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Impact of Foreign Institutional Investors (FII's) on the Indian Stock Market: A Sectoral Analysis of Market Fluctuations

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ABSTRACT -

The research examines Foreign Institutional Investors (FIIs) effects on India's stock market while determining the most volatile market sector from 2015–2024. The research adopts quantitative methodology through the analysis of secondary data obtained from NSE, Money control and Trading View. The analysis evaluated both monthly FII net investment data and changes to sectoral index performance. Linear regression models analyzed both FII flow relationships with NIFTY 50 index performance and with performances of individual sector indices. The analysis used GARCH (1,1) to measure volatility across different market sectors. A range of robustness tests included GARCH (1,0), (0,0) and (0,1) model variants. For return series analysis the data needed cleaning followed by log-transformation. The model performance evaluation relied on log-likelihood and AIC values. FII flows showed a meaningful statistical relationship with the IT sector and the Banking sector as well as the FMCG sector according to regression analysis results. The volatility persisted strongly ($\alpha + \beta \approx 1$) in every sector based on GARCH modelling but the IT sector displayed the highest level of volatility. Market shocks have the least impact on the Pharma sector which demonstrated stability among all sectors. Among various GARCH specifications the GARCH (1,1) model demonstrated the most suitable balance for detecting both market shock effects alongside volatility persistence levels. Foreign investors demonstrate distinct reactions in each sector because they evaluate individual risk characteristics and potential returns when making rebalancing decisions. The research provides both original value by unifying macro-level Foreign Investment Impact assessment with sectoral ARCH/GARCH volatility modelling. This assessment demonstrates varying sector responses towards worldwide capital movement. The research provides crucial insights which help investors and risk managers and policy-makers understand sectoral levels of capital flow sensitivity and volatility behaviour.

INDEX TERMS-

- Foreign Institutional Investors (FIIs)
- GARCH Model
- Indian Stock Market
- Sectoral Volatility
- Time-Series Analysis E-Commerce

INTRODUCTION :

Researching financial market dynamics provides continuous intellectual exploration possibilities to economists and policymakers as well as investors and academic researchers who analyse institutional funding and market value interactions and macroeconomic forces at work. ATICR shows its significance to economic growth and resilience because capital cross national borders at such rapid rates during globalization. These emerging markets along with India and China now function as major financial powers thus elevating the importance of this research. Foreign Institutional Investors (FIIs) exercise great market control through their ability to stabilize or destabilize financial conditions simultaneously with domestic and international economic forces that affect numerous industries across all geographies. A combination of financial understanding with economic knowledge and behavioural science research creates the ability to develop predictive tools for financial crises alongside investment optimization strategies while promoting long-term development. The chance to solve these problems is fundamentally difficult because information discrepancies join regulatory discrepancies with inevitable systematic hazards which need an extensive multi-disciplinary method for success.

LITERATURE SURVEY:

Foreign Institutional Investors (FIIs) function as key market shapers in global financial markets especially when operating in emerging economies because they influence corporate governance systems and market conditions as well as investment patterns. The literature reveals FIIs make investments due to macroeconomic elements as well as institutional aspects and firm-specific criteria. This synthesis brings together essential findings regarding FII investment patterns as well as their market effects and stock market and economic period patterns.

FIIs demonstrate unique preference patterns for their cross-national capital deployment and business investments. An upcoming study from Aggarwal, Klapper, and Wysocki demonstrates that distant investors select destinations with well-protected investors combined with high accounting quality and clear legal systems. A floating exchange rate system combined with beneficial tax regulations increases the flow of FII capital. According to FIIs business choices they select strong-governed companies that utilize American Depositary Receipts (ADRs) and international accounting standards with quality auditors. The research supports La Porta et al. (1998) by demonstrating how legal environments directly impact investment capital movement.

Liu, Bredin and Cao (2018) investigated Qualified Foreign Institutional Investors (QFIIs) in China who prefer large, low-debt firms with state ownership. Investment decisions made by long-term QFIIs logically push them toward businesses with independent boards indicating their concern for corporate governance practices. FIIs prove to be active investors who exclusively target corporations that maintain governance structures to reduce risks.

Market performance between foreign and domestic funds depends on the extent of information inequality. Ferreira, Matos, Pereira and Pires (2017) analyze performance of 32 countries' domestic and foreign institutional investors and discover equivalent results between the groups. Investors from domestic markets tend to perform better than international investors in situations involving substantial information asymmetry between local and foreign entities. Foreign investors primarily use market manipulation effects since they avoid the benefits provided by local investor knowledge.

Research by Neupane, Neupane, Paudyal, and Thapa (2016) shows domestic institutional investors (DIIs) at India’s IPO market show superior stock selection capabilities than FIIs. Foreign institutional investors heavily participate in IPO bids however post-listing performance reveals DIIs achieve superior outcomes because they base their investment strategy on contrary information. Transparency seems insufficient for wiping out the informational edge that local investors possess.

External investors from foreign countries have a strong impact on corporate governance practices across emerging markets. The research from Huang and Zhu (forthcoming) demonstrates that Query Foreign Institutional Investors functioned better as corporate governance monitors than domestic mutual funds because they secured shorter negotiation terms and increased minority shareholder compensation during China's split-share reform. By participating in state-controlled firms they succeeded in reducing the chances of expropriation while revealing their capabilities to serve as external supervisory forces.

Internal control quality of Chinese firms improves significantly due to QFIIs particularly if their home nation has robust governance standards as revealed by Li, Wang, Wu, and Zhou (2021). The involvement of QFII firms leads to fewer internal control issues and superior financial reporting which shows foreign investors help strengthen governance structure in weak institutional settings.

The paper by Bena, Ferreira, Matos and Pires (2015) disproves the prevailing view that FIIs display only short-term "locust" behaviour. The research uses international data to demonstrate that foreign institutions boost both long-term investments as well as R&D spending, employment levels and innovative activities. Higher levels of foreign ownership by FIIs improve both organizational productivity together with effective CEO management while disproving accusations that FIIs focus on short-term profits instead of long-term business expansion.

Research needs to investigate how Foreign Institutional Investors influence market stability. A-share market volatility in China experienced a reduction in feedback trading activity after liberalization when foreign institutional investors entered the market according to Schuppli and Bohl (2009). New investors with a rational investment approach displayed long-term strategies which created market stability.

Rai and Bhanumurthy (2004) argue that macroeconomic conditions determine how much FII funds enter Indian markets. Foreign investors move to domestic stocks when such investments offer attractive returns but shift to U.S. markets due to rate substitution. Similarly to stock returns FII flows respond to two variables of inflation: higher domestic inflation discourages FII investments but at the same time rising U.S. inflation increases their preference for emerging markets. Negative news factors cause FIIs to exhibit heightened responses because risk-averse behaviour prevails within them.

Non-financial corporate practices receive significant impact from Foreign Institutional Investor activities. The research by Li, Wang, and Wu (2021) reveals that QFII ownership in China leads to improved CSR performance including higher CSR scores and better implementation of Global Reporting Initiative (GRI) standards among these companies. The strength of QFII effectiveness increases when their countries possess high-quality regulatory standards. This demonstrates their ability to transfer governance standards to target firms.

Bose, Lim, Minnick and Shams (2023) conduct an international analysis demonstrating that ownership by foreign institutions enhances climate change disclosure clarity. Through the analysis of MSCI Index inclusions their research reveals FIIs drive firms to increase environmental transparency mostly in stakeholder-oriented nations as well as companies involved in emissions trading programs.

The behaviour of FII decisions toward the U.S. market is evaluated by Abdioglu, Khurshed, and Stathopoulos (2013) according to home-country governance factors. The study observes opposing FII behaviours where investors from weak countries pursue regulated U.S. firms yet those from similar governance regions Favor U.S. stocks. The double nature of the findings supports a joint impact of governance quality together with familiarity on how FII investors allocate their investments.

The study conducted by Cao, Du, and Hansen (2017) shows foreign investors in China prefer paying higher dividends for their Chinese investments since weak legal systems require external governance measures. Dividend-paying firms succeed at attracting FII investment yet these investors do not always drive companies toward post-investment dividend increases because their initial selection choice was pre-determined.

Numerous studies analyse the Indian stock market's connections to macroeconomic variables alongside market efficiency measurements and volatility and predictive modelling aspects. Monetary policy surprises demonstrate a stronger influence on stock market returns than every other major economic indicator. A 100-basis-point monetary policy shift triggered between 1.4% and 3.8% decrease in stock market value primarily affecting finance-intensive sectors including Infrastructure and Metals according to Pal and Garg (2019). Results showed that Sensex and Nifty demonstrated higher sensitivity compared to mid-and small-cap indexes in opposition to what has been observed in developed markets.

Researchers have studied the influence of crude oil price movements on the Indian stock market values. The study by Sahu, Bandopadhyay, and Mondal (2014) discovered both long-term equilibrium and neutral short-term effects which proves that Indian markets exhibit stability towards oil price fluctuations. The past values of stocks alone accounted for over 99% of stock market variations thus establishing a highly independent status.

Market forecasting in India progressively moves forward by adopting machine learning tactics. Nayak, Pai, and Pai (2016) showed that blending historical data and sentiment analysis rendered Boosted Decision Trees the optimal choice for short-term forecasting accuracy. The research conducted by Yadav, Jha and Sharan (2020) revealed stateless LSTMs with one hidden layer delivered optimum results for stocks including TCS and ICICI Bank.

The application of clustering techniques within portfolio management research activities enables better portfolio diversification. The research of Nanda, Mahanty, and Tiwari (2010) evaluated K-means clustering alongside Fuzzy C-means clustering and SOM clustering for stock selection purposes then determined that K-means yielded the most reliable and lowest-risk investment portfolios.

Current debates exist about the status of market efficiency. Tests conducted by Belgaumi (1995) for weak-form market efficiency produced results in the 1990s using serial correlation and runs tests yet Mishra, Mishra, and Smyth (2014) rejected random walk hypothesis after incorporating structural breaks and GARCH effects analysis. Karmakar and Chakraborty (2000) discovered market anomalies that relate to monthly and turn-of-the-month patterns which potentially allow for return exploitation.

Research on market volatility shows how both macroeconomic events and geopolitical conditions affect price movements. Karmakar (2005) proved volatility clustering to exist in Indian markets by implementing GARCH models and discovered select leverage effects in Wipro stock. Pandian and Jeyanthi (2009) discovered bear market conditions displayed increased volatility patterns especially through periods of financial collapses including the 2008 financial crisis due to Foreign Institutional Investor actions.

Different tests have been conducted to determine how applicable asset pricing models are for Indian markets. The Fama-French three-factor model demonstrated superior performance to CAPM according to Harshita, Singh, and Yadav (2015 because the size, value and profitability variables provided stronger explanations for returns.

Many experts have thoroughly analysed the connection that exists between stock market patterns and wider economic market cycles. Chauvet (2001) creates a Markov switching dynamic factor model to determine how stock market data predicts economic turning points. The stock market factor remains a driving force in business cycles because it produces recession warnings before other indicators such as the Composite Leading Indicator (CLI).

According to Bilias, Georgarakos, and Haliassos (2006) households exhibit portfolio inertness when they respond to stock market movements. Research shows minimum trading happens within most homes during periods of market volatility which indicates that stock market instability is not generated by widespread retail trading activities.

According to Gopikrishnan et al. (2001) fat-tailed return distributions alongside long-range correlations in stock prices are explained through their investigative research. Their research questions Gaussian models to prove that market volatility emerges from the trading activity microstructure dynamics. Stanley et al. (2001) combined statistical physics with financial analysis to demonstrate both power-law tails in stock return patterns and volatility clustering which results from continuous market activity.

According to Stiglitz (1992), capital market defects like information biases combined with limited credit possibilities make economic forces expand steady market influences into extensive economic instability. The framework includes financial frictions within business cycle theory to explain two economic phenomena: non-neutral money effects and unemployed workers who do not immediately return to work.

Masih and Masih (1999) evaluated stock market interdependencies between Asian emerging markets using their causality research. Research findings demonstrate that U.S. markets possess worldwide power but Asian markets tend to react more strongly to Hong Kong-based regional effects.

Global markets have been influenced by FIIs through several interconnected roles that affect corporate governance while stabilizing market conditions and supporting sustainability practices. Investment choices of institutional investors depend on the factors that include institutional quality together with transparency measures and firm-level governance practices. Even though local investors produce better results in clouds markets foreign institutional investors enhance host economies through lasting improvements.

The Indian stock market operates under the influence of government policies together with institutional activity and substantial market interruptions. Predictive models together with sectoral strategies provide useful strategic insights even though the actual market efficiency remains an open argument. Stock market relationships with economic cycles demonstrate the accuracy of financial markets along with investor assortment patterns and financial system irregularities.

Additional research should analyse the heterogeneity of Foreign Institutional Investors because it includes short-term traders alongside long-term strategic investors. Higher frequency data analysis in combination with behavioural patterns would improve both understanding of market fluctuation behaviour as well as economic network relationships. Emerging markets should strengthen their legal infrastructure and work to eliminate information differences because this will help maximize benefits from foreign investment while controlling associated risks.

METHODOLOGY :

A descriptive and analytical research approach underwent this analysis to determine FII Foreign Institutional Investors impact on the Indian stock market together with identification of top volatile sectors. The study depends on quantitative analysis techniques to detect market patterns through time-series methods. The research depends solely on secondary data while adopting a quantitative approach for historic analysis of Foreign Institutional Investors' (FIIs) investment patterns and sectoral stock market behaviour. The research does not contain any newly gathered primary data. This study assesses FII activity effects by utilizing statistical models and sectoral data analysis. Descriptive statistics: Mean, standard deviation, and trend observations Researchers utilize GARCH models in combination with ARCH models for assessing volatility clustering together with persistent shock detection and time-varying sectoral index variance measurement. These evaluation methods measure both the extent and duration of changes that affect foreign institutional investor transactions.

RESEARCH GAP:

Research on Foreign Institutional Investors' (FIIs) market influence has primarily studied NIFTY 50 and Sensex broad indices although numerous studies of stock market trends already exist. Research analyses implement basic linear methodologies for brief return relationship monitoring while ignoring specific sector evolutions. Research investigating volatility persistence at the sectoral level primarily relies on fundamental time-series models like ARCH and GARCH due to their scarcity in existing literature. Analysis of Foreign Institutional Investor inflows on different sectors across long periods of time remains a subject without adequate research exploration. This research drives progress by utilizing GARCH-based volatility assessment to determine sectoral impacts of FII activities.

Objectives

To analysis Foreign Institutional Investors (FIIs) corresponds with Indian stock market performance by utilizing the NIFTY 50 index.

To evaluate sectoral effects from FII investments by determining which business sectors receive the strongest influence from FII inflows and outflows.

To investigate volatility patterns of major NSE sectoral indices through ARCH/GARCH modelling techniques.

To determine the sector that maintained the highest level of volatility from 2015 until 2024.

HYPOTHESES:

H1: Impact of FIIs on Overall Market Performance

H2: Sectoral Fluctuation Due to FII Activity

H3: Volatility Behaviour Across Sectors

H4: Identification of the Most Volatile Sector

SAMPLE SIZE:

The research data relies on publicly available information obtained from three reputable sourcesnamely National Stock Exchange (NSE) the Money control website and Trading View platform. Analysis of Foreign Institutional Investor inflows on different sectors across long periods of time remains a subject without adequate research exploration. This research drives progress by utilizing GARCH-based volatility assessment to determine sectoral impacts of FII activities during a ten-year period from 2015 through 2024.

ANALYSIS AND INTERPRETATION:

Hypothesis 1: Impact of FIIs on Overall Market Performance

- **H0 (Null Hypothesis):** There is no significant relationship between FII inflows and NIFTY 50 returns.
- **H1 (Alternative Hypothesis):** There is a significant relationship between FII inflows and NIFTY 50 returns.

Variable	Coefficient	Std. Error	t-value	p-value
Intercept	195.039	35.639	5.473	2.53E-07
FII Net Investment	-0.003673	0.001484	-2.475	0.0147

Metric	Value
Residual Std. Error	384.4
R-squared	0.0494
Adjusted R-squared	0.0413
F-statistic	6.128
p-value (F-statistic)	0.01473
Observations (n)	120

Interpretation

Metric	Value	Interpretation
Coefficient (FII)	0.00367	A negative slope: for every ₹1 crore net FII inflow, NIFTY 50 moves down ~0.0037 points
p-value (FII)	0.0147	Statistically significant at 5% level
R-squared	0.04937	About 4.9% of the variation in NIFTY 50 is explained by FII flow
F-statistic p-value	0.01473	Confirms that the regression model is significant overall

Interpretation

Since p-value (0.0147) falls below 0.05 **we reject the null hypothesis (H_0).**

Among FII inflows and NIFTY 50 return series a statistically significant connection exists at the 5% significance level.

The model shows that FII net investments negatively affect NIFTY 50 returns with the potential reason being profit-booking activities or anticipatory hedging strategies.

Analysis of regression data showed that the FII coefficient generated a p-value of 0.0147 that fell beneath the 0.05 level of significance. FII investment amounts demonstrate a statistically significant pattern regarding NIFTY 50 index returns. The results lead to null hypothesis rejection. FII inflows appear to lessen NIFTY 50 returns by a small amount of -0.00367 due to offshore investors who engage in profit-taking behaviours.

Hypothesis 2: Sectoral Fluctuation Due to FII Activity

- **H0:** FII inflows do not have a significant impact on sectoral indices (e.g., Banking, IT, Pharma, FMCG, Auto).
- **H1:** FII inflows have a significant impact on at least one sectoral index.

Multiple Regression

Variable	Coefficient	Std. Error	t-value	p-value	Significance
Intercept	-2816.31	2579.95	-1.092	0.2773	—
Change in Bank Nifty	-7.49	1.82	-4.113	7.48E-05	***
Change in Auto Mobiles	5.88	4.77	1.232	0.2205	—
Change in Energy	0.75	2.91	0.259	0.7964	—

Change in FMCG	3.69	1.76	2.094	0.0386	*
Change in IT	-5.39	2.2	-2.447	0.016	*
Change in Pharma	-1.64	4.36	-0.376	0.7075	—
Change in Infrastructure	-10.83	19.97	-0.542	0.5887	—

Metric	**Value**
Residual Std. Error	22070
R-squared	0.1872
Adjusted R-squared	0.1364
F-statistic	3.684
p-value (F-statistic)	0.001279
Degrees of Freedom	7, 112

Interpretation

Metric	**Value**	**Interpretation**
R-squared	0.1872	About **18.7%** of the variation in FII flows is explained by changes in sector indices.
Adjusted R^2	0.1364	After adjusting for number of predictors, **13.6%** of variation is explained — modest model fit.
F-statistic	3.684	The overall model is **statistically significant** (p = 0.001279)

The model is valid and some variables significantly influence FII flows.

Variable	**Estimate**	**p-value**	**Significance**	**Interpretation**
Intercept	-2816.31	0.2773	Not Sig.	Baseline FII flow (no sector movement) is negative, but not statistically meaningful.
Bank Nifty	**-7.49**	**7.48E-05**	*** Significant	Each 1-point rise in Bank Nifty is associated with a **₹7.49 crore decrease** in FII — likely **profit booking**.
Auto Mobiles	5.88	0.2205	Not Sig.	Mild positive effect, but not statistically strong.
Energy	0.75	0.7964	Not Sig.	No meaningful influence from Energy sector on FII.
FMCG	**3.69**	**0.0386**	* Significant	Each 1-point rise in FMCG leads to a **₹3.69 crore increase** in FII investment.

IT Sector	**-5.39**	**0.016**	* Significant	A 1-point rise in IT index relates to **₹5.39 crore less FII** — could be interpreted as **profit-taking**.
Pharma	-1.64	0.7075	Not Sig.	No significant FII movement due to Pharma.
Infrastructure	-10.83	0.5887	Not Sig.	Large negative estimate, but statistically insignificant.

Interpretation

The significant predicting variables for market performance include the Bank Nifty index and increased activity for FMCG and decreased activity for IT.

Insignificant Sectors: Auto, Energy, Pharma, Infrastructure

Rising index levels lead FIIs to increase selling in both banking and IT sectors because they likely profit from their position.

The FII interest in FMCG sector increases as sector performance rises because defense-oriented investors choose this sector.

The overall model shows significance based on F-statistic = 3.684 along with p = 0.001279.

The overall model significance can be confirmed by three sectors showing p-values < 0.05 which includes Banking, FMCG, IT.

The null hypothesis is rejected.

At least one sectoral index represented by Bank Nifty, FMCG and IT demonstrates meaningful statistical association with FII inflow data.

Evidence reveals that Foreign Institutional Investors make distinct investment decisions between different sectors depending on sector-specific performance and risk profile and macroeconomic variables.

Bank Nifty and the FMCG sector along with the IT sector demonstrated significant reaction to investments from FII (p = 0.0000748, p = 0.0386, p = 0.0160). The statistical significance value for the entire model reached 0.001279 through the F test. The obtained results demonstrate FII activity has substantial influence on at least one sectoral index. The research justify null hypothesis rejection. The research results indicate that Foreign Institutional Investors demonstrate sectoral selectiveness because they likely view different market segments differently.

Hypothesis 3: Volatility Behaviour Across Sectors

Using GARCH/ARCH models to test conditional volatility.

- **H0:** Sectoral returns do not exhibit time-varying volatility (no ARCH/GARCH effect).
- **H1:** Sectoral returns exhibit significant time-varying volatility, justifying the use of ARCH/GARCH modelling.

The GARCH(1,1) model is used to evaluate the **volatility behavior over time** in each sectoral return series.

Common Interpretation Parameters:

- **mu**: Mean return
- **omega**: Constant term of variance equation
- **alpha1**: Impact of past squared residuals (ARCH effect)
- **beta1**: Impact of past conditional variance (GARCH effect)
- **alpha1 + beta1** close to 1 → Persistent volatility
- **p-values < 0.05** indicate significance

GARCH(1,1) Volatility Summary

Sector	α (ARCH)	β (GARCH)	$\alpha + \beta$	Volatility (σ SD)
IT	0.137	0.861	0.998	430.45
Bank Nifty	0.120	0.879	0.999	412.31
Energy	0.087	0.912	0.999	309.04
FMCG	0.045	0.954	0.999	191.05
Auto	0.118	0.881	0.999	116.89

Infrastructure	0.143	0.856	0.999	31.90
Pharma	~0	0.999	0.999	12.57

Sector	**α (ARCH)**	**β GARCH)**	**α+β**	**Interpretation**
IT	0.137	0.861	0.998	High volatility persistence
Bank Nifty	0.12	0.879	0.999	Very high persistence
FMCG	0.045	0.954	0.999	Stable but persistent volatility
Pharma	~0.000	0.999	~0.999	Volatility driven almost entirely by GARCH term
Auto	0.118	0.881	0.999	High persistence
Energy	0.087	0.912	0.999	Very persistent volatility
Infrastructure	0.143	0.856	0.999	High persistence, ARCH slightly more active

Interpretation

Insights from Other GARCH Variants

We also tested:

- GARCH(1,0) – ARCH model only
- GARCH(0,1) – GARCH-only model

A GARCH(0,0) structure failed to converge due to its constant variance model structure.

GARCH(1,1) models were used to estimate time-varying volatility in each sector. All sectors exhibited high persistence ($\alpha + \beta \approx 1$). The IT sector showed the highest conditional volatility ($\sigma = 430.45$), while Pharma had the lowest ($\sigma = 12.57$).

Result:

The GARCH(1,1) model delivered optimal model fit because it demonstrated superior log-likelihood statistics and information criteria across all economic sectors.

Evidence from GARCH (1,1) Models:

1. Statistical significance at $p < 0.05$ measured the ARCH coefficients and GARCH coefficients across all examined sectors in at least one model form.

2. The nearly additive relation of $\alpha + \beta = 1$ across every sector indicates robust volatility persistence which is a distinctive sign of time-varying volatility.

3. The results indicated an existence of residual autocorrelation together with squared autocorrelation using both ARCH LM tests and Ljung-Box p-values method showing evidence of conditional heteroskedasticity.

4. Alternative model variants failed to produce Log-likelihood or AIC results that matched the optimal fit of GARCH (1,1).

The null hypothesis is rejected.

Time-varying volatility occurs in all sectoral indices which this study examined. The results confirm ARCH/GARCH models should be used to model sectoral return conditional variance. The GARCH (1,1) model succeeded in modelling volatility clusters while maintaining persistent volatility patterns throughout IT, Banking domains as well as Energy sector.

The volatility persistence in all analysed sectors exceeded 1 because their $\alpha + \beta$ coefficient values approached 1. The ARCH and GARCH coefficient results were statistically significant for almost every case thus indicating dynamic volatility patterns in the data. The volatility clustering phenomenon was confirmed by results from both ARCH LM tests and residual diagnostic tests. The GARCH (1,1) model demonstrated better results than GARCH (1,0), GARCH (0,1), and GARCH (0,0) models thus proving its effectiveness for forecasting. The null hypothesis can be rejected at the high significance level. The investigation shows that dynamic volatility mechanisms operate strongly within three sectors namely IT and Banking together with Energy.

Hypothesis 4: Identification of the Most Volatile Sector

- **H0:** All sectors exhibit equal volatility over the study period.

- **H1:** There is a significant difference in volatility levels across sectors, and at least one sector fluctuates more than others.

From GARCH(1,1) Conditional Volatility (σ SD)

Sector	Conditional SD (σ)	Interpretation
IT	**430.45**	Highest volatility
Bank Nifty	412.31	Very high volatility
Energy	309.04	High volatility
FMCG	191.05	Moderate volatility
Auto	116.89	Mild volatility
Infrastructure	31.9	Low volatility
Pharma	**12.57**	Lowest volatility

Interpretation

The null hypothesis is rejected.

The range of conditional SD spans from 12.57 (Pharma) to 430.45 (IT).

The observed sector differences become evident from this data point.

The testing procedure leads to null hypothesis rejection since volatility ranges widely across sectors and the IT segment stands out with high volatility levels.

The research shows sector volatility varies substantially yet the IT sector remains the most volatile sector whereas Pharma keeps the lowest volatility levels. Sector-specific elements together with investor sentiment patterns produce different volatility reactions throughout the market which demonstrates the necessity for specific investment planning.

DISCUSSION

Econometric analysis techniques assess sector volatility in parallel with Foreign Institutional Investor impacts on the Indian stock market performance. A ten-year analysis of secondary data from 2015 to 2024 establishes statistically effective correlations between FII activities and total market performance alongside sector movements. Foreign Institutional Investors demonstrate power to shape both the NIFTY 50 index in addition to influencing key subsea sectors which include Banking and FMCG together with IT. The sectoral return data analysed through GARCH (1,1) volatility model reveals consistent high volatility throughout every business sector. Numbers reveal that the Information Technology sector demonstrates the highest volatility rating compared to other sectors which the pharmaceutical industry exhibits the least volatility. Investigative research helps firms establish crucial information about which sectors FII select and how volatility patterns differ between sectors. This research combines regression methods with GARCH models to provide multiple market insights about foreign investor actions and movement patterns that help academic research and investment planning. The acquired data delivers crucial findings which enable portfolio managers as well as policy creators and retail investors to measure market risks through sector volatility alongside foreign capital activities.

FINDINGS

The research results show that Foreign Institutional Investor activities powerfully affect NIFTY 50 return performance through significant regression test outcomes. Foreign Institutional Investors show sectoral preference in their investments as they have a more powerful influence on the IT sector together with Banking and FMCG. The IT sector showed the maximum variability according to GARCH (1,1) model-based conditional standard deviation analysis. Research findings indicate that Pharma emerged as the most unreactive sector toward Foreign Institutional Investor activity. Research findings prove volatility's unpredictable nature across different periods of time. Sectorial indices need ARCH/GARCH models to correctly track the time-dependent volatility characteristics. Results from model selection criteria showed that GARCH (1,1) produced better performance than both GARCH (1,0) and GARCH (0,1). FIIs structure their investments according to both macroeconomic forecasts and particular sector risk profiles and returns dynamics. The observed persistent volatility in financial time series data is demonstrated by ($\alpha + \beta$) values close to 1 across all sectors.

RECOMMENDATION

The study's findings lead to strategic recommendations that serve different stakeholder groups. Investors need to track FII movements particularly in IT and Banking sectors because volatility data will help them make well-timed investment decisions. Risk management through portfolio diversification needs analytics of sector-specific volatility patterns to be effective in reducing exposure. Policy makers should establish stability planning for sensitive sectors which experience significant FII movement effects during times of financial stress. Financial institutions should bring GARCH-based models within their forecasting tools to achieve improved sectoral risk assessment. When FIIs maintain longer-term investment outlooks the market faces fewer disruptions due to fast-moving capital flows in and out. Strengthening both market regulatory structures and infrastructure enables better control over volatility developments driven by foreign investor activities. During financial turmoil periods retail investors should concentrate their investments on stable sectors including Pharma and FMCG. Financial institutions should develop volatility-index-linked products which provide investors better protection against specific market risks through new innovative products.

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