Volatility Spillovers from the US to Indian Stock Market: A Comparison of GARCH Models

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This paper empirically investigates the short-run dynamic linkages between NSE Nifty in India and NASDAQ Composite in US during the period 1999-2001, using intra-daily data which determine the daytime and overnight returns. Specifically, the study employs the most popular MGARCH model, to capture the inter-linkages between NASDAQ and NSE equity markets and compares performance of MGARCH model with other models, such as two-stage GARCH model and a simple ARMA-GARCH model, employed in Kumar and Mukhopadhyay (2002). The paper reports that the simple ARMA-GARCH model performs better than the more complex MGARCH model. The volatility spillover effects from NASDAQ Composite are only significant implying that the conditional volatility of Nifty overnight returns is imported from US. It also 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, it was found that including the information revealed by NASDAQ day trading provides only better forecasts of the level of Nifty overnight returns but not its volatility.

Introduction

Research on emerging capital markets has been the focus of academic research as the restrictions on capital flows are getting relaxed in a phased manner. Indian stock market emerged as one of the favorite destination of Foreign Institutional Investments (FIIs). In particular, deregulation and market liberalization measures, rapid development 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 the US exchanges. At present, 12 Indian companies have issued (American Depository Receipts) ADRs and are cross-listed in the US exchanges and many more companies are planning to cross-list in the near future. Apart from the underlying economic linkages between US and India, three features motivate

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the interest in examining the short-run dynamics of stock returns and volatility between (National Association of Securities Dealers Automated Quotations System) NASDAQ Composite and (National Stock Exchange) NSE Nifty indices. They are:

- 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 like, *The Economic Times* and *Economic Survey* have been full of stories of a newfound alliance between the NSE and the NASDAQ. Through these news reports, market regulators, traders, and the general investing public in India have become sensitized to market movements in the NASDAQ Composite index and its impact on NSE Nifty.
- Finally, a quick examination of movements of these two stock markets, during the study period, suggests that there exists a substantial degree of interdependence between NASDAQ Composite and NSE Nifty indices.

The objective of this paper is to empirically examine the performance of (Multivariate Generalized Autoregressive Conditional Heteroskedasticity) MGARCH model to capture the short-run inter-linkages between the US and the Indian stock markets. We make a careful selection of appropriate model from MGARCH family and fit the (Baba, Engle, Kraft and Kroner) BEKK version of MGARCH model. The rich structure of MGARCH framework does not give an edge over the forecasts compared to the simple GARCH models.

Review of Literature

A number of studies examined return and volatility spillovers across the markets. The early studies viz., Ripley (1973); Hilliard (1979), and others report low correlations between the markets and hence there is possibility of higher diversification benefits. This is in line with the trade and economic linkages prevailing in those years. 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 and Shim, 1989; Von Furstenberg and Jeon, 1989; King and Wadhwani, 1990; Schwert, 1990; Kee-Hong Bae and Karolyi, 1994; King *et al.,* 1994; Longin and Solnik, 1995; Brooks and Henry, 2000; and Tse, 2000 are few examples of such studies). These papers used monthly/weekly/daily data and employed different methodologies like VAR, spectral analysis, simple regression, ARCH models, etc., and reported several empirical features:

- The correlations across the stock markets are time-varying;
- Movements in major markets are closely related under volatile conditions; and
- 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 the US stock market movements.

The literature concentrated mostly on well-developed equity markets in the US, Japan and Europe, and do not pay much attention to other stock markets. Little research exists on how Indian market moves with the major markets around the world. Sharma and Kennedy (1977) and Rao and Naik (1990), examined linkages between developed markets and Indian stock market before liberalization and concluded that the Indian market is 'independent' of the economic phases of the developed markets. Given the present state of India, these studies lose their relevance. With active liberalization and rapid growth of information technology in the recent past, a number of studies started looking at response of the Indian Stock Market to world markets viz., US, Japan and other East Asian Stock Markets (see for example, Kumar and Mukhopadhyay, 2002; Nair and Ramanathan, 2002; Hansda and Ray, 2002; Wong *et al.,* 2005; and Sadhan and Samir, 2005). Except Kumar and Mukhopadhyay (2002), all other studies that used daily or lower frequency data, recognized the non-overlapping trading hours between US and Indian markets and employed intra-day data to examine the short-run inter-linkages. Most of the other studies concentrate on examining the long-run relationship between India and other markets by employing the cointegration techniques. The existing studies concluded that India is not yet integrated (and hence no long-run relationship) with the developed markets.

Till date, in the literature, there has been no in depth analysis of interdependence between mean and volatility structure of Indian markets and other national markets. This paper attempts to fill that gap.

Data

As NASDAQ and NSE markets don't have overlapping trading hours, following Hamao *et al.* (1990); Lin *et al.* (1994); and Kee-Hong Bae and Karolyi (1994), a daily ($close_t$-to-$close_{t-1}$) return is divided into a daytime ($close_t$-to-$open_t$) and an overnight ($open_t$-to-$close_{t-1}$) return for both NSE Nifty and NASDAQ Composite indices. When there is no overlap between the trading hours of the two markets, this decomposition of daily return into daytime and overnight return enables one 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.

In most major stock markets, there are problems in calculating the opening prices for the market indices due to delayed opening of individual stocks. For NSE Nifty, the first open quote of the index is available at around 9.55 a.m. At this first open quote, as all the 50 constituent scrips of Nifty have not been traded, so taking this value as the open quote would be inappropriate. But usually by the official opening time of 10.00 a.m, 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 a.m. The National Stock Exchange Research Initiative provides the 10.00 a.m data of NSE Nifty. Daily official open (9.30 a.m, Eastern Standard Time (EST)) and close (4.00 p.m, EST) quotes of NASDAQ Composite index have been downloaded from www.nasdaq.com. So, in this study, the returns are calculated as follows:

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 day t-1)**100

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

The hypothesis of unit root is strongly rejected for all these four return series. Therefore, all stock return series follow a stationary process.

Methodology: GARCH Modeling

Preliminary Analysis

Table 1 presents a wide range of descriptive statistics for the returns of NASDAQ Composite and NSE Nifty indices. The sample moments indicate that empirical distributions of returns are all skewed and highly leptokurtic, compared to the normal distribution. This is reinforced by the Jarque-Bera tests for normality, which are highly significant. To further analyze the behavior of stock returns, the Ljung-Box (LB) statistic for lags 10 and 20, for returns as well as squared returns, have been performed (Table 1). 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 squared series indicates that volatility is time-varying for all return series. The significant 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 *et al*. (1992). These features of the data lead us to consider the

Table 1: Descriptive Statistics of Returns

	NIFON	*NIFD*	*NASD*	*NASON*
Mean	0.011913	–0.053361	–0.229837	0.155801
Std. Deviation	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)

(Generalized Autoregressive Conditional Heteroskedasticity) GARCH type models that can accommodate time-varying and persistent behavior of volatility of returns.

We start modeling with a two-stage GARCH approach as suggested in the literature for non-overlapping markets and then move on to a MGARCH model capturing the time-varying correlation between the returns. The problem is also approached with a simple (Vector Autoregressive Moving Average–Generalized Autoregressive Conditional Heteroskedasticity) ARMA-GARCH model, where the squared returns proxy for volatility. This simple model turns out to be as good as its more complex counterparts.

Spillover Effects with Two-Stage GARCH Model

Hamao *et al.* (1990); Kee-Hong Bae and Karolyi (1994); and Lin *et al.* (1994) used a two-stage GARCH model for estimating the spillover effects between New York, London and Tokyo markets. In the first stage, they estimated an appropriate MA-GARCH model for foreign market daytime returns. In the second stage, they estimated an appropriate MA-GARCH model for domestic overnight returns, where they included the residuals or residual squares obtained in the first stage GARCH model as a regressor, which captured the potential volatility spillover effect from the previously open foreign daytime returns into the domestic overnight returns. Their main finding was 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 Japanese market.

A two-stage GARCH model (**Model 1**) is first used to explore 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 *et al.* (1987) as follows:

$$R_{D,t} = \phi_{1,0} + \sum_{i=1}^{p} \phi_{1,i} R_{D,t-i} + \sum_{j=1}^{q} \theta_{1,j} \varepsilon_{t-j} + \lambda_{1,m} DUM + \chi_1 h_{1,t} + \varepsilon_{1t}$$

$$\varepsilon_{1t} / \Omega_{t-1} \sim N\left(0, h_{1,t}\right)$$

$$h_{1,t} = \alpha_{1,0} + \sum_{i=1}^{r} \alpha_{1,i}\, \varepsilon_{1t-i}^2 + \sum_{j=1}^{s} \beta_{1,j} h_{1t-j} + \lambda_{1,v}\ DUM \quad \text{...(1)}$$

The dummy variable, *DUM*, accounts for multiple-day returns associated with weekends and holidays in either market. The χ_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 Equation 1 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 the residual squares obtained from Equation 1 for $NIFD_t$ and $NASD_t$ in variance equation, to capture the volatility spillover effects. That is, for NSE Nifty overnight returns, our model is given by:

$$NIFON_t = \phi_{2,0} + \sum_{i=1}^{u} \phi_{2,i} NIFON_{t-i} + \sum_{j=1}^{v} \theta_{2,j} \varepsilon_{t-j} + \lambda_{2,m} DUM + \psi NIFD_{t-1} + \rho NASD_{t-1} + \chi_2 h_{2,t} + \varepsilon_t$$

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

$$h_{2,t} = \alpha_{2,0} + \sum_{i=1}^{k} \alpha_{2,i} \varepsilon_{t-i}^2 + \sum_{j=1}^{l} \beta_{2,j} h_{t-j} + \lambda_{2,v} DUM + \delta NASDRES_{t-1}^2 + \eta NIFDRES_{t-1}^2 \quad ...(2)$$

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 'ψ' indicates that the conditional mean of NSE Nifty overnight returns is influenced by the previous daytime returns of NSE Nifty (own-mean spillovers). On the other hand, a statistically significant 'ρ' value suggests that past daytime returns of NASDAQ Composite affects the conditional mean of NSE Nifty overnight returns (cross-mean spillover). Statistically significant values for 'δ' and 'η' 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.

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

Table 2: Estimation Results and Diagnostics for Daytime Returns of NASDAQ Composite and NSE Nifty Indices from July 1, 1999 to June 30, 2001

$$NASD_t = \phi_{1,1} NASD_{t-1} + \theta_{1,1} \varepsilon_{1,t-1} + \lambda_{1,m} DUM_t + \varepsilon_{1,t}$$

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

$$h_{1,t} = \alpha_{1,0} + \alpha_{1,1} \varepsilon_{1,t-1}^2 + \beta_{1,1} h_{1,t-1}$$

$$NIFD_t = \phi_{1,1} NIFD_{t-1} + \theta_{1,1} \varepsilon_{1,t-1} + \varepsilon_{1,t}$$

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

$$h_{1,t} = \alpha_{1,0} + \alpha_{1,1} \varepsilon_{1,t-1}^2 + \beta_{1,1} h_{1,t-1}$$

Stage 1	NASDAQ Composite Day Returns		NSE Nifty Day Returns	
Panel A	Estimate	*p*-value	Estimate	*p*-value
$\phi_{1,1}$	0.698595	0	–0.937656	0
$\theta_{1,1}$	–0.777019	0	0.967435	0
$\lambda_{1,m}$	–0.509481	0	–	–
$\alpha_{1,0}$	0.099749	0.03110	0.137085	0.08030
$\alpha_{1,1}$	0.092249	0.00480	0.165535	0.00210
$\beta_{1,1}$	0.892866	0	0.790656	0

(Contd...)

Table 2: Estimation Results and Diagnostics for Daytime Returns of NASDAQ Composite and NSE Nifty Indices from July 1, 1999 to June 30, 2001 *(...contd)*				
Panel B	**Residual Diagnostics**			
Skewness	–0.13624	–	0.046403	–
Kurtosis	0.48599	–	4.775925	–
Jarque-Bera	7.08848	0.02889	71.94739	0
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

Note: 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; *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.

of Akaiki Information Criterion (AIC). All models are estimated using the numerical maximum likelihood procedures of Berndt *et al.* (1974) in RATS 5.0 package. Table 2 reports the final estimation results for the first-stage model after dropping all the insignificant terms in the general model considered in Equation 1, and then refitting the 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 only NASDAQ Composite daytime returns. The estimates of GARCH parameters, α_1 and β_1, are significant and the sum of these two coefficients, measuring the persistence of volatility, is close to unity. The portmanteau statistics (LB) 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 modeled reasonably well. The excess kurtosis is not a problem and there is some residual negative skewness.

Spillover Effects on NSE Nifty Overnight Returns

We next estimate the second-stage GARCH model (Equation 2) that allows both NSE Nifty and NASDAQ Composite daytime returns and shocks to influence the conditional mean and volatility of the NSE Nifty overnight returns. The ARMA(1,1)-GARCH(1,1) model turns out to be appropriate in describing the NSE Nifty overnight returns. Since $\phi_{2,0}$, Maximum Likelihood Estimator (MLE) of the constant in GARCH equation is negative; we constrained it to be non-negative, yielding an estimate of zero.[1] The holiday dummy is insignificant in both mean and variance equation as is the GARCH-in-Mean coefficient, χ^2 The final model for the NSE Nifty overnight returns are summarized in Panel A of Table 3 after dropping the insignificant terms in the general model (Equation 2) and then refitting the reduced model. The objective diagnostic tests of this final model are presented in Panel B of Table 3.

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

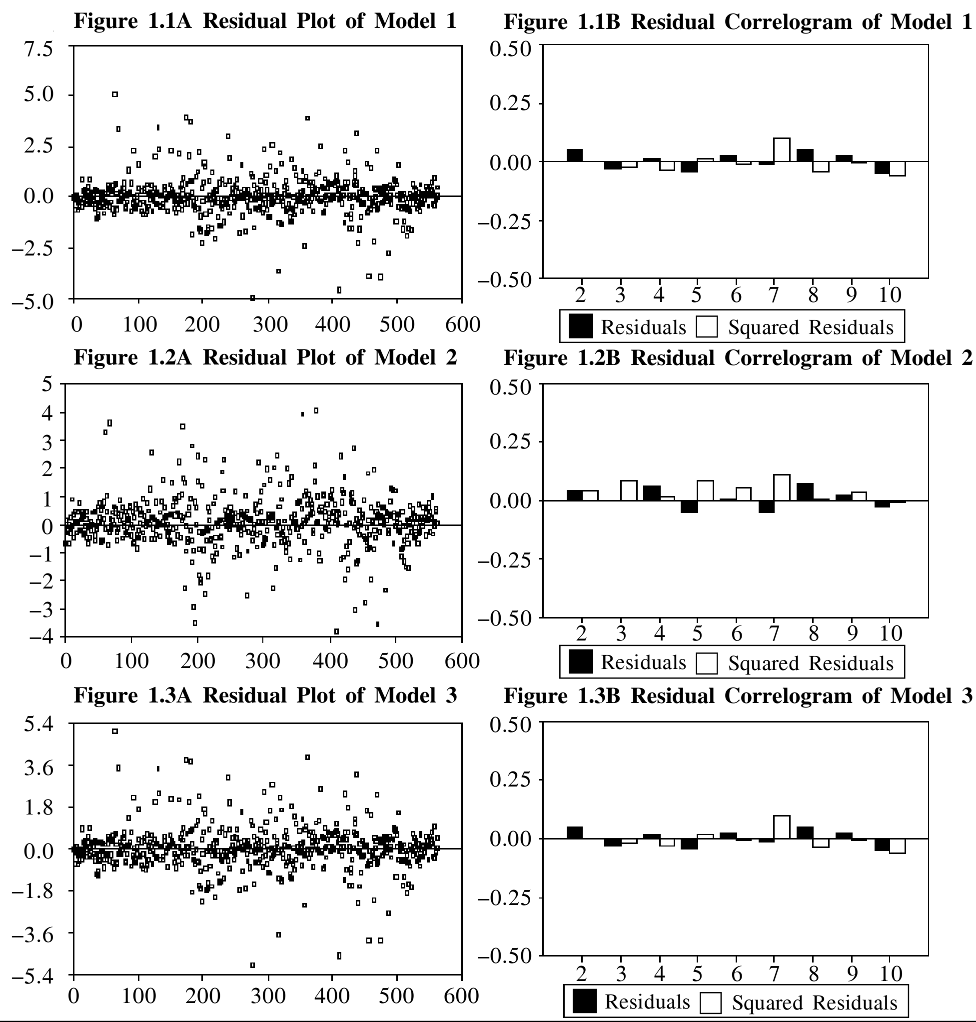
Table 3: Nifty Overnight Returns		
$NIFON_t = \phi_{2,0} + \phi_{2,1} NIFON_{t-1} + \theta_{2,1}\varepsilon_{t-1} + dNIFD_{t-1} + fNASD_{t-1} + \varepsilon_{2,t}$ $\varepsilon_{2,t} \sim N\left(0, h_{2,t}\right)$ $h_{2,t} = \alpha_{2,0} + \alpha_{2,1}\varepsilon^2_{2,t-1} + \beta_{2,1}h_{2,t-1} + \eta NIFDRES^2_{t-1} + \delta NASDRES^2_{t-1}; \alpha_{2,0} > 0$		
Stage 2	**NSE NIFTY Overnight Returns**	
Panel A	**Coefficients**	***p*-value**
$\phi_{2,0}$	0.0441	0.0008971
$\phi_{2,1}$	0.3695	0.0037494
$\theta_{2,1}$	–0.3297	0.0216947
d	0.0756	0.0000384
f	0.0934	0.0000002
$\alpha_{2,0}$	9.2774e-16	0
$\alpha_{2,1}$	0.2076	0.0000001
$\beta_{2,1}$	0.7597	0
η	3.8148e-04	0.7778724
δ	0.0129	0
Panel B	**Residual Diagnostics**	
Skewness	0.1443	
Kurtosis	9.3640	
Jarque-Bera	953.7258	0
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
Negative Bias	0.4097	0.682230
Positive Bias	0.0856	0.931780
Joint Bias	0.1190	0.948920

Note: 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 tests developed by Engle and Ng (1993).

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 high NSE Nifty overnight returns. We find clear evidence that the most recent daytime returns of NASDAQ Composite have positive influence on the opening price of NSE Nifty. The parameter estimates for the conditional variance, $\alpha_{2,1}$ and $\beta_{2,1}$, 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. The model diagnostic graphs namely the residual plot and the correlogram of residuals and residual squares are displayed in Figures 1.1A and 1.1B.

Figure 1: Model Diagnostic Plots



These diagnostics show that the residuals of the models are reasonably well-behaved. The portmanteau LB statistics in Panel B of Table 3 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 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 the Nifty overnight return linkages with NASDAQ daytime returns fairly well.

Multivariate GARCH Model Specification

Simultaneous modeling of returns through an MGARCH model has several advantages over the two-stage GARCH approach though it is very intuitive in capturing the effects of volatility spillover that has been used so far. First, MGARCH model eliminates the two-step estimation procedure, thereby avoiding problems associated with estimated regressors in the second stage of model building viz., the terms $NASDRES^2$ and $NIFDRES^2$ in Equation 2. Second, the ability of capturing cross-market spillovers increases with MGARCH specification. Finally, the two-stage model may be viewed as a very special case of a MGARCH model, the one with zero covariances. Thus, after fitting a more general MGARCH model the adequacy and aptness of a two-stage model may be verified as it is nested within this bigger model.

Before proceeding to model the variance-covariance matrix explicitly, one has to first capture the dependency in mean returns. The mean vector of all the concerned series is jointly modeled using a simple VAR(1) equation. However, for added leverage each mean equation is also allowed to contain an additional MA(1) term.

$$\begin{bmatrix} R_{1,t} \\ R_{2,t} \\ R_{3,t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} + \begin{bmatrix} \gamma_1 & \gamma_2 & \gamma_3 \\ \phi_1 & \phi_2 & \phi_3 \\ \varphi_1 & \varphi_2 & \varphi_3 \end{bmatrix} \begin{bmatrix} R_{1,t-1} \\ R_{2,t-1} \\ R_{3,t-1} \end{bmatrix} + \begin{bmatrix} \theta_1 \\ \theta_2 \\ \theta_3 \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-1} \\ \varepsilon_{2,t-1} \\ \varepsilon_{3,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \end{bmatrix} ; \cdots \varepsilon_t \sim N\left(0, H_t\right) \quad ...(3)$$

where the subscripts 1, 2 and 3 refer to *NIFON, NIFD and NASD* respectively. The appropriate model will be chosen on the basis of AIC or (Schwartz Bayesian Criterion) SBC model selection criteria. If H_t displays volatility-clustering phenomena then we go for MGARCH modeling for the conditional variance-covariance matrix of trivariate return series.

Among the multivariate extensions of the GARCH model, there are three popular multivariate GARCH models based on the way H_t is parameterized. Within the literature of volatility spillovers, Diagonal VECH model proposed by Bollerslev *et al.* (1988), the Constant Conditional Correlation (CCC) model of Bollerslev (1990); and BEKK model of Engle and Kroner (1995) versions of MGARCH model are popular.

Though it is a natural multivariate generalization of GARCH, the VECH model has drawbacks of huge number of parameters (78 parameters for a trivariate system) to be estimated and it is hard to ensure that the covariance matrix H_t is positive definite. The Diagonal VECH model proposed by Bollerslev *et al.* (1988) reduces the number of parameters to be estimated greatly at the cost of allowing and it eliminates the possibility of examining potential interactions in the variances and covariances of the markets. In CCC model, the conditional covariances are proportional. Though this model is simple and most popular in literature, Longin and Solnik (1995) and Tse (2000), showed that the stock returns across different national markets violate the constant correlation assumption. The discussion now proceeds to BEKK-MGARCH model, proposed by Engle and Kroner (1995) that incorporates time-varying correlations and yet retains the appealing feature of satisfying the positive definite condition during the optimization, and its specification is as follows:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \qquad ...(4)$$

where, A and B are matrices of dimension 3x3, and C is a 3x3 upper triangular matrix. In BEKK framework, the conditional variance-covariance of return series consists of outer product of matrices of past return shocks. The BEKK specification offers the advantage of estimating fewer parameters along with weak restrictions on how the markets can interact.

Estimation Results of the MGARCH-BEKK Model

For the reasons of model tractability, we make the innocuous assumption that there is no spillover from the Indian market to the US market (Kumar and Mukhopadhyay, 2002). This will lead to the following parameterization of the A and B matrices:

$$A = \begin{bmatrix} \alpha_{11} & \alpha_{12} & 0 \\ \alpha_{21} & \alpha_{22} & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \; and \; B = \begin{bmatrix} \beta_{11} & \beta_{12} & 0 \\ \beta_{21} & \beta_{22} & 0 \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix}$$

The quasi-maximum likelihood estimates of the parameters are reported in Table 4 along with the residual diagnostics. The residual diagnostic plots namely residual plot and correlogram are presented (for brevity only *NIFON* equation) in Figures 1.2A and 1.2B. The LB statistics for up to 10th order serial correlation in standardized residual squares as well as the standardized cross-residuals are given in the Panel B of Table 4. It indicates that there is no more linear or quadratic dependence in standardized residuals and the estimated BEKK model captures the dynamics of conditional volatilities and covariances as well. The cross-residual autocorrelation between the series show that we are successful in allowing for cross-correlation between the series. All these residual diagnostics led to confirm that the fitted BEKK model is a correct specification of the return generating process. Henceforth, this model is referred to as **Model 2**.

The parameter estimates of conditional variance, α_{ii} and β_{ii}, are mostly significant, indicating that the conditional variances for the returns are indeed time-varying, implying that the information arrives in the market in clusters and not evenly. The stability condition for the volatility process is satisfied because for each return series the sum of estimates of α_{ii}^2 and β_{ii}^2 is always less than unity, suggesting that the conditional variances follow a stationary process.

Table 4: Results of ARMA(1,1)-MGARCH(1,1) with BEKK Specification

$$NIFON_t = \gamma_1\ NIFON_{t-1} + \varphi_1\ NASD_{t-1} + \phi_1\ NIFD_{t-1} + \varepsilon_{1,t}$$

$$NIFD_t = \phi_2\ NIFD_{t-1} + \gamma_2\ NIFON_t + \varphi_2\ NASD_{t-1} + \varepsilon_{2,t}$$

$$NASD_t = \varphi_3\ NASD_{t-1} + \theta_3 \varepsilon_{3t-1} + \varepsilon_{3,t}$$

$$H_t = A' \varepsilon_{t-1} \varepsilon'_{t-1} A + B' H_{t-1} B$$

$$A = \begin{bmatrix} \alpha_{11} & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix}, \quad B = \begin{bmatrix} \beta_{11} & \beta_{12} & 0 \\ \beta_{21} & \beta_{22} & 0 \\ \beta_{31} & \beta_{32} & \beta_{33} \end{bmatrix}$$

Panel A	Estimate	Std. Error	*t*-statistic	Significance
γ_1	0.07188	0.02078	3.45832	0.00054
φ_1	0.16774	0.01557	10.77664	0
ϕ_1	0.16138	0.02430	6.64030	0
ϕ_2	0.43653	0.06491	6.72524	0
γ_2	–2.74543	0.16662	–16.47688	0
φ_2	0.42341	0.05522	7.66713	0
φ_3	1.10687	0.57342	1.93029	0.05357
θ_3	–1.16082	0.56968	–2.03770	0.04158
α_{11}	–0.36401	0.05191	–7.01225	0
α_{21}	0.19572	0.01764	11.09255	0
α_{22}	0.31104	0.02497	12.45886	0
α_{31}	0.08620	0.01137	7.58140	0
α_{32}	0.26035	0.03555	7.32316	0
α_{33}	0.34053	0.02573	13.23407	0
β_{11}	0.80955	0.03552	22.78972	0
β_{12}	0.24440	0.05859	4.17118	0.00003
β_{21}	0.03950	0.01228	3.21704	0.00130
β_{22}	0.87762	0.01679	52.28371	0
β_{31}	–0.02559	0.00278	–9.19131	0
β_{32}	–0.06147	0.00994	–6.18515	0
β_{33}	0.95228	0.00624	152.65517	0

(Contd...)

Table 4: Results of ARMA(1,1)-MGARCH(1,1) with BEKK Specification *(...contd)*						
Panel B	***NIFON***		***NIFD***		***NASD***	
	Estimate	***p*-value**	**Estimate**	***p*-value**	**Estimate**	***p*-value**
Skewness	0.06766	0.51372	0.12352	0.23818	–0.12698	0.21993
Kurtosis	4.22071	0	5.99196	0	3.60977	0.00333
Jarque-Bera	417.58280	0	211.05063	0	10.23563	0.00598
LB(10)	9.8034	0.45791	14.53920	0.14978	6.38850	0.78164
Sq.LB(10)	17.92893	0.05617	8.14930	0.61425	4.09040	0.94318
Panel C	***NIFON* and *NIFD***		***NIFD* and *NASD***		***NASD* and *NASD***	
	Statistic	***p*-value**	**Statistic**	***p*-value**	**Statistic**	***p*-value**
Cross-LB(10)	16.83380	0.07812	11.75250	0.30196	18.02680	0.05451
F-test	4.08020	0.00022	0.16920	0.99480	0.03750	0.99998

Let us now concentrate on the estimated parameters of the A matrix and look for the evidence of transmission of volatility shocks between the markets. As expected, news generated in previous NASDAQ daytime returns and past volatility, spillover to the next day Nifty overnight and daytime returns and its effect is more pronounced in the case of Nifty overnight returns. Also, the news generated in the previous Nifty daytime returns and its past volatility has significant impact on Nifty overnight returns. Further, only the past volatility of Nifty overnight return, spillovers to the Nifty daytime return volatility but not the news. In line with the relative sizes of the market, the MGARCH model predicts that there is no news spillover from Nifty daytime or overnight returns to the following NASDAQ daytime return volatility.

Spillover Effects with ARMA–GARCH Model

Multivariate GARCH techniques and their special case, the two-stage GARCH approach, though popular in the literature of modeling spillover effects across the markets, are inherently non-parsimonious and complex. After achieving these technically more sophisticated results, we next seek whether a simple univariate ARMA-GARCH model can adequately capture the dynamics of volatility transmission from NASDAQ to NSE. This attempt is being made in spirit of the philosophy of 'Occam's razor', which compels one to choose the simplest possible model for explaining a phenomenon. In ARMA-GARCH model, we use the squared returns as a proxy for volatility of foreign market and is appended in the conditional variance equation of domestic market. Here, we model the $NIFON_t$ returns by allowing for possible autocorrelation from the preceding overnight returns, possible cross-autocorrelation or 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:

$$NIFON_t = \phi_0 + \sum_{i=1}^{a} \phi_i NIFON_{t-i} + \sum_{j=1}^{b} \theta_j u_{t-j} + \tau DUM_t + \varpi NIFD_{t-1} + \nu NASD_{t-1} + \chi h_t + u_t \quad ...(5)$$

In Equation 5, the NASDAQ information is effected through the parameter ν and that of NIFTY through the parameter ϖ. 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 the above explanation that, the volatility of $NIFON_t$ series is time-varying, we extend the above specification of $NIFON_t$ in Equation 5 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,

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

$$h_t = \varphi + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} + \kappa NIFD_{t-1}^2 + \pi NASD_{t-1}^2 + \lambda DUM_t \qquad ...(6)$$

The maximum likelihood estimation results of Equations 5 and 6, 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 3**.

Table 5: ARMA-GARCH Model

$$NIFON_t = \phi_0 + \phi_1 NIFON_{t-1} + \theta_1 u_{t-1} + \varpi NIFD_{t-1} + \nu NASD_{t-1} + u_t$$

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

$$h_t = \varphi + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} + \pi NASD_{t-1}^2 + \kappa NIFD_{t-1}^2;\ \varphi > 0$$

Panel A	Results	
Parameter	**Coefficient**	***p*-value**
ϕ_0	0.0444	0.005131
ϕ_1	0.3586	0.002098
θ_1	–0.3168	0.010469
ϖ	0.0771	0.000039
ν	0.0944	0.000001
ϕ	6.0425e-18	0
α	0.2082	0.010735
β	0.7544	0
γ	0.0131	0.087150
κ	6.3996e-04	0.724463

(Contd...)

Table 5: ARMA-GARCH Model		*(...contd)*
Panel B	**Residual Diagnostics**	
Skewness	0.13783	
Kurtosis	9.15399	
Jarque-Bera	891.76771	0
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
Negative Bias	0.3735	0.708940
Positive Bias	0.0386	0.969190
Joint Bias	0.0916	0.964660

Note: 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 tests developed by Engle and Ng (1993). Estimation is performed by the BHHH algorithm with robust errors option in RATS 5.0.

The appropriate ARMA-GARCH order again turns out to be ARMA(1,1)-GARCH(1,1). Since φ, MLE of the constant in GARCH equation is negative, we constrained it to be non-negative, yielding an estimate of zero.[2] The dummy variable is insignificant in both mean and variance equations implying that there is 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, α_1 and β_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 which is mildly significant, whereas the own-volatility spillover effect from NSE Nifty daytime returns is only 6.3996e-04, which is statistically not significant. This is again in tune with the findings of the earlier two-stage approach. The model diagnostic graphs namely the residual plot and the correlogram of residuals and residual squares are displayed

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

in Figure 1.3A and 1.3B. These diagnostics show that the model's residuals are reasonably well behaved. The portmanteau LB statistics in Panel B of Table 5 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 series is captured 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.

Model Comparison and Validation

Here, the models estimated earlier in this paper are evaluated on the basis of in-sample and out-of-sample forecast performance. To examine the relevance of considering NASDAQ information, we specify Domestic model **(Model 4)**, which ignores the effect of NASDAQ both in mean and variance equations. The Domestic model is specified as follows:

$$NIFON_t = \phi_{d,0} + \sum_{i=1}^{p} \phi_{d,i} NIFON_{t-1} + \sum_{j=1}^{q} \theta_{d,j}\ \varepsilon_{t-j} + \lambda_{d,m} DUM + \psi_d NIFD_{t-1} + \chi_d h_{d,t} + \varepsilon_t$$

$$\varepsilon_t \sim N\left(0, h_{d,t}\right)$$

$$h_{d,t} = \alpha_{d,0} + \sum_{i=1}^{r} \alpha_{d,i}\ \varepsilon_{t-i}^2 + \sum_{j=1}^{s} \beta_{d,j} h_{d,t-j} + \gamma_{d,v} DUM + \kappa_d NIFD_{t-1}^2 \quad ...(7)$$

The Domestic model (**Model 4**) has been fitted with an appropriate ARMA-GARCH model, where only the spillover effects from Nifty daytime returns have been included.

In-Sample Validation

Here, we consider the evaluation of competing models of international transmission of stock returns and volatility by examining the in-sample validation of each of the models apart from the usual AIC/SBC model selection criteria. Figure 2 plots the last 50 observed *NIFON* returns in the estimation sample and the corresponding estimated *NIFON* returns obtained from each model, and Figure 3 plots that of *NIFON* return volatility. It is very evident from the plot that the Domestic model clearly gives the poorest fit both in mean and volatility. Not much significant difference is found between Models 1, 2 and 3 in predicting the observed *NIFON* returns.

To objectively assess the in-sample validity of the different models, we use mean squared error for *NIFON* returns and MGARCH model turns out to be the best predictor of *NIFON* returns. While empirically validating a model for volatility process is not straightforward, as volatility process itself is inherently unobservable. We circumvent this problem by using a proxy for actual realized volatility, which is the squared return. To study the in-sample performance of different models, we check the concordance of predicted volatility (h_t) of the estimated model to the volatility proxy of squared returns, r_t^2. Specifically this amounts to regressing r_t^2 on h_t as follows (Engle and Patton, 2000):

$$r_t^2 = a + b * h_t + u_t \qquad ...(8)$$

A good model of h_t should have the properties: a = 0 and b = 1. Equation 8 is estimated using the usual OLS procedure with White's heteroscedasticity consistent standard errors and the results are reported in Table 6. The in-sample volatility estimates from Models 1 and 3 appears to be close to squared returns as we are not able to reject the hypothesis, that a and b are equal to zero and one respectively. However, the in-sample volatility estimates from Models 2 and 4 are poor approximations to squared returns, conveying poor performance of MGARCH model.

Figure 2: In-Sample Mean Forecast Comparison

Figure 2.1: Two-Stage Mean Forecast vs. Actual

MSE: 1.134687775

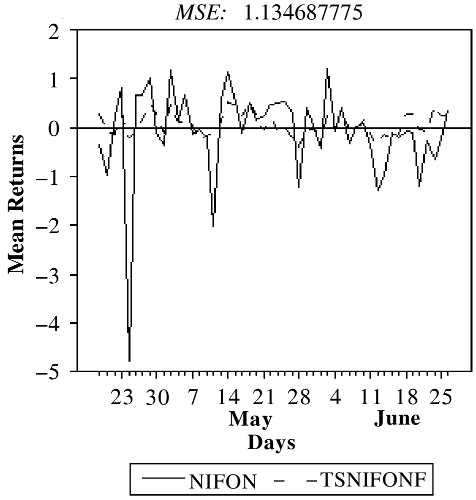


Figure 2.3: Univariate Mean Forecast vs. Actual

MSE: 1.13200243

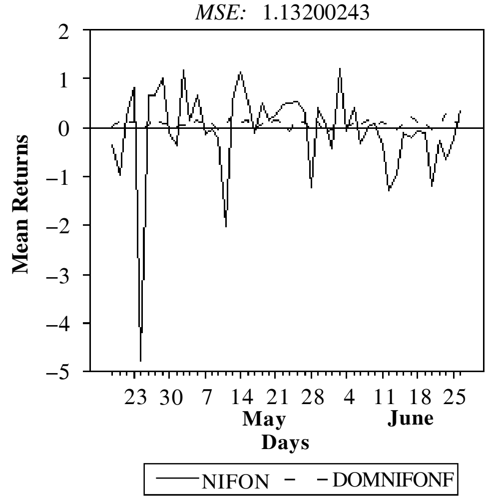


Figure 2.2: MGARCH Mean Forecast vs. Actual

MSE: 1.025874761

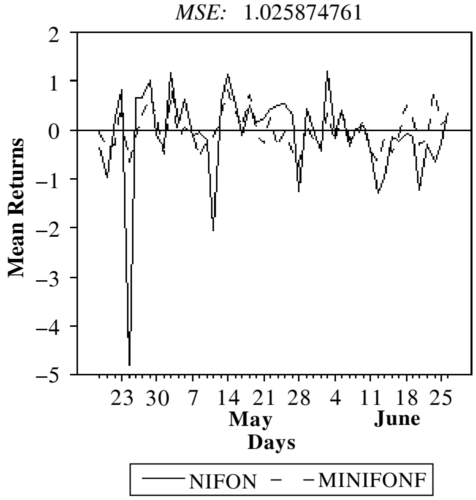


Figure 2.4: Domestic Mean Forecast vs. Actual

MSE: 1.3500485

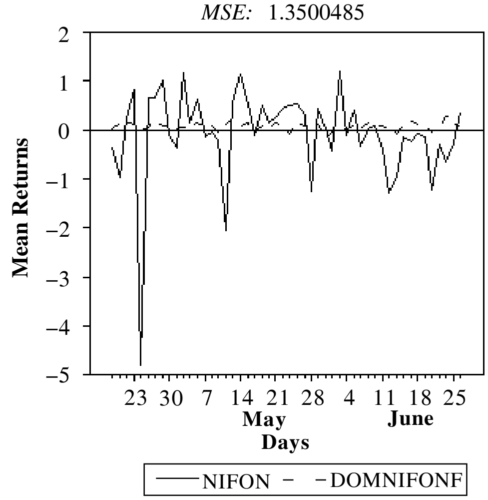


Figure 3: In-Sample Volatility Forecast Comparison

Figure 3.1: Two-Stage Volatility Forecast vs. Actual

MSE: 12.945267078

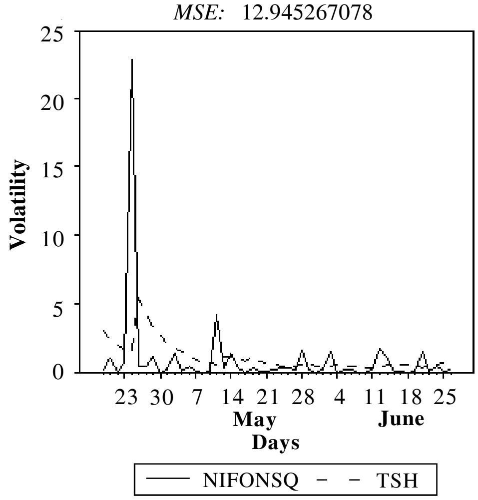


Figure 3.3: Univariate Volatility Forecast vs. Actual

MSE: 12.882185540

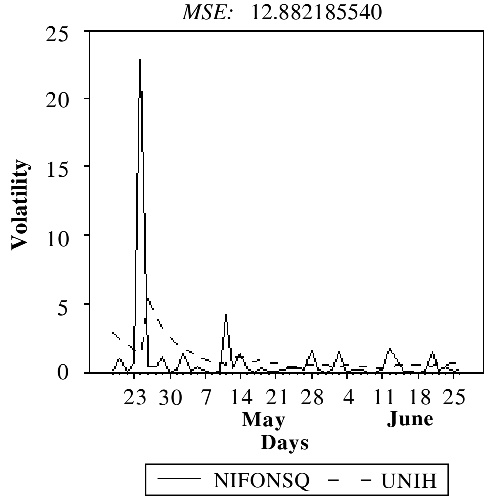


Figure 3.2: MGARCH Volatility Forecast vs. Actual

MSE: 13.7498592874

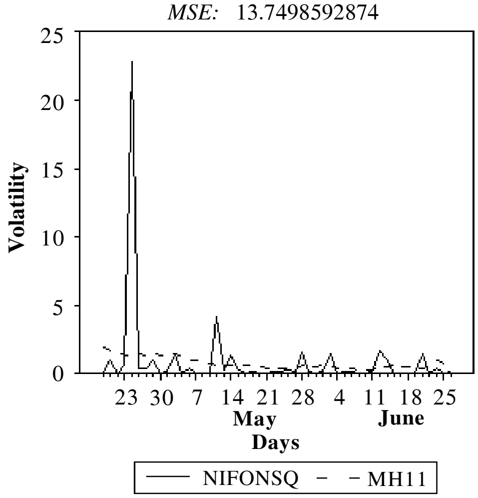


Figure 3.4: Domestic Volatility Forecast vs. Actual

MSE: 19.4372772

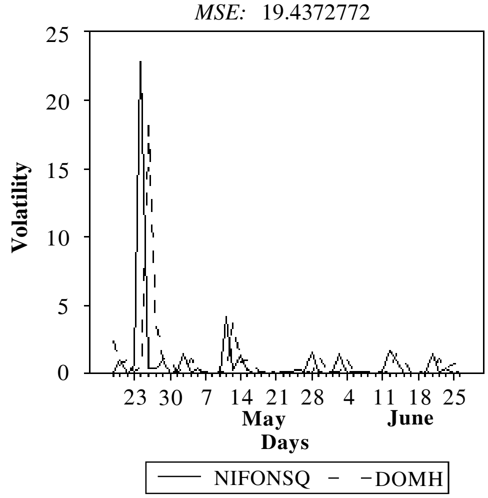


Table 6: Volatility Forecast Performance: Regression Results

$h_{t,i}$ is the forecasted volatility as predicted by different models (i = 1,2,3,4).

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

The following regression is estimated for each model:

$$\log\left(r_t^2\right) = a + b * \log\left(h_t\right) + u_t$$

(Contd...)

Table 6: Volatility Forecast Performance: Regression Results (...contd)				
Coefficient → **Model ↓**	**In-Sample Volatility Evaluation**		**Out-of-Sample Volatility Evaluation**	
	a	***b****	***a***	***b****
Two-Stage (Model 1)	0.1361672848 (0.69911)	0.9806542665 (0.22196)	0.0448275618 (0.51793)	0.4766396175 (1.890404)
MGARCH (Model 2)	–1.261420162 (–5.00623)	2.610488313 (8.2717875)	0.0774665973 (0.18566)	0.1658272168 (1.8570104)
ARMA-GARCH (Model 3)	0.1376028391 (0.70275)	0.9884399101 (0.130005)	0.0436087747 (0.50177)	0.4673380811 (1.99421)
Domestic (Model 4)	0.8693933120 (4.82609)	0.3898081598 (12.48786)	0.1429707439 (3.59062)	0.1926732439 (4.61597)

Note: White's (1980) heteroskedasticity consistent *t*-statistics are in brackets below the coefficient estimates. * *t*-statistic of *b* is for null of *b* = 1.

Out-of-Sample Validation

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 the out-of-sample forecasts of all models and compare them with the actual realized values. We calculate multistep ahead forecasts for the next 45 days, from July 1, 2001 to August 31, 2001. Figure 4 plots the actual Nifty overnight return, mean forecast values, TSNIFONF, MNIFON, UNINIFONF and DOMNIFONF obtained respectively from Models 1, 2, 3 and 4. It is evident that the models with NASDAQ information (Models 1, 2 and 3) clearly outperform Model 4, and Model 3 is marginally better than Models 1 and 2 in predicting the

Figure 4: Out-of-Sample Mean Forecast Comparison

Figure 4.1: Two-Stage Mean Forecast vs. Actual
MSE: 0.12518197973

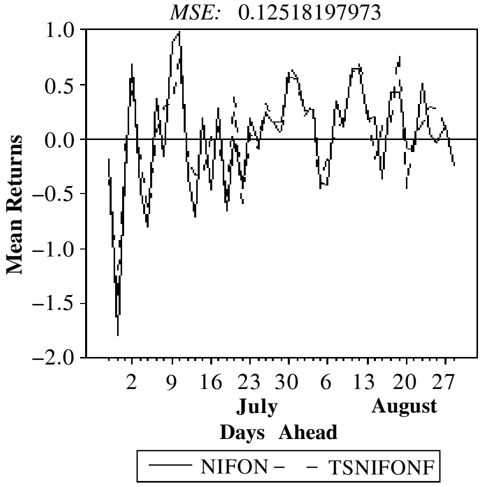
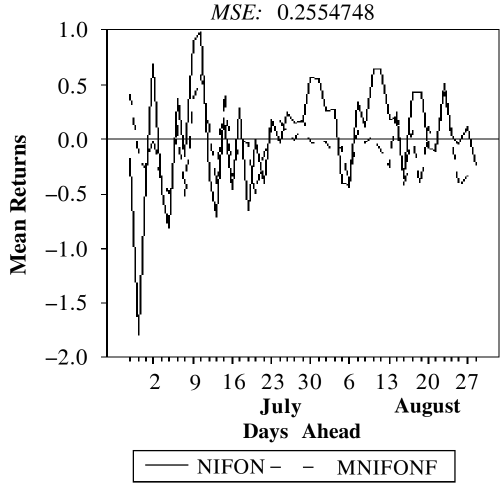


Figure 4.2: MGARCH Mean Forecast vs. Actual
MSE: 0.2554748



(Contd...)

Figure 4: Out-of-Sample Mean Forecast Comparison *(...contd)*

Figure 4.3: Univariate Mean Forecast vs. Actual

MSE: 0.0702665644

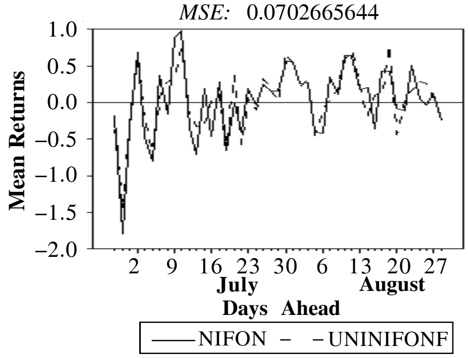


Figure 4.4: Domestic Mean Forecast vs. Actual

MSE: 0.3769951866

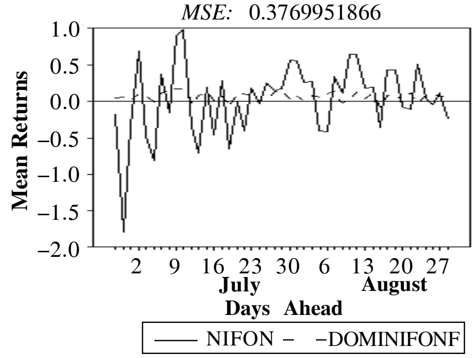


Figure 5: Out-of-Sample Volatility Forecast Comparison

Figure 5.1: Two-Stage Volatility Forecast vs. Actual

MSE: 0.2434410837

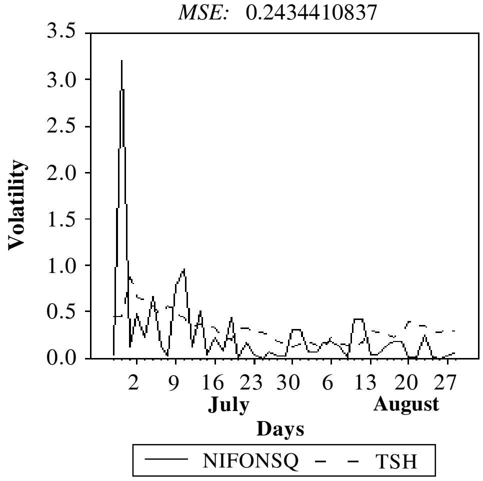


Figure 5.3: Univariate Volatility Forecast vs. Actual

MSE: 0.24107989052

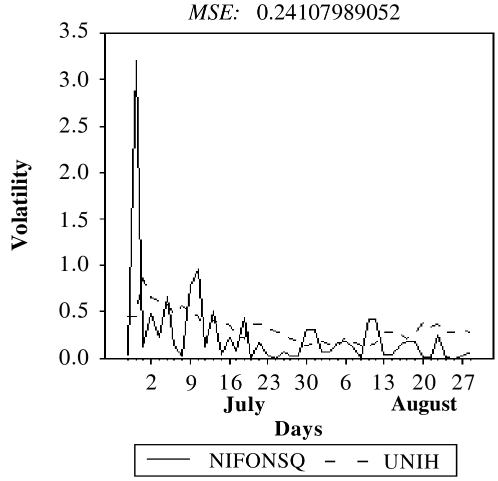


Figure 5.2: MGARCH Volatility Forecast vs. Actual

MSE: 0.39040654676

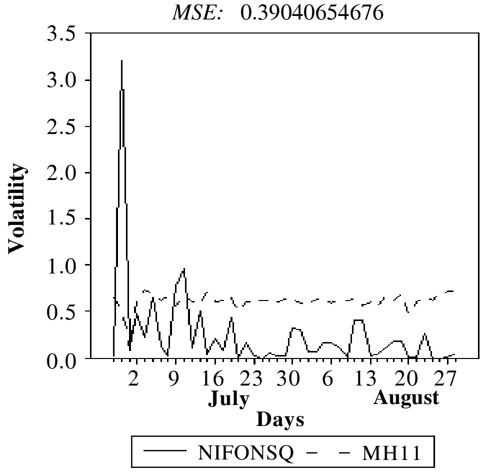
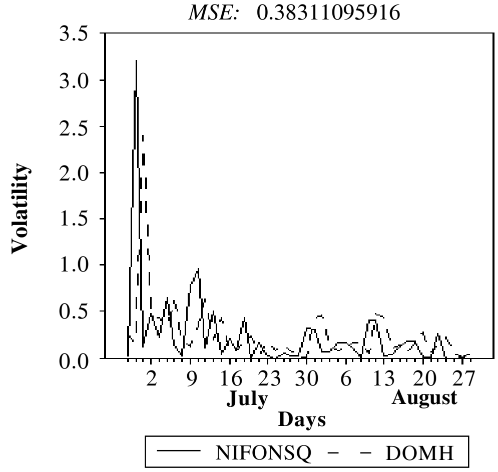


Figure 5.4: Domestic Volatility Forecast vs. Actual

MSE: 0.38311095916



actual Nifty overnight returns. This is further reinforced by the least mean squared error forecast of Model 3. Figure 5 plots the out-of-sample volatility forecast errors, TSH, MH11, UNIH and DOMH respectively from Models 1, 2, 3 and 4. In predicting the out-of-sample volatility, it is not so clear which model performs better. From Figures 4 and 5, we conclude that using NASDAQ information is relevant only in predicting Nifty overnight returns.

Table 7 reports the ranking of two-stage GARCH, MGARCH, ARMA-GARCH model and Domestic model on the basis of out-of-sample MSE forecasts, regression criterion and AIC model selection criterion. The comparison is based on the same dataset but different model specifications. The model comparison with the Domestic model strongly supports the use of NASDAQ information as it clearly gives the poorest fit. Between the models that use NASDAQ information, the parsimonious model, ARMA-GARCH captures the empirical features of data better. On the whole, Model 3 outperforms the other two models and hence next we use Model 3 to see the importance of NASDAQ effect.

Table 7: Model Comparison

Model	AIC	Log L	Regression Criterion	MSE Out-of-Sample		Rank
				Mean Forecast	Volatility Forecast	
Two-Stage GARCH	4233.92	–149.03	Satisfied	0.1251820	0.2434411	2
MGARCH	4585.96	–1402.10	Not Satisfied	0.2554748	0.3904065	3
ARMA-GARCH	4221.26	–147.68	Satisfied	0.0702666	0.2410799	1
Domestic	4285.34	–181.63	Not Satisfied	0.3769952	0.3831109	4

Importance of NASDAQ

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:

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

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. Nifty overnight return volatility is more dependent on the *NASD* volatility than on the *NIFD* volatility over the entire sample period. On an average, the *NASD* volatility accounts for 9.51% of the Nifty overnight volatility, while the *NIFD* volatility captures only 0.5%.

Conclusion

The paper investigates 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 July 1, 1999 to June 30, 2001. GARCH methodology is extensively applied to capture the mechanism by which NASDAQ Composite daytime returns and volatility, affect not only the conditional returns but also the conditional volatility of Nifty overnight returns. The model building process starts with popular GARCH models in the literature of volatility transmission, namely, the two-stage GARCH model and the MGARCH model. Then the problem is approached with a simple ARMA-GARCH model where the squared returns proxy for volatility. The results report that the simple ARMA-GARCH model performs better than the more complex two-stage GARCH model and MGARCH model. The study also benchmarks the fitted models with a model involving information pertaining to only the domestic market, discarding any information revealed by the NASDAQ. The paper concludes by quantifying the relative importance of $NASD_t$ vis-à-vis $NIFD_t$ in predicting Nifty overnight return volatility. ❖

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References

1. Angela Ng (2000), "Volatility Spillover Effects from Japan and the US to the Pacific-Basin", *Journal of International Money and Finance*, Vol. 19, pp. 207-233.
2. Berndt E R, Hall B H, Hall R E and Haussman J A (1974), "Estimation and Inference in Nonlinear Structural Models", *Annals of Economic and Social Measurement*, Vol. 4, pp. 653-665.
3. Bollerslev T (1990), "Modelling the Coherence in Short-Run Nominal Exchange Rate: A Multivariate Generalized ARCH Approach", *Review of Economics and Statistics*, Vol. 12, pp. 498-505.
4. Bollerslev T, Engle R F and Wooldridge J M (1988), "A Capital Asset Pricing Model with Time-Varying Covariances", *Journal of Political Economy*, Vol. 96, pp. 116-131.
5. Bollerlsev T, Chou Ray Y and Kroner K F (1992), "ARCH Modeling in Finance: A Review of the Theory and Empirical Evidence", *Journal of Econometrics*, Vol. 52, pp. 5-59.
6. Brooks Chris and Henry T (2000), "Linear and Non-Linear Transmission of Equity Return Volatility: Evidence from the US, Japan and Australia", *Economic Modelling*, Vol. 17, pp. 497-513.
7. Cheung Lilian K and Ng (1992), "Interactions between the US and Japan Stock Market Indices", *Journal of International Financial Markets, Institutions & Money*, Vol. 2, No. 2, pp. 51-70.
8. Engle R F and Andrew J Patton (2000), "What Good is a Volatility Model?", *Quantitative Finance*, Vol. 1, pp. 237-245.
9. Engle R F and Kroner K F (1995), "Multivariate Simultaneous Generalized ARCH", *Econometric Theory*, Vol. 11, pp. 122-150.
10. Engle R F and Ng V (1993), "Measuring and Testing the Impact of News on Volatility", *Journal of Finance*, Vol. 48, pp. 1749-1778.

11. Engle R F, David M Lilien and Russell P Robins (1987), "Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model", *Econometrica*, Vol. 55, pp. 391-407.

12. Eun C and Shim S (1989), "International Transmission of Stock Market Movements", *Journal of Financial and Quantitative Analysis*, Vol. 24, pp. 241-256.

13. Hamao Y, Masulis R and Ng V (1990), "Correlations in Price Changes and Volatility Across International Stock Markets", *Review of Financial Studies*, Vol. 3, pp. 281-307.

14. Hansda S K and Ray P (2002), "BSE and Nasdaq—Globalization, Information Technology and Stock Prices", *Economic Political Weekly*, February 2.

15. Hilliard J (1979), "The Relationship Between Equity Indices on World Exchanges", *Journal of Finance*, Vol. 34, No. 1, pp. 103-117.

16. Kee-Hong Bae and Karolyi (1994), "Good News, Bad News and International Spillovers of Stock Return Volatility between Japan and the US", *Pacific-Basin Finance Journal*, Vol. 2, pp. 405-438.

17. King M A and Wadhwani S (1990), "Transmission of Volatility Between Stock Markets", *Review of Financial Studies*, Vol. 3, pp. 5-33.

18. King M, Sentana E and Wadhwani S (1994), "Volatility and Links Between National Markets", *Econometrica*, Vol. 62, No. 4, pp. 901-933.

19. Kumar K K and Mukhopadyay (2002), "Equity Market Interlinkages: Transmission of Volatility: A Case of US and India", NSE Research Initiative Paper No. 16.

20. Lin, Engle and Ito (1994), "Do Bulls or Bears Move Across Borders? International Transmissions of Stock Returns and Volatility", *Review of Financial Studies*, Vol. 7, pp. 507-538.

21. Longin F and Solnik B (1995), "Is the Correlation in International Equity Returns Constant: 1960-1990?", *Journal of International Money and Finance*, Vol. 14, pp. 2-26.

22. Nair and Ramanathan (2002), "Analysis of Co Movements of Select US & Indian Stock Price Indexes", UTI Capital Markets Conference 2002.

23. Rao B S R and Umesh Naik (1990), "Inter-Relatedness of Stock Markets: Spectral Investigation of USA, Japanese and Indian Markets Note", *Artha Vignana*, Vol. 32, Nos. 3 and 4, pp. 309-321.

24. Ripley D (1973), "Systematic Elements in the Linkage of National Stock Market Indices", *Review of Economics and Statistics*, Vol. 15, pp. 356-361.

25. Sadhan Kumar C and Samir Ranjan B (2005), "Financial Integration for Indian Stock Market", Working Paper.

26. Schwert G W (1990), "Stock Volatility and the Crash", *Review of Financial Studies*, Vol. 3, pp. 77-102.

27. Sharma J L and Kennedy R E (1977), "Comparative Analysis of Stock Price Behavior on the Bombay, London & New York Stock Exchanges", *Journal of Financial and Quantitative Analysis*, September, pp. 391-403.

28. Tse Y K (2000), "A Test for Constant Correlations in a Multivariate GARCH Model", *Journal of Econometrics*, Vol. 98, pp. 107-127.

29. Von Furstenberg G M and Jeon B N (1989), "International Stock Price Movements: Links and Messages", *Brooking Papers on Economic Activity*, Vol. 1, pp. 125-167.

30. Wong W, Agarwal A and Du J (2005), "Financial Integration for Indian Stock Market, A Fractional Cointegration Approach", National University of Singapore, Department of Economics, Working Paper No. 50.

Bibliography

1. Becker K G, Finnerty J E and Manoj Gupta (1990), "The Intertemporal Relation between the US & Japanese Stock Markets", *Journal of Finance*, Vol. 45, pp. 1297-1306.

2. Granger Clive W J (1969), "Investigating Causal Relations by Econometric Models and Cross Spectral Methods", *Econometrica*, Vol. 37, pp. 424-438.

3. John Wei K C, Yu-Jane Liu, Yang and Chaung (1995), "Volatility and Price Change Spillover Effects Across the Developed and Emerging Markets", *Pacific-Basin Finance Journal*, Vol. 3, pp. 113-136.

4. Koch P and Koch R (1991), "Evolution in Dynamic Linkages Across Daily National Stock Indexes", *Journal of International Money and Finance*, Vol. 10, pp. 231-251.

5. Koutmos G (1999), "Asymmetric Price & Volatility Adjustments in Emerging Asian Stock Markets", *Journal of Business Finance & Accounting*, Vol. 26, Nos. 1 and 2, pp. 83-101.

6. Panton D, Lesseg V and Joy O (1976), "Co-Movement of International Equity Markets: A Taxonomic Approach", *Journal of Financial and Quantitative Analysis*.

7. Stoll H and Whaley R (1990), "Stock Market Structure and Volatility", *Review of Financial Studies*, Vol. 3, pp. 37-71.

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