Technological University, Singapore.

Gulen, Huseyin & Stewart Mayhew (2000). Stock Index Futures Trading and Volatility in International Equity Markets. Working Paper, Purdue University.

Harris, L. H. (1989). The October 1987 S&P 500 stock-futures basis. Journal of Finance, 44, 77-99.

Hodgson, A. & Nicholls, D. (1991). The impact of index futures on Australian share-market volatility. Journal of Business Finance & Accounting, 18(2), pp. 267-280.

Hogan, Kedreth C. J, Kroner, Kenneth F. & Sultan, Jahangir (1997). “Program trading, nonprogram trading, and market volatility. Journal of Futures Markets, 17(7), 733-756.

Kamara, A., T.Miller & Siegel, A (1992). The effects of futures trading on the stability of the S&P 500 returns. Journal of Futures Markets, (12), 645 – 658.

Lee, Sang Bin & Ohk, Ki Yool (1992). Stock Index Futures Listing and Structural Change in Time-Varying Volatility. Journal of Futures Markets, 12(5), 493-509.

Montgomery, C. Dougals. (1991). Introduction to Statistical Quality Control (2nd ed.). John Wiley & Sons, pp 280-299

Pagan, A. & Schwert, G. W. (1990). Alternative Models For Conditional Stock Volatility. Journal of Econometrics, 45, 267-290.

Ross, Stephen A. (1989). Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. Journal of Finance, 44, 1-17.

Taylor, Wayne A. (2000). Change-Point Analysis: A Powerful New Tool For Detecting Changes. Submitted to Quality Engineering.

Thenmozhi, M. (2002). Futures Trading, Information and Spot Price Volatility of NSE-50 Index Futures Contract. NSE Research Initiative Working Paper, NSE, Mumbai.

Table I: Descriptive Statistics

	NIFTY			JUNIOR		
	Full	Before	After	Full	Before	After
Mean	-0.018904	0.055368	-0.091954	-0.073798	0.059229	-0.193684
Variance	3.451060	3.981166	2.933170	6.594886	8.147417	5.188254
F-test		***1.357291 (0.0184)***			***1.570358 (0.0006)***	
Skewness	-0.07231	0.126819	-0.426629	-0.429369	-0.407416	-0.562835
Kurtosis	4.687262	4.696344	4.281641	3.5663	3.317125	3.587648
Jarque-Bera	57.59433	29.29657	24.00288	21.25074	7.549617	15.99027
LB(20)	25.605(0.179)	21.747(0.354)	37.920(0.009)	56.724(0.000)	43.700(0.002)	27.915(0.111)
$LB^2(20)$	74.222(0.000)	47.646(0.000)	61.502(0.000)	301.08(0.000)	252.57(0.000)	48.190(0.000)

Table II**: Regression Results: Evidence of GARCH effects**

$$R_t = \phi_0 + \phi_1 R_{t-1} + \theta_1 \varepsilon_{t-1} + \gamma_1 RW_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim N(0,1)$$

VARIABLE	Estimate	p-value
ϕ_0	0.0037	0.9655
ϕ_1	-0.7473	0.0000
θ_1	0.8365	0.0000
γ_1	0.3886	0.0000
F-stat	10.3719	0.0000
LB (20)	22.0460	0.2300
LB^2 (20)	60.0150	0.0000
LM (4)	5.5988	0.0002
Skewness	0.1065	
Kurtosis	4.4492	0.0000
Jarque-Bera	42.8231	0.0000

LB(k) is the portmanteau statistic testing joint significance of return autocorrelations up to lag k;
LB^2(k) is the portmanteau statistic testing joint significance of return autocorrelations up to lag k;
LM(k) is the portmanteau statistic testing the presence of ARCH effects up to lag k.

Table III: Results of AR (1)-GARCH (1,1) model with BHHH algorithm using Bollerslev-Wooldrige robust standard errors. R_t takes either NSE Nifty or NSE Junior, RW_{t-1} takes MSCI one D_t takes on a value of zero before futures introduction and a value of one after futures introduction.

$$R_t = \phi_0 + \phi_1 R_{t-1} + \theta_1 \varepsilon_{t-1} + \gamma_1 RW_{t-1} + \varepsilon_t$$

$$\varepsilon_t \sim N(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \alpha_{0,d} D_t + \alpha_{1,d} D_t * \varepsilon_{t-1}^2 + \beta_{1,d} D_t * h_{t-1}$$

Parameter	NSE Nifty		NSE Junior	
	Estimate	p-value	Estimate	p-value
ϕ_0	0.0592	0.0236	0.1851	0.3578
ϕ_1	0.6210	0.0000	-0.8272	0.0000
θ_1	0.3762	0.0000	0.1267	0.0051
γ_1	-0.6679	0.0000	0.9373	0.0000
α_0	0.2498	0.1597	0.2462	0.2675
α_1	0.0784	0.0186	0.1529	0.02944
β_1	0.8587	0.0000	0.8267	0.0000
$\alpha_{0, D}$	0.4197	0.1194	1.3833	0.1079
$\alpha_{1,D}$	0.4129	0.0010	0.0579	0.6554
$\beta_{1, D}$	-0.5357	0.0000	-0.3916	0.1212
Diagnostics				
Residual Mean	-0.0882	(Mean=0) 0.0520	-0.0519	(Mean=0) 0.2469
Skewness	0.0683	(Sk=0) 0.5424	-0.2236	(Sk=0) 0.0431
Kurtosis	4.1477	(Ku=3) 0.0000	3.1620	(Ku=3) 0.4656
Jarque-Bera	26.7749	(JB=0) 0.0000	4.6579	(JB=0) 0.0974
LB (20)	27.7249	0.1160	35.6837	0.0167
LB^2 (20)	14.8044	0.7875	7.8398	0.9929
LM (4)	0.2627	0.9019	0.1536	0.9614
Sign Bias	0.6252	0.5321	1.7826	0.0753
Negative Size Bias	-0.5963	0.5512	0.8630	0.3885
Positive Size Bias	-1.0204	0.3080	-0.1503	0.8806
Joint Bias	2.2437	0.0824	2.0044	0.1125
Wald Test				
$H_0 : \alpha_1 + \beta_1 = 1$	1.5985	0.2061	0.2757	0.5995
$H_0 : \alpha_1 + \alpha_{1,d} + \beta_1 + \beta_{1,d} = 1$	2.6862	0.1012	3.9714	0.0463

LB(k) is the portmanteau statistic testing joint significance of return autocorrelations up to lag k;
LB^2(k) is the portmanteau statistic testing joint significance of return autocorrelations up to lag k;
LM(k) is the portmanteau statistic testing the presence of ARCH effects up to lag k.
Sign bias, Negative size, Positive size and Joint bias tests are asymmetric test statistics given by Engle and Ng (1993)

Fig 1 : CUSUM Plot for Nifty Squared Daily Returns

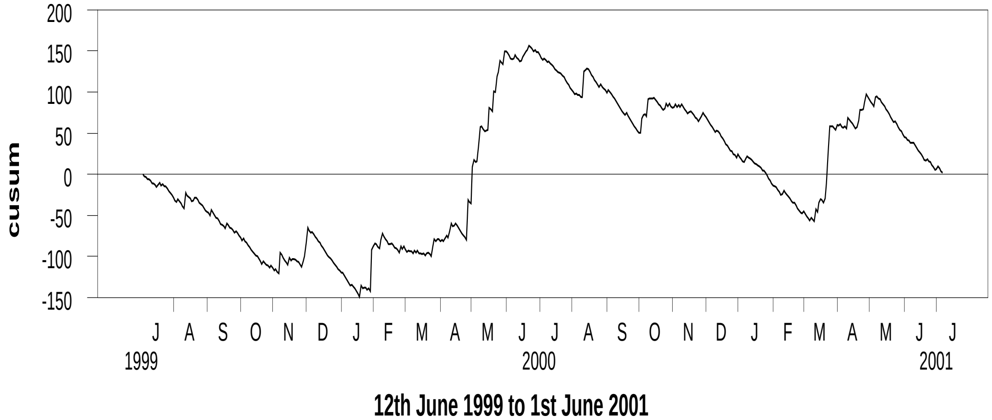


Fig 2 : Plot of Marginal Distribution of Kappa

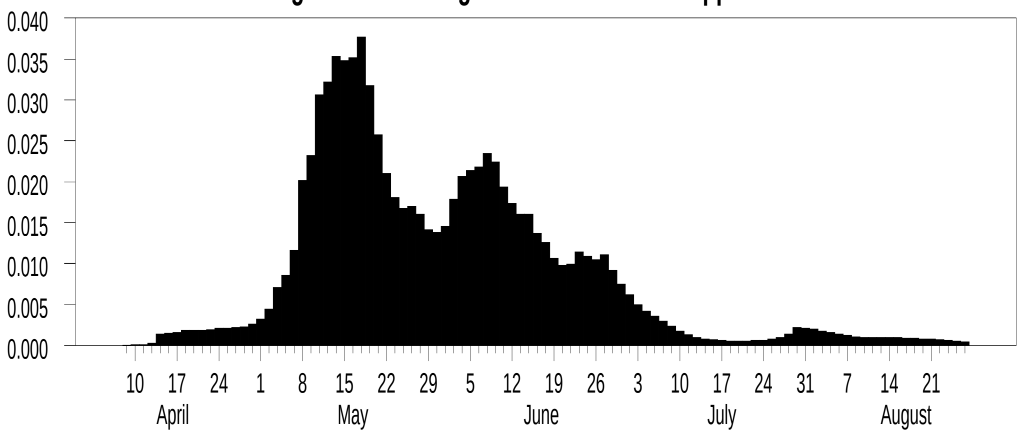
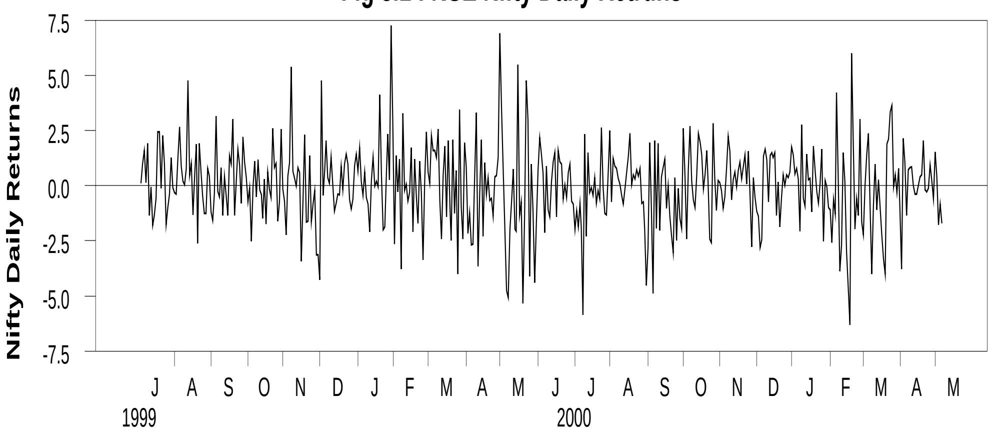


Fig 3.1 : NSE Nifty Daily Retruns



Standardized Residual Plots

Fig 4.1 : Regression Standardized Residual Plot

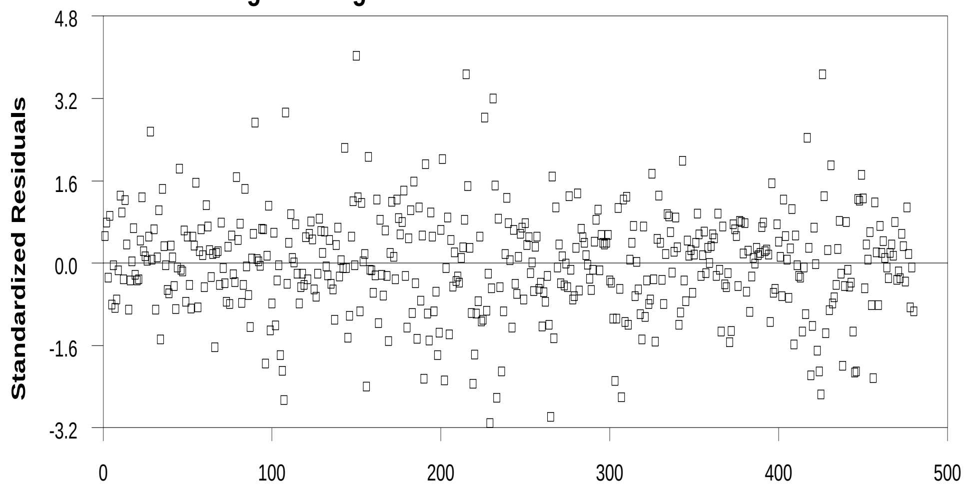
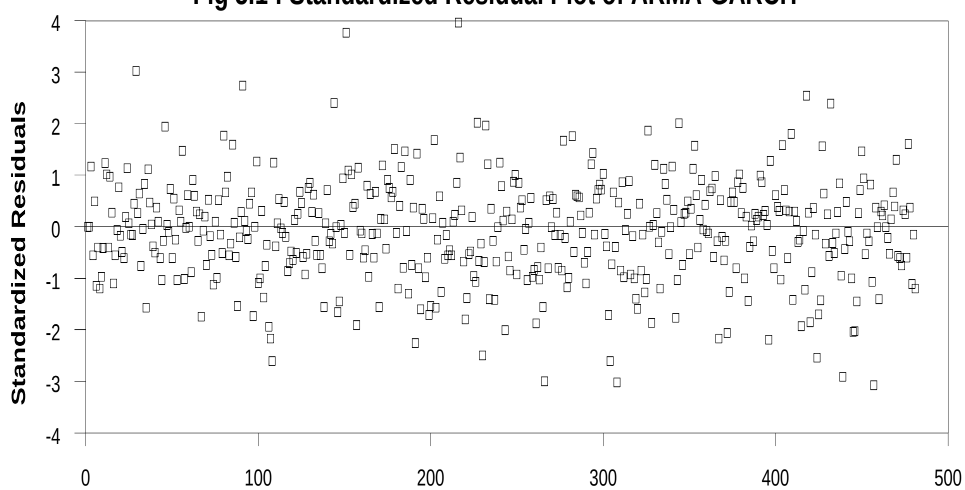


Fig 5.1 : Standardized Residual Plot of ARMA-GARCH



COrrelogram Plots

Fig 3.2 : NSE Nifty Daily Retruns Correlogram

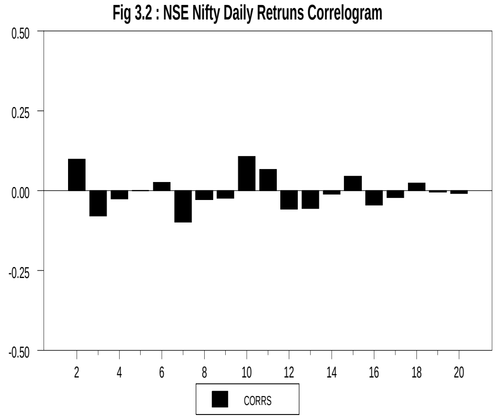


Fig 3.3 : NSE Nifty Daily Squared Retruns Correlogram

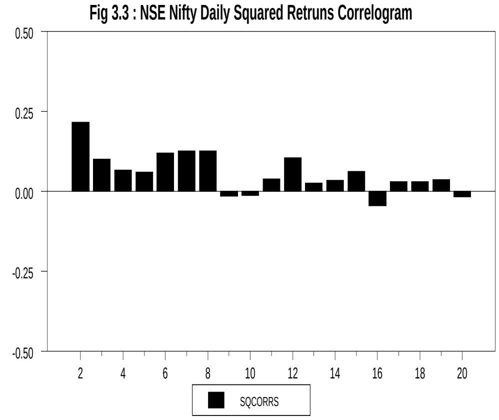


Fig 4.2 : Regression Residuals Correlogram

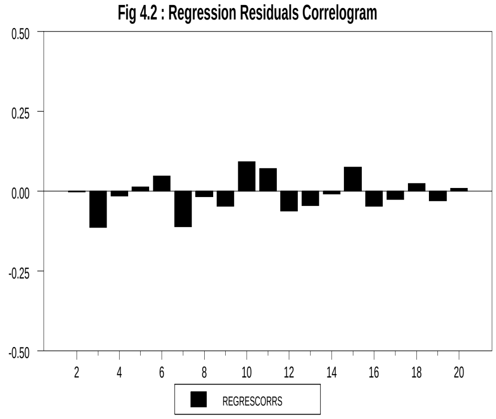


Fig 4.3 : Regression Squared Residuals Correlogram

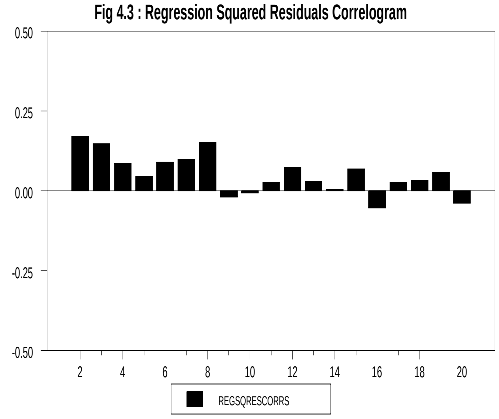


Fig 5.2 : Residual Correlogram of ARMA-GARCH

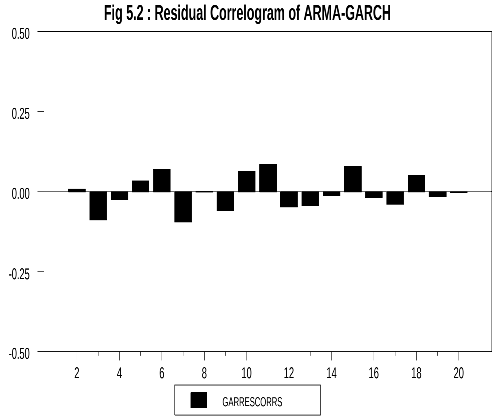


Fig 5.3 : Residual Correlogram of ARMA-GARCH