This paper investigates the nature and characteristics of stock market volatility in India. The volatility in the Indian stock market exhibits characteristics similar to those found earlier in many of the major developed and emerging stock markets. Various volatility estimators and diagnostic tests indicate volatility clustering, i.e., shocks to the volatility process persist and the response to news arrival is asymmetrical, meaning that the impact of good and bad news is not the same. Suitable volatility forecast models are used for Sensex and Nifty returns to show that:

- The ‘day-of-the-week effect’ or the ‘weekend effect’ and the ‘January effect’ are not present while the return and volatility do show intra-week and intra-year seasonality.
- The return and volatility on various weekdays have somewhat changed after the introduction of rolling settlements in December 1999.
- There is mixed evidence of return and volatility spillover between the US and Indian markets.

The empirical findings would be useful to investors, stock exchange administrators and policy makers as these provide evidence of time varying nature of stock market volatility in India. Specifically, they need to consider the following findings of the study:

- For both the indices, among the months, February exhibits highest volatility and corresponding highest return. The month of March also exhibits significantly higher volatility but the magnitude is lesser as compared to February. This implies that, during these two months, the conditional volatility tends to increase. This phenomenon could be attributed to probably the most significant economic event of the year, viz., presentation of the Union Budget. The investors, therefore, should keep away from the market during March after having booked profits in February itself. The surveillance regime at the stock exchanges around the Budget should be stricter to keep excessive volatility under check.
- Similarly, the month of December gives high positive returns without high volatility and, therefore, offers good opportunity to the investors to make safe returns on Sensex and Nifty. On the contrary, in the month of September, i.e., the time when the third quarter corporate results are announced, volatility is higher but corresponding returns are lower. The situation is, therefore, not conducive to investors.
- The ‘weekend effect’ or the ‘Monday effect’ is not present. For other weekdays, the ‘higher (lower) the risk, higher (lower) the return’ dictum does not hold consistently and Wednesday provides higher returns with lower volatility making it a good day to invest.
- The domestic investors and the stock exchange administrators do not need to lose sleep over gyrations in the major US markets since there is no conclusive evidence of consistent relationship between the US and the domestic markets.
- The volatility forecast models presented for Sensex and Nifty can be used to forecast future volatility of these indices.
Volatility is the most basic statistical risk measure. It can be used to measure the market risk of a single instrument or an entire portfolio of instruments. While volatility can be expressed in different ways, statistically, volatility of a random variable is its standard deviation. In day-to-day practice, volatility is calculated for all sorts of random financial variables such as stock returns, interest rates, the market value of a portfolio, etc. Stock return volatility measures the random variability of the stock returns. Simply put, stock return volatility is the variation of the stock returns in time. More specifically, it is the standard deviation of daily stock returns around the mean value and the stock market volatility is the return volatility of the aggregate market portfolio.

Volatility of stock returns has been mainly studied in the developed economies. After the seminal work of Engle (1982) on the Autoregressive Conditional Heteroscedasticity (ARCH) model and its generalized form (GARCH) by Bollerslev (1986), much of the empirical work has used these models and their extensions (see, for example, French, Schwert and Stambaugh 1987; Akgiray, 1989; Connolly, 1989; Ballie and DeGennaro, 1990; Lamoureux and Lastrapes, 1990; Corhay and Tourani, 1994; Geyer, 1994; Nicholls and Tonuri, 1995; Booth, Martikainen and Tse, 1997; de Lima, 1998; and Sakata and White, 1998).

There is relatively less empirical research on stock return volatility in the emerging markets. In the Indian context, Roy and Karmakar (1995) focused on the measurement of the average level of volatility as the sample standard deviation and examined whether volatility has increased in the early 1990s; Goyal (1995) used conditional volatility estimates as suggested by Schwert (1989) to study the nature and trend of stock return volatility and the impact of carry forward system on the level of volatility; Reddy (1997-98) analysed the effects of market microstructure, e.g., establishment of the National Stock Exchange (NSE) and the introduction of Bombay Stock Exchange Online Trading (BOLT) system on the stock return volatility measured as the sample standard deviation of the closing prices; Kaur (2002) analysed the extent and pattern of stock return volatility during 1990-2000 and examined the effect of company size, day-of-the-week, and FII investments on volatility measured as the sample standard deviation.


This paper empirically investigates the pattern of volatility in the Indian stock market during 1993-2003 in terms of its time varying nature, presence of certain characteristics such as volatility clustering, ‘day-of-the-week effect’ and ‘calendar month effect,’ and whether there exists any ‘spillover effect’ between the domestic and the US stock markets. It contributes to the body of knowledge by providing a holistic treatment to the subject of stock market volatility in India and providing evidence on its main characteristic features with the help of econometric techniques and employing GARCH models.

The Indian stock market is represented by two most prominent stock indices, viz., Bombay Stock Exchange’s (BSE) Sensitive Index (Sensex) and NSE’s S&P CNX Nifty (Nifty). The Sensex is generally considered to be the bellwether of the Indian stock market. It is the older and the more often quoted index. However, of late, with the growing popularity of the NSE, due to its more transparent trading mechanism and lower trading cost, Nifty has come to be considered as an important and broader-based market index. As per SEBI’s Annual Report of 2002-2003 (available at www.sebi.gov.in), the BSE and NSE together account for more than 95 per cent of the total business transacted on all the stock exchanges of the country. Additionally, according to the data available on the respective exchange web sites (www.bseindia.com and www.nseindia.com), a major portion (around 75%) of the total market turnover of the respective stock exchanges is accounted for by the index (Sensex and Nifty) stocks.

We have examined the following issues with respect to the Indian stock market for the period spanning more than a decade (January 1993 - March 2003):

- Is there any evidence of time varying volatility in daily return on Sensex and Nifty and what is the nature of the volatility process?
- Does any particular weekday have significant impact on mean returns and/or volatility, i.e., is there any ‘day-of-the-week effect’?
- Does any particular month of the year have signi-
significant impact on mean returns and/or volatility, i.e., is there any ‘calendar month effect?’

- Is there return and/or volatility spillover across the Indian and the US stock markets?

RESEARCH DESIGN

Period of Study

The study spans the period January 1993 through March 2003. Besides being the most recent period, major changes were brought about in the structure and functioning of the Indian stock markets during these ten years. In the wake of the scam of 1992 and the information, communication, and entertainment (ICE) meltdown of 2001, major regulatory activities took place. For example, screen-based trading was introduced on the NSE (1994) and BSE (1995), circuit filters were introduced by the NSE in 1995, dematerialization of shares and hence ‘paperless trading’ begun in 1997 was made compulsory in January 1999, rolling settlements were introduced in December 1999 in a limited manner, index-based futures were introduced in June 2000 and index options in June 2001, and carry forward of trades was abolished from 2nd July 2001. It is, therefore, important to study the nature of stock market volatility during these years.

The Sample

The stock market indices are fairly representative of the various industry sectors and trading activity mostly revolves around the stocks comprising the indices. Thus, the sample population of the study consists of the two most prominent domestic market indices, viz., Sensex and Nifty, and S&P 500 and Nasdaq (NASDAQ) corporate indices to represent the US market.

Database

The daily stock price data on Sensex and Nifty have been taken from PROWESS, the online database maintained by the Centre for Monitoring of Indian Economy (CMIE). CMIE maintains this database for calculating its various indices. The database contains all the actively traded stocks at any given time on the BSE and the NSE. Daily opening, high, low, and closing prices have been taken for the two indices for the period of study. These prices have been adjusted for bonus and right issues. In addition to PROWESS, for the daily return series of S&P 500 and Nasdaq composite index, web resources such as www.Economagic.com and www.Yahoo.com/Finance have been used.

Daily stock prices have been converted to daily returns. The present study uses the logarithmic difference of prices of two successive periods for the calculation of rate of return. The logarithmic difference is symmetric between up and down movements and is expressed in percentage terms for ease of comparability with the straightforward idea of a percentage change.

If $I_t$ be the closing level of Sensex on date $t$ and $I_{t-1}$ be the same for its previous business day, i.e., omitting intervening weekend or stock exchange holidays, then the one day return on the market portfolio is calculated as:

$$ r_t = \ln \left( \frac{I_t}{I_{t-1}} \right) \times 100 $$

where, $\ln(z)$ is the natural logarithm of ‘z.’

Econometric Methodology

One of the key assumptions of the ordinary regression model is that the errors have the same variance throughout the sample. This is also called the homoscedasticity model. If the error variance is not constant, the data are said to be heteroscedastic. Findings of heteroscedasticity in stock returns are well documented (Mandelbrot, 1963; Fama, 1965; Bollerslev, 1986). These studies have found that stock return data is typically characterized by:

- serial correlation in the returns indicating that successive returns are not independent.
- serial correlation in the squares of returns resulting in distinct periods of high volatility and relative stability, i.e., volatility clustering.
- negative asymmetry in the distribution of returns questioning the assumption of an underlying normal distribution.
- leptokurtosis in the distribution of returns with too many values near the mean and in the tails of the distribution when compared with the normal distribution.

In econometric literature, volatility clustering is modeled as an ARCH process. Robert Engle (1982) in his seminal work on inflation in the UK first introduced the idea of ARCH effect. Later on, Bollerslev (1986) generalized this type of model and introduced the GARCH model. In the last 15 years, many variants of the GARCH model have been proposed in the literature.

The ARCH and the GARCH models assume conditional heteroscedasticity with homoscedastic unconditional error variance. That is, the changes in variance are a function of the realizations of preceding errors and these changes represent temporary and random depen-
tures from a constant unconditional variance as might be the case when using daily data. The advantage of GARCH model is that it captures the tendency in financial data for volatility clustering. It, therefore, enables us to make the connection between information and volatility explicit since any change in the rate of informational arrival to the market will change the volatility in the market. Thus, unless information remains constant, which is hardly the case, volatility must be time varying even on a daily basis.

We have modeled the mean return as an ARMA (Auto Regressive Moving Average) \((p,q)\) process in our analyses. This requires the testing of stationarity of the series at the onset. Stationarity implies that mean and covariance of the return distribution are time independent. In any time series analysis, the test for stationarity is important because, in the presence of non-stationary series, the standard estimation procedures are not applicable. Thus, we begin our analysis with testing for stationarity, i.e., unit root testing. We then fit an ARMA model to the data generating process and follow the process suggested by Box and Jenkins (1976). Finally, we model the conditional variance as a symmetrical or asymmetrical GARCH process.

**Statistical Tools**

The daily and intra-day stock price data have been first processed by using Microsoft Excel. Subsequently, econometric analysis package EViews has been used to test the return and volatility data for various statistical properties and to estimate ARCH/GARCH class of models.

**Diagnostic Tests**

As part of the diagnostics, we begin with a visual inspection of the plot of daily returns on Sensex as shown in Figure 1. It can be seen that returns continuously fluctuate around a mean value that is close to zero. The movements are in the positive as well as negative territory and larger fluctuations tend to cluster together separated by periods of relative calm. This is consistent with Fama’s (1965) observation that stock returns exhibit volatility clustering where large returns tend to be followed by large returns and small returns by small returns leading to contiguous periods of volatility and stability.

Descriptive statistics on Sensex and Nifty returns are summarized in Table 1. For both Sensex and Nifty, the skewness statistic for daily returns is found to be different from zero indicating that the return distribution is not symmetric. Furthermore, the relatively large excess kurtosis suggests that the underlying data is leptokurtic or heavily tailed and sharply peaked about the mean when compared with the normal distribution. The Jarque-Bera statistic calculated to test the null hypothesis of normality rejects the normality assumption. The results confirm the well-known fact that daily stock returns are not normally distributed but are leptokurtic and skewed.

Both the indices appear to have strong autocorre-
relations in one-day lag returns with significant coefficient. Also, the autocorrelation in the squared daily returns suggests that there is a clustering of variance. The correlation appears strongest in daily data with almost every coefficient of the returns squared series being outside the asymptotic bounds. The correlation is reduced for the monthly series. The daily return and squared return series show strong first order correlation. The results clearly reject the independence assumption for the time series of daily stock returns.

Unit Root Tests

Stationarity of the Sensex and Nifty return series were tested by conducting Dickey-Fuller and Phillip-Peron tests. The results of both the tests confirm that the series are stationary. Table 2 presents the results of these tests.

Application of Box-Jenkins Methodology

The autocorrelation function (ACF) and partial autocorrelation function (PACF) were computed. Highly significant Ljung-Box-Pierce Q statistic, as shown in Table 1, confirms the presence of first order correlation in the return series and negates random walk behaviour. Diagnostics for AR and MA models confirm AR (1) structure of the mean equation for both Sensex and Nifty.

The above findings indicate the possible presence of ARCH effect which is confirmed by the computed value of Lagrange Multiplier (LM). This finding shows the clustering effect in daily returns, i.e., large shocks to the error process are followed by large ones and small shocks by small ones of either sign.

The existence of a leptokurtic distribution, volatility clustering, and a changing conditional variance means

### Table 1: Descriptive Statistics of Daily Returns

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Sensex</th>
<th>Nifty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations (T)</td>
<td>2,453</td>
<td>1,842</td>
</tr>
<tr>
<td>Mean</td>
<td>0.006</td>
<td>-0.0008</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>1.686</td>
<td>1.6554</td>
</tr>
<tr>
<td>Skewness</td>
<td>-0.08</td>
<td>-0.1236</td>
</tr>
<tr>
<td>Excess kurtosis</td>
<td>5.39</td>
<td>5.8353</td>
</tr>
<tr>
<td>Jarque-Bera statistic</td>
<td>587.59 (2-tailed p=0.00)</td>
<td>621.70 (2-tailed p=0.00)</td>
</tr>
<tr>
<td>Q(1)</td>
<td>24.42 (2-tailed p=0.00)</td>
<td>5.58 (2-tailed p=0.018)</td>
</tr>
<tr>
<td>Q(22)</td>
<td>109.55 (2-tailed p=0.00)</td>
<td>59.29 (2-tailed p=0.00)</td>
</tr>
<tr>
<td>Q(22)</td>
<td>60.02 (2-tailed p=0.00)</td>
<td>49.16 (2-tailed p=0.001)</td>
</tr>
<tr>
<td>Q(22)</td>
<td>442.37 (2-tailed p=0.00)</td>
<td>179.60 (2-tailed p=0.00)</td>
</tr>
<tr>
<td>ARCH LM statistic (at lag=1)</td>
<td>132.26</td>
<td>110.89</td>
</tr>
<tr>
<td>ACF at lag=1 for returns</td>
<td>0.1 (Asymptotic bound = 0.04)</td>
<td>0.055 (Asymptotic bound = 0.047)</td>
</tr>
<tr>
<td>ACF at lag=1 for squared returns</td>
<td>0.2 (Asymptotic bound = 0.04)</td>
<td>0.179 (Asymptotic bound = 0.047)</td>
</tr>
</tbody>
</table>

### Notes

a. $Q(K)$ is the Ljung Box statistic identifying the presence of first order autocorrelation in the returns. Under the null hypothesis of no autocorrelation, it is distributed as $\chi^2(K)$.

b. $Q^2(K)$ is the Ljung Box statistic identifying the presence of first order autocorrelation in the squared returns. Under the null hypothesis of no autocorrelation, it is distributed as $\chi^2(K)$.

c. ARCH LM statistic is the Lagrange multiplier test statistic for the presence of ARCH effect. Under the null hypothesis of no heteroscedasticity, it is distributed as $\chi^2(K)$. Critical value of $\chi^2$ at 1 per cent level of significance is 6.63 at 1 degree of freedom. Values for higher lags are also significant.

d. ACF is the auto correlation function.

### Table 2: Unit Root Testing of Daily Returns

<table>
<thead>
<tr>
<th>Augmented Dickey-Fuller Tests</th>
<th>Number of Lags = 44</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null Hypothesis</td>
<td>Test Statistic</td>
</tr>
<tr>
<td>Constant = 0</td>
<td>-6.926</td>
</tr>
<tr>
<td>Intercept = 0</td>
<td>-6.927</td>
</tr>
<tr>
<td>Constant = 0</td>
<td>-7.000</td>
</tr>
<tr>
<td>Trend Coeff. = 0</td>
<td>-44.734</td>
</tr>
<tr>
<td>Intercept = 0</td>
<td>-44.740</td>
</tr>
</tbody>
</table>

### Phillips-Perron Tests

<table>
<thead>
<tr>
<th>Truncation Lag = 7 (Nifty)</th>
<th>Truncation Lag = 8 (Sensex)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Null Hypothesis</td>
<td>Test Statistic</td>
</tr>
<tr>
<td>Intercept = 0</td>
<td>-44.734</td>
</tr>
<tr>
<td>Constant = 0</td>
<td>-44.740</td>
</tr>
<tr>
<td>Trend Coeff. = 0</td>
<td>-44.734</td>
</tr>
<tr>
<td>Intercept = 0</td>
<td>-44.740</td>
</tr>
</tbody>
</table>
that our next logical step in modeling exercise should be to express the conditional volatility as an ARCH or GARCH process with the mean return process as an AR (1) process.

**Behaviour of Volatility Estimates**

The analyses in the preceding section reveal that the volatility of daily return on Sensex might follow an ARCH or a GARCH process. Hence, we believe that daily return does not follow a homoscedastic pattern. Before moving on to modeling the conditional volatility as a GARCH process, we take up a simple exercise to study the inter-temporal pattern of volatility in daily return series during the period of 1993-2003.

Our exercise begins with the most commonly used measure of volatility in statistical literature. We compute the variance of the daily returns over a 30-day horizon. Thus, for any date ‘t,’ the variance of daily returns is given by:

\[
\text{Var}(\bar{r}_{30\text{day}}) = \frac{1}{30} \sum_{i=1}^{30} (\bar{r}_i - \bar{r}_{30\text{day}})^2
\]

where, \(\bar{r}_{30\text{day}}\) is the average return for the 30-day period under consideration. In the next step, we exclude the first observation and include the 31st observation. Thus, in this case, we consider \(t = 2, 3... 31\). It is like constructing moving average of a series. This way we construct the variance for the remaining period and check whether the variance has changed over time or not.

The schematic diagram for the 30-day variance of Sensex daily return series is shown in Figure 2. The pattern is similar for Nifty also. This graphical presentation reveals that, of late the stock market has become more volatile than what it was at the beginning of the period under study. Moreover, some degree of clustering is also evident in the plot. We find that during 1993-94, 1996-97, and 1998 onwards, large variations are generally appearing together whereas periods of small variations appear separately.

We can also use other estimators that use easily available information on the stock prices, viz., daily opening, closing, high, and low prices. The simplest of these is the classical estimator \(\hat{\sigma}^2 = (C_t - C_{t-1})^2\); where, \(C_t\) is the closing price on day \(t\) and \(C_{t-1}\) on the previous business day. A different class of volatility estimators, known as the ‘extreme-value volatility estimators’ is proposed by Parkinson (1980), Garman and Klass (1980), and Rogers and Satchell (1991). In addition to the daily closing price, these estimators take into account the daily opening, high, and low prices for arriving at the measure of volatility. Due to their superior information content, these estimators are more efficient as compared to the classical estimator.

**Figure 2: 30-day Moving Variance of Sensex Returns (1993-2003)**

![30-day Moving Variance of Sensex Returns (1993-2003)](image-url)
Of these, Parkinson (1980) was the first to suggest the following estimator based on the highest and the lowest prices observed in a day, i.e., the trading range:

\[ \frac{1}{(4n \ln 2)} \times 0.511 (\ln H_t/L_t)^2 \]

where,

- \( n \) = number of observations
- \( H_t \) = highest price on day \( t \)
- \( L_t \) = lowest price on day \( t \)

The basic criticism of the high-low estimators like Parkinson’s is that they ignore the joint effects of the high and low prices with the opening and closing prices. Garman and Klass (1980) extended Parkinson’s (1980) work to include the opening and closing prices as well as the trading range. Accordingly, they propose the following best analytic scale invariant estimator:

\[ \frac{1}{n} \times (0.511 (\ln H_t/L_t)^2 - 0.019 (\ln C_t/O_t) \times (\ln (H_t/L_t) + \ln (L_t/O_t)) - 0.383 (\ln C_t/O_t)^2) \]

where,

- \( n \) = number of days over which volatility is to be estimated.
- \( H_t \) = highest price on day \( t \)
- \( L_t \) = lowest price on day \( t \)
- \( C_t \) = closing price on day \( t \)
- \( O_t \) = opening price on day \( t \)

Roger and Satchell (1991) suggested yet another, more robust, volatility estimator that, unlike the two other estimators described above, does not assume a driftless Geometric Brownian Motion of the prices between the points of observation. Their estimator is as follows:

\[ \frac{1}{n} \times (\ln (H/C) \times (\ln (H/O) + \ln (L/C) \times (\ln (L/O))) \]

However, all estimators based on finite set of observations are biased due to limited transaction volume. While the classical estimator has a slight positive bias, the other estimators involving opening, high, and low prices have a downward bias (Pandey, 2002; Garman and Klass, 1980). All the same, these are useful for our purpose of gathering first information about the time varying nature of stock price volatility.

In our analysis of the pattern of volatility (i.e., \( n = 1 \)) of daily returns on Sensex, we employ these measures as well and find that volatility has, in fact, changed over time as shown in Figure 3 which plots the Garman and Klass estimator values obtained for Sensex. The results are similar for Nifty. Largely similar volatility clustering pattern is seen when the estimates from the other two extreme value estimators are plotted. From Figure 3, it is evident that volatility has changed over time and there

Figure 3: Estimated Volatility of BSE Sensex Returns (Garman&Klass Estimator)
are distinct periods of heightened volatility and relative calm, i.e., significant amount of volatility clustering is present. For instance, high levels of volatility occurred in the 1999-2000 period while the period 1995-1998 was relatively calm.

Model Specification

Existence of significant ARCH effect in the residuals of the fitted AR(1) process to the return generating process and also the various other volatility estimators indicating graphically the existence of clustering of volatility led us to the next step of modeling. We model the conditional variance of the residuals as an ARCH(q) process with the mean return being governed by the AR(1) process. Hence, our model becomes:

\[ r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t \]

\[ h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \eta_t \]

where, \( \varepsilon_t \mid I_{t-1} \sim N(0, h_t) \)

In all the cases, the ARCH parameters are found to be significant. The ARCH parameters were insignificant from ARCH (8) onwards in the case of Sensex and ARCH(6) for Nifty. The AR(1) parameter is significant in all the models. Hence, our diagnosis of the return process as an AR(1) process under the Box-Jenkins methodology still holds good. What is of more importance is that the conditional variance of the errors is now being modeled as an ARCH process. These results reinforce our earlier finding that significant clustering effect is present in the data. The sum of all ARCH coefficients in all the models is less than unity, which implies that the process is second-order stationary. The parameter estimates also satisfy the assumption of non-negativity.

The model selection criteria selects the AR(1)-ARCH(7) process for Sensex and AR(1)-ARCH(5) for Nifty. These models have the highest log-likelihood values and minimum AIC and SBC values. Hence, at this stage, we select the AR(1)-ARCH(7) and AR(1)-ARCH(5) models, for Sensex and Nifty respectively, as the representative of the conditional volatility process.

As a diagnostic check on the appropriateness of ARCH processes for daily return series, the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the squared residual series \( \{\varepsilon_t^2\} \) are examined. It is found that although the estimated ACF of the squared residual series seems to decay as the lag increases (the rate of decay may be slower than exponential), the PACF does not become zero after seven lags for Sensex and five lags for Nifty. It becomes zero at much higher lags and oscillates further. Therefore, as far as the ACF and PACF are concerned, the data do not seem to show full agreement with a pure ARCH process.

We now fit the GARCH models to the daily return series. The results are presented in Table 3 for Sensex and Nifty, respectively. We find that all the parameters in the GARCH (1,1) model are significant.

Higher order GARCH models either did not converge or the parameters were insignificant at the conventional levels of significance. Thus, at this stage, we find that GARCH (1,1) can be the possible representative of the conditional volatility process for the daily return series. Further diagnostic checking for model selection reveals that GARCH (1,1) is a better fit than the highest order ARCH models available. For both the Sensex and Nifty, the log-likelihood function has a higher value and both AIC and SBC are smaller as compared to the ARCH models. Hence, we come to the conclusion that for the Sensex as well as Nifty, the conditional volatility of the daily return distribution follows GARCH (1,1) process.

The parameter estimates of the GARCH (1,1) models in Table 3 are all statistically significant. It is also seen that the standardized residuals from the GARCH (1,1) model have ACF coefficients that are not significant — almost all of them lie between the asymptotic bounds of \( \pm 2/\sqrt{T} \) (equal to \( \pm 0.041 \) for Sensex and \( \pm 0.044 \) for Nifty), meaning that the GARCH model is specified correctly.

The estimates of \( \beta_1 \) are always markedly greater than those of \( \alpha_1 \) and the sum \( \beta_1 + \alpha_1 \) is very close to but smaller than unity. The fact that \( \beta_1 + \alpha_1 \) is close to unity, however, is useful for purposes of forecasting conditional variances. As for the stationarity of the variance process, it can be observed that \( \beta_1 + \alpha_1 \) is equal to 0.96 for Sensex and 0.95 for Nifty. This is less than unity indicating no violation of the stability condition. The sum, however, is rather close to one, which indicates a long persistence of shocks in volatility. Poterba and Summers (1986) have argued that for a long period asset like stocks, persistence of shocks is needed to be able to explain the time-varying risk premium. The reason for such an argument is that if shocks to the variance is only transitory in nature, i.e., has only short-term effect, investors will not make any changes in their discounting factor while
obtaining the present discounted value of the stock and hence its price.

Lamoureux and Lastrapes (1990) have proposed a half-life period of a shock to the variance. Half-life period is that period in which the shock diminishes to half of its original size. The half-life for GARCH (1,1) process is \(1 - \frac{\log_e 2}{\log_e (\alpha + \beta)}\). In our study, this is coming out to be 17.2 days for Sensex and 15.85 days for Nifty. Thus, the effect of a shock to the volatility process of daily return takes about 17 days to diminish by half its original impact in the case of Sensex and 16 days for Nifty. It appears that any bad or good news does have a significant and long lasting impact on the volatility of the stock prices. Persistence of volatility is quite trivial in the case of many other stock markets. A large body of financial literature has mentioned about this persistence effect (see, for instance, Poterba and Summers, 1986; Lamoureux and Lastrapes, 1990).

IS THERE ASYMMETRICAL RESPONSE TO THE ARRIVAL OF NEWS?

Schwert (1989), French, Schwert and Stambaugh (1987), Christie (1982) and Black (1976) have shown that returns are negatively correlated with volatility. This implies that returns tend to be more volatile in response to bad news and less volatile in response to good news. This kind of differential response to the kind of news arriving in the market leads to the issue of asymmetric response by stock market returns to various shocks. In the standard GARCH model, it is assumed that only the magnitude of the shock, not the positivity or negativity of the shock, determines the volatility. Hence, GARCH process generates a symmetric response function for the stock returns. This suggests that separate modeling techniques need to be used to capture the asymmetry in the response functions as suggested by Engle and Ng (1993).

Estimating the TARCH (Threshold ARCH) and EGARCH (Exponential GARCH) models and testing the significance of the asymmetric terms is one way to test for asymmetric effects. Alternatively, we can look at the cross correlation between the squared standardized residuals and lagged standardized residuals. These cross-correlations should be zero for a symmetric GARCH model and negative for a TARCH or an EGARCH asymmetric model.

In our study, we have computed the cross-correlation between the squared standardized residuals and lagged standardized residuals for up to 36 lags and found negative correlation at most of the lag lengths. The results of the estimations of the two models that allow for asymmetric shocks to volatility, viz., TARCH and EGARCH, are discussed next.

The TARCH Model

TARCH was introduced independently by Zakoian (1990) and Glosten, Jagannathan, and Runkle (1993). The specification for the conditional variance is:

\[
 h_t = w + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \varepsilon_{t-1}^2 d_{t-1} \\
\]

where \(d_{t-1} = 1\) if \(\varepsilon_{t-1} < 0\), and \(d_{t-1} = 0\) otherwise.

In this model, good news \((\varepsilon_{t-1} < 0)\), and bad news \((\varepsilon_{t-1} > 0)\), have differential effects on the conditional variance—good news has an impact of \(\alpha\), while bad news has an impact of \(\alpha + \gamma\). If \(\gamma > 0\), we say that the leverage effect exists. If \(\gamma \neq 0\), the news impact is asymmetric.

The outcomes of this model are shown in Table 3. All the parameters in the variance equation are significant. Most importantly, the leverage term is highly significant both for Sensex (0.095) and Nifty (0.085). This

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Sensex</th>
<th>Nifty</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>GARCH (1,1)</td>
<td>EGARCH (1,1)</td>
</tr>
<tr>
<td>A_t</td>
<td>0.1500 (0.0000)</td>
<td>0.1587 (0.0000)</td>
</tr>
<tr>
<td>a_0</td>
<td>0.1327 (0.0000)</td>
<td>-0.1697 (0.0000)</td>
</tr>
<tr>
<td>a_1</td>
<td>0.1389 (0.0000)</td>
<td>0.3036 (0.0000)</td>
</tr>
<tr>
<td>\beta_1</td>
<td>0.8206 (0.0000)</td>
<td>0.927 (0.0000)</td>
</tr>
<tr>
<td>\beta_1 + \alpha</td>
<td>0.9595</td>
<td>-0.052 (0.0000)</td>
</tr>
<tr>
<td>K</td>
<td>0.095 (0.0000)</td>
<td>0.0851 (0.0000)</td>
</tr>
<tr>
<td>\theta \ [(\text{Res}&lt;0)^*]</td>
<td>-4573.74</td>
<td>-4564.63</td>
</tr>
<tr>
<td>ARCH(1)</td>
<td>3.7339</td>
<td>3.7273</td>
</tr>
</tbody>
</table>
reinforces the assumption that negative and positive shocks have different impact on the volatility of daily returns. The AIC and SBC of this model are lowest as compared to GARCH (1,1) model and also it has higher log-likelihood value.

The EGARCH Model

The EGARCH model was proposed by Nelson (1991). The specification for the conditional variance is:

$$\log(h_t) = w + \beta \log(h_{t-1}) + \alpha \left( \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} - \frac{2}{\sqrt{\pi}} \right) + \gamma \left( \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right)$$

The left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be non-negative. The presence of leverage effects can be tested by the hypothesis that $\gamma < 0$. The impact is asymmetric if $\gamma \neq 0$.

Results of the EGARCH model estimation are listed in Table 3. We find that all the coefficients are significant. Both in the case of Sensex (-0.052) and Nifty (-0.061), the leverage term is negative and statistically different from zero indicating the existence of the leverage effect for the stock market returns during the sample period. The log-likelihood is higher and AIC and SBC are lower as compared to GARCH (1,1) model for both indices.

The EGARCH and TARCH models outperform the GARCH class of models. However, when we compare the EGARCH and TARCH models, we find that, for Sensex, the EGARCH model is a better fit and, for Nifty, the TARCH model is a better fit. This has been done in accordance with the lowest AIC and SBC and highest log-likelihood value. The improvements in model fitting signify the fact that returns respond differently to the arrival of negative and positive shocks unlike the GARCH models. Figure 4 plots the estimated conditional vari-

**Figure 4: Conditional Variance from EGARCH (1,1) Model versus Squared Returns on Sensex**
ance from EGARCH (1,1) model for Sensex against the square of daily returns. It is seen that the model tracks variance well. Similar results are also achieved from the TARCH (1,1) model estimated for Nifty.

Day-of-the-week Effect

Ho and Cheung (1994) observe that a formal test on the variations of returns and volatility across days of the week is interesting because it is important to know if the higher return on a particular weekday is just a reward for higher risk on that day, or, in other words, is the day-of-the-week effect in volatility the same as that in returns?

According to French (1980), stock prices should rise higher on Mondays than on other weekdays because the time between the close of trading on Friday and the close of trading on Monday is three days rather than the normal one day between other trading days. Accordingly, Monday returns should be three times higher than other weekday returns. But, results from empirical studies have documented that the average return on Friday is abnormally high and the average return on Monday is abnormally low. This documented high Friday return and low Monday return has been dubbed the ‘day-of-the-week effect’ or the ‘weekend (Monday) effect.’

Aggarwal and Tandon (1994) and Mills and Coutts (1995) have done excellent surveys of papers investigating the effects of day-of-the-week and the weekend on stock returns. Among the many studies that have been done are Lakonishok and Levi (1982), Keim and Stambaugh (1984), Jaffe and Westerfield (1985), Rogalski (1984), and Smirlock and Starks (1986).

Similarly, Godfrey, Grangerand Moregenster (1964), Fama (1965), and Gibbons and Hess (1981) have shown that return variance is higher on Mondays in the US. In other words, these studies claim that the day-of-the-week has an effect on the conditional variance of stock returns also. French and Roll (1986) and Foster and Viswanathan (1990) claim that stock return variance should be the highest on Mondays when the informed trader has maximum information advantage. Variance should decline through the week with the arrival of public information and the decrease in the advantage of the private information leads to lower returns variance on Fridays.

In the Indian context, a few studies done have seen only the day-of-the-week effect in returns. Chaudhury (1991) studied the Bombay Stock Exchange Sensitive Index between June 1988 and January 1990. He found that the average return on Monday is negative and the highest returns are on Friday. Poshakwale (1996), in his study on the Bombay Stock Exchange National Index between January 1987 and October 1994, found that mean returns except for Monday and Wednesday are positive and that weekend effect on returns support the presence of first order autocorrelation. Broca (1992) has used Kruskall-Wallis test on BSE National Index daily returns during the period April 1984 - December 1989 to show that there is evidence of significant variations in stock returns according to the day-of-the-week. Arumugam (1998-99) has comprehensively investigated the ‘day-of-the-week effect’ in Sensex returns during 1979-1997 and found that Monday returns are significantly positive during a bull market, significantly negative during a bear market, and insignificant otherwise. However, none of these studies has used ARCH/GARCH modeling.

Our study attempts an analysis of the day-of-the-week effect in Sensex and Nifty stock returns and volatility with the help of asymmetrical GARCH models for a substantially long period (1993-2003) of time. We have also examined the impact of the introduction of rolling settlements on the phenomenon.

We study the issue of day-of-the-week effect in returns and conditional volatility by including dummies for various days of the week one-by-one in the mean equation and then in the conditional variance equation, respectively, of the GARCH model over the period under consideration. Since it can be expected that the timing of the settlement period will have some impact on stock return and volatility, i.e., investors building fresh positions on the first day of new settlement and squaring up on the last day, we divide the study period into two distinct periods, viz., the period before the introduction of rolling settlement and the period after the introduction of rolling settlement by BSE and NSE. Before the introduction of rolling settlement, the trading cycle on BSE was from Monday to Friday and on NSE from Wednesday to Tuesday.

Table 4 summarizes the results of the above exercise. The following inferences can be made from the data presented in Table 4.

For both the indices, the generally expected exceptional behaviour on Monday, i.e., the day-of-the-week effect or the weekend effect, is absent. The returns on Monday are not higher than returns on other days of the
week. While the coefficient of the Monday dummy in the mean equation is insignificant in the case of Sensex, the negative sign of the same coefficient in the case of Nifty indicates lower returns on Monday.

In fact, returns are significantly higher (positive) on Wednesday as is borne out by the positive sign of the coefficient in the mean equations for both Sensex and Nifty. Another important indication from the mean equations is that returns are significantly lower (negative) on Tuesday.

With respect to volatility also, there is no "day-of-the-week effect". Neither does Monday exhibit higher variance than the other days of the week nor does the volatility taper off as the week progresses.

Tuesday, consistently, is the least volatile day for both Sensex and Nifty. The coefficient of the Tuesday dummy in the variance equations is negative. During the pre-rolling period, for both the indices, Friday exhibits significantly lower volatility, while, during the post-rolling period, volatility on Wednesday is significantly higher than on the other weekdays.

Another point to note is that the 'higher (lower) the risk, higher (lower) the return' dictum does not consistently hold good for the Indian market. From Table 4, it is seen that though lower volatility leads to lower returns on Tuesdays, no definite conclusion can be drawn for higher returns on Wednesdays and lower returns on Mondays and Fridays vis-à-vis volatility.

### Calendar Month Effect

Presence of monthly seasonal, i.e., significantly higher returns during a particular calendar month has been reported in several developed stock markets. This ‘calendar month effect’ could exist due to the traditional release of important firm-specific or macroeconomic data during certain months. Specifically, Rozeff and Kinney (1976) have shown that in the US, stock returns in the first month of the year have been statistically different (larger) from the other months. Other country-specific studies include Officer (1975) on the Australian market;

However, to the best of our knowledge, no one has yet examined the presence of the ‘calendar month effects’ in the Indian stock market. Our study makes a humble attempt to fill the knowledge gap. We attempt an analysis of the ‘calendar month effect’ in Sensex and Nifty stock returns and volatility with the help of asymmetrical GARCH models and the possible reasons for the same.

We explore the possibility of any monthly seasonal, i.e., ‘calendar month effect,’ in the daily returns and volatility in the same fashion as we have done for the “day-of-the-week effect” in the previous section, i.e., by including dummies for various days of the week one by one in the mean equation and then in the conditional variance equation, respectively, of the GARCH model over the period under consideration. From the results of estimations given in Table 5, the following conclusions can be drawn.

The ‘January effect’ is absent. This means that the returns during January are not significantly higher than the other months. For both the indices, February exhibits highest volatility and corresponding highest return. The month of March also exhibits significantly higher volatility but the magnitude is lesser as compared to February. This implies that during these two months the conditional volatility tends to increase. We feel that, in this case, market expectation has an important role to play. For example, in the month of February, when the budget is placed, a lot of speculations go on. This leads to excessively net long positions in certain sectors of the market. With every report coming out before the budget, this position goes through various changes and it leads to greater degree of movements in the Sensex. The month of March bears the impact of the budget and the year-end expectations. After the budget is placed, market goes for a selling spree in certain sectors and this leads to excess volatility without matching returns. The investors, therefore, should keep away from the market during this month after booking profits in February itself.

The months of April, May, June, and July do not influence returns and volatility significantly while August exhibits lower volatility for both Sensex and Nifty. In the case of Nifty, the month of September, i.e., the time when third quarter corporate results are announced, volatility is higher but corresponding returns are lower. The situation is, therefore, not conducive to investors. Finally, December gives high positive returns without high volatility and, therefore, offers good opportunity to the investors to make safe returns on Sensex and Nifty.

**Spillover from US Markets**

In 1993, when foreign institutional investors (FII) were allowed to invest in the Indian equity market, the fate of the domestic investors started becoming increasingly integrated with the ups and downs in the other stock markets of the world. Over time, foreign portfolio investments have increased. Moreover, quite a few Indian listed companies have issued instruments such as American Depository Receipts (ADR) and Global Depository Receipts (GDR) and got their equity shares listed on the US bourses such as NASDAQ and NYSE and European bourses such as LSE. The trend specially gathered momentum during the ICE boom of 1998-2001. The simultaneous listing of a number of large market

<table>
<thead>
<tr>
<th>Table 5: Calendar Month Effect</th>
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<tbody>
<tr>
<td>Significant Dummies in Conditional Volatility Models</td>
</tr>
<tr>
<td>Sensex EGARCH (1,1) Mean Equation</td>
</tr>
<tr>
<td>January (-0.2003)</td>
</tr>
<tr>
<td>February (0.2245)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>December (0.1956)</td>
</tr>
</tbody>
</table>

*Note: Coefficients of the dummies are in parentheses.*
capitalization of the Indian companies in the ICE sector on the Indian bourses and NASDAQ was then expected to generate sympathetic movements or return and volatility ‘spillover’ across the two markets. These stocks also had significant weight in both the domestic indices, viz., Sensex and Nifty.


Hansda and Ray (2003) studied the price interdependence of ten Indian companies whose stocks are dually listed, i.e., on the BSE and NSE and the Nasdaq/NYSE. The finding of a bi-directional causality in a vector auto-regression model corroborates the strong correlation between the prices of the dually listed stocks. Furthermore, the impulse responses pattern indicates that a positive shock in the domestic (international) price of a stock gets transmitted in terms of strong positive movement in the international (domestic) price the next trading day. Thus, in addition to stock specific bi-directional causality, the markets are efficient in processing and incorporating the pricing information. The authors in their 2002 study examined the nature of relationship between the BSE/NSE and the Nasdaq/NYSE at aggregate market level and by considering only the technology stocks. In both the cases, they found only unidirectional causality from the Nasdaq/NYSE to BSE/NSE.

Kumar and Mukhopadhyay (2002) employed a two-stage GARCH and ARMA-GARCH model to capture the mechanism by which NASDAQ composite daytime returns and volatility have an impact on the conditional mean and the conditional volatility of Nifty overnight returns during the July 1999-June 2001 period. They found that the previous day’s daytime returns of both NASDAQ composite and Nifty have significant impact on the 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 the US.

Choudhury (2000) examined the relationship between Sensex and Nasdaq returns and found that the correlation is not significant. Similarly, Rao and Naik (1990) examined the inter-relatedness of the US, Japanese, and Indian stock markets using cross-spectral analysis. They concluded that the relationship of the 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.

Sharma and Kennedy (1977) examined the price behaviour of the 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. They concluded that stocks on the Bombay Stock Exchange obey a random walk and are, in this sense equivalent to the behaviour of stock prices in the markets of advanced industrialized countries like the UK and the US.

In this study, we apply asymmetrical GARCH models to study the relationship between the US and the domestic markets. We use the Nasdaq composite (NASDAQ) and Standard and Poor’s 500 (S&P 500) indices as the proxies for the US market. We compute the daily return series on NASDAQ and S&P 500 in the same way as we have done for Sensex and Nifty but with a day’s lag to the Indian bourses. This means, for instance, that return on NASDAQ on the 3rd day of a month is synchronized with the 4th day’s return on Sensex. These series are then introduced as explanatory variables first in the mean equation and then in the variance equation. Thus, the EGARCH (1,1) models to be estimated for the Sensex have now become:

\[ r_t = \alpha_0 + \alpha_1 r_{t-1} + \psi \text{NASDAQ (or S&P 500)} + \varepsilon_t, \]

\[ \log(h_t) = \omega + \beta \log(h_{t-1}) + \alpha \left( \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} - \frac{1}{\sqrt{\pi}} \right) + \gamma \left( \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right) \]

and

\[ r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t, \]

\[ \log(h_t) = \omega + \beta \log(h_{t-1}) + \alpha \left( \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} - \frac{1}{\sqrt{\pi}} \right) + \gamma \left( \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right) + \psi \text{NASDAQ (or S&P 500)} \]

where, \( \varepsilon_t | I_{t-1} \sim N(0, h_t) \)

Similarly, the TARCH (1,1) models to be estimated for Nifty are:

\[ r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t + \psi \text{NASDAQ (or S&P 500)} \]

\[ h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \varepsilon_{t-1} d_{t-1} \]

and

\[ r_t = \alpha_0 + \alpha_1 r_{t-1} + \varepsilon_t, \]

\[ h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \varepsilon_{t-1} d_{t-1} + \psi \text{NASDAQ (or S&P 500)} \]

where, \( d_{t-1} = 1 \) if \( \varepsilon_t < 0 \), and \( d_{t-1} = 0 \) otherwise.
Due to the fact that information technology stock came into the Sensex and Nifty portfolios only after 1998, we have done a three-part analysis. We have introduced S&P500 and NASDAQ as explanatory variables into the mean and variance equations estimated separately for 1993-98, 1999-2003, and 1993-2003 periods. This approach was followed to verify a) the presence of significant correlation between the two markets and b) whether the correlation between the US stock markets was any different during the ICE boom that began towards the end of 1998 and went bust thereafter in 2001. The results of the estimations are presented in Table 6.

From the information in Table 6, we can draw the following inferences: With respect to returns, while S&P 500 exhibits significant positive correlation only with Nifty throughout the two sub-periods, NASDAQ exhibits significant albeit weak positive correlation only with Sensex but only in the 1999-2003 sub-period. The picture is different in the context of volatility. Negative correlation is seen between the US indices and the domestic indices only during the 1993-1999 period. The effect is stronger in the case of Nifty than in the case of Sensex.

These findings are contrary to those of Kumar and Mukhopadhyay (2002) and Hansda and Ray (2002) who have reported one-way causality (from NASDAQ to BSE/NSE) of daily prices and returns and significant volatility spillover from NASDAQ to NSE. This could be partly due to the fact that while they have considered overnight (i.e., NASDAQ close to Nifty open and vice versa) and daytime returns, we have used close-to-close returns. However, our discovery of the positive correlation between S&P 500 and Nifty (but not between S&P 500 and Sensex) and between NASDAQ and Sensex (but not between NASDAQ and Nifty) returns together with consistent negative correlation between conditional variances of the foreign indices and domestic indices tells a different story. If the return or volatility spillover existed at the aggregate market level due to the fact that almost all the Sensex stocks are and have been part of the Nifty portfolio also, the results should have been consistent in respect of both the domestic indices. Clearly, more research is required to unravel the true nature of the ‘spillover effect’ between the US and Indian markets.

From the estimations done in the previous three sections for analysing the ‘day-of-the-week effect,’ ‘calendar month effect’ and ‘spillover effect,’ we now construct EGARCH (1,1) and TARCH (1,1) models for Sensex and Nifty, respectively, by introducing all the significant dummy variables together in the mean equations and the variance equations. The final models selected on the basis of best values of the model selection criteria are as follows:

For Sensex,
\[
r_t = a_0 + a_1 r_{t-1} + \varepsilon_t
\]
\[
\log(h_t) = \omega + \beta \log(h_{t-1}) + \alpha \left( \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right) + \gamma \left( \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right) + \delta_{d_{\text{Mar}}} + \phi_{d_{\text{Feb}}} + \psi_{5 \text{D}} \text{S&P500}
\]

where, \( \varepsilon_t \mid I_{t-1} \sim N(0, h_t) \)

For Nifty,
\[
r_t = a_0 + a_1 r_{t-1} + \varepsilon_t + \delta_{d_{\text{Wed}}} + \psi_{5 \text{D}} \text{S&P500}
\]
\[
h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} + \gamma \varepsilon_{t-1}^2 a_{t-1} + \delta_{d_{\text{Fri}}} + \phi_{d_{\text{Mar}}}
\]

where, \( d_{t-1} = 1 \text{ if } \varepsilon_t < 0, \text{ and } d_{t-1} = 0 \text{ otherwise.} \)

These models perform well as is evident from the estimation results summarized in Table 7. All the coefficients in the mean equation and the variance equation are statistically significant. The AIC and SBC values of these models are the lowest among all the models estimated previously.

### CONCLUSION

The volatility in the Indian stock market exhibits characteristics similar to those found earlier in many of the major developed and emerging stock markets, viz., autocorrelation and negative asymmetry in daily re-

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**Table 6: Spillover Effect**

<table>
<thead>
<tr>
<th>Index</th>
<th>Sensex EGARCH (1,1)</th>
<th>Nifty TARCH (1,1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Equation (Effect on Returns)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>-0.0139 (0.6391)</td>
<td>0.0061 (0.7203)</td>
</tr>
<tr>
<td>NASDAQ</td>
<td>0.0124 (0.7067)</td>
<td>0.0367* (0.0381)</td>
</tr>
<tr>
<td>Variance Equation (Effect on Volatility)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>S&amp;P 500</td>
<td>-0.0486* (0.0000)</td>
<td>-0.0051 (0.5181)</td>
</tr>
<tr>
<td>NASDAQ</td>
<td>-0.0527* (0.0000)</td>
<td>-0.0063 (0.3818)</td>
</tr>
</tbody>
</table>

* denotes statistically significant coefficient at 5 per cent level.
turns. It is shown that asymmetrical GARCH models outperform the conventional OLS models and symmetrical GARCH models. By the application of asymmetrical GARCH models EGARCH (1,1) to Sensex and TARCH (1,1) to Nifty returns, it is shown that ‘day-of-the-week effect’ or the ‘weekend effect’ and the ‘January effect’ are not present while the return and volatility do show intra-week and intra-year seasonality. The return and volatility on various weekdays have somewhat changed after the introduction of rolling settlements. Finally, there is mixed evidence of return and volatility spillover between the US and the Indian markets. While S&P500 exhibits significant positive correlation only with Nifty returns, NASDAQ returns exhibit significant albeit weak positive correlation only with Sensex but only in the 1999-2003 sub-period. Similarly, significant negative correlation is seen between the US indices and the domestic indices only during the 1993-1999 period but not during the ICE boom and bust during the 1999-2003 period. We, therefore, do not find conclusive evidence of the existence of aggregate market level sympathy between the US and the Indian markets.

IMPLICATIONS FOR INVESTORS

The empirical findings would be useful to investors as it provides evidence of time varying nature of stock market volatility in India. Investors aim at making more profitable and less risky investments. Therefore, they need to study and analyse stock market volatility, among many other factors, before making investment decisions.

For both the indices, among the months, February exhibits highest volatility and corresponding highest return. The month of March also exhibits significantly higher volatility but the magnitude is lesser as compared to February. This implies that, during these two months, the conditional volatility tends to increase. For example, in the month of February when the budget is placed, a lot of speculations go on and investors ‘buy on rumours.’ This leads to excessively net long positions in certain sectors of the market. In March, after the budget is presented, investors ‘sell on news’ in case of a ‘good’ as well as a ‘bad’ budget for them. The investors should, therefore, keep away from the market during March after having booked profits in February itself. Similarly, the month of December gives high positive returns without high volatility and therefore offers good opportunity to the investors to make safe returns on Sensex and Nifty, and, on the contrary, in the month of September, i.e., the time when third quarter corporate results are announced, volatility is higher but corresponding returns are lower. The situation is, therefore, not conducive to investors.

The ‘weekend effect’ or the ‘Monday effect’ is not present. For other weekdays, the ‘higher (lower) the risk, higher (lower) the return’ dictum does not consistently hold good and Wednesday provides higher returns with lower volatility making it a good day to invest.

Domestic investors do not need to lose sleep over gyrations in the major US markets since there is no conclusive evidence of consistent relationship between the US and the domestic markets. Also, the asymmetric GARCH models for Sensex and Nifty can be used by investors to forecast future volatility of these indices.

IMPLICATIONS FOR POLICY MAKERS

The implications for investors presented above are also important for the stock exchange administrators and policy makers. The surveillance regime around the Budget should be stricter to keep excessive volatility under check. Also, there is no reason to be concerned over the spillover from the US markets as the evidence suggests weak and somewhat inconsistent relationship between the two markets.

<table>
<thead>
<tr>
<th>Table 7: Parameters of the Finally Selected Conditional Volatility Estimation Models</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
</tr>
<tr>
<td>-----------------------------------------------</td>
</tr>
<tr>
<td>Mean Equation</td>
</tr>
<tr>
<td>$a_1$</td>
</tr>
<tr>
<td>$\delta_5$ (Wednesday)</td>
</tr>
<tr>
<td>$\psi_1$ (NASDAQ)</td>
</tr>
<tr>
<td>$\psi_2$ (S&amp;P 500)</td>
</tr>
<tr>
<td>Conditional Variance Equation</td>
</tr>
<tr>
<td>$\omega$</td>
</tr>
<tr>
<td>$\alpha$ (ARCH)</td>
</tr>
<tr>
<td>$\beta$ (GARCH)</td>
</tr>
<tr>
<td>$\gamma$ (Asymmetrical component)</td>
</tr>
<tr>
<td>$\delta_2$ (Tuesday)</td>
</tr>
<tr>
<td>$\delta_3$ (Friday)</td>
</tr>
<tr>
<td>$\phi_2$ (February)</td>
</tr>
<tr>
<td>$\phi_3$ (March)</td>
</tr>
<tr>
<td>$\psi_1$ (NASDAQ)</td>
</tr>
<tr>
<td>Log likelihood</td>
</tr>
<tr>
<td>AIC</td>
</tr>
<tr>
<td>SBC</td>
</tr>
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REFERENCES


Creativity is the power to connect the seemingly unconnected.

William Plomer