A CASE OF US AND INDIA

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ABSTRACT

This paper empirically investigates the short run dynamic linkages between NSE Nifty in India and NASDAQ Composite in US during the recent 1999-2001 period using intra-daily data, which determine the daytime and overnight returns. The study carries out a comprehensive analysis from correlation to Granger causality and then to application of GARCH models to examine the co movement and volatility transmission between US and Indian stock markets. Specifically, the study employs a two stage GARCH model and an ARMA-GARCH model to capture the mechanism by which NASDAQ Composite daytime returns and volatility have an impact on not only the mean but also on the conditional volatility of Nifty overnight returns. It is found that the simple ARMA-GARCH model performs better than the more complex Two-stage GARCH model, described in the literature. The main findings of this study are as follows: First, the granger causality results indicate unidirectional granger causality running from the US stock markets (both NASDAQ Composite and S & P 500 indices) to the Indian stock market, NSE Nifty index. Second, the previous daytime returns of both NASDAQ Composite and NSE Nifty have significant impact on the NSE Nifty overnight returns. However, the volatility spillover effects are significant only from NASDAQ Composite implying that the conditional volatility of Nifty overnight returns is imported from US. We found that on an average the effect of NASDAQ daytime return volatility shocks on Nifty overnight return volatility is 9.5% and that of Nifty daytime return is a mere 0.5%. In out of sample forecasts, however, we found that by including the information revealed by NASDAQ day trading provides only better forecasts of the level of Nifty overnight returns but not its volatility.

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1. INTRODUCTION

It is well known that the movements in the stock prices are influenced by the flow of market information. One possible source of this information is movements in other stock markets in the world. There are several reasons why the returns of two different equity markets might be related. The two markets belonging to two different economies might be related through trade and investment, so that any news about economic fundamentals of one country permeates to another and thus affect each other's equity markets. Given the degree of openness to trade and investment, it is a well-accepted fact that the national markets are inter-related and increasingly global (vide John et. al. (1995)). When making decisions, traders incorporate information pertaining to price movements and volatility in the asset they are trading including information about related assets. The movement of markets in rhythm and chorus could nullify much of the gain out of diversification across borders, besides being vulnerable to the caprices of global capital. Thus, understanding how markets influence one another is important in pricing, hedging and regulatory policy.

In recent years, globalization of capital flows has led to the growing relevance of emerging capital markets and India is one of the countries with an expanding stock market that is increasingly attracting funds from the FIIs[1]. In particular, deregulation and market liberalization measures, rapid developments in communication technology and computerized trading systems, and increasing activities of multinational corporations have accelerated the growth of Indian capital market, which is now slowly moving towards global financial integration. From 1999 onwards, Indian firms are raising capital from the US market by listing themselves in US exchanges. At present 12 Indian companies have issued ADRs and are cross-listed in US exchanges and many more companies are planning to cross list in the near future. Moreover as per the Economic Survey 1999-2000, 23% of Indian exports go to US and 10% of total Indian imports are from US making US the major trading partner of India. Thus it will be interesting to examine the co-movement of Indian stock markets with US markets and the mechanism through which the price changes and volatility are transmitted at the wake of lifting restrictions on capital flows and foreign ownership.

Three features of these markets motivate our interest in examination of the short run dynamics of stock returns and volatility between NASDAQ Composite and NSE Nifty. **First**, the exchanges do not have any overlapping trading hours and hence the case of volatility transmission can be clearly examined. **Second,** the economic dailies as well as official publications have been full of stories of a newfound alliance between the NSE and the NASDAQ. The Economic Times of November 14, 2000 has a story with the headline "Uncertainty in US polls, steep NASDAQ fall triggers crash", and says, "short-covering by operators and a rebound in the NASDAQ indices reversed the trend on the domestic markets on Tuesday". Similar report has been echoed in official documents as well. For example, RBIs Annual Report, 2000-2001 has noted that, "Market sentiment

[1] According to SEBI, the net investment of FIIs in the calendar year 1998 is -Rs.1479 crores, in 1999 Rs 6696 crores, in 2000 it is Rs. 6511 crores and in 2001 Rs. 13292.7 crores.

decline in the NASDAQ index during the second half of the month (November 2000)... .also affected the market sentiment adversely" (p104). In a similar vein, The Economic Survey, 2000-01 has noted, "... . This erosion in share prices reflected the influence of share price movements abroad, specially at the tech-heavy NASDAQ' (p 19). Through these news reports, market regulators, traders, and the general investing public in India have become sensitized to market movements in the NASDAQ Composite and its impact on NSE Nifty. **Finally**, a quick examination of stock market movements of these two markets, during the study period under consideration, suggests that there exists a substantial degree of interdependence between NASDAQ Composite & NSE Nifty indices. (See figure 1a & 1b)

The objective of this paper is to empirically examine the short run inter linkages between the US and Indian stock markets. In investigating these issues, we take NSE Nifty index as the core barometer of the Indian stock market as it captures the major chunk of Indian stock market. On the other hand, NASDAQ Composite Index has been taken as a representative of US market as it is a pacesetter of the global stock market having a bearing on national markets worldwide including India, its mecca status among technology stocks, volume lead, no. of listed companies and its star attraction as a unique source of capital even in exchange of a small equity stake. The exercise has been simultaneously carried out for the competing representative of US stock market, namely S & P 500 index. The study carries out a comprehensive analysis from correlation to Granger causality and then to application of GARCH models to examine the co movement and volatility transmission between US and Indian stock markets. We found unidirectional granger causality running from NASDAQ Composite to NSE Nifty. The results are broadly the same even if we use S & P 500 instead of NASDAQ Composite to represent the US stock market.

The rest of the report is organized as follows: Section 2 presents a snapshot of the literature on stock market integration, Section 3 provides a selected account of the structural development in the 1990s, having a bearing on the integration process of the Indian stock market. Section 4 deals with Data and hypotheses, Section 5 delve into the methodological issues of modeling the co movement of markets. Section 6 does a model selection and section 7 does evaluation of selected model both in-sample validity and out of sample forecast performance. Finally, Section 8 summarizes the findings.

2. LITERATURE REVIEW

The nature of the international transmission of stock returns and volatility has been focus of extensive studies. Earlier studies (e.g., Ripley 1973, Lessard 1976, and Hilliard 1979, among many others) generally find low correlations between national stock markets, supporting the benefits of international diversification. The links between national markets have been of heightened interest in the wake of the October 1987 international market crash that saw large, correlated price movements across most stock markets: Eun & Shim (1989), Von Furstenberg and Jeon (1989); King and Wadhwani (1990); Schwert (1990); King et.al. (1994); Longin & Solnik (1995), to name a few. These

Analysis, Simple Regression, ARCH models etc. and report several empirical features:: (i) the correlations across the stock markets are time-varying (ii) when volatility is high, the price changes in major markets tend to become highly correlated (iii) correlations in volatility and prices appear to be causal from the US market which is the most influential market and none of the other market explains US stock market movements. The literature concentrated mostly on well-developed equity markets in the U.S., Japan, and Europe, and do not pay much attention to other stock markets.

To capture the dynamic inter-linkages between the markets, which have non-overlapping trading hours, the literature largely applied a Two Stage GARCH model with intra-daily data that define overnight and daytime returns. **Becker et al** (1990) employ opening and closing data for Tokyo Stock Exchange (Nikkei) and New York Stock Exchange (S&P 500), from 1985 to 1988, to study the synchronization of stock price movements. Their simple regression analysis indicate that the US daytime performance greatly influences overnight returns in Japan the following day and the change in the TSE only has a marginal impact on the NYSE overnight returns on the same day. **Cheung and Ng (1992)** investigate the dynamic properties of stock returns in Tokyo and New York, using daily close-to-close market indices from January 1985 to December 1989. GARCH type models are used to describe the inter-temporal behavior of these stock indices. They included foreign market index's lagged return in the mean equation and lagged squared returns in the variance equation of the home market model to capture mean and volatility spillovers. They found that in the pre-crash period Tokyo stock price movements can be partially explained by those in New York, but the former has very little impact on the latter. In contrast, however, the spillover market effects in the mean and variance exist in both directions after the crash. **Hamao et al (1990), Kee-Hong Bae and Karolyi(1994) and Lin et al (1994)** examined the short-run interdependence of prices and price volatility across three major international stock markets namely, the Tokyo, London and New York with daytime and overnight returns data. Their analysis utilizes a Two-stage GARCH model, where in the first stage they extract the unexpected shocks from the daytime returns of one market and use it as a proxy for volatility surprise while modeling the other market's overnight returns in the second stage GARCH model. They found that cross-market interdependence in returns and volatilities is generally bi-directional between the New York and Tokyo markets particularly after 1987 crash.

So far very few studies have examined the co-movement of Indian stock market with foreign markets. **Sharma & Kennedy (1977)** examined the price behavior of Indian market with US and London markets. The objective of their study was to test the random-walk hypothesis by runs analysis and spectral densities, for the Bombay Variable Dividend Industrial Share Index (BVDISI), the New York Standard and Poor's 425 Common Stock Index (S &P 425), and the London Financial Times-Actuaries 500 Stock Index (London F.T.-A). The test period covered 132 monthly observations for the 11-year period 1963-1973. They found that the behavior of the BVDISI is statistically indistinguishable from that of London F.T.-A. and S&P 425. In the runs analysis of and expected distribution of runs length turns out to be very similar, with probability equal to 0.5 for rise or fall. Further, the spectral densities, estimated for the first difference series (raw and log transformed) of each index, confirmed the randomness of the series, with no evidence of systematic cyclical component or periodicity was present. Based on these tests, they concluded that stocks on the Bombay Stock Exchange obey a random walk and are equivalent in this sense to the behavior of stock prices in the markets of advanced industrialized countries, like UK and US.

Rao & Naik (1990) examined the inter-relatedness of USA, Japanese and Indian stock markets. Their study uses monthly stock indices of the Bombay, New York and Tokyo exchanges, for the period Jan 1971 to December 1988. Their approach is to use Cross-Spectral analysis for the three pair-wise sets of data and the gains estimates to determine which market should be considered as 'independent' in a bivariate relationship. For the USA and Indian series set, the gains estimates suggest that USA series is 'independent'. For the Japan and India series set, the gain estimates suggest that Japanese market is 'independent'. For the USA and Japan series set, it appears that Japan should be considered as 'independent', which may seem to go against the notion that Japan is a follower in international stock markets. On the whole, they concluded that the relationship of Indian market with international markets is poor reflecting the institutional fact that the Indian economy has been characterized by heavy controls throughout the entire seventies with liberalization measures initiated only in the late eighties.

To date, no in-depth analysis of interdependence structure of Indian markets with other national markets is available in the literature. The purpose of this study is to provide such an analysis with a special emphasis on the international transmission mechanism of stock market movements between the US and Indian stock markets.

3. INDIAN STOCK MARKET AND GLOBALIZATION

The Indian stock market though one of the oldest in Asia being in operation since 1875, remained largely outside the global integration process until the late 1980s. A number of developing countries in concert with the International Finance Corporation and the World Bank took steps in the 1980s to establish and revitalize their stock markets as an effective way of mobilizing and allocation of finance. In line with the global trend, reform of the Indian stock market began with the establishment of Securities and Exchange Board of India in 1988. However the reform process gained momentum only in the aftermath of the external payments crisis of 1991 followed by the securities scam of 1992. Among the significant measures of integration, portfolio investment by FIIs allowed since September 1992, has been the turning point for the Indian stock market. As of now FIIs are allowed to invest in all categories of securities traded in the primary and secondary segments and also in the derivatives segment. The ceiling on aggregate equity of FIIS including NRIs (non-resident Indians) and OCBs (overseas corporate bodies) in a company engaged in activities other than agriculture and plantation has been enhanced in phases from 24 percent to 49 per cent in February 2001.

sea change in terms of technology and market practices. Following the commissioning of the NSE in June 1994, National Securities Clearing Corporation in April 1996 and National Securities Depository in November 1996, a screen-based, anonymous, order-driven online dematerialized trading has been the order of the day coupled with improved risk management practices for clearing and settlement.

Finally, the process of integration received a major impetus when the Indian corporate was allowed to go global with GDR / ADR issues. Starting with the maiden issue of Infosys in March 1999, ADR issues has emerged as the star attraction due to its higher global visibility. Till date, around 12 Indian companies have taken advantage of the US market and 76 companies have captured the global market. In March 2001, two-way fungibility for Indian GDR / ADRs was introduced whereby converted local shares could be reconverted into GDR/ADR subject to sectoral caps.

Thus, the Indian stock market, which was in isolation until recently, turns out to have been sensitive to developments in the rest of the world by the end of the 1990s. Pursuit of a novel set of policy initiatives with FII portfolio investment and Indian ADR issues at its center-stage seems to have contributed significantly to the emerging stock market integration. Besides, India's cautious experiment with openness appears to have facilitated the steady pursuit of a policy milieu for stock market integration. In this report, we make a symptomatic analysis of the relation between domestic and foreign equity indices. In the next section, we examine the relationship between the US and Indian stock indices and report some stylized facts.

3.1 Price Movement: Stylized Facts

The media as well as financial press have been replete with instances and counterfactuals of a strong (or weak) and positive (or negative) correlation between the two crucial barometers of stock markets in the Indian psyche, namely the S & P CNX Nifty and NASDAQ Composite (henceforth referred to as Nifty and NASDAQ respectively). Do such claims and counter-claims arise from the causal issues and inter-linkages between these markets? To this end, as a first instance the plot of the daily closing quotes of the Nifty and NASDAQ (vide Fig 1A) over a five year-period (1996 to 2001) reveal a distinct positive trend. The picture is comparable if the S & P 500 is substituted for the NASDAQ Composite (vide Fig 1B). As is obvious from the plot, the Nifty, which was insensitive to the global stock trend, has started to mirror and magnify the twists and turns of the NASDAQ (S&P500) in the recent years.

While a priori the shape of the graph could be a motivating reason in pursuing the relationship between Nifty and NASDAQ, it is also clear from the graph that on a number of occasions, the association is just the reverse. So, we have calculated the year wise correlation coefficient between Nifty and NASDAQ over a five-year period. It is interesting to note that the correlation coefficient changed from negative (-0.254) in 1996-97 to positive (0.008) in 1997-98 and (0.225) in 1998-99 and then it has become significantly positive (0.789) in 1999-00 and (0.653) in indicates that from the period around mid of 1999, NSE Nifty is moving in tandem with NASDAQ Composite / S & P 500. Thus the recent period, 1st July 1999 to 30th June 2001, is the period that becomes the focus of our investigation.

3.2: Granger Causality::

The high correlation between the NSE Nifty and NASDAQ is in no way indicative of any causation. So to examine the causality between NASDAQ Composite and NSE Nifty, we use the test suggested by Granger (1969). The standard Granger causality test examines whether past changes in one stationary variable X help to predict current changes in another stationary variable Y, beyond the explanation provided by past changes in Y itself. If not, then X does not "Granger cause" Y. The test of X not Granger-causing Y is simply a test of a linear hypothesis H_0: $?_1 = ?_2 = \ldots = ?_q = 0$ in a linear model $Y_t ? ? \; ? \overset{p}{\underset{j?1}{?}} ? \,_j Y_{t?j} ? \overset{q}{\underset{j?1}{?}} ? \,_j X_{t?j} ? u_t \ldots$ ... ... **(1)** where p and q are the optimal lag lengths determined by AIC model selection criteria. The null hypothesis of "no-Granger-causality" can be tested using the standard linear F-test under model (1).

To examine the Granger causality between daily returns[2] of NASDAQ (S&P500) and Nifty, a maximum length of eight lags are selected and reduced according to the AIC and SBC model selection criterion. Table 1 shows that only for $NIFTY_t$, the F-statistic is significant indicating that the past values of $NASDAQ_t$ / S & P 500_t help to predict current changes in $NIFTY_t$. This suggests a unidirectional granger causality running from $NASDAQ_t$ / S & P 500_t returns to $NIFTY_t$ returns but not the other way round. The effect of NASDAQ is a little more pronounced than S&P500 on Nifty in terms of the value of the F-statistics and the resulting p-values. The fact that NSE Nifty can't influence the NASDAQ Composite is hardly surprising given the relative sizes of the equity markets of the two economies. As this unidirectional granger causality from NASDAQ (S &P 500) to Nifty is very apparent from this preliminary analysis, now we seek to examine and quantify the impact of NASDAQ (S & P 500) fluctuations on NSE Nifty.

4. DATA AND HYPOTHESES

4.1. TIME ZONE CONSIDERATIONS::

In order to understand the international transmission mechanism between the two markets under consideration, first it is important to recognize that the NSE and NASDAQ markets do not have any overlapping trading hours.There is a time lag of twelve-and-half hours between US Eastern Standard Time and Indian Standard Time. The trading hours of both the markets are shown in Fig. 2. As shown in Fig.2, in Indian Standard Time (IST), NSE opens at 10.00 AM and closes at 3.30 PM.,

[2] Nifty Daily Returns ($NIFTY_t$) = Log (Nifty close on day t / Nifty close on day t-1)*100
NASDAQ Daily Returns ($NASDAQ_t$) = Log (NASDAQ close on day t / NASDAQ close on day t-1)*100
S&P 500 Daily Returns (S&P 500_t) = = Log (S&P 500 close on day t /S&P 500 close on day t-1)*100

common time interval in which both markets remain open.

Following Hamao et al (1990), Lin et al (1994) and Kee-Hong Bae & Karolyi (1994) to study the synchronization of stock price movements, a daily (close-to-close) return is divided into a daytime (open-to-close) and an overnight (close (t-1)-to-open) return for both NSE Nifty and NASDAQ Composite indices. Since there is no overlap between the trading hours of the two markets, it is possible to study the influence of daytime return in one market on the overnight return of the other. Intuitively, traders in India use any relevant information revealed overnight in NASDAQ in pricing their stocks as soon as the opening bell rings. So, the decomposition of daily price changes (returns) into daytime [Close (t)–to-Open (t)] and overnight [Open (t)-to-Close (t-1)] returns is crucial in modeling and understanding how information is transmitted from one market to the other.

4.2. DATA SOURCES

In most major stock markets, there are problems in calculating opening prices for these market indices due to delayed opening of individual stocks. Stoll& Whaley (1990) report that after the market opens for the first transaction to occur on an average it takes 5 minutes for large stocks and 67 minutes for small stocks in NYSE for the first transaction to occur after the market opens. When delays occur, the prior day closing prices are used for the unavailable current price in calculating the high-frequency index of stock market. This creates artificial serial correlations in close-to-open and open-to-close returns, which biases intra day return and volatility estimates. In order to minimize the effects of these stale prices, the literature suggests one to use the index quotes 15 minutes after the first open quote, so that the artificial correlation between the intra-day returns are minimized.

For NSE Nifty, the first open quote of the index is available at around 9.55 AM. At this first open quote, since all the 50 constituent scrips of Nifty have not been traded, taking this value as the open quote would be inappropriate. But usually by the official opening time of 10.00 AM, around 10,000 trades take place on a typical day in NSE. So we take the open quote of Nifty in the analysis as its value at 10.00 0'clock. The 10.00 0'clock data of NSE Nifty is provided by National Stock Exchange Research Initiative. Daily official open(9.30AM, EST) and close (4.00PM, EST) quotes of NASDAQ Composite Index have been downloaded from www.nasdaq.com and that of S & P 500 index are downloaded from www.finance.yahoo.com. For S & P 500 index on most of the days the open quote of most of is exactly same as that of previous day's close quote having serious stale quote problems. For NASDAQ Composite index the close quote on day t-1 is different from open quote on day t, the stale price effect will be minimal as compared to S&P 500 index. We unable to get the intra-day data of S & P 500, so as to minimize the stale quote problem. Hence we unable to use S & P 500 index in our further intra day similar to that of NASDAQ. Specifically, in this study, we calculate the returns as follows[3]:

Nifty Overnight Returns ($NIFON_t$) = Log (Nifty open on day t / Nifty close on day t-1)*100

Nifty Daytime Returns ($NIFD_t$) = Log (Nifty close on day t / Nifty open on day t)*100

NASDAQ Overnight Returns ($NASON_t$)=Log (NASDAQ open on day t / NASDAQ close on dayt-1)*100

NASDAQ Daytime Returns ($NASD_t$)= Log (NASDAQ close on day t / NASDAQ open on day t)*100

4.3. Hypotheses

In our analysis, we gauge the marginal effect of the NASDAQ and Nifty daytime returns and volatilities on the Nifty overnight returns and volatility. To this end, we formulate the following hypothesis tests as follows.

H_0: NASDAQ daytime returns do not influence Nifty overnight returns

H_0: NASDAQ daytime volatility does not influence Nifty overnight volatility.

H_0: Nifty daytime return does not influence Nifty overnight return

H_0: Nifty daytime volatility does not influence Nifty overnight volatility.

These hypotheses tests will be examined by looking at the marginal significance of the respective coefficients by Wald's test in our empirical model in the next section.

5. METHODOLOGY :: GARCH MODELING

5.1. Preliminary Analysis

Table 2 presents a wide range of descriptive statistics for the stock index returns of the NASDAQ Composite and NSE Nifty. The sample moments indicate that empirical distributions of returns are all skewed and highly leptokurtic, when compared with the normal distributions. This is reinforced by the Jarque-Bera tests for normality, which are highly significant. From the raw return series plots in Fig 3 it appears that the volatility of returns varies over time. All the return series display the volatility-clustering phenomenon, large (small) shocks of either sign tend to follow large (small) shocks. To further analyze the stock returns behavior, the Ljung-Box statistic for 10 & 20 lags for returns and squared returns are also reported in Table 2. The presence of significant autocorrelations, except for NASD return series, suggests that markets are not efficient as the past returns can be used to predict the future returns. The presence of significant autocorrelations in the

[3] Preliminary analysis has shown that the hypothesis of a unit root is strongly rejected for the logarithmic first difference of the price index. Therefore, all stock return series follow a stationary process

autocorrelation among squared returns and excess kurtosis are compatible with the volatility clustering phenomenon that has been documented for most developed stock markets, e.g., Bollerslev, Chou and Kroner (1992). These features of the data, lead us to consider GARCH type models that can accommodate the time varying and persistent behavior of volatility of returns.

We start modeling with a Two-stage GARCH model as suggested in the literature for non-overlapping markets. Also we approach the problem with a simple ARMA-GARCH model where the squared returns will proxy for volatility. This simple model turns out to be as good as the more complex Two-stage GARCH model.

5.2. Spillover - effects with Two-Stage GARCH model::

Hamao et al (1990), Kee-Hong Bae & Karolyi (1994) and Lin, Engle & Ito (1994) use a Two-stage GARCH model for estimating the spillover effects between New York, London & Tokyo markets. In the first stage they estimate an appropriate MA-GARCH model for foreign market daytime returns. In the second stage, they estimate an appropriate MA-GARCH model for domestic overnight returns, where they include the residuals or residual squares obtained in the first stage GARCH model as a regressor, which captures the potential volatility spillover effect from the previously open foreign daytime returns into the domestic overnight returns. Their main finding is that Japanese market is most sensitive to volatility spillover effects from New York market, while the New York market is at most moderately sensitive to volatility spillovers from Japan market.

We estimate this Two-stage GARCH model (**Model 1**) to see the spillover effects from NASDAQ daytime returns to NSE Nifty overnight returns. We begin by specifying an appropriate ARMA-GARCH-in-Mean model, for both daytime returns of NSE Nifty and NASDAQ Composite, introduced by Engle, Lilien and Robins (1987) as follows:

$$R_{D,t} \; ? \; ?_{1,0} \; ? \; \overset{p}{\underset{i?1}{?}} \; ?_{1,i} R_{D,t?i} \; ? \; \overset{q}{\underset{j?1}{?}} \; ?_{1,j} ?_{t?j} \; ? \; ?_{1,m} DUM \; ? \; ?_1 h_{1,t} \; ? \; ?_t \qquad \ldots \ldots ..(2)$$

$$?_t \sim N(0, h_{1,t})$$

$$h_{1,t} \; ? \; ?_{1,0} \; ? \; \overset{r}{\underset{i?1}{?}} \; ?_{1,i} ?^2_{t?i} \; ? \; \overset{s}{\underset{j?1}{?}} \; ?_{1,j} h_{t?j} \; ? \; ?_{1,v} DUM \; ; \; R_D \; ? \; NIFD_t, NASD_t$$

The dummy variable DUM accounts for multiple-day returns associated with weekends and holidays in either market. The $?_1$ coefficient links the conditional market volatility to expected returns and its significance can be used to test for time-varying market risk premia. We refer to this model as the first-stage GARCH, as the estimated residual squares from (2) will proxy for the news shocks that spillover from daytime returns of NSE Nifty and NASDAQ Composite to the volatility of the next day NSE Nifty Overnight returns.

In the second stage we fit an appropriate ARMA-GARCH-in-Mean model for NSE Nifty Overnight returns. We allow for mean spillover effects by including previous daytime returns of NASDAQ and Nifty in the mean equation and include residual squares obtained from (2) for $NIFD_t$

Overnight returns, our model is given by:

$$NIFON_t ?? _{2,0} ? \overset{u}{\underset{i?1}{?}} ? _{2,i} NIFON_{t?i} ? \overset{v}{\underset{j?1}{?}} ? _{2,j} ? _{t?j} ?? _{2,m} DUM ?? NIFD_{t?1} ?? NASD_{t?1} ?? _2 h_{2,t} ?? _t$$

$$? _t \sim N(0, h_{2,t})$$

$$h_{2,t} ?? _{2,0} ? \overset{k}{\underset{i?1}{?}} ? _{2,i} ? ^2_{t?i} ? \overset{l}{\underset{j?1}{?}} ? _{2,j} h_{t?j} ?? _{2,v} DUM ?? NASDRES^2_{t?1} ?? NIFDRES^2_{t?1} \quad \textbf{(3)}$$

where $NASDRES_{t-1}$ is the most recent residual estimated from the first-stage model for the NASDAQ Composite daytime return and $NIFDRES_{t-1}$ is the same measure obtained for the previous NSE Nifty daytime return.

A statistically significant value for ? ' indicates that the conditional mean NSE Nifty Overnight returns is influenced by previous daytime returns of NSE Nifty (own-mean spillovers). On the other hand, a statistically significant ? 'value suggests that past daytime returns of NASDAQ Composite affect the conditional mean of NSE Nifty Overnight returns (cross-mean spillover). Statistically significant values for ? ' and ? ' respectively indicate the influence of cross and own volatility spillovers from previous daytime returns of NASDAQ Composite and NSE Nifty to the NSE Nifty Overnight returns.

5.2.1. First Stage Results::

The ARMA (1,1)-GARCH (1,1) with normal distribution as conditional error distribution fits well for both NSE Nifty daytime returns and NASDAQ Composite daytime returns on the basis of AIC criteria. All models are estimated using the numerical maximum likelihood procedures of Berndt et al. (1974) in RATS 5.0. Table 3 reports the final estimation results for the first stage model after dropping all the insignificant terms in the general model considered in (2) and then refitting this reduced model. Panel A reports the coefficient estimates and Panel B presents a number of residual diagnostics. The constant in the mean equation of both daytime returns is insignificant and hence dropped from the model. The GARCH-in-Mean term is insignificant for both daytime returns and hence there is no evidence of time varying risk premia. The dummy variable for holiday and weekend returns is significant for NASDAQ Composite daytime returns only. The estimates of GARCH parameters $?_1$ and $?_1$ are significant and the sum of these two coefficients, measuring the persistence of volatility, is close to unity. The portmanteau (Box-Ljung) statistics evaluate the serial correlations in the raw and squared standardized residuals of the model up to lags 10 and 20 and find that most of the conditional dependence in the returns is also modeled reasonably well. The excess kurtosis is not a problem and there is some residual negative skewness.

5.2.2. Spillover effects to NSE Nifty overnight returns::

We next estimate the second stage GARCH model (3) that allow both NSE Nifty and NASDAQ Composite daytime returns and shocks to influence the conditional mean and volatility of NSE Nifty overnight returns. The ARMA (1,1) – GARCH (1,1) model turns out to be appropriate in describing hence we constrained it to be non-negative, yielding an estimate of zero.[4] The holiday dummy is insignificant in both mean and variance equations and is the GARCH-in-Mean coefficient, $?_{2}$. The final model for the NSE Nifty overnight returns are summarized in Panel A after dropping the insignificant terms in the general model (3) and then refitting the reduced model. The objective diagnostic tests of this final model are presented in Panel B of Table 4.

The results for the conditional mean equations show statistically significant positive mean spillover effect from the previous NASDAQ Composite daytime returns; a high return in the NASDAQ market is followed by a high return in the NSE Nifty Overnight returns. We find clear evidence that the most recent daytime returns of NASDAQ Composite have positive influences on the opening price in the NSE Nifty. The parameter estimates for the conditional variance, $?_{2,1}$ and $?_{2,1}$ are highly significant, indicating that the conditional variance process of $NIFON_t$ is indeed time varying. The stability condition for the volatility process is satisfied because the sum of the estimated GARCH parameters is less than unity, suggesting that the conditional variances follow a stationary process. The cross volatility spillover effect from NASDAQ Composite daytime returns is 0.0129 and highly significant whereas the own volatility spillover effect from NSE Nifty daytime returns is 3.8148e-04 and insignificant, indicating that conditional volatility in NSE Nifty overnight returns is "imported" from the U. S. The model diagnostic graphs namely the Residual Plot, Correlogram of residuals and residual squares are displayed in Fig 4.1 to Fig 4.3. These diagnostics show that the model's residuals are reasonably well behaved. The portmanteau (Box-Ljung) statistics in Panel B of Table 4 evaluate the serial correlations in the raw and squared standardized residuals of the model up to lags 10 and 20 and find that most of the conditional dependence in the return has also been modeled reasonably well. Finally, we report the sign and size bias test statistics indicating no measurable degree of asymmetry in the residuals. On the whole the Two Stage GARCH model seems to capture well the Nifty overnight return linkages with NASDAQ daytime returns fairly well.

5.3. Spillover - effects with ARMA – GARCH model::

Although the Two Stage GARCH approach is very intuitive in capturing the effects of volatility spillover, it entails the generated regressors problem. So one simple alternative is to go for ARMA-GARCH model where the squared returns, as a proxy for volatility, of foreign market are appended in the conditional variance equation of domestic market. In this section, we model the $NIFON_t$ returns by allowing for possible autocorrelation from the preceding overnight returns, possible cross autocorrelation / influence from previous daytime returns of both NASDAQ and Nifty, and for Monday or post holiday effects through a dummy variable, DUM. In general this model for $NIFON_t$ can be written as

[4] If we unrestrict the constant out of sample variance series is negative though it is positive for observed data

$$NIFON_t ? ?_0 ? \sum_{i?1} ?_i NIFON_{t?i} ? \sum_{j?1} ?_j u_{t?j} ? ? DUM_t ? ? NIFD_{t?1} ? ? NASD_{t?1} ? ? h_t ? u_t \quad \ldots (4)$$

In (4) the NASDAQ information is effected through the parameter ? and that of NIFTY through the parameter ? . A shock (news) revealed after the close of NASDAQ but before the opening of NIFTY market is denoted by u_t. As it has been noticed in section 4.3 that the volatility in the $NIFON_t$ series is time varying, we extend the above specification of $NIFON_t$ in (4) by modeling u_t as a GARCH process instead of white noise. To capture the volatility transmission effects from the daytime returns of both Nifty and NASDAQ, following Cheung and Ng (1992), we include their squared returns as proxy for volatility in the GARCH specification of conditional variance of u_t. We also include a dummy variable for Monday or post holiday effects, in the GARCH specification yielding,

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

$$h_t ? ? ? \sum_{i?1}^{p} ?_i u_{t?i}^2 ? \sum_{j?1}^{q} ?_j h_{t?j} ? ? NIFD_{t?1}^2 ? ? NASD_{t?1}^2 ? ? DUM_t \quad \ldots ..(5)$$

The Maximum likelihood estimation results of (4) & (5), with the same set of data as the Two-stage GARCH model, are reported in Table 5 along with diagnostic tests. Henceforth this model is referred to as **Model 2.**

The appropriate ARMA-GARCH order again turns out to be ARMA (1,1) – GARCH (1,1). Since ?, MLE of the constant in GARCH equation is negative and hence we constrained it to be non-negative, yielding an estimate of zero.[5] The dummy variable is insignificant in both mean and variance equations implying that no systematic effect of holidays in either mean returns or volatility. The results for the conditional mean equations show statistically significant positive mean spillover effect from the previous NASDAQ Composite daytime returns; a high daytime return in the NASDAQ market is followed by a high overnight return in the NSE Nifty, as was also revealed by the Two-stage approach. The parameter estimates for the conditional variance, $?_1$ and $?_1$ are highly significant, indicating that the conditional variance process of $NIFON_t$ is indeed time varying. The stability condition for the volatility process is satisfied because the sum of the estimated GARCH parameters is less than unity, suggesting that the conditional variances induce a stationary process. The cross volatility spillover effect from NASDAQ Composite daytime returns is 0.0131 and highly significant whereas the own volatility spillover effect from NSE Nifty daytime returns is only 6.3996e-04, which is not statistically significant either, indicating that conditional volatility in NSE Nifty overnight returns is "imported" from the U. S. This is again in tune with the findings of the earlier Two-stage approach. The model diagnostic graphs namely the Residual Plot, Correlogram of residuals and residual squares are displayed in Fig 5.1 to Fig 5.3. These diagnostics show that the model's residuals are reasonably well behaved. The portmanteau (Box-Ljung) statistics in Panel B of Table 5 evaluate the serial correlations in the raw and squared standardized residuals of the model up

[5] If we unrestrict the constant, out of sample variance series is negative though it is positive for observed data

modeled reasonably well. Finally, as before the sign and size bias test statistics also do not indicate any measurable degree of asymmetry in the residuals. On the whole the simple ARMA-GARCH model also seems to capture the Nifty overnight return linkages with NASDAQ daytime returns fairly well.

6. MODEL COMPARISON

To compare competing models of international transmission of stock returns and volatility, we employ AIC / SBC model selection criteria, which gives a comparative indication of the goodness-of-fit of competing models. Table 6 compares three models: Two-stage GARCH, simple ARMA-GARCH model and Domestic model. The first two models have already been described in section 5. Ignoring the effect of NASDAQ information altogether both in mean and variance equations, the domestic model is specified as follows:

$$NIFON_t ?? _{d,0} ? \overset{p}{\underset{i?1}{?}} ? _{d,i} NIFON_{t?1} ? \overset{q}{\underset{j?1}{?}} ? _{d,j} ? _{t?j} ?? _{d,m} DUM ?? _d NIFD_{t?1} ?? _d h_{d,t} ?? _t$$

$$? _t \sim N(0, h_{d,t})$$

$$h_{d,t} ?? _{d,0} ? \overset{r}{\underset{i?1}{?}} ? _{d,i} ? ^2_{t?i} ? \overset{s}{\underset{j?1}{?}} ? _{d,j} h_{d,t?j} ?? _{d,v} DUM ?? _d NIFD^2_{t?1} \qquad \ldots (6)$$

The domestic model (**Model 3**) been fitted with an appropriate ARMA-GARCH model, where the spillover effects have been included only from Nifty daytime returns. As the volatility spillovers from $NIFD_{t-1}$ to $NIFON_t$ are insignificant, measured either $NIFD^2_{t?1}$ or by $NIFDRES^2_{t?1}$, the final estimated reduced model would be the same for both Two-stage GARCH model and simple ARMA-GARCH model. The model comparison with the domestic model examines whether the inclusion of information revealed by NASDAQ daytime return provides better forecast of NIFON return than the domestic model. The comparison is based on the same data set but different model specifications. Table 6 reveals some interesting results for the models' performance. In terms of the AIC / SBC criterion and Log Likelihood value, the simple ARMA-GARCH model (Model 2) is better than the other two models for NIFTY overnight returns.

7. MODEL EVALUATION & FORECASTING

In this section, we evaluate weather the estimated ARMA-GARCH model is an adequate description of the $NIFON_t$ volatility process. Establishing the effectiveness of a volatility forecast is not straightforward as volatility process itself is inherently unobservable. We circumvent this problem by using a proxy, squared returns for actual realized volatility. To see the in-sample performance of estimated ARMA-GARCH model, we simply check the ability of predicted volatility from the estimated model (denoted by h_t) to forecast the actual volatility, the proxy of squared returns, r_t^2. Specifically this amounts to regressing volatility proxy on a constant and predicted volatility (Engle & Patton 2000)

A good forecast should have the properties: a =0, b=1 and a high R^2. Eqn 7 is estimated using the usual OLS procedure with White's heteroscedasticity consistent standard errors and results are reported in Table 7. We see that, the predicted volatility satisfies the two desirable properties viz. the estimated values of a and b are insignificantly different from 0 and 1 respectively. However, the R^2 of the regression is around 20%, seems to be quite low. The reason for this seemingly poor R^2 is the choice of what is considered as the "true" volatility, which can't be observed directly.

Finally, in order to examine the relative importance of the Nifty daytime and NASDAQ daytime return volatilities on the Nifty overnight return volatility, the following variance ratios, as suggested by Angela Ng (2000), are computed from the estimated ARMA-GARCH model:

$$VR_t^{NASD} = \frac{? NASD_{t-1}^2}{h_t} \in [0,1]; VR_t^{NIFD} = \frac{? NIFD_{t-1}^2}{h_t} \in [0,1]$$

The ratios VR_t^{NASD} and VR_t^{NIFD} measure the proportions of conditional variance of $NIFON_t$ accounted for by the NASDAQ and Nifty daytime return volatilities respectively. Fig 6 presents these variance ratios along with their mean values. It is very clear that the relative influence of the NASD and NIFD volatilities shifts over time. Nifty overnight return volatility is more dependent on the NASD volatility than on the NIFD volatility over the whole sample period. On an average, the NASD volatility account for 9.51% of the Nifty overnight volatility while the NIFD volatility capture only 0.5%.

Now we turn to out of sample forecast evaluation. The only real test of the performance of a forecasting model is to see, how well it performs in reality, and the way to do it is to use the model to forecast returns beyond the time- period during which it was estimated and then compare the model forecasts with the real observed returns. We report these out-of-sample mean forecasts of ARMA-GARCH model and compare it with the actual realized Nifty overnight returns. We calculate multi-step ahead forecasts for the next 45 days, from 1st July 2001 to 31st August 2001. To benchmark the forecast performance against an alternative, we also calculate the mean forecasts based on the domestic model (Model 3), which does not consider information flow from NASDAQ. Fig 7 plots the actual Nifty overnight return, forecast values, NIFONF and NIFONF_DOM, from model 2 and 3. It is evident that the model with NASDAQ information (model 2) clearly outperforms model 3 in predicting the actual Nifty overnight returns. This is further reinforced by the least mean squared error forecast of model 2. Fig 8 plots the out of sample volatility forecast errors, HF_error and HFDOM_error, from model 2 & 3. In predicting the out of sample volatility, its not so clear which model performs better. However, the MSE of volatility forecast error of model 2 is marginally smaller than that of model 3.From figs 7 & 8, we conclude that using not volatility.

8. CONCLUSION

We investigate the short run dynamic inter linkages between the US and Indian stock markets, using daytime and overnight returns of NSE Nifty and NASDAQ Composite from 1st July 1999 to 30th June 2001. This approach provides an explicit, empirically based, quantitative description of the way information propagates from NASDAQ and is being incorporated by NSE overnight returns. The study employs Two- stage GARCH model and a simple univariate ARMA-GARCH model to capture the mechanism by which NASDAQ Composite daytime returns and volatility have an impact on not only the conditional returns but also on the conditional volatility of Nifty overnight returns. We found that the simple ARMA-GARCH model performs better than the more complex Two Stage GARCH model suggested in the literature. We also benchmark the simple univariate model with a model involving information pertaining to only the domestic market and discarding the information revealed by NASDAQ.

The main findings are as follows: First, the granger causality results indicate unidirectional "granger causality" running from the US stock markets (both NASDAQ Composite and S & P 500) to Indian stock market, NSE Nifty index. Second, the previous day's daytime returns of both NASDAQ Composite and NSE Nifty have significant impact on the NSE Nifty overnight return of the following day. However, the volatility spillover effects are significant only from NASDAQ Composite implying that the conditional volatility of Nifty overnight returns is imported from US. We found that the effect of NASDAQ daytime return volatility shocks, on average, is 9.51% and that of Nifty daytime return volatility is a mere 0.5%. Turning to out of sample forecasts however, we found that by including the information revealed by NASDAQ day trading provides better forecasts of mean levels of Nifty overnight returns but does not significantly improve the prediction of volatility.

At foremost interest in much of the empirical international financial literature is to study the extent to which markets have become internationally integrated. Insights into information flows in markets will increase the understanding of the relevant mechanisms at work during extreme situations such as market crashes, which in turn can provide guidelines for intervention and tax policies. This paper contributes in a modest manner with reference to Indian stock market integration with the US stock market. The results reported are in contrast with the previous studies, which have examined the co-movement of Indian markets with other markets and suggested a very low degree of correlation. Here there is strong evidence that NSE Nifty is in tune with NASDAQ Composite over the sample period. Various explanations can be offered for this phenomenon and these range from (i) Deregulation of Indian financial market since 1992, including increased efforts to implement liberalization measures. (ii) Increase in macro economic policy coordination, (iii) Expanding influence of multinational corporations, (iv) Increased participation of FIIs in Indian stock market. (v) Increasing international cross-listing of Indian firms in US markets and (vi) transmitted from one market to the other.

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1^{st} July 1999 to 30^{th} June 2001.

Cause (X)	Effect (Y)	F-statistic	p-value	Causality Inference
$NASDAQ_{t-i}$	$Nifty_t$	18.17839	0.00000	NASDAQ ? Nifty
$Nifty_t$	$NASDAQ_t$	2.394235	0.12239	Nifty ? NASDAQ
$S \& P\ 500_{t-i}$	$Nifty_t$	10.77280	0.00001	S & P 500 ? Nifty
$Nifty_t$	$S \& P\ 500_t$	0.012293	0.91176	Nifty ? S & P 500

Nifty Daily Returns ($NIFTY_t$) = Log (Nifty close on day t / Nifty close on day t-1)*100

NASDAQ Daily Returns ($NASDAQ_t$) = Log (NASDAQ close on day t / NASDAQ close on day t-1)*100

S&P 500 Daily Returns (S&P 500_t) = = Log (S&P 500 close on day t /S&P 500 close on day t-1)*100

Table 2: Descriptive Statistics of Returns

	NIFON	NIFD	NASD	NASON
Mean	0.011913	-0.053361	-0.229837	0.155801
Std. Dev.	1.181816	1.706881	2.437789	1.341334
Skewness	-0.855389	0.034545	0.462996	-0.415359
Kurtosis	9.259764	4.276174	6.329029	5.121630
Jarque-Bera	908.904	35.2540	257.702	109.019
Probability	(0.000)	(0.000)	(0.000)	(0.000)
LB(10)	23.967	17.641	13.242	23.307
	(0.008)	(0.061)	(0.210)	(0.010)
LB(20)	68.619	29.264	28.337	40.103
	(0.000)	(0.083)	(0.101)	(0.005)
$LB^2(10)$	324.850	96.071	80.476	35.212
	(0.000)	(0.000)	(0.000)	(0.000)
$LB^2(20)$	442.340	104.95	106.14	69.700
	(0.000)	(0.000)	(0.000)	(0.000)

Table 3::
Estimation results and diagnostics for daytime returns of NASDAQ Composite and NSE Nifty indices from 1^{st} July 1999 to 30^{th} June 2001.

STAGE – I :

$$NASD_t\ ?\ ?_{1,1}\ NASD_{t?1}\ ?\ ?_{1,1}\ ?_{1,t?1}\ ?\ ?_{1,m}\ DUM_t\ ?\ ?_{1,t}$$

$$?_{1,t} \sim N(0, h_{1,t})$$

$$h_{1,t}\ ?\ ?_{1,0}\ ?\ ?_{1,1}\ ?^{2}_{1,t?1}\ ?\ ?_{1,1}\ h_{1,t?1}$$

$$NIFD_t\ ?\ ?_{1,1}\ NIFD_{t?1}\ ?\ ?_{1,1}\ ?_{1,t?1}\ ?\ ?_{1,t}$$

$$?_{1,t} \sim N(0, h_{1,t})$$

$$h_{1,t}\ ?\ ?_{1,0}\ ?\ ?_{1,1}\ ?^{2}_{1,t?1}\ ?\ ?_{1,1}\ h_{1,t?1}$$

DUM is a dummy variable for holiday and weekend returns.
Estimation is performed by the BHHH algorithm with robust errors option in RATS 5.0 package.

Panel A	Estimate	p-value	Estimate	p-value
$?_{1,1}$	0.698595	0.00000	-0.937656	0.00000
$?_{1,1}$	-0.777019	0.00000	0.967435	0.00000
$?_{1,m}$	-0.509481	0.00000	- - -	- - -
$?_{1,0}$	0.099749	0.03110	0.137085	0.08030
$?_{1,1}$	0.092249	0.00480	0.165535	0.00210
$?_{1,1}$	0.892866	0.00000	0.790656	0.00000

Panel B : Residual Diagnostics

Skewness	-0.13624		0.046403	
Kurtosis	0.48599		4.775925	
J-B test	7.08848	0.02889	71.94739	0.00000
LB(10)	9.48810	0.30300	10.18200	0.25202
LB(20)	20.49400	0.30600	22.80710	0.19801
$LB^2(10)$	2.15970	0.97600	13.45300	0.09701
$LB^2(20)$	9.63060	0.94400	17.83460	0.46797

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;

Table 4::

Nifty Overnight Returns

$$NIFON_t \;?\; ?_{2,0} \;?\; ?_{2,1} NIFON_{t?1} \;?\; ?_{2,1} ?_{t?1} \;?\; dNIFD_{t?1} \;?\; fNASD_{t?1} \;?\; ?_{2,t}$$

$$?_{2,t} \sim N(0, h_{2,t})$$

$$h_{2,t} \;?\; ?_{2,0} \;?\; ?_{2,1} ?^2_{2,t?1} \;?\; ?_{2,1} h_{2,t?1} \;?\; ? NIFDRES^2_{t?1} \;?\; ? NASDRES^2_{t?1} ; ?_{2,0} \;?\; 0$$

Stage II	NSE NIFTY Overnight Returns	
	Coefficients	p-value
$?_{2,0}$	0.0441	0.0008971
$?_{2,1}$	0.3695	0.0037494
$?_{2,1}$	-0.3297	0.0216947
d	0.0756	0.0000384
f	0.0934	0.0000002
$?_{2,0}$	9.2774e-16	0.0000000
$?_{2,1}$	0.2076	0.0000001
$?_{2,1}$	0.7597	0.0000000
?	3.8148e-04	0.7778724
?	0.0129	0.0000000

Panel B: Residual Diagnostics

Skewness	0.1443	
Kurtosis	9.3640	
J-B test	953.7258	0.000000
LB (10)	6.4103	0.779696
LB (20)	29.3061	0.081904
LB^2 (10)	9.7069	0.466574
$LB^2(20)$	15.5187	0.745996
LM (20)	0.2934	0.882290
Sign Bias	0.5433	0.587150
Neg. Bias	0.4097	0.682230
Pos. Bias	0.0856	0.931780
Joint Bias	0.1190	0.948920

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 developed by Engle and Ng (1993)

$$NIFON_t\ ?\ ?\ _0\ ?\ ?\ _1 NIFON_{t?1}\ ?\ ?\ _1 u_{t?1}\ ?\ ?\ NIFD_{t?1}\ ?\ ?\ NASD_{t?1}\ ?\ u_t$$

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

$$h_t\ ?\ ?\ \ ?\ ?\ _1 u^2_{t?1}\ ?\ ?\ _1 h_{t?1}\ ?\ ?\ NASD^2_{t?1}\ ?\ ?\ NIFD^2_{t?1};?\ \ ?\ 0$$

Estimation is performed by the BHHH algorithm with robust errors option in RATS 5.0

Panel A::Results

Parameter	Coefficient	p-value
a	0.0444	0.005131
b	0.3586	0.002098
c	-0.3168	0.010469
d	0.0771	0.000039
f	0.0944	0.000001
?	6.0425e-18	0.000000
?	0.2082	0.010735
?	0.7544	0.000000
?	0.0131	0.087150
?	6.3996e-04	0.724463

Panel B : Residual Diagnostics

Skewness	0.13783	
Kurtosis	9.15399	
Jarque-Bera st	891.76771	0.000000
LB(10)	6.4785	0.773587
LB(20)	29.4603	0.079084
$LB^2(10)$	9.7704	0.460859
$LB^2(20)$	15.8158	0.727985
LM(20)	0.3052	0.874530
Sign Bias	0.4599	0.645750
Neg. Bias	0.3735	0.708940
Pos. Bias	0.0386	0.969190
Joint Bias	0.0916	0.964660

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 developed by Engle and Ng (1993)

Table 6 :: Model Comparison

Model	AIC / SBC	Log Likelihood value	Rank
Two Stage GARCH	4233.92095 / 4255.10280	-149.02611700	2
ARMA-GARCH	4221.25378 / 4242.43563	-147.68181011	1
Domestic Model	4285.34021 / 4306.52206	-181.63003405	3

Table 7: Forecast Performance of ARMA-GARCH Model

h_t is the predicted volatility as predicted by ARMA-GARCH model in Table 5.

r_t^2 is the actual estimate of volatility calculated as the squared daily returns.

The following two regressions are estimated.

$$r_t^2\ ?\ a\ ?\ b * h_t\ ?\ u_t$$

Adjusted R^2 is in percent.

	Coefficient	t-statistic	p-value	Adjusted R^2
a	0.126039	0.443172	0.6578	19.64
b[?]	0.992045	0.000748	0.978185	

? *t*-statistic of *b* is for null of *b* = 1

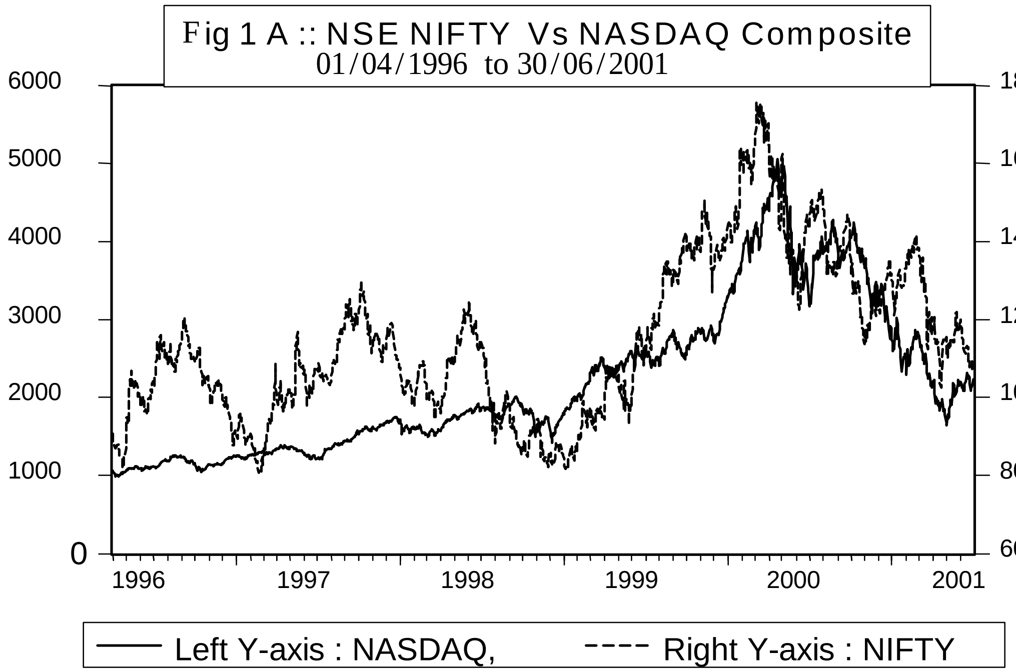


Fig 1 A :: NSE NIFTY Vs NASDAQ Composite
01/04/1996 to 30/06/2001
6000
5000
4000
3000
2000
1000
0
1800
1600
1400
1200
1000
800
600
1996
1997
1998
1999
2000
2001
Left Y-axis : NASDAQ,
Right Y-axis : NIFTY

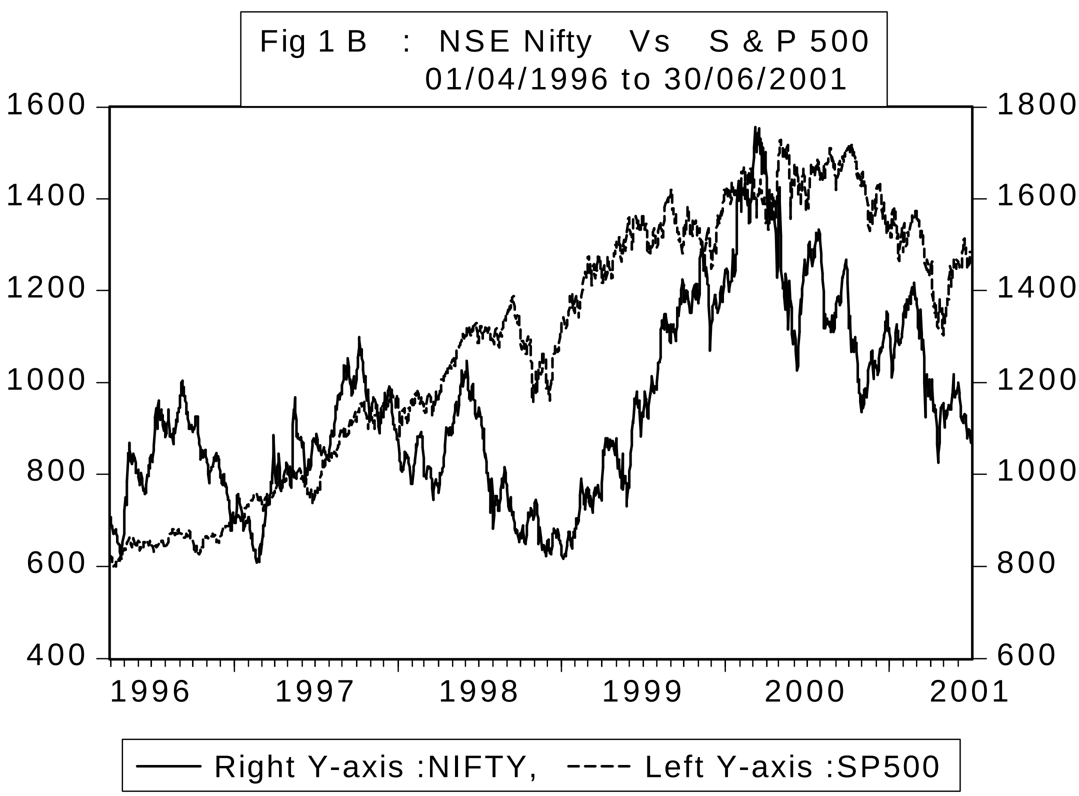


Fig 1 B : NSE Nifty Vs S & P 500
01/04/1996 to 30/06/2001
1600
1400
1200
1000
800
600
400
1800
1600
1400
1200
1000
800
600
1996
1997
1998
1999
2000
2001
Right Y-axis :NIFTY,
Left Y-axis :SP500

Fig 2:: Market Trading hours:: Indian Standard Time

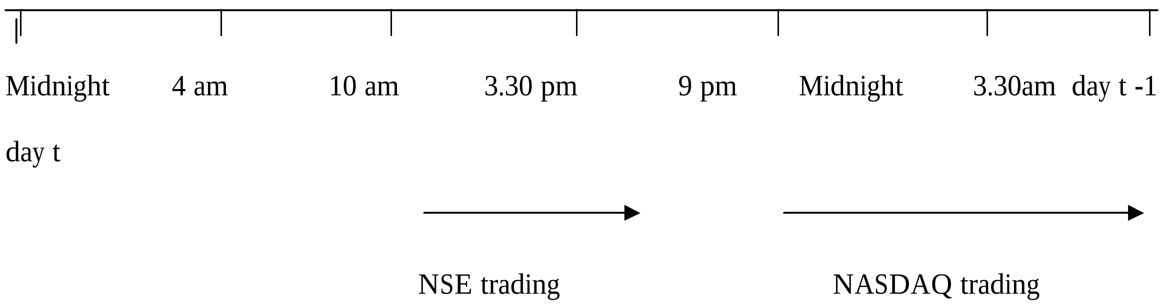


Fig 3 :: Return Series Graphs :: 01/07/1999 to 30/06/2001

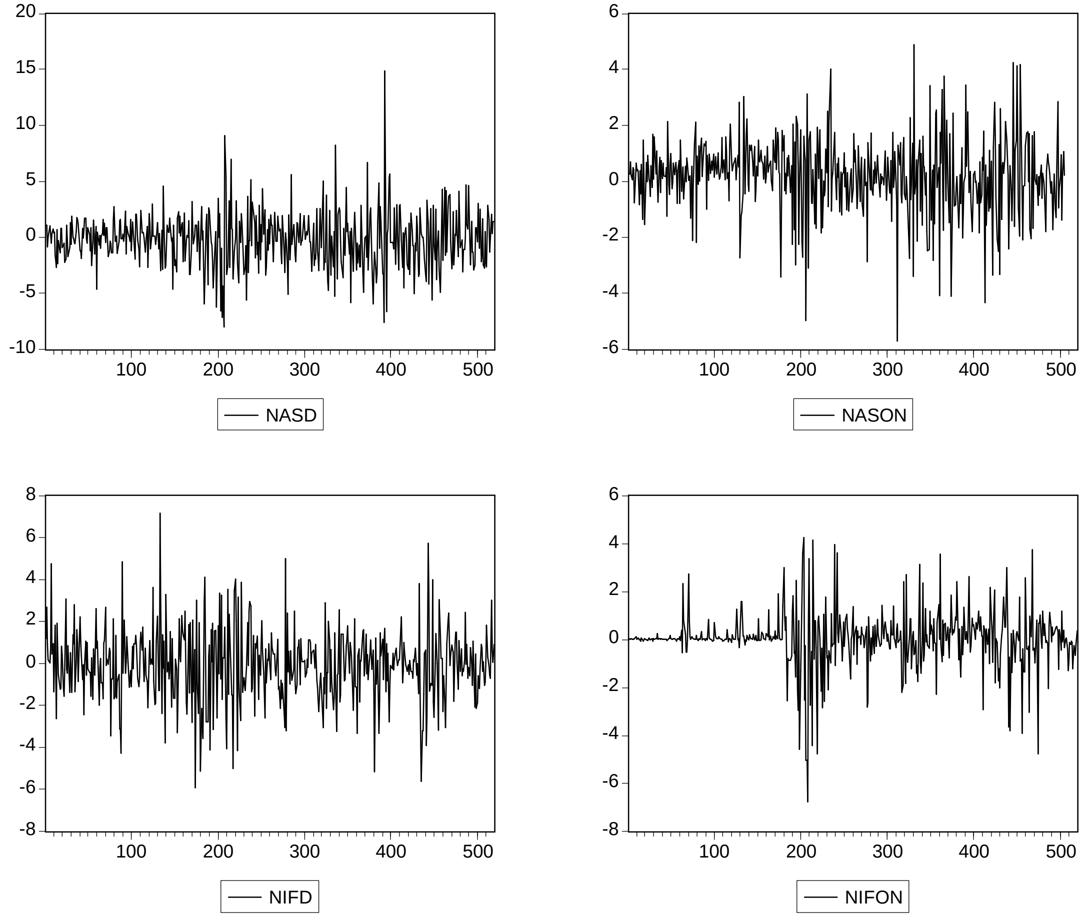


Fig 4.1 :: Std Residual Plot : 2nd Stage GARCH model

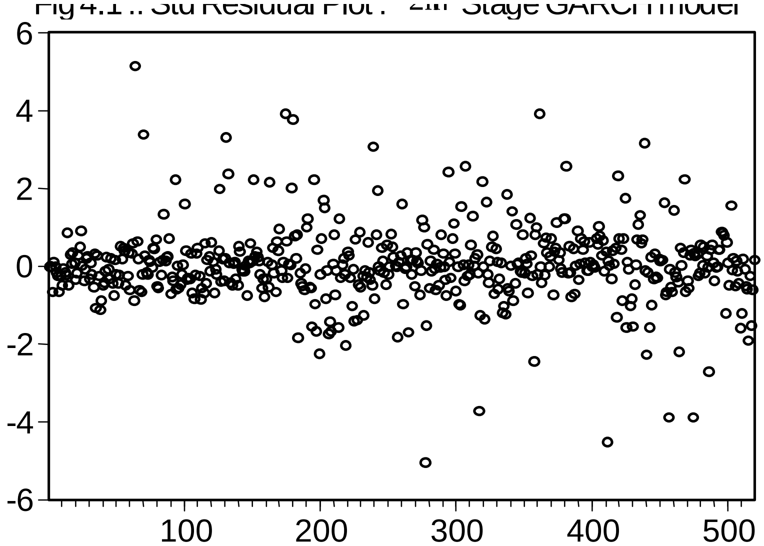


Fig 4.2 Std Residual Correlogram

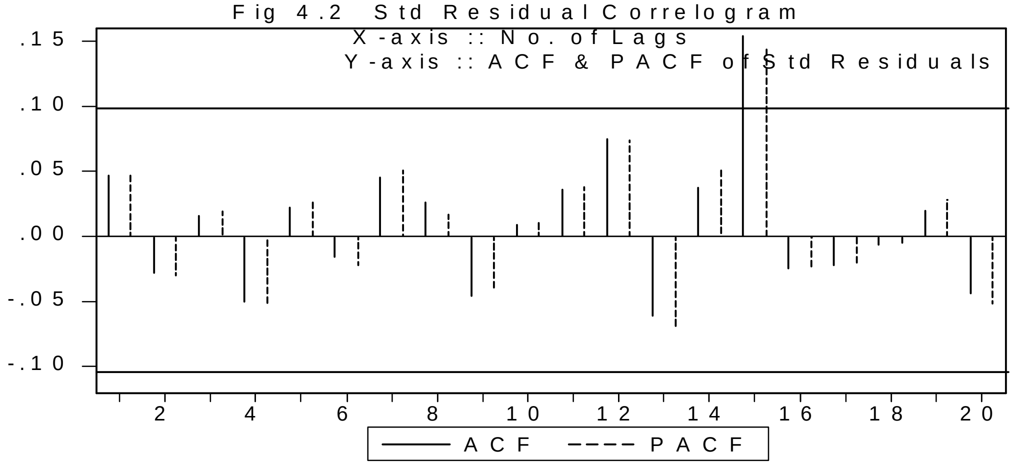
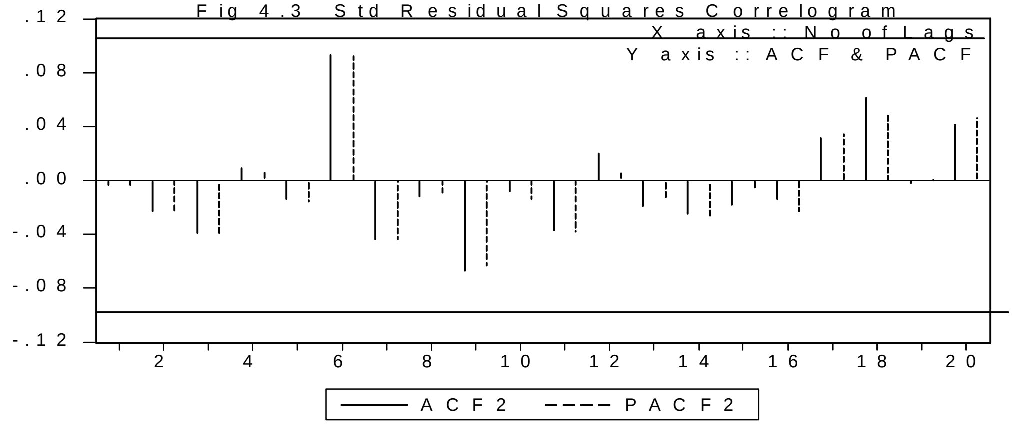


Fig 4.3 Std Residual Squares Correlogram



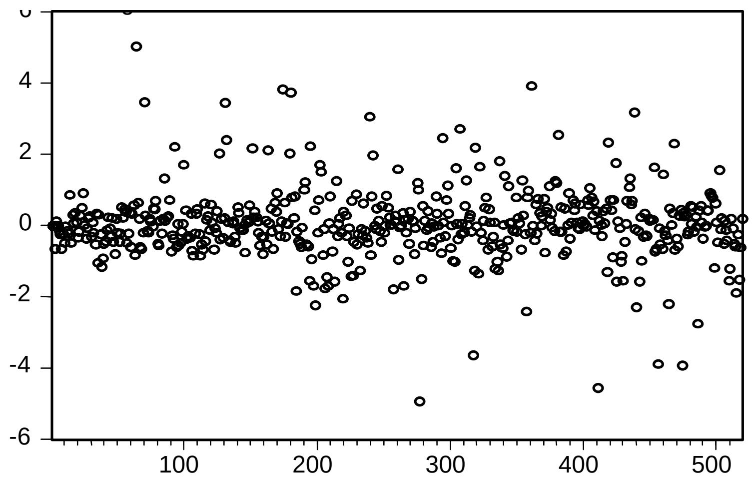


Fig 5.2 Std Residuals Correlogram

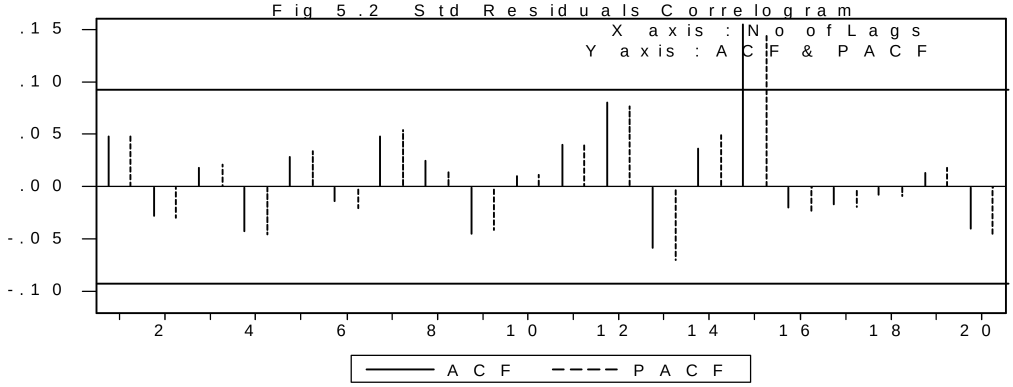
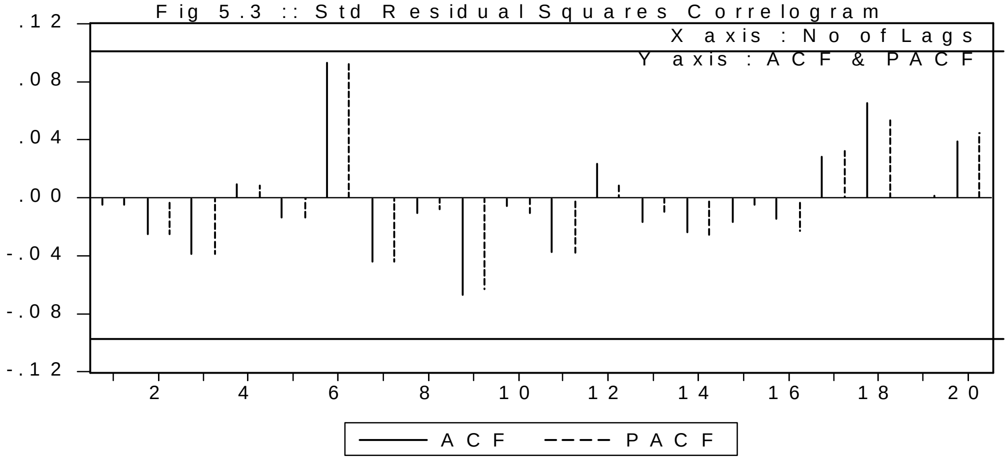


Fig 5.3 :: Std Residual Squares Correlogram



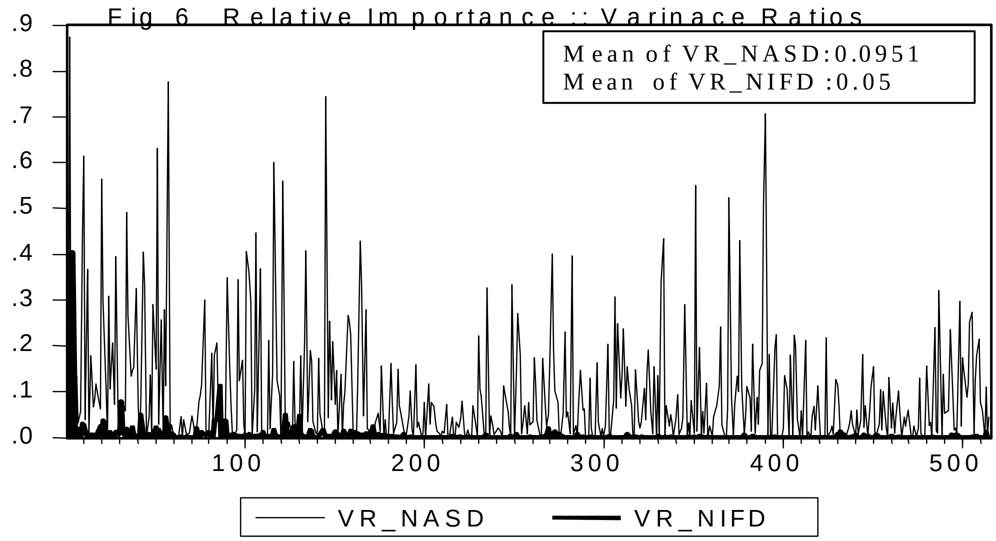
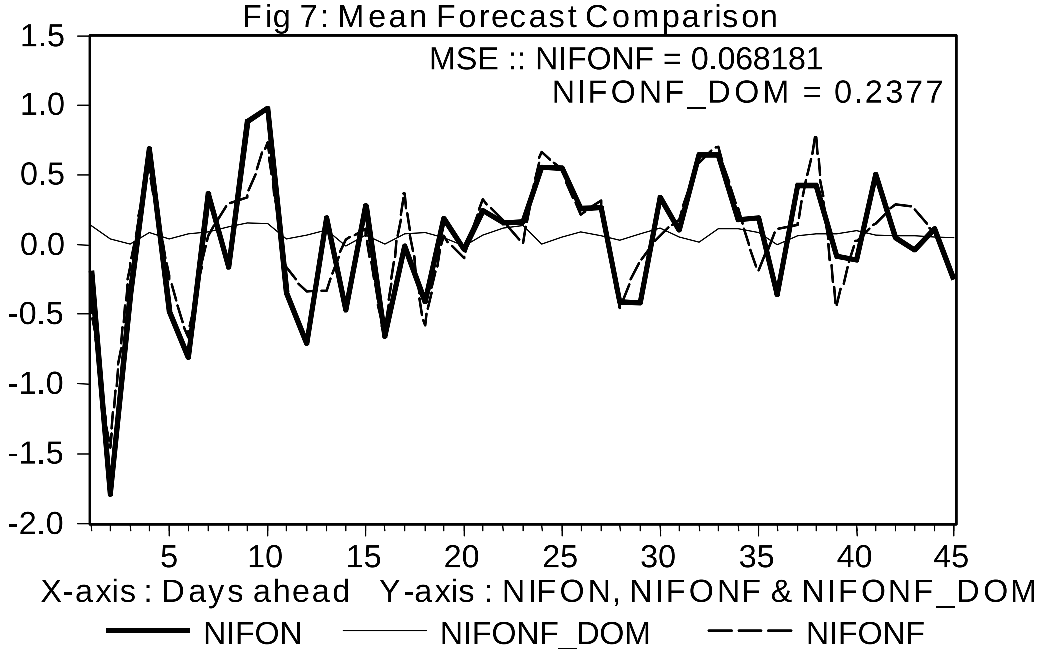
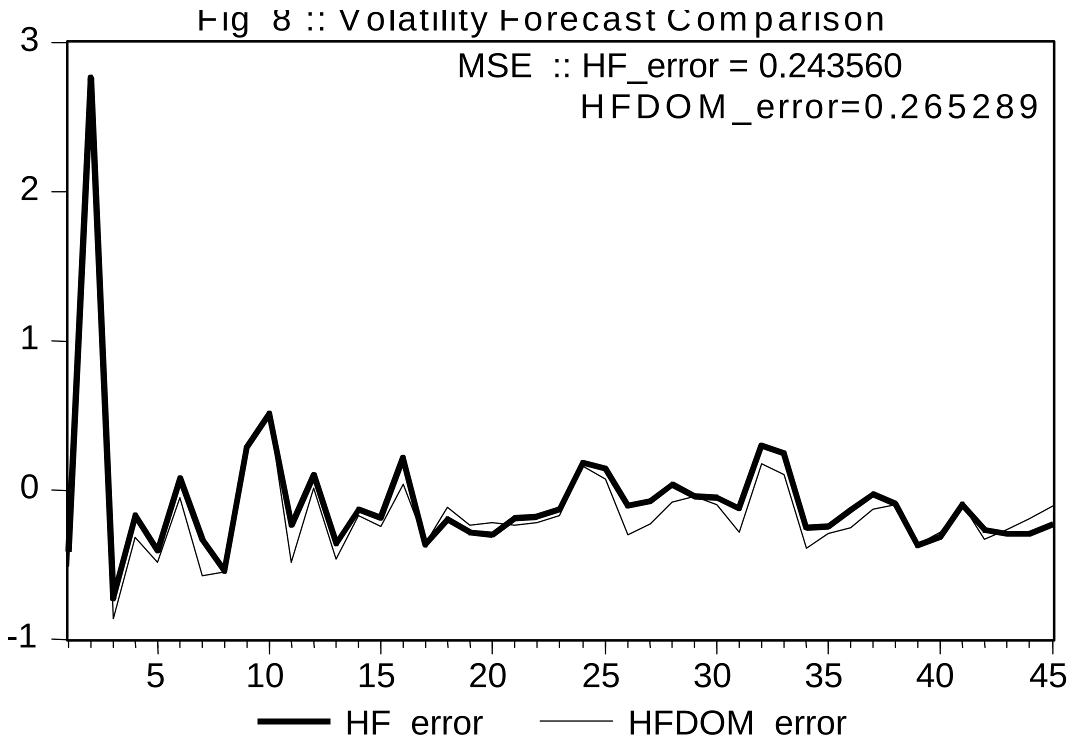


Fig 7: Mean Forecast Comparison





X-axis :: Days ahead   Y-axis :: Volatility forecast error