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Impact of Institutional Investors and Mutual Funds on BSE Volatility

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ABSTRACT: Investing in the stock market is inherently unpredictable, influenced by the trading patterns of various players. This study examines the trading behavior of Foreign Institutional Investors (FIIs), Domestic Institutional Investors (DIIs), and Mutual Funds (MFs) in the Indian stock market from 2007 to 2024. It aims to uncover patterns in their investments and assess their impact on market volatility using advanced econometric techniques, including Vector Autoregression (VAR), Impulse Response Function (IRF), and Variance Decomposition Analysis (VDA). Despite the well-documented behavior of FIIs and DIIs, this study addresses a significant gap in the literature by focusing on the often-overlooked role of MFs as significant institutional players in the Indian market. MFs have their own distinct investment strategies and behavior, which can have a substantial impact on market volatility. By including MFs in the analysis, a more comprehensive understanding of how institutional investors collectively influence market dynamics is provided. The findings reveal distinct patterns in the trading behavior of institutional investors. FIIs tend to chase returns, leading to increased market volatility. In contrast, DIIs and MFs act as stabilizing forces, investing counter-cyclically to support the market during periods of volatility. A Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model quantifies the impact of institutional investments on market volatility, offering a granular understanding of the volatility transmission mechanisms. One significant finding from the same was seen to be the positive impact of MFs on market volatility, reflecting their herding tendencies. This study contributes to the literature by offering a more extensive analysis compared to previous studies that often focus on shorter time periods or individual investors. It also has significant implications for investors, policymakers, and market regulators.

KEYWORDS: Behavioral and Social Sciences, Sociology and Social Psychology, Institutional Investors, Trading Behavior, Market Volatility.

Introduction

Investing in the stock market, regardless of one's country of origin or the scale of investment, is an inherently unpredictable endeavor. To minimize the uncertainty that accompanies any sales or purchases, one must consider various factors that influence the market, such as the performance of certain stocks, as well as the psychology of investors. Therefore, for one to be able to invest in the stock market with little to no risk of loss, one must possess the capability to forecast future market behavior with reasonable accuracy, using both historical data and current events. To minimize risks for buying and selling stocks for investors, one must keep various components of the market under a microscope and make them undergo a thorough analysis. When it comes to performing said analysis, one considers two components of the stock market, that is, volatility and trading behavior. The same are also, in turn, influenced by a myriad of factors, and determine the future of any market. The former, *volatility*, is the measure of unpredictability of a market, and hence how likely it is that the market exhibits unexpected behavior.[1] Naturally, investors would like to minimize volatility, allowing for a more predictable market that ensures high returns. On the other hand, *trading behavior* is the reaction of investors to different events in the stock market, often referred to as investor sentiment.[2] They exist as significant influences in the market that must undoubtedly be taken into account to predict anything about the market.

Recent global financial research increasingly focuses on how institutional trading patterns and large fund movements drive volatility across markets, emphasizing further the need to study their influence in emerging economies such as India. When analyzing the Indian stock market, two primary types of investors are typically considered: retail investors and institutional investors. Retail investors are individual investors who buy and sell securities for their personal accounts, usually dealing in smaller investments. Most retail investors lack access to advanced tools for market analysis and prediction.[3] Conversely, institutional investors are organizations that pool together significantly larger sums of money for investment purposes. Although there are many more retail investors compared to institutional ones, the latter typically engage in large-scale transactions, thereby exerting more substantial influence on the market behavior. Consequently, it is reasonable to assume that institutional investors represent a significant portion of the investments in the Indian stock markets. Institutional investors can be categorized as either foreign or domestic. Domestic institutional investors (DIIs), such as the State Bank of India (SBI) and the Life Insurance Corporation of India (LIC), are among the most prominent Indian institutional investors.[4] Foreign institutional investors (FIIs) are entities based in other countries, such as the UK and Japan, that invest in the Indian market. Mutual funds (MFs), a subgroup of DIIs, hold a particularly prominent position in the Indian market.[4] Mutual funds involve large numbers

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of retail investors pooling their money together, with the fund managers deciding where to invest these collective sums.[5] In the 1990s, following the establishment of the National Stock Exchange (NSE), the Indian market was opened to foreign institutional investors for the first time. This event marked a significant shift in market perception, leading to substantial foreign investment and a positive net investment trend almost every subsequent year.[6]

Institutional investors have the power to influence the volatility and trading behavior of the stock market. For example, coordination and organization among institutional investors would lead to a more stable and predictable market, whereas any panic among such investors would lead to selling and buying stocks in bulk, leading to increased volatility in the market. Similarly, the investment strategies of institutional investors significantly impact trading behavior. Due to the high-value trades being regularly conducted on a scale that can affect the market as a whole, any variation in these trades influences overall investor sentiment and reactions, further shaping market dynamics.[2] Understanding the nature of the relationship between institutional investors and the stock market is essential for comprehensive market analysis.

1.1. Evolution of the Indian Financial Market:

As the Indian stock market boomed in the past decade, it has not only achieved worldwide recognition for its rapid advancement but has also established itself as a highly noteworthy part of the global economy. The Indian market capitalization is ranked among the top 7 in the world, with some of the reasons for its growth being high domestic participation and policy continuity.[3] The first Indian Stock Exchange (and the oldest in all of Asia), the BSE, was founded in Mumbai in 1875,[7] marking the start of India's active participation in the stock market. In 1988, the Securities and Exchange Board of India (SEBI) was founded,[7] soon followed by the liberalization of the Indian economy. The establishment of the National Stock Exchange,[8] currently the leading Exchange in all of India, is another milestone in the history of the Indian market. As the stock market became increasingly popular across India, the market officially became open to Foreign Portfolio investors in 1992.[6] The sudden, but welcome surge of foreign investors in the Indian market led to a positive net investment emerging almost every year (except for the financial crisis years 2007 and 2008, as well as COVID-19 impacted the year 2020) from then forth.[9]

During the Global Financial Crisis (GFC) of 2007-08, after many years of great performance of the Indian market and heavy investing from foreign investors, inflows of approximately US$20 billion in 2007–2008 turned into outflows of US$15 billion from Indian markets during 2008–2009.[10] This resulted in a US$1 trillion decline of the Indian market capitalization. At this time, a 60% index decline in the market was noticed, a definite setback for the Indian market. This event demonstrated the crucial role played by FIIs in the Indian market. But it also demonstrated their unpredictability and the need to protect against a scenario requiring self-dependence of the Indian market, in the event of another such episode in the future. Similarly, as the dangerous and highly contagious disease COVID-19 spread throughout the world in 2020, the world ground to a halt, as everyone was forced to stay in lockdown for an extended time. The same greatly affected stock market performance all over the world. Given India's high population, it was one of the most brutally affected.[11] FIIs engaged in selloffs similar to the previous crisis. A notable fact was that the market turned increasingly volatile, even compared to countries such as the United States. The Indian government's decision to demonetize the Rs. 500 and Rs. 1000 currency notes marks another significant point in the history of the Indian economy. During this period, it was found that while stock market returns were not greatly affected, some of the bigger indices suffered price drops due to the unexpectedness of the action.

At present, the Indian market represents a significantly vast arena, offering a promising opportunity for investors of all levels of experience to make investments. The Indian market volatility is influenced by monetary policies, inflation rates, and investments from foreign countries,[1] where the latter two of the list have recently reached all-time highs. It is also noticeable that the liquidity of the Indian market has substantially increased over the past two decades.[12] This can be explained due to efficient trading systems and strict guidelines set in place by the Securities and Exchange Board of India (SEBI), which has led to more active participation from FIIs and DIIs alike. However, it would be unwise to work under the assumption that the behavior of market investors does not play a role in the same.

Literature Review

2.1. Trading Behavior of Institutional Investors and Stock Market Returns:

The current literature explains the effects of trading behavior (that is, investment patterns of FIIs and DIIs) on market returns, and vice versa. DII investments are found to have a positive impact on market returns, and there is weak evidence of a negative relationship between FII investments and market returns. The literature shows that foreign investors only invest in the market during times of high market returns, whereas the opposite is attributed to DIIs, who tend to buy at low returns and sell at higher returns.[4] Mutual funds in the Indian stock market generally act as passive investors during calm periods but become more active and influential during volatile periods, significantly impacting and being impacted by other investors' trading patterns. Analysis of specific behavior in institutional investors, such as herding, has also yielded results. Herding behavior in FIIs relates positivity to lagged market returns.[13-15]

Factors affecting FII, DII, and MF net investments in the Indian stock market have been well explored in the literature. FII net investment in India is significantly influenced by stock market returns, exchange rates, and inflation, with higher returns, favorable rates, and low inflation causing higher investment. The Index of Industrial Production (IIP) also plays a factor. While investment patterns of institutional investors are highly impacted by stock market returns, returns are also susceptible to changes due to a variety of factors. Media coverage has a significant impact on returns, with the quantity, tone, and quality of news announcements holding significance. Investor sentiment also influences market returns.[2, 16-18] FIIs' behavior as "return-chasers" causes instability in the market, whereas DIIs are responsible for bringing stability to the market. This shift in behavior indicates that mutual funds play a crucial stabilizing role during market turbulence. Political events such as elections can also impact the market. The Indian election of 2019, for example, caused a drastic increase in average returns, similar to the election of 2014.[14, 19-21]

2.2. Institutional Investors and Market Returns Volatility (And Vice Versa):

The existing literature highlights various influential factors affecting market volatility. The dominant role of Foreign Institutional Investors (FIIs) typically overshadows Domestic Institutional Investors (DIIs) in the Indian stock market, a result which is supported by regression analysis of FII and Foreign Direct Investment (FDI) data.[3] Other significant factors include inflation rates, exchange rates, interest rates, and monetary policies. Similar results have been found in the Nairobi stock market, noting inconsistent returns, volatility, and noticeable leverage effects. Investor Behavior is one of the most influential factors. It is seen that FII investment greatly contributes to market volatility. Their relation is found to be positive. The FII investment impact of volatility is further studied, showing significant correlations between FII inflows and NIFTY 50 market returns through Pearson correlation and regression analysis.[22-24] The little-considered factor of mutual funds is also studied, and its net investment is found to positively impact market volatility. The market shows higher sensitivity to negative news, which causes greater volatility than positive news. Additionally, historical volatility has a lasting impact, indicating that past market behaviors affect current conditions. Investors should consider both historical trends and negative news when making investment decisions.[20] DII investment also has a significant relation with market volatility.[4]

Investor sentiment has a significant impact on volatility. It has been shown that market sentiment significantly increases volatility in a market. Similar to the market reaction to news, positive sentiment is seen to have a less significant effect on market volatility compared to negative sentiment.[25,26] Specific trading behavior can also influence volatility. For example, herding exhibited by FIIs and MFs is seen to cause an increase in volatility.

Economic anomalies ranging from student buy and sell-offs from large-scale investors, unexpected domestic as well as foreign events, global crises, etc, greatly affect the stock market. Their specific effects are well explored in the literature. In the context of the Indian market, the 2007-08 Global Economic Crisis caused a dramatic increase in volatility and negatively impacted returns.[27] Parab and Reddy (2020) studied the effect of India's demonetization on FII and DII investments, concluding the impact was insignificant.[28] The COVID-19 pandemic's effects, found using measures of volatility like standard deviation, skewness, and kurtosis of index returns, include negative returns across all sectors except healthcare and increased market volatility during the pandemic compared to the pre-pandemic period.[11]

While international studies on emerging markets highlight shared features such as volatility clustering and the influence of institutional herding, India remains comparatively under-examined in this context.[29] Cross-country work on BRICS economies and on Chinese mutual-fund behavior provides valuable benchmarks, but these findings cannot be directly generalized to India's distinct regulatory structure and mixed dominance of foreign and domestic investors. Global evidence on cross-border institutional flows further underscores how capital mobility amplifies local market shocks, yet Indian studies seldom integrate these transmission channels within a unified volatility framework.[30,31] This gap motivates the present research, which isolates the individual contributions of Foreign Institutional Investors, Domestic Institutional Investors, and Mutual Funds to stock-market volatility in India, offering a context-specific extension to global institutional-behavior literature.

Methodology

3.1. Research Aim and Rationale:

The following are the specific objectives for this research:

1. To understand the relationship between FIIs, DIIs, and MFs' trading behavior and the Indian stock market returns.
2. To understand the response of FIIs, DIIs, and MFs to shocks in market returns and vice versa.
3. To uncover the impact of FII, DII, and MF investments on stock market volatility.

In analyzing the effect of institutional investors on the returns and volatility of the stock market, one can understand and hence make assertions about how fluidly transactions of stocks can be carried out, as well as accurately find a risk factor for investors in the market. FIIs, DIIs, as well as MFs work together to ensure the stability of the market. Being aware of how returns impact investments by FIIs, DIIs, and MFs can help policymakers decrease the chances of panic during market crises. Analyzing volatility helps investors predict periods of high volatility and adjust their investment strategies to prepare for the same. Therefore, the implications of such a study are not only in stock market prediction but also in policy implementation and investor strategizing. Understanding the effect of investor sentiment, especially in times of financial crisis, can also help in predicting market crashes, as well as how to avoid them. This comprehensive understanding allows the discovery of superior investment approaches. That in turn encourages the development of strategies that leverage institutional behaviors to achieve superior market performance.

Moreover, MFs are a highly understudied but impactful part of the stock market. While many study it under the domain of DIIs, they have their own behavior and relationships with the market and its returns. These relationships must be studied separately due to the important role mutual funds play in the context of the Indian financial markets. The time period of 2007-2023 under consideration allows for more variation in data than previous studies. This means that one can study the

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market in times of crisis, including major global and domestic events like the 2007-08 Global Financial Crisis, the demonetization of the Rs. 500 and Rs. 1000 notes in 2016, elections, as well as the COVID-impacted year 2020. In these cases, analysis of how and why investors may change their behavior to minimize losses, allowing for a more complete picture of the market, can be found.

3.2. Research Design:

This study employs a quantitative analysis using secondary data sources to investigate the study objectives. The Bombay Stock Exchange (BSE) is used as a proxy for the Indian Stock Market, with data sourced from Money Control.[32] To capture stock market returns, daily closing prices of the BSE were collected for a period of 17 financial years, from April 2007 to March 2024. Market returns for a given day are calculated by subtracting the closing price of the previous day from the closing price of the current day, divided wholly by the closing price of the previous day. The selected time period provides a comprehensive dataset that enhances the accuracy and reliability of the study's results. This period is particularly significant as it includes several major national and global events, such as the 2007-08 Global Financial Crisis, demonetization of Indian currency notes, and the COVID-19 pandemic. In addition to stock market data, this study includes daily data on Foreign Institutional Investors (FII) and Domestic Institutional Investors (DII), including net investment, sales, and purchases, also sourced from Money Control. Mutual Fund (MF) data, encompassing net investment, sales, and purchases, was obtained from the Securities and Exchange Board of India (SEBI) archives.[33,34] The initial raw data consisted of 4211 daily samples. However, 49 dates were omitted from the BSE and MF datasets to compensate for missing values in the FII and DII data, resulting in a final dataset of 4162 daily samples. For simplicity, shorthand notations are used to denote the different variables in this study. A list is given in *Table 1*.

To properly account for the effects of investor sentiment and the behavioral differences between foreign and domestic investors, we make use of Stationarity and heteroskedasticity tests to ensure that the time series properties of returns are consistent with behavioral patterns such as overreaction and mean reversion. We use models in the order shown in *Figure 1*. The use of the VAR framework, along with Impulse Response Functions (IRF) and Variance Decomposition Analysis (VDA) allow the study to trace how behavioural shocks, often triggered by news, sentiment, or market panic, propagate through time and across variables. Finally, the application of ARCH and GARCH models captures the clustering of volatility that behavioural finance attributes to waves of optimism and fear among investors. In this way, the econometric design translates theoretical ideas about collective behaviour into measurable patterns within the data.

3.3. Model Specification & Hypotheses:

The data considered is in the form of a time series. The Augmented Dicky Fuller (ADF) test was applied to test for the stationarity of the variables. The hypotheses are thus given as:

H_0 = There exists a unit root in the time series.

H_1 = There does not exist a unit root in the time series.

As seen in Table 2, the p-values of all variables except DIIP, MFP, DIIS, and MFS are less than 0.05 at the level. DIIP, MFP, DIIS, and MFS have p-values of 0.9628, 0.8020, 0.9557, and 0.9389, respectively. However, even these variables are seen to be stationary at the logarithmic first difference. Thus, the null hypothesis and the unit root problem can be rejected. All the values considered by the algorithms are taken at logarithmic first difference for consistency. This allows for the null hypothesis to be rejected for all variables. Discussed below are the preliminary diagnostic tests conducted for the analysis related to trading behavior and volatility testing.

Table 1: Variable names and their shorthand, showing the stock market return metric and the net, purchase, and sales variables for FIIs, DIIs, and mutual funds used in the analysis. These shorthand notations are applied consistently throughout the study to simplify regression outputs and diagnostic tables.

Variable	Abbreviation
Bombay Stock Exchange returns	BSER
FII net investment	FIIN
FII purchases	FIIP
FII sales	FIIS
DII net investment	DIIN
DII purchases	DIIP
DII sales	DIIS
MF net investment	MFN
MF purchases	MFP
MF sales	MFS

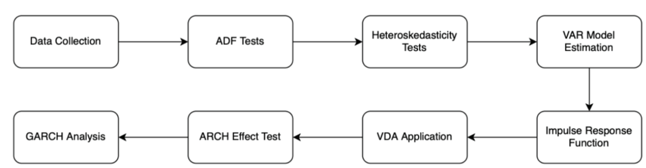

Figure 1: Conceptual Model Diagram, explaining the flow between the various tests and models used throughout the study.

Table 2: Stationarity of selected variables, indicating the level or first difference at which each series becomes stationary based on the Augmented Dickey-Fuller test and its corresponding p-value. The results confirm that all series achieve stationarity, ensuring the validity of VAR and GARCH modeling.

Variable	Stationarity Achieved at	p-value
BSER	At Level	0.0000
FIIN	At Level	0.0000
DIIN	At Level	0.0000
MFN	At Level	0.0000
FIIP	At Level	0.0000
DIIP	At 1st Difference	0.0000
MFP	At 1st Difference	0.0000
FIIS	At Level	0.0000
DIIS	At 1st Difference	0.0000
MFS	At 1st Difference	0.0000

3.3.1. VAR Diagnostics:

In order to perform Vector Autoregression (VAR), the suitable lag orders must first be selected to maximize accuracy. This study employs Sequential modified LR test statistics, Final prediction error, Akaike information criterion, Schwarz information criterion, and Hannan-Quinn information criterion to select the appropriate lag values for the VAR model comprising BSER and net investments. The results are given in *Table 3*. Each criterion agrees on the appropriate lag order being two. The same is true for purchases and sales, as shown in *Tables 4 and 5*, respectively.

Table 3: VAR lag order selection criteria results: net investments, showing the LogL, LR, FPE, AIC, SC, and HQ values for different lags, with asterisks marking the optimal lag based on each criterion. All tests converge on lag order two, which is used in subsequent VAR models for net investment flows.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-91050.97	NA	1.36E+14	43.89249	43.89859	43.89465
1	-89548.52	3001.28	6.62E+13	43.17596	43.20647	43.18675
2	-88919.99	1254.342*	4.93e+13*	42.88069*	42.93562*	42.90012*

Table 4: VAR lag order selection criteria results: purchases, presenting the evaluation metrics across lags to determine the most suitable lag length for the VAR model. A lag length of two is consistently selected, capturing both short- and medium-term dynamics of institutional purchases.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-96977.12	NA	2.36E+15	46.74915	46.75526	46.75131
1	-95514.8	2921.103	1.18E+15	46.05197	46.08248	46.06276
2	-94926.79	1173.466*	8.92e+14*	45.77623*	45.83116*	45.79567*

Table 5: VAR lag order selection criteria results: sales, summarizing the lag selection metrics for the sales variables and indicating the optimal lag with asterisks under each criterion. Again, lag two is identified as optimal, highlighting consistent temporal dependencies across investor sales data.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-97835.49	NA	3.57E+15	47.16292	47.16903	47.16508
1	-96248.9	3169.359	1.67E+15	46.40583	46.43635	46.41663
2	-95595.03	1304.904*	1.23e+15*	46.09835*	46.15328*	46.11778*

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic, FPE: Final prediction error, AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion (each test at 5% level)

3.3.2. GARCH Diagnostics:

3.3.2.1. Presence of ARCH Effect:

The presence of an ARCH effect is a preliminary condition to administer generalized autoregressive conditional heteroskedasticity (GARCH) models.[35] This effect can be tested in two ways: the presence of volatility clustering in the dependent variable and the existence of heavy tails in the histogram of the same. As can be seen in Figures 1 and 2, both of these conditions are being met for the dependent variable in this study, BSER. Volatility clustering occurs when a high level of volatility generally leads to an even higher level of volatility, and low volatility leads to lower volatility. Similarly, 'heavy tails' in a histogram indicate there are more extreme values than would be expected under a normal distribution; this can again be a sign of volatility clustering.

The heteroskedasticity test is also performed on the BSE returns time series for the presence of the ARCH effect. Its results are given in *Table 6*. The p-value for the RESID^2(-1) value is <0.05. Thus, the null hypothesis is rejected, and thus the ARCH effect is present.

3.3.2.2. GARCH Model Selection:

Post the confirmation of the ARCH effect in the BSER time series, the appropriate GARCH model has to be selected in order to test the impact of different variables on the volatility of stock market returns. The most suitable GARCH Model fulfills the following criteria: lowest number of parameters, presence of a significant ARCH or GARCH effect, highest R^2 value, highest log likelihood ratio, lowest SIC, absence of heteroskedasticity, and absence of serial correlation. The five different models that are considered are the Normal Gaussian, Student's t, GED, Student's t with fixed degrees of freedom, and GED with fixed parameters. The results for the same are summarized in *Table 7*. After consideration, it is found that out of the considered range, the Student's t method is the best choice model for the present analysis.

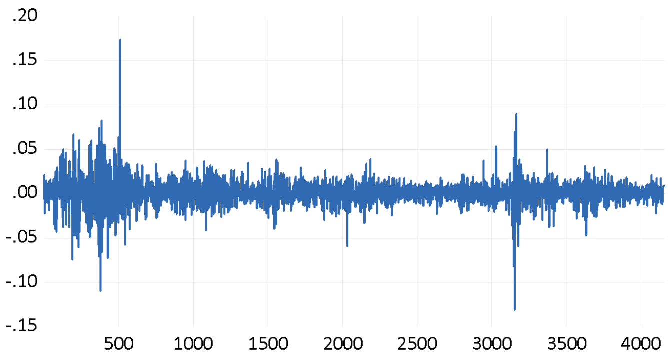

Figure 2: Volatility Clustering in BSE Returns (BSER) Over Time, illustrating periods of heightened fluctuation followed by sustained high volatility, characteristic of financial time series behavior. This pattern confirms that the BSE exhibits volatility clustering similar to other emerging markets, supporting the use of GARCH-type models in subsequent analysis.

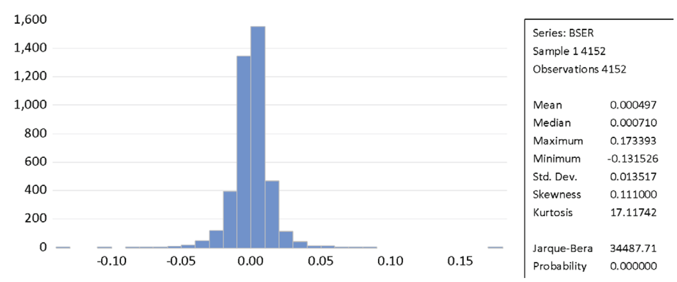

Figure 3: Histogram of BSE daily returns (BSER) distribution, showing the leptokurtic shape with a high peak and fat tails, indicating frequent small changes and occasional extreme movements in returns. This distribution demonstrates that BSE returns are non-normal and heavy-tailed, reinforcing the need for conditional volatility modeling to capture behavior accurately.

Table 6: Heteroskedasticity test results, presenting the ARCH test output with coefficient estimates, significance levels, and model diagnostics. The significant p-value for RESID² confirms the presence of an ARCH effect in BSE returns, justifying the use of GARCH modeling.

Variable	Coefficient	Std. Error	t	p-value
C	0.000156	1.16E-05	13.42985	0.0000
RESID^2(-1)	0.145081	1.54E-02	9.443888	0.0000
R-squared	0.021049	Mean dependent var		0.000182
Adjusted R-squared	0.020813	S.D. dependent var		0.000734
S.E. of regression	0.000726	Akaike info criterion		-11.61745
Sum squared resid	0.002187	Schwarz criterion		-11.6144
Log likelihood	24108.21	Hannan-Quinn criter.		-11.61637
F-statistic	89.18703	Durbin-Watson stat		2.056775
Prob (F-statistic)	0			

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Table 7: Selection of GARCH model, comparing different error distributions and reporting key metrics such as log-likelihood, R^2, and SIC. The Student's t distribution outperforms others, providing the best fit for capturing volatility clustering in the BSE returns.

	Normal Gaussian	Student's t	GED	Student's t with fixed df	GED with fixed parameters
Lowest number of parameters	2	2	2	2	2
Significant ARCH/GARCH effect	YES	YES	YES	YES	YES
Highest R^2	0.00078	0.00051	0.00058	0.00061	0.00060
Highest log likelihood ratio	12,976.56	13,067.92	13,054.64	13,062.86	13,052.16
Lowest SIC	-6.2422	-6.2842	-6.2778	-6.2838	-6.2786
No heteroskedasticity	YES	YES	YES	YES	YES
No serial correlation	YES	YES	YES	YES	YES

3.3.3. Hypotheses of the Study:

Vector Autoregression (VAR), Impulse Response function (IRF), as well as Variance Decomposition Analysis (VDA), are all applied to understand the relation between FII, DII, and MF investment behavior and stock market returns. The three tests serve different purposes:

VAR helps to understand the type of relation between the considered variables. That is to say, whether it is positive or negative. The following are the null hypotheses for the same:

H_1 = There is no significant impact of DII investments on market returns.

H_2 = There is no significant impact of market returns on DII investments.

H_3 = There is no significant impact of MF investments on market returns.

H_4 = There is no significant impact of market returns on MF investments.

H_5 = There is no significant impact of FII investments on market returns.

H_6 = There is no significant impact of market returns on FII investments.

H_7 = There is no significant impact of MF investments and DII investments.

H_8 = There is no significant impact of FII investments and DII investments.

IRF explains the nature of the reaction of a variable to unexpected innovation or shocks in another. The following null hypotheses are considered:

H_9 = There is no significant reaction by market returns to DII innovation.

$H_1 0$ = There is no significant reaction by market returns to FII innovation.

H_{11} = There is no significant reaction by market returns to MF innovation.

H_{12} = There is no significant reaction by DIIs to market returns innovation.

H_{13} = There is no significant reaction by MFs to market returns innovation.

H_{14} = There is no significant reaction by FIIs to market returns innovation.

H_{15} = There is no significant reaction by MFs to DII innovation.

H_{16} = There is no significant reaction by DIIs to MF innovation.

H_{17} = There is no significant reaction by FIIs to DII innovation.

H_{18} = There is no significant reaction by DIIs to FII innovation.

VDA allows one to tell the percentage of the variance of a variable that is attributed to another variable.

The null hypotheses for it are given by:

H_{19} = There is no contribution of FII investment to the forecast error variance of market returns.

H_{20} = There is no contribution of DII investment to the forecast error variance of market returns.

H_{21} = There is no contribution of MF investment to the forecast error variance of market returns.

H_{22} = There is no contribution of market returns to the forecast error variance of FII investment.

H_{23} = There is no contribution of MF investment to the forecast error variance of FII investment.

H_{24} = There is no contribution of DII investment to the forecast error variance of FII investment.

H_{25} = There is no contribution of market returns to the forecast error variance of DII investment.

H_{26} = There is no contribution of MF investment to the forecast error variance of DII investment.

H_{27} = There is no contribution of FII investment to the forecast error variance of FII investment.

H_{28} = There is no contribution of market returns to the forecast error variance of MF investment.

H_{29} = There is no contribution of DII investment to the forecast error variance of MF investment.

H_{30} = There is no contribution of FII investment to the forecast error variance of MF investment.

Finally, GARCH is used to analyze the effect of investments by FIIs, DIIs, and MFs on the volatility of the stock market. The following are the sets of null hypotheses for the same:

H_{31} = There is no significant impact of FII investment on market returns volatility.

H_{32} = There is no significant impact of DII investment on market returns volatility.

H_{33} = There is no significant impact of MF investment on market returns volatility.

Results and Discussion

The data and results from the above-mentioned tests are summarized and interpreted in the context of the Indian institutional investors and financial markets. Thus, the specific interdependence between institutional investors and BSE returns, as well as the impact of their actions, as given by the data sample, is analyzed. The results are divided into two parts: trading behavior and volatility analysis. In the first part, VAR, IRF, and VDA were applied, and their results are given below.

4.1. Vector Autoregression (VAR) Analysis:

VAR is a method to measure the relation between selected variables' lagged values to each of the other variables under consideration.[36] In this case, it allows one to study the impact of past behavior of institutional investors and stock market returns on current market trends, both in the short and long term. Vector autoregression was applied in three models. The first considered the net investments of FIIs, DIIs, and MFs and BSE returns, and the second and third considered BSE returns along with purchases and sales, respectively. *Tables 8, 9, and 10* show the results of the same. In each of the models, the first lag order represents the short term, and the second order represents the long term. A t-value of two is taken as significant.

BSER has a positive relation with its past values. Thus, if the market yields high returns, it would be predicted to yield even higher returns in the future. Over time, however, the relationship in the long term becomes insignificant, and thus, the market loses its memory. FIIN has a positive relation with market returns in the first lag. When market returns are high, foreign investors view it as a sign of a thriving market, prompting them to purchase more and sell less, thereby increasing net investments. Conversely, when market returns are low, FIIs withdraw from the market, cease investing, and sell more to minimize losses. This behavior showcases FIIs as return chasers and emphasizes the need for the Indian market to reduce its reliance on them. In the second lag, FIIN has a negative relation with BSER. DIIN and MFN, however, have a negative relationship with BSE returns in both the first and second lag. When market returns are low, FIIs exit the market, causing instability, and DIIs and MFs step in to invest and stabilize the market, acting as supporters. The opposing relations, the impact of institutional investments on market returns, are insignificant, except for FII investments in the first lag. This shows that FIIs have the only significant impact on market returns, with higher investments leading to higher returns, and the opposite if otherwise. FIIN shows a negative relationship with its lagged values, indicating FIIs' tendency to contrast their investments by frequently changing investment patterns. DII and MF net investment also oppose the first lag FIIN values, but their response to the second lag values is insignificant. DIIs, like FIIs, invest contrary to their previous investments and constantly adapt their strategies. Mutual Funds are positively influenced by the second lag DII investment values. However, DIIs react negatively in the first lag to MF investments. MFN, like FIIs and DIIs, contrasts with its lagged values.

The relation between institutional investor purchases and lagged values of BSER is similar to that of net investments. The results show that BSE returns exhibit a significant positive relationship with their own first lag. Conversely, there is a negative relationship between lagged BSE returns and both DII purchases and MF purchases in the first lag, the reason for which is similar to that of net investments. Additionally, FII purchases have a significant positive relationship with the first lag BSE returns in the first lag. For the FII purchases, the model reveals a significant negative relationship with DII purchases in the first lag, signifying that in times when FIIs purchase more, DIIs tend to do less. Furthermore, past FII purchases exhibit a significant negative correspondence with current purchases, as shown by the significant negative relationship with their own first and second lag. There is also a significant positive relation between previous second lag DII purchases and FII purchases, contradictory to the opposite relation of the first lagged value of FIIP and DIIP. This may be because of differing investment strategies employed by the two types of investors. MFs are shown to purchase similarly to first lag purchases by DIIs. Second lag MF purchases show significant negative relationships with FII purchases in the second lag. This contrasts FIIs' relationship with DIIs, showing that FIIs invest similarly to MFs but not DIIs, emphasizing the importance of considering MFs as an independent type of investor from DIIs.

In the case of investor sales, the opposite is generally true for purchases (with some exceptions). The results show that in the first lag, BSER exhibits a positive relationship with its past values, indicating that in the short term, good returns lead to better returns, and vice versa. However, in the long term, the market tends to lose this memory. In the short term, BSER has a positive relationship with both DIIS and MFS, suggesting that they tend to sell less when the market is in crisis, thereby supporting the market. On the other hand, FII sales are shown not to affect market returns in the short and long term. The model reveals that in the first lag, FIIS has an insignificant relationship with BSER, DII sales, and MF sales. However, in the second lag, FIIS exhibits a significant negative relationship with its past values.

Table 8: VAR model results for net investments and BSE returns representing the relationship between stock market returns and net investment flows of FIIs, DIIs, and mutual funds.

	BSER	D(FIIN)	D(DIIN)	D(MFN)
BSER(-1)	0	11,612	-9,129	-8,573
	[2.01408]	[6.69450]	[-9.32859]	[-8.84430]
BSER(-2)	-0.02	-9,394.86	-3,637.74	-3,564.35
	[-1.29329]	[-5.42600]	[-3.72411]	[-3.68409]
D(FIIN(-1))	0.00	-0.54	-0.03	-0.04
	[2.22249]	[-32.8338]	[-3.26478]	[-4.37046]
D(FIIN(-2))	0.00	-0.30	0.00	0.00
	[1.14203]	[-18.3646]	[0.46725]	[-0.01189]
D(DIIN(-1))	0.00	0.01	-0.46	0.11
	[0.31110]	[0.27999]	[-18.2543]	[4.32761]
D(DIIN(-2))	0.00	0.02	-0.21	0.07
	[-0.14774]	[0.41228]	[-8.21415]	[2.79277]
D(MFN(-1))	0.00	-0.04	-0.12	-0.74
	[0.23614]	[-0.82981]	[-5.06818]	[-30.6954]
D(MFN(-2))	0.00	0.01	-0.04	-0.35
	[-0.01819]	[0.21211]	[-1.80663]	[-14.7781]

Table 9: VAR model results for purchases and BSE returns, showing the short-term interactions between market returns and the purchase-side activities of FIIs, DIIs, and mutual funds.

	BSER	D(FIIP)	D(DIIP)	D(MFP)
BSER(-1)	0	12,321	-4,327	-5,039
	[2.70718]	[2.97152]	[-3.26852]	[-4.04003]
BSER(-2)	-0.0209	-7,999.0570	-1,544.6220	-1,696.5460
	[-1.33112]	[-1.92254]	[-1.16276]	[-1.35565]
D(FIIP(-1))	0.00	-0.67	-0.01	0.00
	[0.83063]	[-41.1054]	[-2.29082]	[-0.38716]
D(FIIP(-2))	0.00	-0.33	-0.01	0.00
	[1.06050]	[-19.9897]	[-1.71356]	[0.27473]
D(DIIP(-1))	0.00	0.17	-0.53	0.06
	[0.85880]	[1.92629]	[-18.9345]	[2.17445]
D(DIIP(-2))	0.00	0.33	-0.22	0.08
	[-0.13565]	[3.73853]	[-7.99047]	[2.91293]
D(MFP(-1))	0.00	-0.03	0.02	-0.57
	[-0.31010]	[-0.27450]	[0.64003]	[-20.9579]
D(MFP(-2))	0.00	-0.23	-0.03	-0.34
	[0.34552]	[-2.48572]	[-1.13971]	[-12.4816]

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Table 10: VAR model results for sales and BSE returns, illustrating how market returns respond to the sales-side activities of institutional investors and mutual funds over two

	BSER	D(FIIS)	D(DIIS)	D(MFS)
BSER(-1)	0	-3,365	5,865	4,873
	[2.59434]	[-0.85439]	[4.88607]	[3.52655]
BSER(-2)	-0.02	-2,293.85	869.54	427.96
	[-1.35714]	[-0.58176]	[0.72353]	[0.30937]
D(FIIS(-1))	0.00	-0.66	-0.01	0.00
	[-0.23599]	[-39.7977]	[-1.87990]	[-0.26424]
D(FIIS(-2))	0.00	-0.31	0.00	0.01
	[0.19328]	[-18.4584]	[-0.04677]	[1.74821]
D(DIIS(-1))	0.00	0.20	-0.52	0.13
	[1.41118]	[2.58128]	[-22.6244]	[4.82804]
D(DIIS(-2))	0.00	0.31	-0.25	0.09
	[0.67385]	[3.99340]	[-10.5572]	[3.22814]
D(MFS(-1))	0.00	-0.01	-0.03	-0.68
	[-0.38914]	[-0.13471]	[-1.62607]	[-30.8273]
D(MFS(-2))	0.00	-0.26	-0.08	-0.39
	[0.22904]	[-4.18759]	[-4.10926]	[-17.8557]

DIIS demonstrates a significant positive relationship with FIIS in the first lag, suggesting that higher DIIS sales correspond with higher FIIS. There is also a significant negative autocorrelation for DIIS sales in the second lag, indicated by a negative relationship with its own past values. In the first and second lag, DII sales show a significant negative relationship with MFS. MFS shows a significant positive relationship with BSER and DII sales in the first lag, showing that increased MFS leads to increases in BSER and DIIS. Additionally, in the second lag, MFS continues to exhibit significant negative relationships with FIIS and with their past values, indicating a negative trend that persists over time. One can thus see that while FIIs purchase only at times of high returns to maximize profit, DIIs support the market by purchasing in times of crisis. Similar results have been uncovered by Bulsara *et al.*, Singh *et al.*, Bose, and Sathish.[13,14,19,37] MFs invest similarly to DIIs, that is to say, in times of low returns (Singh *et al.*).[14] Furthermore, BSE returns seem to be unaffected by investor sales and purchases.

4.2. Impulse Response Function (IRF) Analysis:

IRF was applied to FII, DII, and MF net investments as well as BSE returns. The IRF allows one to investigate the impact of any anomalous events that may occur in a market to gain insights pertaining to how investors react in times of surprises and panic. *Figure 4* shows the results for the same. BSER responds insignificantly to FII, DII, as well as MF anomalies, but not significantly. It can be observed that FIIN has a positive relation with BSER innovation. This means that an unexpected increase in BSER means FIIs would invest more, and the opposite if returns drop. The same is significant only for 5 days. DIIs and MFs both have a negative relationship between net investments and BSER. This is because any anomalously low returns in BSER would mean that DIIs and MFs would immediately step in to support the market. The period of this positive relation is 5 days, the same as that of FIIs' response. Thus, after FIIs begin to reinvest in the market after 5 days,

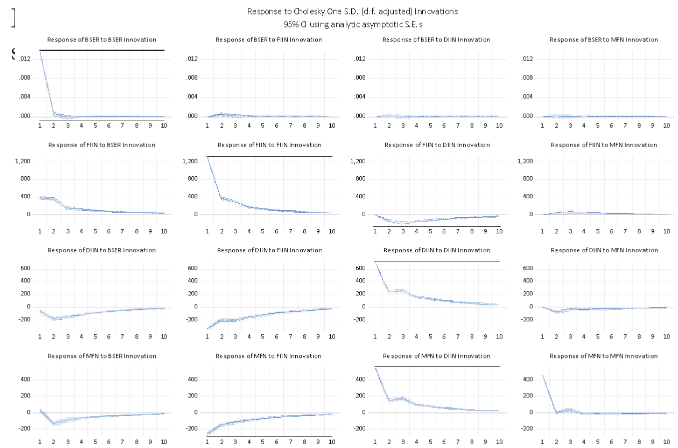

Figure 4: Impulse response function (IRF) results of BSE returns (BSER) and institutional net investments (FIIN, DIIN, MFN). The figures describe the effects of one deviation shock over a ten-period horizon with error bands describing confidence intervals. Shocks to FIIN deliver the largest instantaneous shock to BSER, although the latter dissipates promptly, while shocks from DIIN and MFN deliver smaller though longer–lived effects. Accordingly, shocks from BSER trigger substantial responses from FIIN, reflecting greater interdependence of domestic stock performance with foreign flows as opposed to domestic institutions or mutual funds. This indicates that foreign institutional flows dominate short-term volatility transmission in India's stock market, underscoring the market's sensitivity to external capital movements.

FIIs respond negatively to sudden changes in DIIN, and vice versa. This is because any anomaly in DIIs causing high investment would be when it wants to support the market. During this time, FIIs would typically back out of the market. On the other hand, FIIs respond insignificantly to unexpected investments by MFs; however, the opposite is not true, and MFs respond negatively to FII innovation. MFs respond significantly and positively to any anomalous events in DIIs, following their behavior for 7 days, whereas DIIs do not respond much to MF impulses, as MFs are only a subgroup of DIIs.

4.3. Variance Decomposition Analysis (VDA):

Variance Decomposition Analysis (VDA) tells us the percentage of the variance of a particular variable attributed to all considered variables. It allows us to understand the magnitude of the influence investors have on the market, and vice versa, as well as how much influence they hold on each other's behavior. This algorithm is applied to BSER and net investments. *Tables 11-14* show the results for this. Almost 100% of the variance of BSE returns is attributed to itself, with this number varying negligibly as time goes on. DIIs are responsible for approximately 85% of their variance, with this decreasing to 84% as time goes on. The majority of the rest is attributed to FII investments, which shows that DIIs sometimes do get impacted by FII investments, most likely during times when the FIIs make relatively larger purchases and sales. FIIs are responsible for the majority of their variance. BSER also influences the variance of FII investments, with 6.6% in the first period and 7% in the last. A large part of the variance of MF is attributed to DIIs, as MFs are in themselves a part of DIIs. However, a small portion of MF variance is also attributed to FIIs, thus showing that MFs are indeed responsive to FII investments.

Table 11: Variance decomposition of BSE returns, showing how return variance is driven almost entirely by its own shocks with negligible contributions from institutional flows. This underscores the self-persistent nature of stock market returns compared to external investment flows.

Period	S.E.	BSER	D(FIIN)	D(DIIN)	D(MFN)
1	0.013511	100.000000	0.000000	0.000000	0.000000
2	0.013530	99.893880	0.091908	0.012991	0.001218
3	0.013533	99.880630	0.093284	0.023454	0.002637
4	0.013534	99.867610	0.104928	0.024481	0.002982
5	0.013534	99.865840	0.106628	0.024543	0.002985
6	0.013534	99.865470	0.106712	0.024750	0.003073
7	0.013534	99.865100	0.106985	0.024803	0.003116
8	0.013534	99.865060	0.107020	0.024803	0.003118
9	0.013534	99.865050	0.107023	0.024806	0.003121
10	0.013534	99.865040	0.107030	0.024808	0.003123

Table 12: Variance decomposition of DII net investments, indicating influence from market returns and other flows. DIIs remain largely self-driven, though a small share of their variance is attributed to FIIs, suggesting occasional foreign spillover effects.

Period	S.E.	BSER	D(FIIN)	D(DIIN)	D(MFN)
1	813.6522	0.830550	14.10209	85.06735	0.000000
2	932.2971	1.890496	12.65933	85.02168	0.428494
3	936.2466	1.985754	12.64227	84.64031	0.731663
4	940.5014	1.995106	12.84320	84.43127	0.730425
5	942.5363	2.040919	12.81982	84.37214	0.767128
6	942.8627	2.052413	12.81929	84.33140	0.796896
7	942.9408	2.052079	12.82862	84.32053	0.798778
8	942.9763	2.053668	12.82842	84.31808	0.799835
9	942.9912	2.054357	12.82841	84.31591	0.801319
10	942.9943	2.054361	12.82874	84.31537	0.801528

Table 13: Variance decomposition of FII net investments, showing variance explained by BSE returns and institutional activity. While FIIs are mostly self-determined, BSE returns account for a meaningful share, confirming their return-chasing tendencies.

Period	S.E.	BSER	D(FIIN)	D(DIIN)	D(MFN)
1	1442.247	6.651163	93.348840	0.000000	0.000000
2	1622.390	5.331255	94.651720	0.005108	0.011918
3	1635.994	6.804278	93.107210	0.049832	0.038682
4	1656.712	7.077406	92.791520	0.082662	0.048408
5	1660.950	7.041782	92.825300	0.084694	0.048224
6	1661.310	7.076775	92.786540	0.086648	0.050042
7	1661.860	7.080515	92.778780	0.089262	0.051441
8	1661.969	7.079682	92.779190	0.089575	0.051556
9	1661.978	7.080555	92.778220	0.089622	0.051606
10	1661.993	7.080582	92.777990	0.089736	0.051697

Table 14: Variance decomposition of MF net investments, highlighting contributions from returns and other flows. MFs are influenced significantly by DIIs, consistent with their categorization as a DII subgroup, but also show sensitivity to FIIs in the longer term.

Period	S.E.	BSER	D(FIIN)	D(DIIN)	D(MFN)
1	805.8960	0.189121	8.962347	53.141110	37.707430
2	971.2730	3.002546	7.025309	49.805600	40.166550
3	978.8181	3.136884	7.062497	49.414640	40.385970
4	984.1923	3.206429	7.224040	49.203510	40.366020
5	989.0863	3.315364	7.163686	48.973950	40.547000
6	989.8707	3.333102	7.167487	48.921940	40.577480
7	989.9472	3.333369	7.177833	48.915650	40.573150
8	990.0821	3.337729	7.176157	48.906540	40.579570
9	990.1264	3.338977	7.176339	48.903140	40.581550
10	990.1293	3.338959	7.176829	48.902860	40.581360

4.4. Volatility Analysis:

The GARCH test has been employed to test for the impact of institutional investor investments on the volatility of BSE returns. To apply this test, it is crucial to first verify the presence of the ARCH effect and choose the best possible GARCH model for our analysis, which has been done in Section 3.2. The best model is found to be Student's t. The volatility analysis of the BSER time series, with variables being the net investments, purchases, and sales of the institutional investors, is done. The results are given in *Tables 15-17*.

With net investments of DIIs, FIIs, and MFs as the independent variable, the p-value < 0.05. Thus, the effect on volatility is significant. The effect of FII investments on BSE returns volatility is positive. This shows that higher investments by FIIs in the Indian stock market led to higher volatility and vice versa. There are various possible reasons for this. FIIs often engage in larger buys and sells that significantly impact the market. Herding behavior, when FIIs invest synchronously due to similar investment strategies, also amplifies the effect of their actions. The high sensitivity to market changes, especially due to them not being an intrinsic part of the economy, makes their actions unpredictable, increasing volatility.

On the other hand, the coefficient for DIIN is negative; thus, a higher DII investment is shown to decrease the volatility of the market. This is because they would usually have trust and belief in their home country's market, and would invest accordingly to minimize volatility. They would generally be less affected by anomalies in external markets, and thus their performance would not depend on external factors. They would also be more likely to invest in smaller firms and companies, which would overall stabilize the market. MF investments increase volatility, likely due to factors such as herding, which is shown to increase volatility. DII purchases are shown to decrease volatility for reasons similar to those of net investments. The effect of FII purchases on market volatility is insignificant. This is because the unpredictability of FIIs does not allow them to stabilize the market with their purchases, which leads to their effects being negligible. MF purchases also do not impact volatility, mainly because of their relatively small size. Higher FII and MF sales are shown to decrease volatility in the market. This is because FIIs are known to be return chasers, which causes unpredictability in the market.

Thus, when FIIs sell stocks, they become less active in the market, which causes market volatility to decrease. Moreover, MFs are managed by experienced managers who may tend to avoid large sell-offs that cause market disruption. On the other hand, higher DII sales are seen to increase volatility. DIIs often invest in smaller stocks compared to FIIs. Thus, sell-offs by DIIs can lead to major price drops and thus increased volatility.

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Table 15: Student's t GARCH model for net investments, showing the impact of FII, DII, and MF net flows on BSE return volatility. The model reveals that FIIs and MFs increase volatility through herding, while DIIs exert a stabilizing effect.

Variable	Coefficient	Std. Error	z-Statistic	p-value
D(FIIN)	0.00000147	0.00000008	19.49884000	0.0000
D(DIIN)	-0.00000089	0.00000020	-4.39703900	0.0000
D(MFN)	0.00000158	0.00000018	8.89761000	0.0000
Variance Equation				
C	0.00000150	0.00000036	4.1739	0.0000
RESID(-1)^2	0.07386900	0.00835500	8.8414	0.0000
GARCH(-1)	0.91542000	0.00896600	102.0963	0.0000

Table 16: Student's t GARCH model for purchases, presenting the effect of institutional purchase activity on return volatility. The results indicate that DII purchases reduce volatility, while FII and MF purchases have no significant impact.

Variable	Coefficient	Std. Error	z-Statistic	p-value
D(FIIP)	0.00000004	0.00000003	1.20959800	0.2264
D(DIIP)	-0.00000041	0.00000015	-2.67517400	0.0075
D(MFP)	0.00000014	0.00000017	0.85898200	0.3904
Variance Equation				
C	0.00000141	0.00000036	3.96769000	0.0001
RESID(-1)^2	0.07348100	0.00828700	8.86667100	0.0000
GARCH(-1)	0.91735700	0.00872800	105.10290000	0.0000

Table 17: Student's t GARCH model for sales, highlighting how institutional sales influence volatility. FII and MF sales reduce volatility, while DII sales amplify it, reflecting different roles of institutional investor categories in shaping market stability.

Variable	Coefficient	Std. Error	z-Statistic	p-value
D(FIIS)	-0.00000015	0.00000003	-4.44058600	0.0000
D(DIIS)	0.00000061	0.00000013	4.73253700	0.0000
D(MFS)	-0.00000041	0.00000011	-3.81529200	0.0001
Variance Equation				
C	0.00000140	0.00000035	3.97937100	0.0001
RESID(-1)^2	0.07380900	0.00833800	8.85193900	0.0000
GARCH(-1)	0.91707700	0.00875800	104.71620000	0.0000

Conclusion

The objective of this study was to examine the relationship between institutional investors—namely FIIs, DIIs, and MFs-and their impact on the volatility and returns of the Indian stock market. The primary findings underscore the significant role institutional investors play in influencing market dynamics. FIIs notably affect BSE returns, as they tend to increase their investments when market returns are high, thereby driving the market upward, and withdraw their investments when returns are low, exacerbating market instability. This pattern is also observed in response to shocks in market returns, where FIIs invest more during periods of unusually high returns. Conversely, domestic investors and mutual funds serve as stabilizing forces, intervening to invest during market downturns and providing support when returns are low, a behavior similarly observed during anomalous events. Moreover, while both mutual funds and foreign investors contribute to market volatility, DIIs do not exhibit the same effect. The stark contrast between MFs and DIIs can be attributed to the distinctive behaviors of mutual funds compared to other DIIs, including factors such as herding tendencies.

The implications of these findings are multifaceted, impacting policymakers, market regulators, institutional investors, and individual investors. For policymakers and regulators, understanding the contrasting effects of different types of institutional investors can aid in creating policies that balance market growth with stability. Enhanced surveillance systems to track the investment patterns of institutional investors can help in early identification of potential market disruptions, particularly those caused by FIIs. Adjustments to existing regulations may be necessary to ensure that the activities of FIIs do not lead to disproportionate market swings, such as imposing transaction limits or introducing cooling-off periods. For institutional investors, particularly DIIs and MFs, leveraging their stabilizing role can attract more investments by promoting themselves as safe and reliable options during market downturns, while FIIs can adopt more sophisticated risk management practices to minimize their adverse market impact. Individual investors can benefit from understanding the behavior of institutional investors, making more informed decisions about fund allocation, particularly in volatile market conditions, and adjusting their portfolios accordingly. The stabilizing presence of DIIs and MFs can enhance market liquidity, making it easier for investors to buy and sell securities without causing significant price changes, contributing to a more efficient market where prices reflect true value. During financial crises, the stabilizing influence of DIIs and MFs can prevent market free-falls, ensuring a more orderly correction rather than a chaotic downturn, maintaining investor confidence, and reducing panic selling. Overall, these insights can lead to more resilient and robust financial markets, fostering a more stable and predictable investment environment and contributing to the overall health of the financial system.

Although this study focuses on the Indian stock market, the methods and findings are relevant to other emerging economies with similar market structures and behaviors. The combination of VAR, IRF, VDA, and GARCH models offers a strong way to track the transmission of shocks, measure how long volatility lasts, and capture fluctuations driven by investor sentiment. Many emerging markets have traits like high retail participation, uneven access to information, and sensitivity to economic events. These factors often intensify behavioral effects like herding and overreaction. Using this framework in markets like Brazil, Indonesia, or South Africa could help policymakers and analysts understand how local and global shocks affect investor behavior. This understanding could improve risk management and financial stability strategies in similar contexts.

Despite the comprehensive analysis, this study has limitations. The reliance on historical data may not fully capture the dynamic nature of market behavior. Additionally, the study focuses on net investments, purchases, and sales, which might overlook other factors influencing market returns and volatility, such as macroeconomic variables and geopolitical events. Future research can expand on this study by incorporating a broader set of variables, including macroeconomic indicators and sentiment analysis from news and social media. Additionally, examining the behavior of retail investors alongside institutional investors could provide a more holistic view of market dynamics.

In conclusion, this research highlights the critical role of institutional investors in shaping the Indian stock market's volatility and returns. By addressing the limitations and exploring new avenues for research, a deeper understanding of market dynamics can be achieved, ultimately contributing to more informed investment and policy decisions.

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