Asymmetric Volatility of the Indian Stock Market and Foreign Portfolio Investments : An Empirical Study

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Abstract

Generally, a stock index may respond more to bad news (negative shocks) than to good news (positive shocks). It means stock market volatility may tend to be greater in a declining market than in a rising market. This behavior of stock return volatility is known as asymmetric volatility or leverage effect of volatility. A healthy and vibrant capital market is important for economic development of a nation. In the present Indian scenario, stock prices in India frequently deviate from fundamental values, and it is believed that these variations are mainly due to the presence of the most dominant investment group - foreign portfolio investors. This paper attempted to analyze the stock return volatility, especially the asymmetric effect of Indian stock market return volatility and contribution of foreign portfolio investment to that volatility. The present study was conducted by taking daily data for a period of 12 years from April 1, 2003 to March 31, 2015 consisting of 2898 trading observations. To study the leverage effect and impact of FPI on stock market volatility, the study used ARCH family models; GARCH, E-GARCH, and TARCH. The results of the study confirmed the existence of volatility clustering and leverage effect in the Indian stock market. Hence, it was observed from the study that the investment activities of FPIs have had a significant impact on the volatility of the Indian stock market.

Key words : **foreign portfolio investors (FPIs), foreign portfolio investment (FPI), stock return volatility, leverage effect, volatility clustering, GARCH, E-GARCH , TARCH models**

JEL Classification : C5, F2 , F4, F6

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The capital flows from foreign sources in the form of portfolio participation is an added advantage to the economy because it is a non-debt creating fund for financing the current account deficit and it adds the investment base of the stock market. To tap these benefits, India has permitted foreign portfolio investors (FPIs) to invest in India since 1992. Since then, FPIs are investing immensely in the Indian capital market, and they became the most dominant investment group in India. However, foreign portfolio investments can be considered as 'hot money' as the vulnerable flow of funds is in accordance with market changes across the world. Hence, it is necessary to identify the impact of FPIs' investment activities on the volatility of Indian market returns. The present study tries to model the volatility of the Indian stock market and impact of foreign portfolio investor's investment activities on the volatility of stock market returns.

It is noteworthy that unlike prices, volatilities are not directly observed from the market movements and can only be estimated in the context of a model. The autoregressive conditional heteroscedastic (ARCH) model

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(Engle, 1982) is the popular symmetric model used in capturing volatility clusters in financial time series. The major limitation of the ARCH model is the long lag lengths which lead to large parameters. To overcome this limitation, Bollerslev (1986) introduced generalized autoregressive conditional heteroscedasticity (GARCH) model by modeling the conditional variance to depend on its lagged values as well as squared lagged values of the error term.

The asymmetric volatility or leverage effect in the stock market is one of the common features of most of the developed markets. In simple terms, the leverage effect can be explained that the stock index may respond more to bad news (negative shocks) than to good news (positive shocks). This behavior of stock returns in response to new information flow is known as asymmetric volatility. These asymmetric effects can be studied by models such as the EGARCH (exponential GARCH) model of Nelson (1991) and TARCH (threshold ARCH) model of Glosten.

(i) Foreign Portfolio Investors in India : A FPI means an entity established outside India to make investments in India. According to Securities Exchange Board of India (Foreign Institutional Investors) Regulations Act (1995), foreign institutional investors are defined as an institution established or incorporated outside India, which proposes to make investments in India in securities. From September 1992, foreign portfolio investors were allowed to invest in all securities traded on the primary and secondary markets, including shares, debentures, and

Table 1. Trend of Foreign Portfolio Investments in India

Year	Gross Purchase	Gross Sale	Net Investment (₹ in Cr)	US ($ mn)	Cumulative (US $ mn)
1992-93			13.4	4	4
1993-94	5592	466	5,126.50	1634	1638
1994-95	7631	2835	4,796.30	1528	3166
1995-96	9694	2752	6,942.00	2036	5202
1996-97	15554	6979	8,574.50	2432	7634
1997-98	18695	12737	5,957.05	1649	9284
1998-99	16116	17699	-1,584.20	-386	8898
1999-00	568,55	46734	10,122.10	2339.1	11237.3
2000-01	740,51	64116	9,933.40	2159.8	13395
2001-02	49921	41164	8,755.60	1846	15243
2002-03	47060	44370	2,689.30	562	15803
2003-04	144857	99092	45,763.70	9950	25754
2004-05	2,16,954	1,71,072	45,881.30	10,173	35,925
2005-06	3,46,977	3,05,512	41,466.70	9,331	45,261
2006-07	5,20,508	4,89,667	30,840.40	6,708	51,966
2007-08	9,48,020	8,81,842	66,179.10	16,041	68,008
2008-09	6,14,578	6,60,389	-45,811.00	-9,837	58168
2009 -10	8,46,439	7,03,780	142,658.30	30,252	89,334
2010 -11	9,92,599	8,46,161	146,438.10	32,227	1,21,560
2011 -12	9,21,285	8,27,562	93,725.50	18,923	1,40,483
2012 -13	9,04,845	7,36,481	168,367	31,046	1,71,528
2013 -14	10,21,010	9,69,361	51,649	8,877	1,80,404
2014-15	1521346	1243887	277460	45698	2,26,103

Source: SEBI Bulletin (Various Issues)

warrants issued by companies which were listed or were to be listed on the stock exchanges in India.

(ii) Trend of Foreign Portfolio Investments in India : In the present scenario, FPIs are the major players in the Indian capital market. The Table 1 shows that out of 22 years, the net FPI flows are negative only in the years 1988-99 and 2008-09, and net investment by FPIs during the period was US $ 2,26,103 (in mn).

Review of Literature

Srikanth (2014) applied GJR-GARH and PGARCH model for the period from July 1, 1997 to March 30, 2013 and identified the presence of leverage effect in the Indian stock market. The author also confirmed the effect of periodic cycles on the conditional volatility in the market.

Goudarzi and Ramanarayanan (2010) examined the volatility of the Indian stock markets based on BSE 500 stock index over a period of 10 years from July 2000 to January 2009. They found that the conditional volatility was quite persistent in the Indian stock market. They were of the opinion that the GARCH (1, 1) is the best volatility model to explain volatility of the Indian stock market.

Dhillon and Kaur (2007) examined the contribution of FPIs' investments to stock returns volatility with the help of both symmetric and asymmetric GARCH models. They found that both gross purchases and gross sales by FPIs significantly contributed to stock return volatility.

Kumar (2006) evaluated the comparative ability of different statistical and economic volatility forecasting models in the context of Indian stock and forex markets. He found that EWMA would lead to improvements in volatility forecasts in the stock market, and the GARCH (5. 1) would be the best in the forex market.

Banerjee and Sahadeb (2006) found that compared to simple volatility models, GARCH type models are to be used. Their study found that the asymmetric GARCH model was better as compared to symmetric GARCH model in estimating volatility. The study found that presence of FIIs in the Indian stock market did not lead to an increase in the market volatility.

Karmakar (2005) identified the volatility clustering in Nifty return series for the period from January 1991 to June 2003. He estimated GARCH parameters for 50 Nifty companies and found that volatility seemed to be highly persistent and predictable in nature. But the significant leverage effect existed only in eight shares in the NSE nifty companies. However, which model can best capture the leverage effect was left for further research.

Akigray (1989) identified that the daily return series showed a significant level of second order dependence and could not be modeled as linear white noise processes. A reasonable return generating process was empirically shown to be a first-order autoregressive process, that is, the generalized autoregressive conditional heteroscedastic GARCH (1, 1) processes fit the data very satisfactorarily.

The earlier studies discussed above reveal that the authors have confirmed the superiority of GARCH type and information asymmetry models in studying volatility. A number of studies have been conducted for estimating the volatility of the Indian stock market, but the studies which identified the impact of the investment activities of FPIs such as their purchase, sales, and net investment on the basis of volatility in the Indian stock market are negligible. The present study was conducted to fill this research gap. Moreover, the study is based on daily data rather than monthly and or relatively long period data.

Objectives of the Study

The basic objectives of the study are :

(1) To examine the existence of volatility clustering in the Indian stock market.

(2) To check the asymmetric / leverage effect of the Indian stock market volatility.

(3) To examine the impact of foreign portfolio investors' investment activities on stock market volatility :
(a) The impact of gross purchases and gross sales by FPIs.
(b) The impact of net investment of FPIs.

(4) To identify the best model for predicting the stock return volatility of the Indian stock market.

Data and Methodology

The present study identifies the asymmetric effect of Indian stock returns volatility and impact of investment activities of FPIs on the Indian stock market. The daily returns on Nifty *(NSER),* gross purchase by FPIs in the Indian equity market *(FPIP)*, gross sales by FPIs in the Indian equity market *(FPIS)*, and net investment by FPIs in the Indian equity market *(FPIN)* are the variables used for the study. The study is based on the daily data of 2898 trading observations for the period of 12 years from April 1, 2003 to March 31, 2015. The data were obtained from the website maintained by NSE and SEBI.

The foundation of time-series analysis is stationarity. Hence, before estimating volatility, all the series are checked for stationarity by applying the unit root test. The Augmented Dickey Fuller test of Dicky and Fuller (1994) was used to check the stationarity of the data.

After checking the variables for stationarity, the next step is to check whether we can apply heteroskedasticity (ARCH) models to study the volatility impact. It can be confirmed by checking volatility clustering in the return series with the help of residual diagnosis and ARCH test. The study uses both symmetric as well as asymmetric generalized autoregressive conditional heteroskedasticity (GARCH) type models. The study includes GARCH (1, 1) model, exponential GARCH (E- GARCH), and threshold ARCH (TARCH) model. These models capture the existence of volatility clustering or volatility persistence and leverage/asymmetric effect. By following the methodology adopted by Dhillon and Kaur (2007), the present study applies these models for three times by taking NSE returns as the dependent variable and (a) without any exogenous variables, (b) taking FPIs' purchase *(FPIP)* and FPIs' sales *(FPIS)* as exogenous variables, and (c) by taking FPIs' net investments *(FPIN)* as the exogenous variable.

Stock returns of Nifty were identified by using the following equation :

$$Return_t = Ln\,(P_t / P_{t-1}) * 100 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

where,
R_t is the returns of the market at time t, Ln represents natural log,
P_t, P_{t-1} represent index closing values at t and t -1, respectively.

Data Analysis and Results

(1) Properties of Foreign Portfolio Investments and Market Returns : The descriptive statistics enables a reader to quickly understand and interpret features of the data set. The details are given in the Table 2.

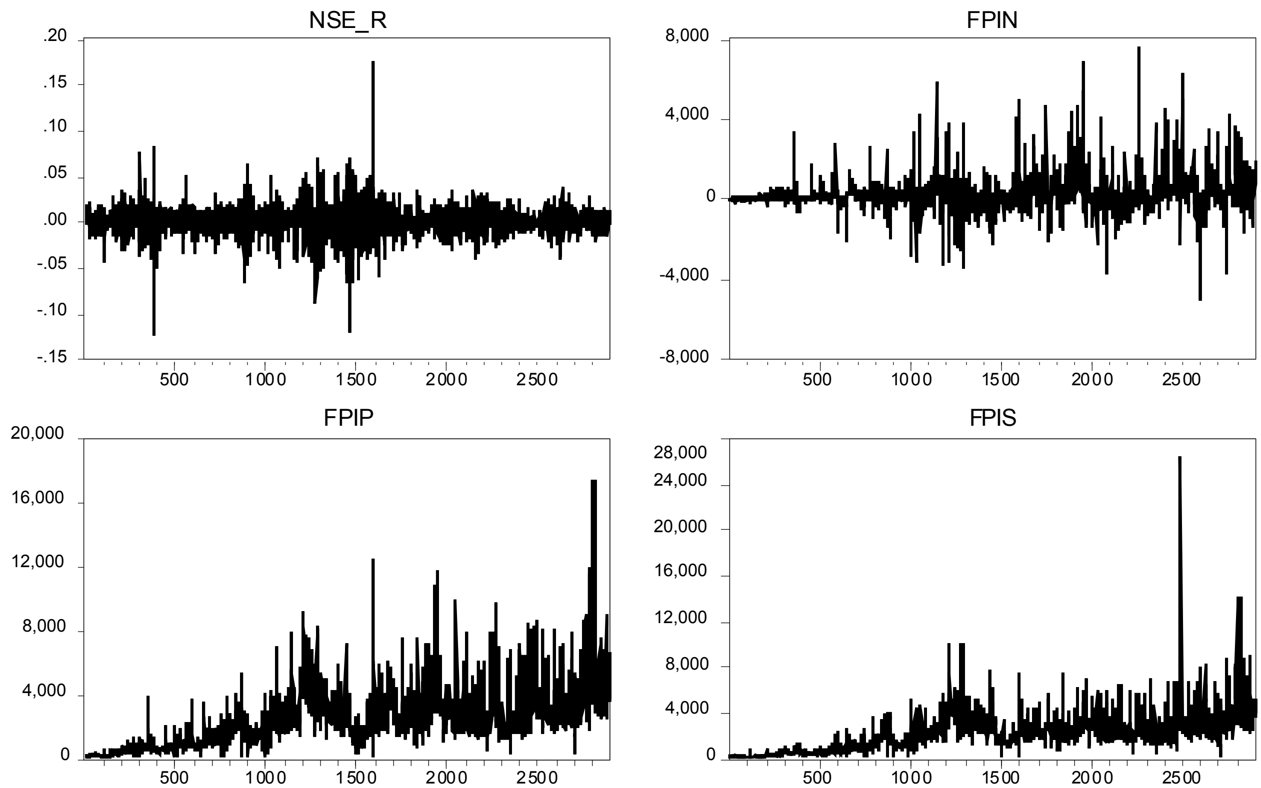
The Table 2 shows that there is a wide gap between the maximum (17.74%) and minimum (-12.24 %) in NSE returns, which shows the probability of high variability of market returns in the Indian stock market. The average positive NSE returns implies that the market has increased over the period. The high standard deviation in the FPI statistics shows high volatility in their investment activities. The line graph (Figure 1) reveals the existence of volatility in market returns and fluctuations in FPIs' investment activities. The positively skewed NSE return series implies that the market has a higher probability of earning positive returns. The value of kurtosis for all the

Table 2. Descriptive Statistics

Variables	NSE Return in Percentage	*FPIN*	*FPIP*	*FPIS*
Mean	0.0875	32.55759	2353.831	2118.250
Median	0.1300	22.523	2192.150	1998.600
Maximum	17.7400	1267.100	17371.00	26326.00
Minimum	-12.24	-509.500	9.900000	1.500000
Std. Dev.	0.015969	128.9370	1668.015	1554.550
Skewness	0.075414	1.62756	1.699309	2.551259
Kurtosis	12.83517	17.98423	10.15398	27.02895
Jarque-Bera	11682.97	7868.041	7574.648	72863.68
Probability	0.00000*	0.00000*	0.00000*	0.00000*
Observations	2898	2898	2898	2898

* Significant at the 5 % level

Figure 1. Line Plot of NSE Daily Return Series, FPIs' Net Investment, Purchase, and Sale for the Study Period



variables are leptokurtic distribution (i.e., >3), which shows the existence of extreme values in the distribution. Based on the Jarque Bera test statistic, the null hypothesis normality is rejected for all the variables.

(2) Test of Unit Root : Augmented Dickey Fuller test was conducted to check the stationarity of the data. The test for a unit root is conducted on the coefficient of y_{t-1} in the regression :

Table 3. ADF Unit Root Test Statistics

Variables	At level			
	With Intercept		With Trend and Intercept	
	Test Statistics	Critical Value	Test Statistics	Critical Value
FPIP	-4.613752*	-3.432425	-6.947916*	-3.961222
FPIS	-5.237939*	-3.432424	-7.44264*	-3.961220
FPIN	-4.6043*	-3.432425	-6.74923*	-3.961222
NSER	-50.02235*	-3.432417	-50.01681*	-3.961222

* Significant at the 1% level

$$\Delta Y_t = \alpha + \beta T + \rho Y_{t\text{-}1} + \sum_{i=1}^{K} \gamma_i \Delta Y_{t-i} + e_t \quad \text{..}(2)$$

where, Y_t is the variable in period t, T denotes a time trend, is the difference operator, e_t is pure white noise error term disturbance with mean zero and variance σ^2 , k represents the number of lags of the differences in the ADF equation and $\Delta Y_t - 1 = (Y_{t\text{-}1}$ - $Y_{t\text{-}2})$. The test for a unit root is conducted with trend and with trend and intercept. The ADF test is based on the null hypothesis that there is unit root (series is non stationary). It is clear from the Table 3 that all the test statistics absolute values are more than the critical value at the 1% level of significance. Hence, the alternate hypothesis of no unit root or stationarity is accepted for all the series.

(3) Volatility Clustering in Stock Return Series : Financial time series like stock prices may exhibit the phenomenon of volatility clustering. From the NSE return series, the regression equation is developed and the residuals distributions for day 1 to day 2898 are plotted as given in the Figure 2.

Figure 2. Residual Distribution

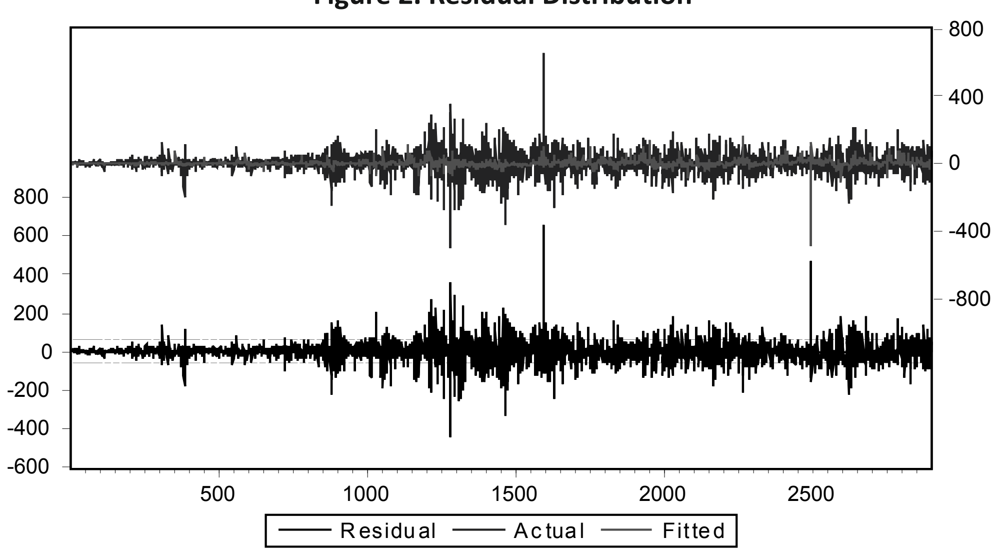


Table 4. Arch Test

No of Observations	*F* - statistic	Prob. *F*	Obs**R* - squared	Prob. Chi-Square
2898	58.23450	0.0000*	57.12562	0.0000*

* Significant at the 5% level

From the Figure 2, we can observe fluctuations in the distribution. The distribution explains that small volatility is causing another small volatility for a long period and period of high volatility is followed by high volatility for a long period. It shows the evidence of volatility clustering. To confirm the volatility clustering, the ARCH test is applied to the series. The results are given in the Table 4. From the Table 4, it is clear that the p - value is 0.0000, which is less than 5%. It shows the existence of ARCH effect. It means volatility clustering can be confirmed and ARCH family models like GARCH, EGARCH, and TARCH models can be applied in the present study.

(i) GARCH (1, 1) Model : The generalized autoregressive conditional heteroscedasticity (GARCH) model is a variation of the auto regressive conditional heteroscedasticity (ARCH) model developed by Engle (1982). The most commonly used GARCH model by the researchers is the GARCH (1, 1) model. GARCH (1,1) means one ARCH TAR and one GARCH TAR or it refers to first order ARCH term and first order GARCH term.
Any GARCH model consists of two distinct specifications. The mean equation is:

$$Y_t = C + e_t \quad \text{..(3)}$$

where, C is constant and e_t is the error term.

The second equation in a GARCH model is the conditional variance equation. The conditional variance equation is a function of three terms. It can be represented as :

$$\sigma_t^2 = \alpha_0 + \alpha_1 e^2_{t-1} + \beta\sigma^2 t_1 \quad \text{.. (4)}$$

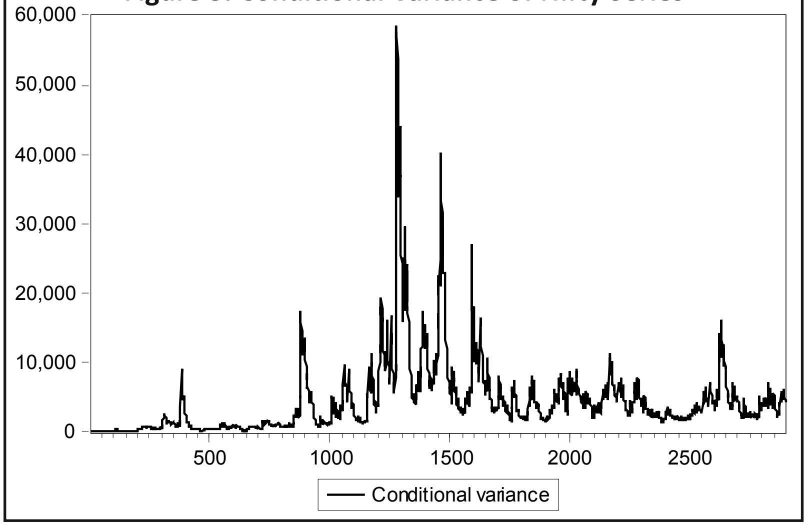
where, the three terms are α_0, which is the mean, e^2_{t-1} is the news about volatility from the previous period which is measured as the mean lag of the squared residual from the mean equation and is the ARCH term, and the last period forecast variance is σ^2_{t-1}, which is called the GARCH term. In order to identify the impact of foreign portfolio,

Table 5. Parameter Estimates of GARCH (1,1) Model

Model	Coefficient	Value of the coefficient	*Z*-Value	*p* -Value
GARCH	Intercept	1.948771	1.710008	0.0873
(1,1)	ARCH	0.094549	14.69763	0.0000*
	GARCH	0.915679	170.4453	0.0000*
	Akaike Information Criterion -10.62445 Schwartz Criterion -10.63063			
GARCH	Intercept	-5.636892	-2.995355	0.0027*
(1,1) with	ARCH	0.090243	11.33837	0.0000*
FPIP & FPIS	GARCH	0.878895	87.10714	0.0000*
	FPIP	-0.028628	-2.219480	0.0265*
	FPIS	0.095382	5.775908	0.0000*
	Akaike Information Criterion - 10.60886 Schwartz Criterion -10.61545			
GARCH	Intercept	0.06123	11.462	0.0000*
(1,1) with	ARCH	0.12810	16.534	0.0000*
FPIN	GARCH	0.87100	97.56	0.0000*
	FPIN	-0.12171	-5.4960	0.0000*
	Akaike Information Criterion - 10.743 Schwartz Criterion - 10.785			

* denotes significance at the 5 % level

Figure 3. Conditional Variance of Nifty Series



investors purchase and sell on the basis of volatility of the market. GARCH (1,1) parameters are estimated by adding *FPIP* and *FPIS* in the variance equation and to know the impact of FPIs' net investment activities, GARCH (1,1) parameters are estimated by adding *FPIN* in the variance equation. The parameters estimated for GARCH (1,1) model for all the three cases are presented in the Table 5. The Table 5 shows that in all the cases, ARCH TAR and GARCH TAR are positive and significant at the 1% level of significance, which implies that past volatility affects the present volatility. It means volatility clustering exists and it is concluded that previous period's volatility in the stock returns influences the present volatility. The *p* - value of *FPIP, FPIS,* and *FPIN* reveals that FPIs' investment activities have a significant impact on return volatility of Nifty and based on the sign of the coefficient, it is concluded that FPIs' purchase and FIIs' net flow have reduced the volatility, and FPIs' sales have increased the volatility of market returns.

The size of GARCH coefficients is large in comparison to ARCH coefficients, which implies that volatility shocks are quite persistent in the Indian stock market returns. It also confirms the volatility clustering effect in the Indian stock market returns. The statistically significant coefficients of foreign portfolio investor's investment activities imply that they their investment activities have a significant impact on the volatility of the Indian stock market.

The Figure 3 presents the conditional variance graph showing the period of high volatility. Significant spikes can be observed in the conditional variance of Nifty series.

(4) Leverage Effect in Indian Stock Returns and FIIs

(i) Volatility Asymmetry Models - E- GARCH Model : Since volatility in emerging stock markets like India is generally not symmetric and the symmetric GARCH model is not capable of capturing leverage effect present in an asymmetric market, hence, in order to capture the presence of leverage effect in the Indian market, asymmetric GARCH model, that is, the E- GARCH model is estimated.

EGARCH or exponential GARCH model was proposed by Nelson (1991). The mean specification of the EGARCH model can be represented as :

$$Y_t = c + e_t \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(5)$$

The general variance equation is :

Table 6. Parameter Estimates of the E- GARCH Model

Model	Coefficient	Value of the coefficient	*Z*-Value	*p*-Value
E-GARCH	Intercept	-0.097472	-6.613299	0.0000*
(1,1)	ARCH	0.219113	18.76019	0.0000*
	GARCH	0.991683	567.8174	0.0000*
	Leveraged	-0.047225	-6.675428	0.0000*
	Akaike Information Criterion - 10.61943 Schwartz Criterion -10.6276			
E-GARCH	Intercept	0.018314	1.026622	0.3046
(1,1) with	ARCH	0.200302	15.58296	0.0000*
FPIP* & *FPIS	GARCH	0.971691	334.8876	0.0000*
	Leveraged *FPIP*	-0.078073	-7.376530	0.0000*
	FPIS	-2.48E-05	-3.952928	0.0001*
		-1.65E-06	-0.246432	0.8053
	Akaike Information Criterion - 10.59934 Schwartz Criterion -10.6117			
E-GARCH	Intercept	-0.167562	-18.07	0.0000*
(1,1) with	ARCH	0.218581	18.88	0.0000*
FPIN	GARCH	0.95971	-10.806	0.0000*
	Leveraged	-0.09312	288.79	0.0000*
	FPIN	-0.077280	-2.2256	0.0391*
	Akaike Information Criterion -10.61271 Schwartz Criterion -10.61901			

* denotes significance at the 5 % level

$$\log(\sigma_t^2) = \alpha_0 + \alpha_1 \left|\frac{u_{t-1}}{\sigma_{t-1}}\right| + \beta_1 \log(\sigma^2_{t-1}) + \gamma \frac{u_{t-1}}{\sigma_{t-1}} \quad \text{..............................} \quad (6)$$

where, β_1 is the GARCH term which measures the impact of the last period's forecast variance. A positive and significant β_1 indicates that volatility clustering is associated with further positive changes and vice-a-versa. γ measures leverage effect. The γ is expected to be negative, implying that bad news has a bigger impact on volatility than good news of the same magnitude. That is, the impact is symmetric if $\gamma = 0$, but here, leverage is present if $\gamma < 0$.

The parameters estimated for E-GARCH (1,1) model for all the three cases are presented in the Table 6. It is clear from the Table 6 that the value of leverage coefficient is negative and significant in asymmetric EGARCH model in each of the three cases, that is, (a) without any exogenous variables, (b) by taking *FPIP* and *FPIS* of FPIs as exogenous variables, and (c) taking *FPIN* of FPIs as exogenous variables. It shows that the existence of leverage effect exists in the Indian stock market volatility. The E-GARCH (1,1) model also reveals that FPIs' purchase and net flow have a significant impact on the volatility of Nifty returns, however, FPIs ' sales have no significant impact on market volatility. Based on the sign of the coefficient, it is concluded that *FPIP* and *FPIN* have a negative impact on market volatility.

(ii) TARCH Model : Threshold ARCH (TARCH) is another variant of asymmetric GARCH model. Positive and negative shocks of the same magnitude will have exactly the same effect in the volatility of the series in ARCH /GARCH models. The T-GARCH model helps in overcoming this constraint. The model can be expressed as :

Table 7. Parameter Estimates of the TARCH Model

Model	Coefficient	Value of the coefficient	Z-Value	p - Value
TARCH	Intercept	3.060333	2.421916	0.0154*
(1,1)	ARCH	0.078612	11.58751	0.0000*
	Leverage	0.047323	4.757898	0.0000*
	GARCH	0.910535	166.4866	0.0000*
	Akaike Information Criterion -10.6214 Schwartz Criterion 10.62966			
TARCH	Intercept	-29.10734	-9.194103	0.0000*
(1,1) with	ARCH	0.320508	20.78762	0.0000*
FPIP & FPIS	Leverage	0.014814	0.360903	0.0782
	GARCH	0.519108	40.42140	0.0000*
	FPIP	-0.113071	-12.07965	0.0000*
	FPIS	0.557406	15.33235	0.0000*
	Akaike Information Criterion - 10.67580 Schwartz Criterion -10.6881			
TARCH	Intercept	-0.27591	-0.20821	0.7329
(1,1) with	ARCH	0.057342	8.67123	0.0000*
FPIN	Leverage	0.11332	8.53045	0.0000*
	GARCH	0.90872	128.3781	0.0000*
	FPIN	-0.007216	-4.8862	0.0000*
	Akaike Information Criterion -10.60968 Schwartz Criterion -10.6199			

* denotes significance at the 5 % level

$$\sigma_t^2 = \alpha_0 + \alpha_1(e^2_{t-1}) + \gamma e^2_{t-1}\, d_{t-1} + \beta\sigma^2_{t-1} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

In this model, good news ($e_t > 0$) and bad news ($e_t < 0$) have different effects on the conditional variance. Good news has an impact to the tune of a_1 while bad news has an impact to the tune of $(a_1 + \gamma)$. If $\gamma > 0$, then the leverage effect exists, that is, bad news increases volatility or the impact of the news is asymmetric.

The parameters estimated for TARCH (1,1) model for all the three cases are presented in the Table 7. It is clear from the Table 7 that leverage coefficients are positive and significant in all the three cases. The positive and significant leverage coefficient in the TARCH also confirms the existence of leverage effect in the Indian stock market volatility. Hence, it can be concluded that in the Indian stock market, negative or bad news has a greater impact on market volatility than positive or good news. *FPIP, FPIS,* and *FPIN* coefficients are significant at the 5% level, which shows that FPIs' investment activities have a significant impact on market volatility. Based on the sign of the coefficient, it is concluded that *FPIP* and *FPIN* have a negative impact, and *FPIS* has a positive impact on market volatility.

(5) Model Selection and Model Adequacy : Akaike information criterion (AIC) and Schwartz criterion (SC) values are minimum for the E-GARCH model compared with other versions of the ARCH family models (GARCH and TARCH) in all the cases ; hence, the asymmetric E-GARCH model best predicts volatility. Here, model adequacy is not a must because we estimated volatility clustering with the help of residual distribution and it was further clarified by checking the ARCH test. But for more clarity, the model adequacy test is conducted for the E GARCH model with *FPIP* and *FPIS*. Three model adequacy tests are hypothesis of no serial correlation, no arch effect, and the residuals are normally distributed.

Table 8. Serial Correlation

No of Observations 2898						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
		1	-0.011	-0.011	0.3634	0.547
		2	-0.001	-0.001	0.3654	0.833
		3	0.009	0.009	0.6227	0.891
		4	0	0	0.6228	0.96
		5	-0.007	-0.007	0.7546	0.98
		6	0.011	0.011	1.1076	0.981
		7	-0.011	-0.011	1.4502	0.984
		8	-0.012	-0.012	1.8683	0.985
		9	0	-0.001	1.8686	0.993
		10	0.023	0.023	3.4192	0.97
		11	-0.006	-0.005	3.5228	0.982
		12	0.003	0.002	3.5431	0.99
		13	0.012	0.011	3.9376	0.992
		14	0.004	0.005	3.993	0.996
		15	0.035	0.035	7.5141	0.942
		16	0.002	0.002	7.5308	0.962
		17	-0.008	-0.008	7.7353	0.972
		18	-0.004	-0.004	7.7809	0.982
		19	0.002	0.001	7.788	0.989
		20	0.001	0.001	7.7892	0.993
		21	0.019	0.019	8.8327	0.99
		22	0.012	0.013	9.2437	0.992
		23	-0.005	-0.005	9.3279	0.995
		24	0.01	0.01	9.6283	0.996
		25	-0.022	-0.024	10.996	0.993
		26	0.017	0.016	11.793	0.992
		27	-0.006	-0.006	11.885	0.995
		28	-0.008	-0.009	12.091	0.996
		29	0.043	0.043	17.486	0.954
		30	-0.02	-0.02	18.613	0.948
		31	0.014	0.014	19.209	0.951
		32	-0.01	-0.011	19.483	0.96
		33	-0.026	-0.026	21.475	0.939
		34	0.041	0.04	26.337	0.823
		35	0.068	0.069	39.964	0.259
		36	-0.011	-0.01	40.299	0.286

Table 9. ARCH Effect

No of Observations	*F*-statistic	Prob. *F*	Obs**R* - squared	Prob. Chi-Square
2898	0.362733	0.5470	0.362938	0.5469*

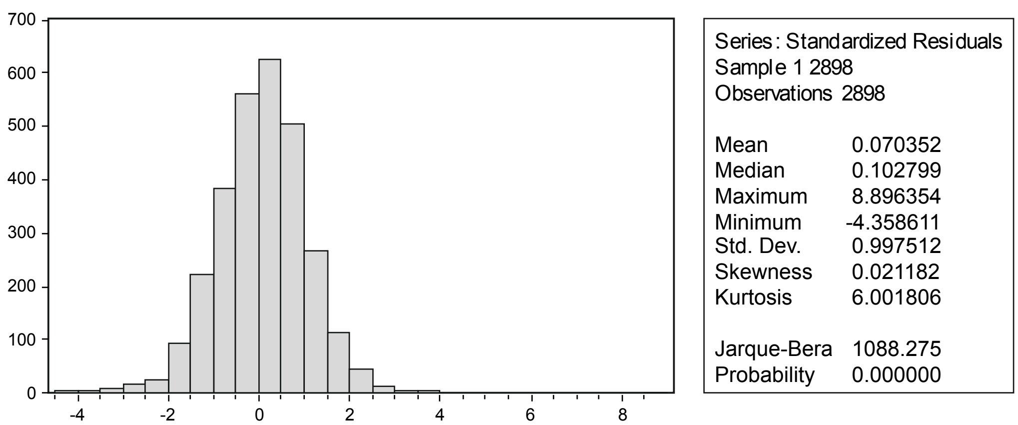
*Significant at the 5% level

(i) Serial Correlation : The correlogram squared residuals to check the serial correlation are presented in the Table 8. It is clear from the Table 8 that all the p - values are more than 5%. Therefore, the null hypothesis of no serial correlation is accepted at the 5% level. It means that there is no serial correlation in the model, which is desirable.

(ii) ARCH Effect : The ARCH test is applied for checking the ARCH effect based on the null hypothesis of no ARCH effect. The details are presented in the Table 9. The Table 9 shows that the p - value (54.69%) is more than 5%. Therefore, we accept the null hypothesis of no ARCH effect. It means that there is no remaining ARCH effect in the model.

(iii) Normality Test : This test checks whether the error term follows normal distribution. To check this, the Jarque Bere test of normality is applied based on the null hypothesis that residuals are normally distributed.

Figure 4. Jarque Bera Test of Normality



*Significant at the 5% level

The Figure 4 shows that the p - value of Jarque Bera statistics 0.00 is less than 5%, which reveals that residuals are not normally distributed. The diagram shows symmetric distribution, and the only problem is with excess kurtosis. From the model adequacy test, we can accept the model because it is applied after checking whether the ARCH family models can be applied and is based on a large number of observations.

Research Implications

The study finds the presence of leverage effect of volatility and the greater impact of foreign portfolio investor's investment activities on the volatility of the market. In India, FPIs' are the major players in the Indian equity market. It indicates that though there is no change in the domestic market conditions, negative news in the international market may spillover to the Indian market and leads to market fall. Such situations will negatively affect the confidence of the domestic investors. Therefore, the Government of India should be very much conscious about the activities of the foreign portfolio investors.

Conclusion

The present study attempts to model the volatility of the Indian stock market as well as examines the impact of foreign portfolio investor's investment activities on market volatility. The descriptive statistics shows that the NSE average returns are positive during the study period. There is wide fluctuation in the returns of NSE and FPIs' investment statistics. The Jarque Bera test statistics reject the null hypothesis of normality for NSE returns and FPI's purchase, sales, and net series. All these series are stationary at level.

Based on the residual distribution and ARCH test, the present study finds the existence of volatility clustering in the Indian stock market. The study also finds evidence for volatility persistence in the Indian stock market. Generally, stock market volatility may tend to be greater in a declining market than in a rising market. This behavior of stock returns in response to new information is known as asymmetric volatility or leverage effect of volatility. The study finds the leverage effect of volatility based on E-GARCH and TARCH models, which is in line with the results of earlier studies conducted by Banerjee and Sahadeb (2006) ; Dhillon and Kaur (2007) ; and Dadhich, Chotia, and Chaudhry (2015). The significant FPI coefficients *(FPIP, FPIS,* and *FPIN)* in the GARCH, E-GARCH, and TARCH models reveal that investment activities of FPIs have a significant impact on market volatility. FPIs' gross sales have greater impact on the volatility of stock returns than that of FPIs' gross purchase. FPIs' gross purchase *(FPIP)* and net flow *(FPIN)* have a negative impact on the Indian stock market volatility. Based on information criterion, the study finds that E-GARCH (1.1) is the best forecasting model for estimating the market return volatility, and the results are in line with the observations made by Dhillon and Kaur (2007), but are contrary to the findings of Karmakar (2005) and Goudarzi and Ramanarayanan (2010). The model adequacy tests confirm that the selected model is acceptable. The study also concludes that FPIs have reduced Indian stock market volatility. These findings are contrary to the findings of Bhattacharya and Mukherjee (2005), Batra (2004), and Rai and Bhanumurthy (2004), but it confirms the findings of Biswas (2005), Dhillon and Kaur (2007), and De and Chakraborty (2015).

Limitations of the Study and Scope for Further Research

The study is entirely based on secondary data and is limited to a period of 12 years and the results of the study may not be applicable to any other period. The present study has analyzed the impact of FPIs in the Indian capital market. Future studies can examine the impact of FPIs on individual securities ; FPIs' impact on Indian debt market ; and the impact of FPIs on market volatility during bull and bear phases .

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