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FIIs and Stock Market Volatility: A Case of Sensex and Nifty Returns

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Abstract

Volatility is the amount of difference between an asset's current price and its mean or average price. The present study aims to investigate the impact of FII on stock market volatility. Using a variety of GARCH models, including GARCH (1,1), M-GARCH (1,1), EXPONENTIAL GARCH (1,1), and T-GARCH (1,1), it was discovered that volatility is high and persistent, but has no significant influence on returns. Asymmetric models demonstrate the presence of leverage effects in returns, meaning that negative shocks have a bigger influence on conditional volatility than positive news. Furthermore, when utilizing asymmetric models, FIIs have a considerable impact on the volatility of Sensex returns but not Nifty returns. AIC, SIC, RMSE, MAE, and Theil's U metrics were used to establish the optimal model, and according to the rule of thumb (lower the number, the better the model), EXPONENTIAL GARCH outperformed in terms of Nifty and Sensex returns.

Keywords: ARCH-GARCH, Asymmetric, Volatility, FIIs, Stationarity, Leverage.

2. LITERATURE REVIEW

Since the implementation of its policy changes in the early 1990s, India has attracted regular inflows of foreign institutional investors. These inflows have had both a beneficial and negative impact on the economy. In light of this, the following studies are examined in the Indian context, concentrating on volatility as follows:

Bekaert and Wu (2000) examined the leverage effect and time-varying risk premium of asymmetric volatility using Nikki 225 and Japanese equities. Volatility asymmetry has been found, and it is accompanied by covariance asymmetry. Furthermore, negative shocks greatly increase conditional variance, but positive news or information has a mixed effect.

Using GARCH Model, Pradhan and Narasimhan (2002) identified increased volatility in the Indian stock market, which might be attributable to FII flows into the economy. Furthermore, it showed asymmetric volatility in the market, meaning that negative shocks had a higher influence on returns than positive ones.

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Batra (2004) investigated the market's volatility over several time periods. Using the asymmetric GARCH model, the researchers discovered that the balance of payments crisis and the start of economic reforms were the most turbulent periods in the Indian securities market, despite the fact that foreign investment had no direct impact on stock market volatility.

Karmakar (2005) looked into the volatility model's use in the Indian stock market. The study also attempted to measure the prevalence of a leverage effect in the Indian stock market. According to the findings, the GARCH (1,1) model accurately predicts market volatility based on current data.

Popat (2012) revealed that FIIs did not cause volatility in the Indian stock market; nevertheless, volatility in the Indian stock market made it difficult for FIIs to sustain their holdings, resulting in increased losses.

Majumder and Nag (2013) employed the GARCH (1,1) model to show that higher stock returns enhance the volatility and amount of FII inflows, but no evidence of a correlation in other directions was found. Second, higher intra-day stock market returns drew more FIIs, increasing FII volatility. However, no evidence that FIIs influence stock market volatility was discovered.

Potharla (2014) used daily BSE Sensex data to explore the asymmetric nature of volatility using two GARCH models: GJR GARCH and PGARCH. The study demonstrated the frequency of asymmetry in the Indian stock market and argued that periodic cycles influence conditional volatility.

Emenike and Opara (2014) employed GARCH (1,1) and GARCH-X (1,1) to find a positive and statistically significant relationship between trading volume and stock return volatility. The conclusion was constant independent of the distribution assumption for the error term, which included the normal distribution, the student-t distribution, and the generalized error distribution.

Dadhich et al. (2015) used daily data from 2004 to 2014 to simulate volatility using the Arch-GARCH technique, confirming that volatility is persistent and that the Indian stock market has a leverage impact. FIIs significantly raise volatility in the Indian stock market. Furthermore, relative to FIIs' gross sales, gross purchases have a bigger impact on volatility.

Kaur (2015) investigated the influence of FII investment on security market volatility in India. The author applied both symmetric and asymmetric GARCH models on daily data collected from January 3rd, 1999 to December 30th, 2013. The researchers discovered the prevalence of leverage in stock market performance. It also discovered that foreign institutional investment increased volatility in Indian stock returns.

Banumathy and Azhagaiah (2015) revealed that the GARCH (1,1) model was best suited to the given data set for understanding symmetric volatility and quantifying the asymmetric effect. The T-GARCH model performed better. GARCH-M (1,1) showed a positive but small risk premium, meaning that increasing risk did not result in higher returns. The leverage effect, as measured by the Threshold GARCH (1,1) and EXPONENTIAL GARCH parameters, revealed that negative shocks or events had a significant impact on conditional volatility.

Rastogi and Nazaquat (2015) evaluated the impact of FIIs on the Indian stock market, using the Bombay Stock Exchange as a proxy and categorizing the time period into pre-FII arrival and post-FII arrival. The study found that the presence of foreign institutional investors had no impact on stock market volatility. To stimulate increasing portfolio investment in the capital market, macroeconomic policies should be stable.

Singh and Tripathi (2016) investigated the volatility pattern of the Indian stock market by examining daily closing prices of the S&P CNX Nifty from April 1st, 2001 to March 31st, 2016. The researchers used the GARCH-M (1,1) model to demonstrate the existence of a positive but small risk premium. The symmetric models EXPONENTIAL GARCH (1,1) and the Threshold GARCH (1,1) describe adverse shocks but have a large influence on conditional volatility. Based on AIC, SIC, and log likelihood criteria, the best models were EXPONENTIAL GARCH (1,1) and GARC-M (1,1).

Ahmed (2017) intended to explore the impact of foreign investor groups on Egyptian stock market volatility, as well as if this impact changed over time in response to current domestic political events. The analysis discovered that total trades had no discernible impact on the volatility of the Egyptian stocks market. In fact, independent buy trades have little impact on volatility. Individual foreign sales boosted volatility in two sub-periods, while foreign institutional investment enhanced volatility in both calm and turbulent times. Foreign institutions selling trades contributed to volatility throughout this tumultuous period.

Sumathi (2018) used GARCH family approaches to forecast volatility on the national stock exchange and discovered long-term persistence of volatility. The preliminary research suggested that the volatility was time-dependent and possessed a long memory. The Threshold GARCH outperformed EXPONENTIAL GARCH 1-1 and GARCH 1-1 at predicting stock market volatility.

Aliyev et al. (2020) used daily data from January 4, 2000 to March 19, 2019, to test univariate GARCH models, specifically EXPONENTIAL GARCH and GJR-GARCH models. They looked examined how persistent volatility shocks affected index performance. Second, the study found that the index had a leverage effect and that the returns were asymmetric. The negative shock had a greater impact than the positive shock.

Aggarwal et al. (2021) used data from 2010 to 2019 to investigate the effects of net equity flows from mutual funds (MF) and foreign institutional investors (FII) on nine Indian stock market indexes. It found significant volatility spillover from FII inflows to five indices, while MF flows had no significant impact except telecom.

With a focus on Foreign Institutional Investors (FII), Jain and Biswal (2022) investigated the effect of trading volume on volatility in Indian equities. It was discovered through the research that FII purchases significantly reduce volatility in individual stocks.

In their study, Wu et al. (2023) developed the Real-Time GARCH-MIDAS model, which outperformed other models in out-of-sample forecasting and empirical return fitting. Its better predicting performance holds up well against MIDAS lags, benchmark models, and other rolling windows.

Patel et al. (2024) found that FIIs and DIIs significantly contribute to return generation and volatility in the Indian stock market using GARCH, GJR-GARCH, and EGARCH. Conversely, during the COVID-19 pandemic, FIIs led volatility and DIIs led market returns. This is because the DIIs were the net buyers at this time, and their net position was positively skewed in distribution. The leverage effect is also mentioned. During COVID-19, the volatility is most enduring.

An analysis of previous research reveals that, while there is an abundance of literature on market volatility, few studies have attempted to identify the impact of FIIs on volatility in India. It is also clear that FII investments have a significant impact on the Indian stock market, influencing stock prices, boosting volatility, and producing market disruptions on an irregular basis. However, FII investments can occasionally increase rather than decrease market liquidity.

3. NEED OF THE STUDY

Foreign Institutional Investors (FII) have become a significant economic phenomenon since the early 90s, attracting academicians, policymakers, and international institutions. FII is a major component of foreign portfolio investment in India, benefiting real sectors and achieving economic development goals. The study evaluates the impact of FIIs on the Indian stock market and identifies market trends due to inflow and outflow. Domestic factors like market risk, high inflation rate and interest rate fluctuations also influence FII inflow. A review of prior studies indicates that although there is a wealth of information on market volatility, not many have looked at how FIIs affect volatility in India. Keeping in mind the literature, the current study endeavors to explore the volatility of the Indian stock market using two essential indices, the Nifty and the Sensex.

4. OBJECTIVES OF THE PAPER

The primary purpose of the study is to look into the volatility of the Indian stock market utilizing two key indices, the Nifty and the Sensex index return series. The following paper seeks to :

- To evaluate the influence of foreign institutional investment on stock market volatility.
- To recognize the stock market volatility patterns by employing symmetric as well as asymmetric models from the GARCH family.
- To appraise the suitability of different models of the GARCH family and come up with the best-fitting model.

5. MATERIALS AND METHODS

The current study relies on secondary data. Stock returns are calculated using the Sensex and Nifty indices. Daily statistics on the BSE Sensex and NSE Nifty were collected between January 1, 1999, and May 31, 2022, excluding public holidays. Similarly, daily data on net FIIs throughout the same time period were considered. The first application, BSE Sensex: Daily Closing Price Index, has 5733 observations from January 1, 1999 to May 31, 2022. Days on which FIIs did not trade were excluded from the analysis of the Nifty's daily closing index data, which spans 5738 observations from January 1, 1999, to May 31, 2022. The formula for converting BSE Sensex and Nifty index data into return series is as follows (Raju & Ghosh, 2004 and Kaur, 2015).

BSERt = logt - logt-1

NSERt = logt - logt-1

Data for the BSE Sensex and NSE Nifty were sourced from the Bombay Stock Exchange and National Stock Exchange websites, respectively. Statistics on FII net worth was obtained from the SEBI portal until 1999, when it was distributed to the NSDL and CDSL websites. As a result, statistics collected after 1999 was accessible through the NSDL's website. Because daily data on FIIs has been available since January 1999, we limited our sample to that time period. Each of the three series, i.e., daily returns on Nifty, Sensex, and Net FIIs, was initially tested for stationarity using the ADF unit root approach.

One of the most important considerations while utilizing the GARCH methodology was to first check the residuals for signs of heteroskedasticity. The current study used the Lagrange test for autoregressive conditional heteroskedasticity (ARCH) (Banumathy and Azhagaiah, 2015) to detect heteroskedasticity in return series residuals. The GARCH model comprises the most commonly used methods for estimating stock market volatility. In the ARCH family, there are various choices such as Basic GARCH (1, 1),

EXPONENTIAL GARCH, GJR-GARCH, -GARCH, M-GARCH, and so on, and the application of each type of test is determined by the study's goal and the nature of the data series. In this case, we have the choice of utilizing symmetric or asymmetric measurement models. The research utilised both symmetric and asymmetric generalized autoregressive conditional heteroskedasticity models. Although stock market volatility is such a dynamic phenomenon that no absolute science can accurately measure it, the GARCH model provides a theoretical explanation for the links between stock market returns and volatility. It also serves as the basis for identifying patterns in stock market volatility (Kalra and Pandey, 2015).

To capture the symmetric standard, GARCH (1,1) is both the fundamental model from the GARCH family and one of the symmetric models. GARCH models, also known as volatility clustering models, are widely used to quantify and anticipate the time-varying volatility of high-frequency financial data such as daily stock prices (Islam and Mahkota, 2013). Although the GARCH (1,1) model is suitable for explaining volatility clustering, it can be expanded to incorporate the q and p numbers of the ARCH and GARCH terms (Goodwin, 2012). The other is the GARCH-in-mean model, a version of the GARCH model designed to emphasize the risk-return relationship. This model is most commonly used to describe the risk-reward trade-off.

The theory depends on the assumption that an asset's expected return is directly proportional to its expected risk. Simply expressed, high risk is expected to produce a substantial return as a risk premium. In the GARCH model, conditional variance is employed in the conditional mean equation to calculate anticipated risk. The next two models focus entirely on the absolute value of the innovation, not its sign. According to these models, a large positive shock has the same impact on market volatility as a large negative shock. However, prior experience in the equity market shows that negative shocks have a much higher impact on market volatility than positive shocks.

In the present research, we utilized two asymmetric models: The Exponential Generalized Autoregressive Conditional Heteroskedasticity Model (EXPONENTIAL GARCH) expresses conditional variability logarithmically. This model is the best at capturing the symmetries of the Indian stock market when determining the presence of the leverage impact (Nelson, 1991). The T-GARCH, or threshold GARCH model, attempts to eliminate asymmetries in terms of both negative and positive shocks by simply adding a multiplicative dummy variable to determine whether there is a significant difference in the sign of the innovation, i.e., whether there is a statistically significant difference when the shocks are negative. Any negative shock increases the volatility of stock market returns more than any favorable news (Karolyi, 2001; Amit and Bammi, 2017; and Emenike and Enoke, 2020).

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6. RESULTS AND DISCUSSION

6.1 Descriptive Statistics

Table 1 highlights the daily returns for Nifty, Sensex, and FII investments. The data demonstrate that daily returns on the Nifty and Sensex are negatively skewed with excess kurtosis, indicating a leptokurtic distribution of returns. FIIs show positive skewness. Furthermore, all of the time series show excess kurtosis and are fat-tailed, indicating that they have a leptokurtic distribution. All three series are non-normal, as the Jarque-Bera test statistic for both returns and FIIs was found to be significant, as is typical of financial time series.

Table 1

Descriptive Statistics of Daily Nifty, Sensex Returns and FIIs

Variable	Skewness	Kurtosis	Jarque-Bera Statistics	P-Value
Sensex Returns	-0.106314	10.39579	11409.33	0.0000
Nifty Returns	-0.159514	11.70617	15834.48	0.0000
FIIs	2.956358	40.69735	303829.2	0.0000

Source: **Computed from Data.**

6.2 Test for Stationarity

Before analysing any association, it is required to check each series' stationarity. The permanent component, like that of non-stationary time series, is always present. As a result, a time series' mean and variance change with time. As a result, there is a possibility of receiving inaccurate results. Table 2 demonstrates that all-time series are stationary at the 1% level of significance. Thus, empirical research has demonstrated that the underlying time series are stationary.

Table 2

Result of Unit Root Test

Series		**ADF Unit Root Test Statistics**		
		None	**With Intercept**	**With Trend and Intercept**
FII	**At Level**	-13.00616 (0.0000)	-13.48360 (0.0000)	-13.49108 (0.0000)
	At First Difference	-28.42364 (0.0000)	-28.42093 (0.0000)	-28.42635 (0.0000)
NSE Returns	**At Level**	-50.56725 (0.0001)	-50.64950 (0.0001)	-50.64587 (0.0000)
	At First Difference	-24.93288 (0.0000)	-24.93036 (0.0000)	-24.93538 (0.0000)
BSE Returns	**At Level**	-66.60737 (0.0001)	-66.67437 (0.0001)	66.66827 (0.0000)
	At First Difference	-24.06281 (0.0000)	-24.06038 (0.0000)	-24.05796 (0.0000)

Source: Computed from Data.

6.3 Test for Heteroskedasticity

The graphs of both series (Figures 1 and 2) indicate that although the graphic depiction of returns purports to use the ARCH/GARCH model, times of high volatility were followed by times of low volatility, suggesting that the graphs demonstrate notable swings in return series for both samples. Still, it makes sense to employ ARCH-LM to detect ARCH effects. Table 3 demonstrates that the ARCH-LM test findings are very significant, indicating the presence of ARCH effects. Obs*R-squared equals 244.3789 and 239.9293 with a probability value of 0.0000, showing a strong rejection of the null hypothesis of 'no ARCH effects' homoskedasticity.

Table 3
ARCH- LM Test of Residuals

	Null Hypothesis	F-Statistic	Probability
F-Statistics (Nifty)	No Heteroskedasticity	256.8185	0.00000
Obs* R-Squared		244.3789	0.00000
F-Statistics (Sensex)	No Heteroskedasticity	251.9195	0.00000
Obs* R-Squared		239.9293	0.00000

Source: Computed from Data.

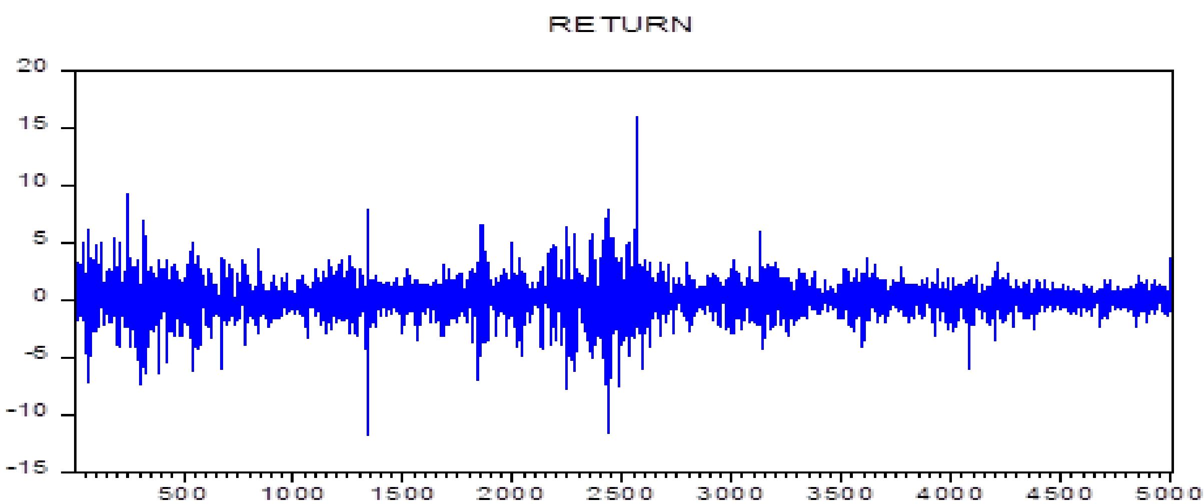

Figure 1. Volatility Clustering of Daily S&P CNX Nifty Returns.

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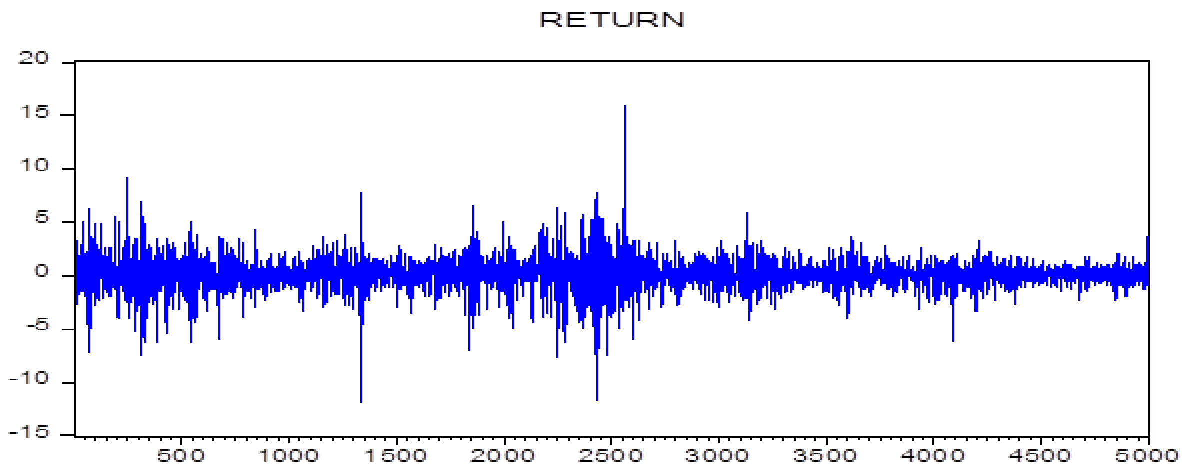

Figure 2. Volatility Clustering of Daily Sensex Returns

6.4 Results and Discussion of GARCH Model

The GARCH test is conducted once it has been established that the two series must use the ARCH/GARCH family of techniques if they show signs of the ARCH effect. The present study employed Exponential GARCH (1,1) and Threshold GARCH (1,1) to describe asymmetric volatility and GARCH (1,1) and GARCH-M (1,1) to model conditional volatility.

The results of GARCH (1,1) and GARCH-M (1,1) for Nifty and Sensex returns are shown in tables 4 and 5, respectively, proving that the GARCH parameters are statistically significant. To elaborate, the coefficients C (constant), ARCH term, and GARCH term were all significant at the 1% level. The estimated coefficient of the GARCH component in the conditional variance equation was substantially larger than the coefficient of the ARCH term, suggesting that the market recalled multiple times and that future volatility was more susceptible to its lagged values. It demonstrated how persistent volatility is. The aforementioned time series' volatility was defined by the values of the variables α and β. With a B coefficient of 89%, it was discovered to be incredibly high, suggesting persistent volatility grouping.

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Table 4

Results of GARCH (1,1) Model for Nifty and Sensex Returns

Variable	Coefficient	Std. Error	z-Statistics	Prob.
μ C	0.088831	0.015531	5.719754	0.0000
AR (1)	0.072691	0.014770	4.921674	0.0000
		Variance	Equation	
ω C	0.028399	0.005985	4.745308	0.0000
α RESID (-1)^2	0.093122	0.008987	10.36193	0.0000
β GARCH (-1)	0.895253	0.009112	98.24997	0.0000
α + β	0.988375			
FIIs	-8.70E-06	5.55E-06	-1.568476	0.1168
Durbin Watson Stat	2.010474			
Q^2 (1)	0.8926			0.345
Q^2 (36)	24.257			0.932
Obs*R-squared (ARCH) LM	0.891967			0.3449
AIC				3.218152
SIC				3.227267
RMSE				1.476659
MAE				1.018895
Theil's U				0.942981
MAPE				168.6668
	Sensex	**Returns**		
μ C	0.090715	0.015301	5.928522	0.0000
AR (1)	0.067979	0.014679	4.631101	0.0000
	Variance	Equation		
ω C	0.021851	0.004838	4.516479	0.0000
α RESID (-1)^2	0.093068	0.008754	10.63159	0.0000
β GARCH (-1)	0.898696	0.008569	104.8715	0.0000
α + β	0.991764			
FIIs	-2.05E-06	4.66E-06	-0.439933	0.6600
Durbin Watson Stat	2.04150			
Q^2 (1)	1.0577			0.297
Q^2 (36)	22.047			0.665
Obs*R-squared (ARCH) LM	1.057698			0.2976
AIC				3.216114
SIC				3.225237
RMSE				1.485102
MAE				1.024499
Theil's U				0.942196
MAPE				135.8080

Source: Computed from Data.

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Table 5
GARCH-M 1,1 Model for Nifty and Sensex Returns

Variable	Coefficient	Std. Error	z-Statistics	Prob.
GARCH (Risk Premium) λ	0.020845	0.013388	1.557001	0.1195
μ C	0.065170	0.021595	3.017796	0.0025
AR (1)	0.072174	0.014832	4.866262	0.0000
	Variance	equation		
ω C	0.028948	0.006056	4.779734	0.0000
α RESID (-1)^2	0.093772	0.009060	10.34976	0.0000
β GARCH (-1)	0.894375	0.009195	97.27110	0.0000
α + β	0.988147			
FIIs	-9.06E-06	5.57E-06	-1.625055	0.1042
Durbin Watson Stat	2.004563			
$Q^2(1)$	0.9408			0.332
$Q^2(36)$	24.358			0.930
Obs*R-squared (ARCH) LM	0.940137			0.3322
AIC				3.218043
SIC				3.228460
RMSE				1.477452
MAE				1.019002
Theil's U				0.928579
MAPE				163.8863
	Sensex	**Returns**		
Variable	**Coefficient**	**Std. Error**	**z-Statistics**	**Prob.**
GARCH (Risk Premium) λ	0.015112	0.012925	1.169228	0.2423
μ C	0.073901	0.020879	3.539458	0.0004
AR (1)	0.067661	0.014738	4.590979	0.0000
	Variance	**Equation**		
ω C	0.022056	0.004875	4.524692	0.0000
α RESID (-1)^2	0.093446	0.008800	10.61883	0.0000
β GARCH (-1)	0.898221	0.008620	104.1964	0.0000
α + β				
FIIs	-2.02E-6	4.69E-06	-0.430343	0.6669
Durbin Watson Stat	2.009488			
$Q^2(1)$	1.0468			0.306
$Q^2(36)$	31.616			0.662
Obs*R-squared (ARCH) LM	1.046768			0.3063
AIC				3.216228
SIC				3.226653
RMSE				1.485882
MAE				1.024708
Theil's U				0.929193
MAPE				146.7700

Source: Computed from Data.

The statistical significance of α and β demonstrated that volatility news from the prior period influenced the current volatility. The total of two calculated coefficients, α+ β, was over 0.98, near to unity, indicating that the shock will continue over long durations. However, α+ β < 1 indicates that the GARCH process is mean-reverting. This also demonstrates significant periods of volatility clustering for both series, as shown in figures 1 and 2. The GARCH-M (1, 1) model indicated no risk-reward relationship. The conditional mean equation revealed a positive but statistically insignificant risk premium, λ, indicating that volatility has no significant impact on expected return. Various error statistics have been utilized in previous empirical studies to investigate the forecast performance of various GARCH models (Goodwin, 2012; Vijayalakshmi & Gaur, 2013 and Potharla, 2014). The most common and popular of these are mean absolute error (MAE), mean absolute percentage (MAPE), root mean squared error (RMSE), and Theil's U.

The ARCH-LM test shows that there is no statistically significant trace of ARCH impact in the residuals, which is a good sign for our findings. Furthermore, squared normalized residuals reveal no substantial autocorrelation until lag 36. Both models indicate that FIIs have a negative but small impact on stock market volatility. Since they may capture anomalies in the return series, asymmetric models are thought to be more efficient than symmetric models. Two models were employed for this: Threshold GARCH (1,1) and EXPONENTIAL GARCH (1,1). The term "ϒ" denotes asymmetric impact in both theories. Table 6 presents the results of the asymmetrical EXPONENTIAL GARCH model for Nifty and Sensex returns. Table 6 demonstrates that the sum of α and β is more than one, showing that conditional variance is explosive. The coefficients for α and β show statistical significance at the 1% level. The data show a negative relationship between past and future returns, which supports the existence of the leverage effect.

The coefficients for α and β show statistical significance at the 1% level. The data show a negative relationship between past and future returns, which supports the presence of the leveraged outcome. In the alternative test of asymmetries (table 7), in the EXPONENTIAL GARCH model, the coefficient of leverage impact, ϒ, is positive and significant at the 1 percent threshold for both Nifty and Sensex returns. The results explain why adverse news have a larger influence on conditional variance than optimistic shocks. For NSE return data, FII has no substantial impact on stock market volatility; however, for the Sensex, FII has a 5% effect on return volatility in both the Exponential GARCH and Threshold GARCH models.

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Table 6

(E-GARCH 1,1) for Nifty and Sensex Returns

Variable	**Coefficient**	**Std. Error**	**z-Statistics**	**Prob.**
Cµ	0.061837	0.015411	4.012525	0.0001
AR (1)	0.080578	0.014523	5.548101	0.0000
		Variance	Equation	
Intercept ω	-0.146000	0.012091	-12.07474	0.0000
ARCH (α)	0.199517	0.016020	12.45405	0.0000
GARCH (β)	0.977484	0.003807	256.7663	0.0000
α + β	1.177001			
Leverage ϒ	-0.102460	0.010677	-9.596488	0.0000
FIIs	6.01E-06	6.70E-06	0.896569	0.3699
Durbin Watson Stat	2.026518			
$Q^2(1)$	0.0702			0.791
$Q^2(36)$	26.772			0.868
Obs*R-squared (ARCH) LM	0.070114			0.7912
AIC				3.200875
SIC				3.211292
RMSE				1.473452
MAE				1.016865
Theil's U				0.914734
MAPE				169.9330
	Sensex	**Returns**		
Variable	**Coefficient**	**Std. Error**	**z-Statistics**	**Prob.**
Cµ	0.061814	0.015243	4.055099	0.0001
AR(1)	0.075285	0.014538	5.178405	0.0000
	Variance	**Equation**		
Intercept ω	-0.143812	0.011822	-12.16512	0.0000
ARCH (α)	0.195114	0.015731	12.40307	0.0000
GARCH (β)	0.979584	0.003383	289.5701	0.0000
α + β				
Leverage ϒ	-0.099583	0.010613	-9.382910	0.0000
FIIs	9.70E-06	5.72E-06	1.696231	0.0458
Durbin Watson Stat	2.029566			
$Q^2(1)$	0.0505			0.822
$Q^2(36)$	27.051			0.511
Obs*R-squared (ARCH) LM	0.050475			0.8222
AIC				3.199283
SIC				3.209709
RMSE				1.484605
MAE				1.024903
Theil's U				0.959461
MAPE				122.6593

Source: Computed from Data.

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Table 7
TARCH (1,1) for Nifty and Sensex Returns

Variable	Coefficient	Std. Error	z-Statistics	Prob.
C µ	0.066871	0.015559	4.297844	0.0000
AR(1)	0.079506	0.014855	5.352121	0.0000
		Variance	Equation	
Intercept ω	0.032895	0.006308	5.214967	0.0000
ARCH (α)	0.032967	0.009403	3.505848	0.0005
GARCH (β)	0.882170	0.009449	93.35635	0.0000
α +β	0.915137			
Leverage (TARCH) ϒ	0.138966	0.016453	8.446011	0.0000
FIIs	1.72E-06	6.46E-06	0.266119	0.7901
Durbin Watson Stat	2.024376			
$Q^2(1)$	0.5184			0.472
$Q^2(36)$	21.427			0.974
Obs*R-squared (ARCH)	0.518046			0.4717
AIC				3.202942
SIC				3.213359
RMSE				1.476269
MAE				1.019058
Theil's U				0.956138
MAPE				173.5902
	Sensex	**Returns**		
C µ	0.067469	0.015350	4.395341	0.0000
AR (1)	0.075716	0.014814	5.111109	0.0000
	Variance	**Equation**		
Intercept ω	0.027280	0.004975	5.483255	0.0000
ARCH (α)	0.031982	0.009053	3.532849	0.0000
GARCH (β)	0.886651	0.008909	99.52760	0.0000
α +β				
Leverage (TARCH) ϒ	0.137596	0.016267	8.458545	0.0000
FIIs	9.30E-06	5.20E-06	1.788319	0.0317
Durbin Watson Stat	2.030281			
$Q^2(1)$	0.3409			0.559
$Q^2(36)$	18.056			0.712
Obs*R-squared (ARCH)	0.34096			0.5593
AIC				3.199722
SIC				3.210148
RMSE				1.484658
MAE				1.024766
Theil's U				0.956003
MAPE				125.1515

Source: Computed from Data.

To summarize, FII has no discernible effect on the NSE series; nevertheless, when examined using asymmetric models, FII has a significant impact on the volatility of Sensex returns. BSE returns and outcomes confirm the authenticity of Nifty returns, as Sensex returns provide the same results. The best-fitting model is picked from among the models used in the analysis using Akaike and Schwarz's information criterion, albeit these criteria alone are insufficient to achieve the desired result. As a result, extra values and forecast error data have been determined to produce a nearly-correct judgment. Other criteria are root mean squared error, mean absolute error, Theil's inequality coefficient, and mean absolute percentage error. The rule of thumb is that the lower these statistics, the better the model.

Table 8 reveals that EXPONENTIAL GARCH is the best model for analysing Nifty returns based on five metrics: AIC, SIC, RMSE, MAE, and Theil's U. Furthermore, for the BSE returns series, EXPONENTIAL GARCH has been shown to perform better on four measures: AIC, SIC, MAPE, and RMSE. The findings are similar with Vijayalakshmi and Gaur (2013) and Kaur (2015).

Table 8

Model Selection Summary Statistics for Nifty and Sensex Returns

Models	Model Selection Criterion	NSE Series	BSE Series
GARCH (1,1)	AIC	3.218152	3.216114
	SIC	3.227267	3.225237
	RMSE	1.476659	1.485102
	MAE	1.018895	1.024499
	Theil’s U	0.942981	0.942196
	MAPE	168.6668	135.8080
GARCH-M (1,1)	AIC	3.218043	3.216228
	SIC	3.228460	3.226653
	RMSE	1.477452	1.485882
	MAE	1.019002	1.024708
	Theil’s U	0.928579	0.929193
	MAPE	163.8863	146.7700
E-GARCH (1,1)	AIC	3.200875	3.199283
	SIC	3.211292	3.209709
	RMSE	1.473452	1.484605
	MAE	1.016865	1.024903
	Theil’s U	0.914734	0.959461
	MAPE	169.9330	122.6593
T-GARCH (1,1)	AIC	3.202942	3.199722
	SIC	3.213359	3.210148
	RMSE	1.476269	1.484658
	MAE	1.019058	1.024766
	Theil’s U	0.956138	0.956003
	MAPE	173.5902	125.1515

Source: Computed from Data.

7. CONCLUSION

This study estimates return volatility and demonstrates the impact of FIIs on volatility using several GARCH techniques. It is concluded that the outcomes vary according to the indices used, especially the Nifty. The GARCH (1,1) model shows significant parameters, with coefficients such as constant, ARCH term, and GARCH term being highly significant. The GARCH term's greater coefficient indicates a longer memory and more sensitive volatility. The volatility is determined by parameters α and β, with β coefficient values of 89% indicating persistence volatility clustering. The GARCH process is mean reverting. FIIs have a negative but insignificant effect on stock market volatility. However, in GARCH-M (1, 1) model no risk return relationship has come out. The parameter of risk premium λ in conditional mean equation is positive but statistically insignificant indicating no significant impact of volatility on the expected return. Constant term given in mean equation, in the GARCH- mean model found significant which interpret that there are abnormal returns available. Again, the findings confirm no impact of FII on stock market.

E-GARCH and T-GARCH models are used to further assess the asymmetry. Asymmetric models are considered more efficient, as they are capable of capturing asymmetries in the return series. ϒ term captures the asymmetric effect. Aggregate of α and β is greater than one which meaning thereby conditional variance is explosive. The estimated coefficients of α and β are statistically significant at 1 percent level. The results interpret negative correlation between past returns and future return confirming the presence of leverage effect. In T-GARCH model the coefficient of leverage effect ϒ is positive and significant at 1 percent level of significant for both NIFTY and SENSEX returns. The result explains that negative shocks or any bad news have a larger or greater impact on the conditional variance than the any positive news or shock. Among four different models, E-GARCH is the best performer based on the statistical values calculated of RMSE, MAE, MAPE and Theil's U tests. Rule of thumb is lower the value, better the model.

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