Volatility Modeling for a three Asset Series

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Abstract

Indian stock market is subjected to various changes from domestic and global factors for the past two decades. Despite certain lows over this period, the economic growth measured in terms of GDP at constant prices (2011-2012) was 7.3% for 2014-15 (Annual Report of SEBI, 2014-15). The investment flows from domestic and foreign institutional investors have positive and significant impact on market capitalisation, volatility and volume traded in Indian market. Hence, this article examines the behaviour of volatility exhibited by the asset series considered here - SENSEX Returns, Foreign Institutional Investors (FIIs) and Mutual Funds (MFs). An attempt has been made to find the best fit model which can capture the different effects of volatility for each series and, has been tested for the presence of Volatility Clustering, Leverage Effect. We find strong evidence for these tendencies of volatility, and, the same was found to be highly persistent throughout the study period. We also find little evidence for the destabilisation effect caused by institutional flows on the volatility of stock market returns.

Introduction

Institutional trading and its impact on stock market have been largely covered by researchers as they have grown huge in the past two decades in India. Institutional investment is defined to be the investment done by institutions or organizations such as banks, insurance companies, mutual fund houses, etc in the financial or real assets of a country. They use pooled funds to trade in securities and assets of their country. An institutional investor is an investor that is registered in the country in which he is trading. Domestic Institutional Investors or DII refers to the Indian institutional investors who are investing in the financial markets of India (Stock Market for example) and Foreign Portfolio or Institutional Investors ,FPI or FII refers to investors that are from other countries, investing in the Indian financial market. Institutional activities were limited to only government owned organisations earlier, but, after the economic reforms in 1991, our policies promoted private participation and foreign investments in financial markets. Both DIIs, especially, Mutual Funds, and FII have been fastest growing Institutional Investors in the post liberalisation era. India, being an emerging market, is very much competent enough like any other matured markets across the world, in attracting institutional funds from domestic as well as foreign countries. Since ours is the most vibrant economy, serves as a favorable destination for Foreign Institutional Investors.

An analysis of the shareholding pattern of Indian listed companies reveals that FIIs are in a very strong position to influence the Indian market. (Major Shareholders of Indian Stock Market, By Vikas Vardhan | Jul 27, 2015). As per the latest available shareholding pattern (as of March 31, 2015), the marketable portion of the equity, which is also known as free float, the biggest holders are the foreign institutional investors (FIIs). FIIs dominate the market by holding 40 per cent of the free float, thus impacting the market movement with their flows of funds. Domestic institutional investors (DIIs), which mainly comprise insurance companies, banks and mutual funds, own about 20 per cent of the free float. It was observed that both DIIs and FIIs keep on growing steadily and have significant share holding pattern in BSE 500 companies.
There are enough literature/research available to understand the causal and contemporaneous relationship between stock market returns and fund flows from Institutional Investors- at different periods, which encompasses certain domestic and global economic conditions like Economic reforms in India(from 1991 onwards), Asian financial crisis(1997), US subprime crisis (2008). Institutional investors, being very large players in secondary market, do enormous trades and hence stock market volatility has amplified with time. There are limited works available to model the volatility behaviour of Institutional investors(IIs) in the Indian scenario, and, hence, this study is aimed at the same and distinguishes itself from others by modeling conditional variances. Much research has been done to find out the influence of IIs on stock market returns, but influence on volatility of stock market has been taken into consideration. Daily data is used for about 15 years, which is quite long term in nature to arrive at firm conclusions.

Volatility, as measured by the standard deviation or variance of returns, is often used as a crude measure of the total risk of financial assets. In Finance, relationships between variables are intrinsically non-linear and linear structural models are unable to explain the features like:

(a) tendency of financial asset returns to have distributions that exhibit fat tails and excess peakedness at mean (leptokurtosis).
(b) tendency of volatility in financial markets to appear in bunches (Volatility Clustering).
(c) tendency of volatility to rise more following a large price fall than following a price rise of the same magnitude (Leverage Effects)

The standard approach to model volatility is through class of ARCH (Auto Regressive Conditional Heteroscedacity) models, which help us to understand the influence of lagged squared errors and their own lagged variances on the current levels of variances (or) volatility in the asset series. The Gross Purchases, Sales and net investments series of FIIs, MFs and Market Returns are examined for persistence of volatility, and, also for the presence of clustering and leverage effects. Attempt has been made to understand the extent of destabilisation effect caused by net institutional flows on the volatility of stock market returns.

The basic objectives of the study are as follows:

(a) To find out the presence of Volatility Pooling or Clustering in Stock Market Returns, Gross Purchases and Sales of Foreign Institutional Investors (FIIs) and Mutual Funds (MFs).
(b) To measure the Leverage Effect of all the variable series of FIIs, MFs and Stock Market Returns.
(c) To understand the extent of destabilisation effect of caused by net flows of FIIs and MFs on Volatility of stock market returns.

Review of existing literature

The investigation of modeling the temporal behavior of stock market volatility has been considered by various researchers, a large part of which focuses on the estimation of the stock return volatility and the persistence of shocks to volatility. Many articles are available for understanding the causality between FII flows and stock market volatility. Very less number of studies exist for examining volatility of mutual fund flows. Some of related literature are given below.

An article on "Major Shareholders of Indian Stock Market| Jul 27, 2015, by Vikas Vardhan " has given insights about the major shareholders of Indian stock market. Most stocks in the portfolio of IIs are the ones that comprise the NIFTY or SENSEX indices and this study reveals that FIIs are in a very strong position to influence the Indian market. Relative growth in the market value of both FIIs and DIIs and the shareholding pattern are presented graphically. Provides very good reference to start the analysis.
"The impact of Institutional trading on Stock Prices" March 1992, by Josef Lakonishok, Andrei Shleifer, Robert W.Vishny "has been attempted to present evidence on the trend chasing and herding behaviour of money managers. Analysis is done on 769 tax exempt equity funds. Though there is no solid evidence to conclude that institutional investors destabilize stock prices, their results do not rule out the possibility of highly inelastic demands for stocks which cause relatively small amounts of institutional herding or positive feedback trading to have large effects on stock prices. Measures of herding and feedback strategy proposed by them form a basis for an abundant research in this area.

A study by Amita Batra on "Stock Return Volatility Patterns in India(Working Paper, Indian Council for Research On International Economic Relations |March 2004)" aimed at giving economic significance to changes in the pattern of stock market volatility in India during 1979-2003. It also examined if there has been an increase in volatility persistence in the Indian stock market on account of the process of financial liberalization in India. The shifts in stock price volatility and the nature of events that apparently cause the shifts in volatility were analysed. Monthly stock returns have been used, and asymmetric GARCH model has been used to estimate the element of time variation in volatility. The analysis reveals that liberalization of the stock market or the FII entry in particular does not have any direct implications for the stock return volatility. No structural changes found in the stock price volatility around any liberalization. Volatility has declined in the post liberalization phase for both the bull and bear phase of the stock market cycle. Hence, this paper helps to understand the behaviour of volatility in Indian stock market.

Authors Dr P Lakshmi, Dr V Alagappan examines the relationship between trading volume of FII flows and volatility of stock returns in "An Empirical Analysis on the Dynamic Relationship Between FII Trading Volume & NIFTY Returns (European Journal of Economics, Finance And Administrative Sciences–Issue52 (2012)". The contemporaneous correlation and asymmetry between NIFTY returns and FII trading volume is studied through OLS. There is evidence for positive contemporaneous correlation between returns and volume. The relationship between conditional volatility and volume is investigated through GARCH model by introducing volume as an explanatory variable in the GARCH equation. The results indicate that GARCH effect is reduced only to a negligible level by the inclusion of trading volume of FIIs as an explanatory variable. This implies that FIIs influence towards persistence of volatility is very low and there may be other factors responsible for the same period from 01.01.2003 to 31.12.2009. Significant relationship of volatility for all pairs of trading volume variables and return variables is found only in respect of the measure of volatility.

The study was conducted Bashir Ahmad Joo, Zahoor Ahmad Mir on "Impact of FIIs Investment on Volatility of Indian Stock Market: An Empirical Investigation (Journal of Business & Economic Policy, Vol. 1, No. 2; December 2014)" using monthly time series on NIFTY, SENSEX and FIIs activity for a period of fifteen years spanning from January, 1999 to December, 2013. GARCH model is also used to study the impact of FIIs capital flows on stock market volatility. The study reveals that there is significant relationship between FIIs capital flows and stock market volatility. Moreover, FIIs investment has statistically significant influence on volatility of NIFTY and SENSEX, used as proxy to Indian stock market.

The dynamics of FII flows on Indian stock market volatility using the daily movements of FII from 2001 to 2011 has been the major focus of "Dynamics of FII flows on Stock market Volatility: An empirical exploration with GARCH approach (Pacific Business review international, August 2013)" by authors Haritika arora Garima Baluja, which provides evidence that FII outflows accelerates the volatility of Indian stock market, by proving that FII outflows negatively influences volatility of SENSEX and CNX Nifty. Hence, FII outflow produce high volatility in stock market.

M.Thenmozhi, Manish Kumar examined the contemporaneous and causal relationship between mutual fund flows (measured as stock purchases and sales) and security returns and between mutual fund flows and volatility, even after controlling for volume, in their study "Dynamic Interaction among Mutual
Fund Flows, Stock Market Return and Volatility". The results provide evidence that the relationship is stable even after including these exogenous variables such as volume and market fundamental variables such as exchange rates, dividend and short term interest rates in the model. Increase in the aggregate inflows and outflows are associated with more volatile market. This study largely helped in terms understanding the various dynamics of interaction of MFs with volatility of stock market.

To obtain some global knowledge, two more articles referred. First one being "Dynamic interdependence and volatility transmission of Asian stock markets-Evidence from the Asian crisis" by Authors Francis Ina, Sangbæe Kimb, Jai Hyung Yoonb, Christopher Vineyc, examines dynamic interdependence, volatility transmission, and market integration across selected stock markets during the Asian financial crisis periods 1997 and 1998. Using (VAR-EGARCH) model, it is found that reciprocal volatility transmission existed between Hong Kong and Korea, and unidirectional volatility transmission from Korea to Thailand. This suggests that Hong Kong played a significant role in volatility transmission to the other Asian markets. The data also indicate market integration in that each market reacted to both local news and news originating in the other markets, particularly adverse news.

The second was "Global and regional spillovers in emerging stock markets: A multivariate GARCH-in-mean analysis, 2010" by Authors John Beirne, Guglielmo Maria Caporale, Marianne Schulze-Ghattas, Nicola Spagnolo.

The main objective of this study was to examine regional and global spillovers in emerging stock markets using a uniform model for a large set of EMEs to facilitate cross-country comparisons. A trivariate VAR-GARCH(1,1)-in-mean model was chosen to capture a broad range of possible spillover channels in means and variance for 41 emerging market economies (EMEs) in Asia, Europe, Latin America, and the Middle East. Wald tests were used to involve restrictions on various spillover parameters to analyse the importance of different transmission channels. The results suggest that spillovers from regional and global markets are present in the vast majority of EMEs. Evidence was found for cross-market GARCH-in-mean effects for half of the EMEs considered in Asia, Europe, the Middle East and North Africa, which, suggested that stock market returns are affected by their volatility (they were responsive to stock market turbulence). So, international financial investors should be concerned with the linkage between returns and volatility in EMEs markets when forming their expectations and consequently their investment strategies.

Data and Research Methodology

Sources of data and variables used
Daily investment details of the following variables are collected from SEBI websites and Capital line database for the period between 2000 and 2015.
1. Gross Purchases of FIIs denoted as GP_FIIs;
2. Gross Sales of FIIs denoted as GS_FIIs;
3. Net Investments of FIIs denoted as NI_FIIs;
4. Gross Purchases of MFs denoted as GP_MFs;
5. Gross Sales of MFs denoted as GS_MFs;
6. Net Investments of MFs denoted as NI_MFs;
7. Stock Market returns denoted as LSENSEX.

The daily investment data of both MFs and FIIs was compared with daily data of SENSEX, and, only those days which had all the three data available were considered. Hence, there are 3820 and 3914 observations available for FIIs and MFs respectively. E-Views software has been used for complete analysis.

Stationary Tests:
As the data of the present study is time series in nature, a test of stationarity of the variables is a prerequisite for employing OLS techniques. The mean variance and co variance of the series should be constant over time. According to Engle and Granger, “a time series is said to be stationary if displacement over time does not alter the characteristics of a series in a sense that probability distribution remains constant over time. A series is said to be integrated of order one, I(1) if it has to
be differentiated once before becoming stationary. **Augmented- Dicky Fuller (ADF)** is used here, as it is a widely accepted unit root test, which is conducted by adding the lagged values of the dependent variable. The ADF test consists of estimating the following regression:

\[
\Delta Y(t) = \rho_0 + \rho Y(t-1) + \sum_{i=1}^{m} \Delta Y(t-i) + \varepsilon_t
\]

where \(\varepsilon_t\) is a pure white noise error term. One advantage of the ADF is that it corrects for higher order serial correlation by adding lagged difference term on the right hand side.

**Modeling Heteroscedasticity**

The Classical Linear Regression Model assumes that the variance of the errors \(\text{var}(u_t) = \sigma^2\) is constant is known as homoscedasticity, and. If the variance of the errors is not constant, this would be known as heteroscedasticity. This could lead to an implication that standard error estimates become wrong. It is unlikely in the context of financial time series that the variance of the errors will be constant over time, and hence it makes sense to consider a model that does not assume that the variance is constant, and which describes how the variance of the errors evolves. Volatility can be measured through conditional variances of all the above mentioned variable series. Hence, ARCH, GARCH, EGARCH and TARCH models are used to investigate the variance and its persistence. The general form of each of them is given below. (Introductory Econometrics for Finance, Chris Brooks, 2008).

(a) **Auto Regressive Conditional Heteroscedacity(Arch)**

The current level of volatility tends to be positively correlated with its level during the immediately preceding periods. This phenomenon of volatility Pooling or Clustering is modeled by ARCH, which allows the conditional variance of the error term, \(\sigma_t^2\), to depend on the immediately previous value of the squared error.

\[
\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2
\]

The above model is known as an ARCH(1), since the conditional variance depends on only one lagged squared error. Under ARCH, the conditional mean equation (which describes how the dependent variable, \(y_t\), varies over time) could take almost any form that the researcher wishes. One example of a full model would be

\[
y_t = \beta_1 + \beta_2 x_{2t} + \beta_3 x_{3t} + \beta_4 x_{4t} + u_t \sim N(0, \sigma_t^2)
\]

\[
\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2
\]

The model given by above equations could easily be extended to the general case where the error variance depends on \(q\) lags of squared errors, which would be known as an ARCH(q) model:

\[
\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_q u_{t-q}^2
\]

The value of conditional variance must always be strictly positive; a negative variance at any point in time would be meaningless.

(b) **Generalised ARCH (GARCH) models**

The GARCH model was developed independently by Bollerslev (1986) and Taylor (1986), which allows the conditional variance to be dependent upon previous own lags, so that the conditional variance equation in the simplest case is represented as follows

\[
\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2
\]

This is a GARCH(1,1) model. \(\sigma_t^2\) is known as the **conditional variance**, since it is a one-period ahead estimate for the variance calculated based on any past information thought relevant. Using the GARCH model it is possible to interpret the current fitted variance, \(h_t\), as a weighted function of a
long-term average value (dependent on $a_0$), information about volatility during the previous period($a_0 u_{t-1}^2$) and the fitted variance from the model during the previous period($\beta \sigma_{t-1}^2$). The GARCH(1,1) model can be extended to a GARCH(p,q) formulation, where the current conditional variance is parameterised to depend upon q lags of the squared error and p lags of the conditional variance. GARCH (p, q) model is given by the following equation.

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_q u_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \cdots + \beta_p \sigma_{t-p}^2 \tag{7}$$

GARCH is a model to describe movements in the conditional variance of an error term and they can be used to forecast volatility. ARCH/GARCH class of models have shown their superiority not only in modeling heteroscedasticity of financial time series but can also be extended to include other effects on conditional variance.

(c) Asymmetric GARCH models-TARCH&EGARCH

One of the primary restrictions of GARCH models is that they enforce a symmetric response of volatility to positive and negative shocks. It has been argued that a negative shock to financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude. Two popular asymmetric formulations are explained below: the GJR model, named after the authors Glosten, Jagannathan and Runkle (1993), The GJR model is a simple extension of GARCH with an additional term added to account for possible asymmetries. The conditional variance is now given by

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 \ I_{t-1} \tag{8}$$

where $I_{t-1}$=1, if, $u_{t-1}<0 = 0$ otherwise. For a leverage effect, we would see $\gamma > 0$. Notice now that the condition for non-negativity will be $\alpha_0 > 0, \alpha_t > 0, \beta \geq 0$, and $\alpha_t + \gamma \geq 0$. That is, the model is still admissible, even if $\gamma < 0$, provided that $\alpha_t + \gamma \geq 0$.

The exponential GARCH (EGARCH) model proposed by Nelson (1991). The conditional variance in E GARCH model is expressed by the following equation

$$\ln (\sigma_t^2) = \omega + \beta \ln (\beta \sigma_{t-1}^2) + \delta u_{t-1} / \sigma_{t-1}^2 + a \left[ u_{t-1} / \sigma_{t-1} - \sqrt{2/\pi} \right] \tag{9}$$

This implies that the leverage effect measured by $\alpha$ is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\alpha < 0$. The impact is asymmetric if $\omega \neq 0$. $\beta$ is our GARCH term that measures the impact of last period's forecast variance. $\delta$ is ARCH term, measures the effect of news about volatility from the previous period on current period's volatility. $\alpha$ measures the leverage effect with asymmetries.

There some major advantages of EGARCH than pure GARCH specification(i) Since $\ln (\sigma_t^2)$ is modeled, even if the parameters are negative, $\sigma_t^2$ is positive, Thus there is no need to impose non-negativity constraints on the model parameters(ii) Asymmetries are also allowed. As the relationship between volatility and returns is negative, $\delta$ will be negative. $\alpha$ measures the symmetric effect of the model, the GARCH effect. $\beta$ measures in the persistence in conditional volatility, when $\beta$ is relatively large, then volatility takes a long time to die out following a crisis in the market. $\delta$ measures the leverage effect.

(d) Estimation of ARCH/GARCH models

This model being non-linear, OLS cannot be used for GARCH model estimation. Though, there are a variety of reasons for this, but the simplest and most fundamental is that OLS minimises the residual sum of squares(RSS). In order to estimate models from the GARCH family, another technique known
as maximum likelihood is employed. Essentially, the method works by finding the most likely values of the parameters given the actual data. More specifically, a log-likelihood function is formed and the values of the parameters that maximise it are sought. Maximum likelihood estimation can be employed to find parameter values for both linear and non-linear models. The steps involved in actually estimating an ARCH or GARCH as follows:

(i) Specify the appropriate equations for the mean and the variance – e.g. an AR(1)-GARCH(1,1) model

\[ y_t = \mu + \varphi y_{t-1} + u_t, \quad u_t \sim N(0, \sigma_t^2) \]

\[ \sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \]

(ii) Specify the log-likelihood function (LLF) to maximise under a normality assumption for the disturbances.

\[ L = -\frac{T}{2} \log(2\pi) - \frac{1}{2} \sum_{t=1}^{T} \log(\sigma_t^2) - \frac{1}{2} \sum_{t=1}^{T} (y_t - \mu - \varphi y_{t-1})^2 / \sigma_t^2 \]

(iii) The computer will maximise the function and generate parameter values that maximise the LLF and will construct their standard errors.

(e) Information criterion

It is generally difficult to interpret Auto correlation and partial auto correlation functions (acf, pacf) with the help of graphs and diagrams. A technique, which removes some of the subjectivity is called as information criteria, which embody two factors: a term which is a function of the residual sum of squares (RSS), and some penalty for the loss of degrees of freedom from adding extra parameters. So, adding a new variable or an additional lag to a model will have two competing effects on the information criteria: the residual sum of squares will fall but the value of the penalty term will increase.

The object is to choose the number of parameters which minimises the value of the information criteria. So, adding an extra term will reduce the value of the criteria only if the fall in the residual sum of squares is sufficient to more than outweigh the increased value of the penalty term. The three most popular information criteria are Akaike’s (1974) information criterion (AIC), Schwarz’s (1978) Bayesian information criterion (SBIC), and the Hannan–Quinn criterion (HQIC). Since, no criterion is definitely superior to others, we have used AIC for the analysis and algebraically, it is expressed as

\[ AIC = \ln(\hat{\sigma}^2) + \frac{2k}{T} \]

where $\hat{\sigma}^2$ is the residual variance (also equivalent to the residual sum of squares divided by the number of observations, $T$), $k = p + q + 1$ is the total number of parameters estimated and $T$ is the sample size. The information criteria are actually minimised subject to $p \leq \overline{p}, q \leq \overline{q}$, i.e.an upper limit is specified on the number of moving average ($\overline{q}$) and/or autoregressive ($\overline{p}$) terms that will be considered.

Analysis and Results

(i) Summary of Statistics

Descriptive statistics provide a historical account of variables behaviour and convey some future aspects of the distribution of dataset. Since FIIs were more active and have been doing voluminous business, the mean values of them are higher than MFs. SENSEX has almost touched 30K during the study period as reflected by its maximum value. Generally, gross purchases and sales of IIs have less variances or standard deviations compared to their net investments. Both Skewness and Kurtosis measure the shape of the probability distribution curve. Skewness(S) measures the symmetry of the
curve and the values of both FIIs and MFs show that they are skewed towards left. Kurtosis (K) measures the flatness or tallness of the curve. As the value of K>3 for all the variables except SENSEX, the shape of the curve is called leptokurtic (long tailed), and, as the value of K is less than 3 for the SENSEX, it is called Platykurtic.

Table 1 - Summary of Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>Median</th>
<th>Maximum</th>
<th>Minimum</th>
<th>Std. Deviation</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>Jarque Bera</th>
</tr>
</thead>
<tbody>
<tr>
<td>NI-FIIs</td>
<td>195.24</td>
<td>88.7</td>
<td>16357.75</td>
<td>-5142.17</td>
<td>815.09</td>
<td>3.32</td>
<td>53.83</td>
<td>418257</td>
</tr>
<tr>
<td>GP-FIIs</td>
<td>2151.24</td>
<td>1924.3</td>
<td>24690.79</td>
<td>9.9</td>
<td>1920.25</td>
<td>2.05</td>
<td>14.5</td>
<td>23748.34</td>
</tr>
<tr>
<td>GS-FIIs</td>
<td>1955.99</td>
<td>1776.7</td>
<td>22382.28</td>
<td>1.5</td>
<td>1755.97</td>
<td>1.8</td>
<td>11.74</td>
<td>14224.19</td>
</tr>
<tr>
<td>NI-MFs</td>
<td>15.52</td>
<td>-3.24</td>
<td>2136</td>
<td>-1719.6</td>
<td>247.1</td>
<td>1.35</td>
<td>13.34</td>
<td>18614.25</td>
</tr>
<tr>
<td>GP-MFs</td>
<td>472.04</td>
<td>417.4</td>
<td>3644.4</td>
<td>0.3</td>
<td>398.05</td>
<td>1.53</td>
<td>7.76</td>
<td>5234.13</td>
</tr>
<tr>
<td>GS-MFs</td>
<td>456.55</td>
<td>434.8</td>
<td>3115.8</td>
<td>0.59</td>
<td>345.08</td>
<td>0.98</td>
<td>5</td>
<td>1283.15</td>
</tr>
<tr>
<td>SENSEX</td>
<td>12969.35</td>
<td>13965.06</td>
<td>29681.77</td>
<td>2600.12</td>
<td>7665.05</td>
<td>0.25</td>
<td>1.94</td>
<td>218.27</td>
</tr>
</tbody>
</table>

(ii) Test of Unit Root

All the variable series are tested for stationarity using Augmented Dicky Fuller (ADF) test. The following Null and alternate hypothesis tested for all the seven variable series. Null Hypothesis (H₀): Series has unit root; Alternate hypothesis (H₁): Series does not have unit root. The results of ADF test are presented below. We find that time series data of Net Investment of FIIs and MFs are stationary at level; and, rest are stationary at their first differences.

Table 2 - Augmented Dicky Fuller Test

<table>
<thead>
<tr>
<th>Variable Series</th>
<th>Test Statistic</th>
<th>Critical Value</th>
<th>Results at 5% confidence level</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSensex</td>
<td>-58.11831</td>
<td>-2.86208</td>
<td>Stationary at first difference</td>
</tr>
<tr>
<td>GP-FIIs</td>
<td>-24.57994</td>
<td>-2.86211</td>
<td>Stationary at first difference</td>
</tr>
<tr>
<td>GS-FIIs</td>
<td>-22.91274</td>
<td>-2.86210</td>
<td>Stationary at first difference</td>
</tr>
<tr>
<td>NI-FIIs</td>
<td>-16.17685</td>
<td>-2.86210</td>
<td>Stationary at level</td>
</tr>
<tr>
<td>GP-MFs</td>
<td>-25.02969</td>
<td>-2.86208</td>
<td>Stationary at first difference</td>
</tr>
<tr>
<td>GS-MFs</td>
<td>-23.46608</td>
<td>-2.86208</td>
<td>Stationary at first difference</td>
</tr>
<tr>
<td>NI-MFs</td>
<td>-14.19141</td>
<td>-2.862095</td>
<td>Stationary at level</td>
</tr>
</tbody>
</table>

(iii) Modeling Volatility Clustering and Leverage Effect

(a) Stock Market Returns

SENSEX Returns is used as a proxy for Market Returns and calculated as the log difference change in the price index.

\[ R_t = \log P_t - \log P_{t-1}, \text{where } R_t \text{-Return at time } "t" \text{ P}_t \text{& } P_{t-1} \text{=closing values of stock price index at time } "t" \text{& } "t-1". \]

The graph of residuals which shows the presence of Volatility Clustering, which is given below.
The log returns are calculated using E-Views software and denoted as LSENSEX. From the above diagram of SENSEX return series, the volatility observed to be high during the years 2004 and 2008. As per SEBI's annual report, the reason was attributed to the fact that there was a rise in international crude oil prices and also apprehension about increase of interest rates in developed economies. Year 2008 accounted for global financial crisis resulted in outflows of Foreign investments and depreciation of currencies in the emerging markets. Volatility Clustering is seen more pronounced after the year 2010 till 2015.

Now, we will model the behaviour of volatility throughout and select the best model to explain the same. The series is tested for the effects of ARCH, GARCH, TARCH and EGARCH in a step by step manner mentioned above. For Stock Market Return series, the coefficients of ARCH, GARCH, TARCH found to have positive values and were statistically significant at 5% level. When all the above models are compared on the values of LLF and AIC, we found the TARCH (1,1) to be the best model to capture the behaviour of volatility of SENSEX returns, as the LLF has the highest and AIC has the lowest values for TARCH model (refer Equation 8).

**Variance Equation (TARCH(1,1) model in E views)**

\[
GARCH = C(4) + C(5) \times RESID(-1)^2 + C(6) \times RESID(-1)^2 \times (RESID(-1) < 0) + C(7) \times GARCH(-1)
\]

\[
GARCH = 0.043963 + 0.141400 + 0.858142
\]

GARCH effect is found to be predominant, so, the series is very much subjected to Leverage Effect. The equation is given above with the coefficient values for ARCH (2nd term on RHS), TARCH (3rd term) and GARCH (4th term) terms. ARCH term measures the Volatility clustering effect. Both TARCH and GARCH measure the asymmetric and symmetric responses to shocks respectively. Hence, the current variance of market returns is greatly influenced by lagged values of its own, and also the squared lagged residuals. The volatility is also highly persistent over time as the sum of these coefficients is 1.00.

(b) **Foreign Institutional Investors (FIIs)**

The below diagrams show the residual series with actual and fitted representations. This helps us to visualise volatility pooling or clustering effect present in each variable series. For GP-FIIs, very less fluctuations found for the period 2000-2006. The presence of volatility clustering has been predominant during the period 2008-2015. This trend is attributed to the fact that FIIs were bullish in Indian Market and engaged in buying activity during this period. The volatility is higher in the years 2009, 2014 and 2015 compared to other years, which may be because the FIIs equity segment had remarkable growth with regard to inflows.
There is almost no volatility fluctuations for the period 2000-2005 for FIIs-Gross Sales. It starts only after the year 2005 and recorded the highest in 2015. There are very less fluctuations of volatility for the period 2000-2004 for Net investments of FIIs also. The presence of ARCH effect, Leverage effect can be further examined by modeling each series with different type of volatility models.

ARCH,GARCH,TARCH and EGARCH models employed for GP-FIIs, GS-FIIs &NI-FIIs. They were compared based on LLF and AIC ,and, we find that $\text{EGARCH}(1,1)$ to be the best fit model (refer equation 9)to represent the volatility series of all the three variable series. The EGARCH model expresses the conditional variance of a given time series as a non-linear function of its own past values and the past values of standardized innovations. The variance equation for each of them with coefficient values is given in the annexure.
Variance Equation (EGARCH (1,1) in E-Views)

\[
\text{LOG(GARCH)} = C(4) + C(5) \times \text{ABS(RESID(-1)/@SQRT(GARCH(-1)))} + C(6) \times \text{RESID(-1)/@SQRT(GARCH(-1))} + C(7) \times \text{LOG(GARCH(-1))}.
\]

The coefficient values of all the parameters are tabulated below:

<table>
<thead>
<tr>
<th>Variables</th>
<th>Coefficient Values - EGARCH(1,1) model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(\omega)</td>
</tr>
<tr>
<td>GP-FPIs</td>
<td>0.002</td>
</tr>
<tr>
<td>GS-FPIs</td>
<td>0.006</td>
</tr>
<tr>
<td>NI-FPIs</td>
<td>0.025</td>
</tr>
<tr>
<td>GP-MFs</td>
<td>0.003</td>
</tr>
<tr>
<td>GS-MFs</td>
<td>0.031</td>
</tr>
<tr>
<td>NI-MFs</td>
<td>-0.058</td>
</tr>
</tbody>
</table>

"\(\omega\)" has the coefficient values of constant. As the value of all the coefficients are positive and statistically significant at 5% significance level, we can conclude that all these series of FIIs suffer from ARCH, GARCH and Leverage effects. Sum of all the coefficients are approximately one and hence volatility is highly present in all the variable series. The values of "\(\beta\)" (GARCH) are almost one and hence, the present volatility in all the FII's series is greatly influenced by forecast variance of previous period (conditional volatility). Since the values are almost one, the conditional volatility is highly persistent and may take long time to die out after a crisis in market. Volatility clustering measured by "\(\delta\)" (ARCH) is widely present for both gross purchases and sales by FIIs, compared to net investments by them. "\(\alpha\)" (EGARCH) accounts for asymmetric responses of volatility to shocks, and positive association of them with current volatility, leads us to conclude that asymmetric responses are captured well.

(c) Mutual Funds

![Residual Series of GP-MFs](image-url)
Residual series of GP-MFs and GS-MFs have similar pattern till 2013. More clusters are found with GS-MFs series and NI-MFs has volatility clustering clearly visible. When all the models of volatility are compared, EGARCH(1,1) was found to be best representing the volatility series of all the variables of Mutual Funds GP-MFs, GS-MFs and NI-MFs.

As the value of all the coefficients are positive and statistically significant at 5% significance level, we can conclude that all these series of MFs suffer from ARCH,GARCH and Leverage effects. Sum of the coefficient is approximately one, which proves that all the variable series are highly volatile. Conditional volatility is highly persistent as the values of "β" are one, and, the present volatility in all the MFs series is highly influenced by forecast variance of previous period. For GP-MFs, the coefficient value of "α" term is negative, which implies that the previous period's forecast variance negatively influences the current variance, and, that the series is greatly affected by leverage effect.

The value of "α", which account for asymmetries, is 1.00 in Gross Sales series, where the leverage effect is pronounced. Thus the volatility and its various responses are well accommodated in this model.

(IV) Destabilizing Effect
The destabilizing effect of both FIIs and MFs on volatility of Market returns is analysed. So, the different FII flow series represented by F_t and MF series represented by M_t are included as exogenous variables in the variance equation for SENSEX returns, estimated as TARCH(1,1) process. The analysis is carried out separately for both FIIs and MFs as below.

The following equations are used to find out the destabilizing effect of FIIs/MFs flows.

\[
\sigma^2_t (V_t) = \alpha_0 + (\alpha_1 + \gamma_1 N_{t-1}) \sigma^2_{t-1} + \beta_1 \sigma^2_{t-1} + \delta_t F_t
\]

\[
\sigma^2_t (V_t) = \alpha_0 + (\alpha_1 + \gamma_1 N_{t-1}) \sigma^2_{t-1} + \beta_1 \sigma^2_{t-1} + \delta_t M_t
\]
σ²_t(V_t)-Volatility of daily SENSEX returns measured as TARCH (1,1) process at time 't'

α₀-Intercept
α₁-ARCH Effect
γ₁-TARCH Effect
β₁-GARCH Effect
F_t-Daily FII (in, out, Net) flows at time 't'
M_t-Daily MF (in, out, Net) flows at time 't'

The results are presented in the following table.

Table -4 Coefficient values of TARCH(1,1) model

<table>
<thead>
<tr>
<th>V_t {TARCH(1,1)}</th>
<th>α₀</th>
<th>α₁</th>
<th>γ₁</th>
<th>β₁</th>
<th>δ₁</th>
<th>SBC</th>
<th>Log Likelihood</th>
</tr>
</thead>
<tbody>
<tr>
<td>GP-FIIs → V_t</td>
<td>5.83E-06</td>
<td>0.04</td>
<td>0.15</td>
<td>0.86</td>
<td>1.47E-08</td>
<td>-5.82</td>
<td>11136.13</td>
</tr>
<tr>
<td>GS-FIIs → V_t</td>
<td>3.65E-05</td>
<td>0.16</td>
<td>0.06</td>
<td>0.61</td>
<td>1.42E-08</td>
<td>-5.74</td>
<td>10979.98</td>
</tr>
<tr>
<td>NI-FIIs → V_t</td>
<td>0.00011</td>
<td>0.15</td>
<td>0.05</td>
<td>0.60</td>
<td>-2.44E-08</td>
<td>-5.53</td>
<td>10582.06</td>
</tr>
<tr>
<td>GP-MFs → V_t</td>
<td>4.68E-06</td>
<td>0.04</td>
<td>0.13</td>
<td>0.87</td>
<td>7.74E-08</td>
<td>-5.86</td>
<td>11490.74</td>
</tr>
<tr>
<td>GS-MFs → V_t</td>
<td>2.63E-05</td>
<td>0.18</td>
<td>0.07</td>
<td>0.63</td>
<td>9.14E-08</td>
<td>-5.79</td>
<td>11355.26</td>
</tr>
<tr>
<td>NI-MFs → V_t</td>
<td>5.75E-06</td>
<td>0.04</td>
<td>0.14</td>
<td>0.86</td>
<td>2.89E-09</td>
<td>-5.84</td>
<td>11447.59</td>
</tr>
</tbody>
</table>

It is found that all the exogenous variables (δₜ) are positive and significant, except NII-FIIs, whose value is negative. This proves the existence of contemporaneous relationship between Fₜ , Mₜ with Vₜ, but, the coefficient values are very small, and hence flows from FIIs and MFs affect the volatility of SENSEX returns to little extent only.

**Summary and Conclusions**

The behaviour of volatility and its responses were modeled for stock market returns and institutional investors, namely, FIIs and MFs. The important findings are mentioned below:

Volatility was found to be highly persistent for all the seven variables of three asset series, throughout the study period of 2000-2015.

Volatility clustering was predominant in the residual series of stock market returns throughout the study period.

Different variable series of FIIs and MFs had very less fluctuations in the initial stages of the study period, but, later stages were subjected to Clustering effect.

Leverage effect was pronounced in all the series and asymmetric responses of volatility to shocks were well accommodated in the models.

All the seven variable series were found have ARCH and GARCH effects. Hence, TARCH(1,1) was selected as best fit model for explaining volatility behaviour for stock market returns, EGARCH(1,1) was selected for FIIs and MFs. These models explain how current level volatility(σ_t²) is influenced by previous value of the squared errors and its own previous lags.

The volatility of stock market returns was affected by the inflows from FIIs and MFs. But, the effect was found to be small.

It is suggested that though India is the most vibrant economy among the developing nations, and attract many domestic and foreign institutional investors, market regulators and policy makers should consider balancing institutional flows and contain stock market volatility through possible means. Long term investor should not be worried about the Institutional Investors action in the equity markets as they hardly have an impact, as per the findings. They have to be concerned about the fundamentals of the company where the investment has been done.
References


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