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Research paper

Modelling Volatility in The Indian Stock Market: A GARCH-Based Analysis of Mutual Funds and Stocks

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Abstract

This study investigates the volatility dynamics of equity and debt mutual funds using advanced econometric techniques, specifically GARCH, EGARCH, and MGARCH models. By analysing daily returns of nifty fifty index and selected mutual funds comprising both debt and equity, the research aims to uncover patterns of volatility persistence, sensitivity to market shocks, and the distinct behaviors exhibited by different fund types. The findings reveal that both equity and debt funds display significant, though moderate, volatility clustering, as indicated by a consistent GARCH term across models. The arch term catches the short-term shocks that have a consistent effect on all funds, highlighting the pervasive effect of sudden market events. Notably, equity funds demonstrate a quicker stabilization following shocks, reflecting their adaptive nature, while debt funds exhibit prolonged volatility responses, underscoring their sensitivity to macroeconomic conditions. The MGARCH analysis further distinguishes the volatility profiles within the debt segment, showing that not all debt instruments react similarly to market disturbances. Portfolio managers and investors can use these results as equity funds may be better suited for dynamic investment strategies and higher risk tolerance, whereas debt funds require more conservative management and careful monitoring of external economic factors. The study also discusses the practical challenges and limitations of applying GARCH-family models, such as data constraints, model assumptions, and the omission of exogenous variables. Despite these limitations, the research provides a robust framework for understanding and managing mutual fund volatility, offering actionable insights for optimizing asset allocation, enhancing risk management, and improving investor communication. Future research is encouraged to incorporate broader datasets, alternative modelling approaches, and additional market factors to further refine volatility forecasting and portfolio strategy.

Keywords: *Volatility; Mutual Funds; EGARCH; MGARCH; Nifty Fifty Index.*

1. Introduction

The Indian stock market has developed as an important and robust segment of the country's financial system because of participation from national as well as international investors over the years (Saxena & Sikdar, 2024). It directs institutional and household savings into productive investments and acts as an important indicator of economic growth, which widens its scope from merely trading (Kaur & Vagrecha, 2023). Alongside this growth, mutual funds have become popular among investors, mainly because of their ability to offer diversification, professional management, and accessibility to a broad base of participants.

Volatility is an important concept in the financial market, which can be described as the degree of price fluctuations in financial assets over a period of time. Volatility is particularly important for investors because it directly impacts both the potential risks and returns associated with their investments (Aggarwal et al., 2020). Because of this, it is important to understand the pattern and reasons for volatility in both the stock market and mutual funds. Investors, financial institutions, and policymakers need to develop effective investment strategies, manage risk, and formulate sound market regulations (Srivastava & Varshney, 2022).

Stock market volatility captures the rapid and unpredictable changes in share prices, which can be triggered by a lot of factors such as macroeconomic indicators, corporate earnings announcements, shifts in interest rates, geopolitical developments, and prevailing investor sentiment (Naik et al., 2021). By closely monitoring volatility, investors can better understand market sentiment, evaluate risk exposure, and make more informed decisions regarding their investment portfolios (Qureshi et al., 2020).

Mutual fund volatility shows the changes in the net asset value (NAV) of mutual fund units over time. These fluctuations are because of many factors, including movements in the prices of the fund’s underlying assets, shifts in interest rates, the strategies employed by fund managers, and overall market trends (Totgi, 2022). Keeping a watch on mutual fund volatility is important for investors as it highlights the

risks associated with different fund categories and helps them to choose investments that match their personal risk tolerance and financial objectives (Aggarwal et al., 2020).
This research sets out to fill an important gap by closely examining both stock market volatility and mutual fund volatility in India. By analyzing what drives these fluctuations and how they behave, the study aims to offer deeper insights into the risks and opportunities these investment options present. The findings are intended to be useful not just for individual investors, but also for financial institutions and policymakers who are shaping strategies and regulations in India's fast-changing financial landscape (Srivastava & Varshney, 2022).

2. Literature Review

Various studies in distinct markets have examined institutional investments and stock markets. Saxena and Sikdar (2024) show with data that domestic institutional investors (DIIs) in India are more prone to cyclic fluctuations through increasing investment during periods of low volatility and reducing exposure during periods of uncertainty. Further, DIIs and the market influence each other mutually. Using a similar methodology, Kaur and Vagrecha (2023) find that the equity mutual fund flows in India are caused by stock returns. The output market volatility is greatly affected. According to Totgi (2022), the mutual fund movement attracts stock market activity, which leads to the necessity of regulatory measures to reduce volatility. Srivastava and Varshney (2022) comment that in volatile conditions, the institutional investors behave with caution, but on occasion, they purposely place an order anticipating a price movement in the future. In the study, Naik et al. (2021) assessed the trading pattern after the onset of the pandemic. The authors find that foreign portfolio investors (FPIs) contribute to volatility through their selling of equity assets. On the other hand, mutual funds do not impact volatility significantly. According to Aggarwal et al. (2020), institutional investment experiences a volatility spillover effect on the Indian VIX, indicating that institutional investments are responsible for making the market volatile. Institutional investors have a significant influence not only in India. Srivastava & Varshney (2020) have investigated the impact of DIIs on Nifty 50 and recommend regulatory interventions in order to limit the domination of foreign traders. Qureshi et al. (2020) examine the BRICS economies, which confirm that equity funds lead macroeconomic indicators for some countries while lagging behind others, underlining the importance of diversification benefits. Alsubaiei et al. (2020) also proved that oil volatility affects equity fund adjustments in Saudi Arabia, particularly oil-exposed funds. Babalos et al. (2019) document one-directional causality from stock returns to fund flows in U.S.A which is consistent with feedback trading, whereas Qureshi et al.(2019) provide evidence that mutual funds predict economic conditions in BRICS as they invest more into riskier asset classes during positive developments in their respective nations' business cycles. Ndei et al. (2019) confirmed unidirectional causality between fund flows and returns in Kenya, with purchases boosting returns and sales depressing them. Similarly, Lee, Lee & Choe(2015), in their study of US markets, posit that contemporaneous effects are more important than historical ones when it comes to market volatility, returns, and equity mutual fund flows; with Westerners being more sensitive toward volatilities as compared to Asians. Similarly, Naik and Padhi (2015) observed in India that domestic institutional investors (DIIs) significantly impact market returns, while foreign institutional investors (FIIs) do not, highlighting a feedback relationship between institutional flows and returns. In Turkey, Aydoğan et al. (2014) identified bidirectional causality between mutual fund flows and stock returns using cointegration tests, suggesting mutual influence in emerging markets. Meanwhile, Kim et al. (2014) demonstrated herding behavior in Korea, where individual investors mimic institutional investors, exhibiting pro-cyclical tendencies. In China, Ko et al. (2014) revealed that mutual fund inflows respond more strongly to market returns than outflows, while Frijns et al. (2014) showed institutional trading exerts significant price pressure, particularly in bullish markets. Studies in OECD countries by Thomas et al. (2014) further indicated that pension fund investments reduce stock market volatility, emphasizing the stabilizing role of institutional investors. Collectively, these findings underscore the complexity of fund flow-market return interactions, shaped by regional, institutional, and behavioral factors.
Collectively, the literature underscores that the interaction between mutual funds, institutional flows, and market volatility is non-linear, regime-dependent, and susceptible to behavioral feedback. However, existing studies rely heavily on traditional GARCH-family models, which, while useful, are often limited in capturing asymmetries, structural changes, and latent investor behavior. Few incorporate machine learning approaches, high-frequency datasets, or multi-agent simulations, which are crucial for understanding volatility under stress or contagion scenarios. There is also a conspicuous gap in examining sector-specific spillovers, dynamic correlations among asset classes, and the role of market microstructure.
In sum, while the recent literature has expanded the scope of inquiry, it remains fragmented across methodologies and regional contexts. A more coherent analytical framework—combining econometric rigor with behavioral finance, regulatory insights, and real-time market data—is urgently needed to fully understand and anticipate volatility in India's evolving investment landscape.
Synthesis of Literature Review

Theme	Key Findings	Critical Gaps	Representative Studies
Institutional Behavior	DIIs are procyclical; FPIs act as volatility amplifiers.	Limited modeling of fund-type heterogeneity and behavioral dynamics.	Saxena & Sikdar (2024); Srivastava & Varshney (2022); Naik et al. (2022)
Fund Flows & Market Returns	Equity mutual funds follow return-chasing patterns, reinforcing volatility.	Insufficient analysis of bidirectional causality and feedback effects.	Kaur & Vagrecha (2023); Totgi (2022); Babalos et al. (2019)
Crisis Period Dynamics	During COVID-19, FPIs experienced intensified volatility while mutual funds appeared passive.	Lack of intra-crisis behavioral segmentation and real-time data usage.	Naik et al. (2022); Malhotra & Sinha (2024)
Spillover Effects	Institutional flows significantly influence volatility indices like India VIX.	Sectoral spillovers and dynamic interdependencies remain underexplored.	Aggarwal et al. (2020); Qureshi et al. (2020)
Cross-Country Insights	Market behavior of mutual funds varies widely across emerging and developed markets.	Contextual dependencies are often ignored in global comparative analyses.	Qureshi et al. (2020); Alsubaiei et al. (2020); Kim et al. (2014)
Methodological Gaps	Most studies rely on GARCH-family models for volatility modeling.	Limited application of machine learning, regime-switching, or intraday data.	Frijns et al. (2014); Lee et al. (2015); Dhanya (2025)

3. Rationale for The Study

This study investigates how mutual fund returns, stock returns, and market volatility interact in India, focusing on the dynamic and asymmetric relationships that play out over time. Although existing literature has shown that mutual fund flows and stock returns can influence each other, most studies rely on straightforward, linear models or use data that doesn't capture the day-to-day shifts and surprises of the market, especially when things get volatile. By analysing deeper into these connections and using more advanced methods, this research aims to provide the simple, real-time ways mutual fund returns can both shape and be shaped by the ups and downs of India's stock market, offering a more complete picture of how these forces work together in an emerging economy.

By applying advanced econometric techniques including ADF (stationarity), ARCH-LM (heteroscedasticity), and GARCH-family models (GARCH, EGARCH, MGARCH), this studies ideal for analysing volatility clustering and asymmetric shocks—key features of India's stock market. EGARCH captures leverage effects, while MGARCH assesses spillovers between variables, offering a holistic view of market dynamics. The findings will boost the understanding of how mutual fund returns are affected by the Nifty 50 index, with implications for investors, regulators, and policymakers aiming to mitigate instability. By leveraging high-frequency data and nonlinear modelling, this study provides deeper insights into India's financial markets, contributing to both academic literature and practical decision-making.

4. Research Methodology

This study adopts a robust quantitative approach to examine the volatility patterns of the Indian stock market and selected mutual funds over sixteen years, from April 2007 to March 2023. The study focuses on the NIFTY 50 index, which is chosen for its prominence among institutional investors and its broad representation of the Indian equity market, and a carefully organised sample of 20 mutual fund schemes. These include 10 equity growth funds and 10 debt funds (medium to long term), each selected for their high net asset values and a minimum operational history of 15 years, ensuring the inclusion of mature and representative funds.

4.1. Data collection and presentation

Daily closing prices for the NIFTY 50 index were sourced from the NSE website due to its established role as a benchmark for market performance. Mutual fund NAVs were obtained from the AMFI website, ensuring data reliability and consistency. To prepare the data for econometric analysis, all daily closing prices and NAVs were transformed into continuously compounded returns using the natural logarithm of the ratio of consecutive prices:

This transformation standardizes the return series, making them suitable for volatility modelling and facilitating meaningful comparisons across different instruments.

The first step in the analysis involved testing for stationarity using the Augmented Dickey-Fuller (ADF) test, ensuring that all return series were suitable for further time series modelling. Next, the presence of conditional heteroscedasticity—a hallmark of financial return series—was assessed using the ARCH-LM test.

This study uses various GARCH family models to interpret the characteristics of volatility. The standard GARCH (1,1) model was used for capturing volatility clustering and continuity in the return series. The EGARCH (Exponential GARCH) model was then used to capture asymmetric volatility because negative and positive shocks have different volatility impacts in financial markets. The MGARCH (Multivariate GARCH) model was used for a more exhaustive view of co-movements and volatility spillovers between the NIFTY 50 and mutual fund returns. Both the magnitude and direction of volatility in the Indian market are deeply understood by the use of this series of models, which provide valuable insights for investors, fund managers, and policymakers interested in risk management and market dynamics

4.2. Data analysis

This section deals with data analysis and a detailed discussion of the empirical results.

Table 1: Descriptive Statistics of Daily Log Returns

Return Series	Mean	Std. Dev.	Maximum	Minimum	Skewness	Kurtosis	Jarque-Bera
Nifty-50_AdCP	0.037258	1.388731	16.33432	-13.9038	-0.27916	13.97406	30144.7
ABSL-FEF_EF_LC	0.047452	1.239893	7.983136	-13.8516	-0.77109	10.37942	16970.82
SBI-BCF_EF_LC	0.043528	1.241397	14.15293	-13.791	-0.47729	13.70972	29109.22
HDFC-THF_EF_LC	0.047204	1.324928	14.33312	-12.8853	-0.3533	9.806067	14897.45
NI-LC_EF_LC	0.045912	1.332908	6.866895	-13.8798	-0.77176	8.877249	12513.1
UTI-MSF_EF_LC	0.042994	1.184933	7.662326	-13.0504	-0.71515	9.445766	14066.72
FI-BCF_EF_LC	0.041608	1.228678	8.058438	-12.0791	-0.55009	8.281057	10755.81
Kotak-BCF_EF_LC	0.042553	1.237376	7.643999	-13.9505	-0.76548	10.26041	16586.91
DSP-THEF_EF_LC	0.039485	1.255647	8.801947	-15.5168	-0.90545	12.38275	24137.79
Tata-LCF_EF_LC	0.04168	1.229893	8.128156	-14.468	-0.85295	11.77526	21818.98
Kotak-BF_DF_MLT	0.030479	0.248226	2.377625	-3.27984	-0.49431	24.08838	89581.71
SBI-MIF_DF_MLT	0.028113	0.211203	2.278673	-3.98493	-1.93364	55.81429	482440.7
ABSL-IF_DF_MLT	0.03126	0.274095	3.158017	-4.78283	-0.93045	44.11342	300460.1
IDFC-BFIP_DF_MLT	0.030477	0.256774	2.13211	-4.14271	-0.8003	32.2874	161066.5
HDFC-IF_DF_MLT	0.02761	0.24234	2.249133	-3.7224	-1.41431	37.58517	218957.1
UTI-BF_DF_MLT	0.026688	0.307846	7.824935	-5.08593	1.439654	179.3789	4960528
NI-IF_DF_MLT	0.030148	0.248582	2.036602	-4.10244	-1.27112	35.3464	193554.9
CR-IF_DF_MLT	0.033141	0.189999	2.435004	-1.53507	0.94421	24.18537	90702.32
LICMF-BF_DF_MLT	0.027828	0.203428	2.957398	-3.01133	-0.24789	56.5918	493643.4
Tata-IF_DF_MLT	0.025864	0.197833	2.196977	-3.39792	-1.55753	44.76916	310404.9
HSBC-DF_DF_MLT	0.027268	0.225044	1.886519	-3.8481	-1.67562	41.13349	262504.9
JM-MLDF_DF_MLT	0.015032	0.245061	2.018122	-10.1295	-19.9605	804.8119	100075819.2

Notes: Daily log returns are computed as the first difference of the natural logarithm of prices and NAVs and are expressed in percentage terms.

Table 1 presents the descriptive statistics for daily log returns of the NIFTY-50 index and the selected equity and debt mutual fund schemes. The mean returns are positive but small in magnitude, reflecting modest average daily performance over the sample period. In contrast, standard deviations indicate considerable variability in returns, particularly for equity-oriented funds, highlighting the presence of substantial market-related risk.

Most return series exhibit negative skewness, suggesting that extreme negative returns occur more frequently than extreme positive returns. Kurtosis values exceed the normal benchmark, indicating leptokurtic distributions with fat tails. Consistent with these distributional characteristics, the Jarque–Bera statistics strongly reject the null hypothesis of normality for all series.

Overall, the descriptive statistics reveal non-normal and heteroskedastic return behavior, providing strong motivation for the use of ARCH- and GARCH-type models to capture time-varying volatility in subsequent analysis.

Table 2: ADF Unit Root Test

Time series	Transformation	ADSF unit root t-statistics	P value	Remark
Log_ NIFTY-50_ADCP	At level	-3.06	0.115	Non-Stationary
	At first difference	-58.09	0.000	Stationary
Log_ABSL-FEF_EF_LC	At level	-2.81	0.192	Non-Stationary
	At first difference	-56.18	0.000	Stationary
Log_SBI-BCF_EF_LC	At level	-2.85	0.177	Non-Stationary
	At first difference	-56.10	0.000	Stationary
Log_HDFC-THF_EF_LC	At level	-2.84	0.182	Non-Stationary
	At first difference	-57.59	0.000	Stationary
Log_NI-LC_EF_LC	At level	-2.88	0.167	Non-Stationary
	At first difference	-57.39	0.000	Stationary
Log_UTI-MSF_EF_LC	At level	-2.89	0.165	Non-Stationary
	At first difference	-56.61	0.000	Stationary
Log_FI-BCF_EF_LC	At level	-2.85	0.177	Non-Stationary
	At first difference	-56.99	0.000	Stationary
Log_Kotak-BCF_EF_LC	At level	-2.90	0.162	Non-Stationary
	At first difference	-56.93	0.000	Stationary
Log_DSP-THEF_EF_LC	At level	-3.20	0.083	Non-Stationary
	At first difference	-57.63	0.000	Stationary
Log_Tata-LCF_EF_LC	At level	-2.93	0.151	Non-Stationary
	At first difference	-56.44	0.000	Stationary
Log_Kotak-BF_DF_MLT	At level	-2.55	0.299	Non-Stationary
	At first difference	-50.38	0.000	Stationary
Log_SBI-MIF_DF_MLT	At level	-2.92	0.153	Non-Stationary
	At first difference	-18.91	0.000	Stationary
Log_ABSL-IF_DF_MLT	At level	-3.34	0.058	Non-Stationary
	At first difference	-49.44	0.000	Stationary
Log_IDFC-BFIP_DF_MLT	At level	-2.55	0.302	Non-Stationary
	At first difference	-17.35	0.000	Stationary
Log_HDFC-IF_DF_MLT	At level	-2.07	0.556	Non-Stationary
	At first difference	-49.54	0.000	Stationary
Log_UTI-BF_DF_MLT	At level	-1.49	0.833	Non-Stationary
	At first difference	-53.81	0.000	Stationary
Log_NI-IF_DF_MLT	At level	-3.22	0.080	Non-Stationary
	At first difference	-16.86	0.000	Stationary
Log_CR-IF_DF_MLT	At level	-1.96	0.619	Non-Stationary
	At first difference	-52.93	0.000	Stationary
Log_LICMF-BF_DF_MLT	At level	-1.62	0.785	Non-Stationary
	At first difference	-43.83	0.000	Stationary
Log_Tata-IF_DF_MLT	At level	-1.84	0.681	Non-Stationary
	At first difference	-51.95	0.000	Stationary
Log_HSBC-DF_DF_MLT	At level	-2.25	0.455	Non-Stationary
	At first difference	-18.05	0.000	Stationary
Log_JM-MLDF_DF_MLT	At level	-1.45	0.844	Non-Stationary
	At first difference	-59.34	0.000	Stationary

Table 2 presents the result of the Augmented Dickey-Fuller (ADF) unit root test to nifty 50 index and various mutual fund series, at both the level and after the first difference. When examining the original log price series, the results show that these series are non-stationary means their mean and variance change over a period of time. This can be observed as most of the p-values are greater than 0.05, hence the null hypothesis of non-stationarity cannot be rejected at the level of significance. The t-statistics for the level form are generally too small to reject the null hypothesis. As in Table 3, Log_NIFTY-50_ADCP has a t-statistic of -3.06 with a p-value of 0.115 and thus is not stationary. This type of non-stationarity is a typical feature of financial markets, where asset prices often trend rather than stay around a constant mean. After converting the data into log returns by taking the first difference, there is a significant change in the results. The ADF test statistics for all return series become highly significant with all p-values as zero, clearly indicating the stationarity of these series at first difference. It means that their statistical properties are stable over time, which is a crucial requirement for time series modelling and volatility analysis.

These results align with well-known financial econometric research, which finds that asset prices aren't stationary, but returns are. This backs up the method of turning daily closing prices and NAVs into log returns before using advanced volatility models. This approach makes sure the study's analysis is strong and trustworthy.

Table 3: ARCH-LM Test Results for Daily Log Returns

Return Series	ARCH-LM Statistic (5 lags)	p-value	Inference
NIFTY-50	372.39	0.000***	Significant volatility clustering exists
ABSL-FEF (Equity)	470.66	0.000***	Significant volatility clustering exists
SBI-BCF (Equity)	292.15	0.000***	Significant volatility clustering exists
HDFC-THF (Equity)	289.85	0.000***	Significant volatility clustering exists
NI-LC (Equity)	477.16	0.000***	Significant volatility clustering exists
UTI-MSF (Equity)	546.71	0.000***	Significant volatility clustering exists
FI-BCF (Equity)	531.58	0.000***	Significant volatility clustering exists
Kotak-BCF (Equity)	539.61	0.000***	Significant volatility clustering exists
DSP-THEF (Equity)	471.2	0.000***	Significant volatility clustering exists
Tata-LCF (Equity)	553.62	0.000***	Significant volatility clustering exists
Kotak-BF (Debt)	355.29	0.000***	Significant volatility clustering exists
SBI-MIF (Debt)	329.02	0.000***	Significant volatility clustering exists
ABSL-IF (Debt)	251.15	0.000***	Significant volatility clustering exists
IDFC-BFIP (Debt)	545.34	0.000***	Significant volatility clustering exists
HDFC-IF (Debt)	219.22	0.000***	Significant volatility clustering exists
UTI-BF (Debt)	15.93	0.007***	Significant volatility clustering exists.
NI-IF (Debt)	217.88	0.000***	Significant volatility clustering exists
CR-IF (Debt)	289.4	0.000***	Significant volatility clustering exists
LICMF-BF (Debt)	167.07	0.000***	Significant volatility clustering exists
Tata-IF (Debt)	190.75	0.000***	Significant volatility clustering exists
HSBC-DF (Debt)	285.68	0.000***	Significant volatility clustering exists
JM-MLDF (Debt)	0.03	0.999	No significant volatility clustering detected

SOURCE: Authors' computations based on daily NIFTY-50 index prices obtained from the National Stock Exchange of India (NSE) and mutual fund NAV data sourced from the Association of Mutual Funds in India (AMFI)

Notes: Daily log returns are computed as the first difference of the natural logarithm of prices and NAVs. The ARCH-LM test examines the null hypothesis of no ARCH effects (homoskedasticity). The LM statistic is reported with a lag length of five trading days. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3 reports the ARCH-LM test results for daily log returns of the NIFTY-50 index and the selected mutual fund schemes. The null hypothesis of homoskedasticity is rejected for the majority of return series, indicating the presence of statistically significant volatility clustering. This finding suggests that return variances are time-varying and exhibit serial dependence, a characteristic commonly observed in financial markets.

An exception is observed for the JM-MLDF scheme, for which the ARCH-LM test fails to reject the null hypothesis, indicating relatively stable variance dynamics. Overall, the ARCH-LM results provide strong empirical justification for employing GARCH-type models to capture conditional heteroskedasticity in the return series.

Table4: GARCH (1, 1) Estimates for Daily Log Returns of NIFTY-50 and Mutual Fund Schemes

Return series	Constant	GARCH term (β)	ARCH term (α)
_Nifty-50_AdCP	0.075580 (4.795***)	0.898 (34.115***)	0.098 (3.669***)
_ABSL-FEF_EF_LC	0.078251 (0.626)	0.884 (85.669***)	0.103 (8.941***)
SBI-BCF_EF_LC	0.076738 (0.156)	0.886 (77.218***)	0.106 (6.909***)
HDFC-THF_EF_LC	0.071921 (4.318***)	0.900 (142.080***)	0.085 (11.254***)
NI-LC_EF_LC	0.083386 (4.830***)	0.893 (86.663***)	0.094 (10.235***)
UTI-MSF_EF_LC	0.077761 (0.219)	0.876 (25.290***)	0.111 (2.784***)
FI-BCF_EF_LC	0.065627 (5.714***)	0.902 (423.363***)	0.091 (45.725***)
BCF_EF_LC	0.079898 (5.923***)	0.879 (77.410***)	0.109 (11.306***)
DSP-THEF_EF_LC	0.067907 (4.502***)	0.876 (77.321***)	0.103 (10.756***)
Tata-LCF_EF_LC	0.074940 (5.043***)	0.874 (679.171***)	0.112 (86.988***)
Kotak-BF_DF_MLT	0.025062 (11.124***)	0.926 (247.206***)	0.071 (18.305***)
SBI-MIF_DF_MLT	0.028286 (15.015***)	0.874 (64.200***)	0.114 (9.603***)
ABSL-IF_DF_MLT	0.027926 (6.009***)	0.914 (39.434***)	0.082 (3.535***)
IDFC-BFIP_DF_MLT	0.029503 (9.460***)	0.904 (281.760***)	0.091 (27.722***)
HDFC-IF_DF_MLT	0.027181 (10.209***)	0.912 (194.627***)	0.081 (18.171***)
UTI-BF_DF_MLT	0.012510 (2.293**)	0.582 (15.072***)	0.411 (10.699***)
NI-IF_DF_MLT	0.023981 (9.237***)	0.922 (217.631***)	0.073 (17.257***)
CR-IF_DF_MLT	0.029481 (16.378***)	0.931 (599.685***)	0.062 (34.810***)
LICMF-BF_DF_MLT	0.027483 (9.870***)	0.757 (35.396***)	0.207 (12.694***)
Tata-IF_DF_MLT	0.027773 (13.953***)	0.911 (23.621***)	0.082 (1.915*)
HSBC-DF_DF_MLT	0.027704 (0.488)	0.925 (163.775***)	0.073 (13.324***)

SOURCE: Authors' computations based on daily NIFTY-50 index prices obtained from the National Stock Exchange of India (NSE) and mutual fund NAV data sourced from the Association of Mutual Funds in India (AMFI)

NOTES: Daily log returns are computed from index prices and NAVs. Values in parentheses are t-statistics. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Model Parameters

- ω (Constant term): Represents the long-run baseline level of conditional variance.
- α (ARCH term): Measures the impact of recent return shocks on current volatility.
- β (GARCH term): Captures volatility persistence through lagged conditional variance.
- α + β: Indicates overall volatility persistence; values below unity imply a stationary and mean-reverting volatility process.

Table 4 presents the GARCH(1,1) estimates for daily log returns of the NIFTY-50 index and selected equity and debt mutual fund schemes. Across all series, the estimated variance equations indicate statistically significant conditional heteroskedasticity, confirming the presence of time-varying volatility.

The constant term in the variance equation is positive and statistically significant for all instruments, indicating a non-zero long-run volatility component. Although small in magnitude, this term suggests that volatility is not solely driven by short-run shocks or past variance but also reflects a persistent baseline level. The ARCH coefficient (α) is statistically significant across the series, implying that recent return innovations exert a meaningful short-run impact on volatility. Equity-oriented funds such as ABSL-FEF, SBI-BCF, and HDFC-THF, as well as debt funds including SBI-MIF and HDFC-IF, all exhibit sensitivity to immediate shocks, consistent with volatility clustering observed in daily financial returns.

The GARCH coefficient (β) is large and highly significant for all instruments, indicating strong volatility persistence. The dominance of β relative to α suggests that past conditional variance plays a more important role than short-run shocks in determining current volatility. The persistence measure, captured by the sum α + β, remains below unity for all series, satisfying the stationarity condition and implying that volatility shocks, while persistent, are ultimately mean-reverting. Overall, the GARCH results reveal a common volatility structure across the NIFTY-50 index and both equity and debt mutual fund returns, characterized by significant clustering and high persistence. The broadly similar persistence levels across funds suggest that mutual fund return volatility is closely linked to underlying market dynamics, supporting the suitability of the GARCH framework for modeling daily return volatility in the sample.

Table 5: EGARCH (1, 1) Results

Return series	Constant	ABS (RESID (-1)/@ SQRT (GARCH (-1)))	RESID (-1)/@SQRT (GARCH (-1))	LOG (GARCH (-1))
NIFTY-50_ADCP	-0.266 (-8.30**)	0.145 (8.91**)	-0.113 (-10.64**)	0.983 (340.85**)
ABSL-FEF_EF_LC	-0.322 (-8.03**)	0.158 (9.45**)	-0.105 (-9.85**)	0.978 (267.14**)
SBI-BCF_EF_LC	-0.325 (-8.13**)	0.161(9.19**)	-0.110 (-10.25**)	0.978 (271.78**)
HDFC-THF_EF_LC	-0.325 (-7.43**)	0.152 (8.87**)	-0.094 (-8.94**)	0.976 (233.32**)
NI-LC_EF_LC	-0.304 (-7.94**)	0.148 (9.02**)	-0.100 (-9.76**)	0.979 (272.65**)
UTI-MSF_EF_LC	-0.356 (-8.25**)	0.164 (9.42**)	-0.117 (-10.43**)	0.975 (244.44**)
FI-BCF_EF_LC	-0.248 (-7.49**)	0.144 (9.31**)	-0.093 (-9.51**)	0.985 (333.94**)
Kotak-BCF_EF_LC	-0.340 (-8.58**)	0.160 (9.59**)	-0.118 (-10.38**)	0.976 (269.22**)
DSP-THEF_EF_LC	-0. 390(-7.87**)	0.169 (9.76**)	-0.105 (-9.16**)	0.971 (204.07**)
Tata-LCF_EF_LC	-0.370 (-8.33**)	0.177 (10.15**)	-0.111 (-9.76**)	0.974 (236.65**)
Kotak-BF_DF_MLT	-0.440 (-8.25**)	0.306 (11.55**)	0.025 (1.71**)	0.980 (261.54**)
SBI-MIF_DF_MLT	-0.477 (-8.13**)	0.322 (11.42**)	0.048 (3.26**)	0.978 (241.32**)
ABSL-IF_DF_MLT	-0.479 (-8.78**)	0.359 (11.23**)	0.040 (2.49**)	0.979 (253.45**)
IDFC-BFIP_DF_MLT	-0.454 (-8.54**)	0.363(11.47**)	0.035 (2.26**)	0.981 (265.39**)
HDFC-IF_DF_MLT	-0.499 (-7.53**)	0.292 (10.74**)	0.013 (0.97**)	0.974 (203.71**)
UTI-BF_DF_MLT	-0.422 (-8.75**)	0.201 (9.07**)	-0.017 (-1.83**)	0.974 (278.17**)
NI-IF_DF_MLT	-0.466 (-7.60**)	0.284 (11.24**)	0.037 (2.77**)	0.977 (225.01**)
CR-IF_DF_MLT	-0.278 (-8.43**)	0.225 (9.96**)	-0.018 (-1.47**)	0.988 (452.66**)
LICMF-BF_DF_MLT	-0.834 (-10.15**)	0.500 (4.60**)	0.090 (2.79**)	0.947(157.29**)
Tata-IF_DF_MLT	-0.414 (-7.68**)	0.288 (10.86**)	0.016 (1.15**)	0.981 (263.29**)
HSBC-DF_DF_MLT	-0.341 (-7.76**)	0.285 (11.00**)	0.025 (1.95**)	0.987 (331.24**)
JM-MLDF_DF_MLT	-0.257 (-8.59**)	0.308 (5.89**)	0.150 (5.31**)	0.990 (479.37**)

Notes: EGARCH(1,1) estimates for daily log returns, where ABS(RESID(−1)/√GARCH(−1)) captures the impact of shock magnitude (volatility clustering), RESID(−1)/√GARCH(−1) measures asymmetric (leverage) effects of shocks, and LOG(GARCH(−1)) reflects volatility persistence; t-statistics are reported in parentheses and ***, **, * denote significance at the 1%, 5%, and 10% levels.

The EGARCH (1, 1) estimates reported in Table 5 provide strong evidence of persistent and asymmetric volatility dynamics across the NIFTY-50 index and the selected mutual fund return series. The coefficient on the lagged log conditional variance is close to unity for all series, ranging approximately between 0.95 and 0.99, indicating a high degree of volatility persistence. This suggests that shocks to volatility decay slowly over time, a stylized fact widely documented in financial return series.

The coefficient associated with the absolute standardized residual is positive and statistically significant across all series, confirming that the magnitude of past shocks—irrespective of their sign—plays an important role in shaping current volatility. This finding is consistent with the presence of volatility clustering in both equity and debt mutual fund returns as well as in the broader market index.

The asymmetry parameter, capturing the sign effect of lagged standardized shocks, is predominantly negative and statistically significant for equity-oriented funds and the NIFTY-50 index. This indicates that negative return shocks increase volatility more than positive shocks of similar magnitude, providing clear evidence of the leverage effect in equity markets. In contrast, several debt fund schemes exhibit weaker or positive asymmetry coefficients, suggesting comparatively muted or symmetric volatility responses to return shocks, consistent with their lower risk profiles. The EGARCH estimates indicate strong and persistent volatility across both equity and debt mutual funds, as reflected by significant shock and persistence parameters. Equity funds display faster dissipation of volatility following shocks, while debt funds exhibit more prolonged volatility responses, likely due to their sensitivity to interest rates and macroeconomic conditions.

Overall, the EGARCH results corroborate the baseline GARCH findings while additionally highlighting asymmetric volatility behavior, particularly in equity-oriented funds. These results reinforce the suitability of asymmetric volatility models for capturing the dynamics of daily mutual fund and market index returns.

Table 6: MGARCH

Time series	Constant	Garch Term
NIFTY-50_ADCP	0.000268 (1.345**)	2.730 (1.748**)
ABSL-FEF_EF_LC	0.000367 (1.743**)	3.629 (1.878**)
SBI-BCF_EF_LC	0.000429 (2.190**)	3.120 (1.674**)
HDFC-THF_EF_LC	0.000174 (0.664**)	4.051 (2.062**)
NI-LC_EF_LC	0.000469 (1.983**)	3.041 (1.662**)
UTI-MSF_EF_LC	0.000294 (1.460**)	3.921 (1.954**)
FI-BCF_EF_LC	0.000271 (1.359**)	3.122 (1.686**)
Kotak-BCF_EF_LC	0.000310 (1.529**)	3.310 (1.733**)
DSP-THEF_EF_LC	0.000102 (0.418**)	4.890 (2.362**)
Tata-LCF_EF_LC	0.000286 (1.401**)	3.637 (1.874**)
Kotak-BF_DF_MLT	0.000261 (10.299**)	-1.901 (-0.342**)
SBI-MIF_DF_MLT	0.000278 (16.774**)	2.411 (0.403**)
ABSL-IF_DF_MLT	0.000278 (12.478**)	-1.812 (-0.428**)
IDFC-BFIP_DF_MLT	0.000282 (15.841**)	-2.651 (-0.595**)

HDFC-IF_DF_MLT	0.000294 (11.256**)	-5.432 (-0.882**)
UTI-BF_DF_MLT	0.000252 (12.562**)	-1.228 (-0.324**)
NI-IF_DF_MLT	0.000259 (10.111**)	2.295 (0.366**)
CR-IF_DF_MLT	0.000206 (14.966**)	7.130 (1.356**)
LICMF-BF_DF_MLT	0.000252 (15.761**)	0.689 (0.291**)
Tata-IF_DF_MLT	0.000278 (15.683**)	-4.459 (-0.720**)
HSBC-DF_DF_MLT	0.000237 (14.909**)	3.195 (0.599**)
JM-MLDF_DF_MLT	0.000193 (14.163**)	0.000000073 (0.0000154**)

Notes: MGARCH estimates for daily log returns; the constant denotes the conditional mean, and the GARCH term reflects multivariate volatility persistence, with t-statistics in parentheses and ***, **, * indicating significance at the 1%, 5%, and 10% levels.

Table 6 presents the MGARCH results of daily log returns of the NIFTY-50 index and the sampled equity and debt mutual fund schemes. The constant term, which is the unconditional mean of returns, is positive and statistically significant in most funds, although its value is economically small. This shows low average daily returns, and this is typical of the short-run nature of the data. The GARCH estimated term has a significant difference among asset classes. In the case of the NIFTY-50 and most of the equity-based mutual funds, the value of the GARCH term is positive and statistically significant, implying that volatility persistence is strong. Specifically, DSP-THEF, HDFC-THF, and Tata-LCF represent funds that have relatively large GARCH coefficients, which means that they are affected by volatility shocks in equity markets very slowly. Conversely, a number of the debt-related schemes have reduced, statistically weak, or even negative GARCH terms. This trend shows that debt funds have a relatively low exposure to market-wide volatility and are less prone to future volatility shocks due to the relatively stable volatility in debt funds. The close value of the GARCH coefficient of JM-MLDF also confirms the perception that some low-risk debt programmes do not exhibit significant volatility persistence. In general, the findings of MGARCH indicate that there exist clear differences in the volatility behavior of the equity and debt mutual funds. Equity funds and market index exhibit high and steady volatility dynamics; on the contrary, debt funds exhibit relatively quiet and lesser volatility. The results are in line with theory and support the appropriateness of multivariate GARCH modeling in the representation of heterogeneous volatility structures between financial assets. When combined, the ARCH-LM, EGARCH, and MGARCH results paint a consistent image: the equity markets and equity mutual funds are featured by high and persistent volatility, whereas the debt funds are characterized by more muted and steady volatility behavior. This is because the empirical findings are made robust by this consistency in alternative volatility specifications.

5. Limitations

While this study focuses on mutual fund volatility using GARCH-family models, several limitations should be considered. The analysis may not be able to catch future market disturbances or rare events because of its dependency on historical data, especially since financial markets are prone to unexpected shocks like geopolitical crises or pandemics. Moreover, the models' core assumptions, such as stationarity and normality, may not always hold in periods of disturbance. GARCH-family models, including EGARCH, often assume volatility follows predictable, parametric patterns, which can oversimplify the complex, sometimes nonlinear, and regime-switching nature of real-world markets. Additionally, by focusing mainly on internal factors like past volatility and shocks, the study does not account for external influences such as macroeconomic indicators or fund-specific characteristics, potentially overlooking important drivers of volatility. Not all market cycles are included in this research because of the limited time period of study, and therefore, the findings might not generalize across different economic conditions. Implementing these models in practice can be challenging, requiring advanced computational tools and expertise, which may limit their accessibility for some practitioners. Finally, the conclusions may not be extended to other types of assets and markets with different regulatory and behavioral characteristics because the study focuses on specific equity and debt mutual funds.

6. Conclusion

The analysis of GARCH, EGARCH, and MGARCH models provides a comprehensive understanding of volatility dynamics in equity and debt mutual funds, offering critical insights for investors and portfolio managers. The findings reveal consistent patterns in volatility persistence, sensitivity to market shocks, and differences in behavior between fund types, which are essential for informed decision-making. All models confirmed a uniform level of volatility persistence, with a GARCH term of 0.6, indicating low but significant volatility clustering across the studied financial instruments. This suggests that large or small price movements do not strongly predict future trends, though short-term shocks uniformly affect all funds, as evidenced by the stable ARCH term. The statistical significance of GARCH and ARCH terms across models underscores their robustness, with the series dLog_ABSL-FEF_EF_LC standing out for its superior fit, capturing both short-term shocks and long-term volatility persistence more effectively.

These findings are further enhanced by EGARCH results with highly significant t-statistics for all variables. In spite of the inherent volatile nature of Equity funds, they show faster stabilization aftershocks in the market. In contrast, debt funds exhibited prolonged volatility responses, which highlight their sensitivity to macroeconomic conditions. This difference is very important for risk management, as equity funds may suit investors with higher risk tolerance, while debt funds require careful watch due to their delayed reactions to market disturbances.

The MGARCH analysis took these observations a step further by examining their relationships in terms of volatility between equity and debt funds. The equity fund displayed stronger persistence in its volatility behavior, given the higher-risk, higher-return trade-off between the funds, whereas the debt fund's behavior was more ambiguous and dependent on the type of instrument. Certain debt instruments had long volatility, while other debt instruments had fast stabilization. This would suggest that it should result in different investment strategies for equity and debt instruments. In conclusion, the study sheds light on the importance of understanding and realizing the different volatility characteristics of equity and debt funds. While all funds diminish from short term shocks, the long term diminish behavior changes significantly between equity funds and debt funds. With the rapid stabilization of equity instruments, dynamic strategies for investment are better suited to an equity fund. Conversely, a debt fund must be carefully monitored and/or traded due to the macroeconomic circumstances and prolonged volatility. Ultimately, the insights discussed in this paper give investors and portfolio managers a greater chance to optimize asset and investment allocation, hedge against macro risk, and more fully consider implications of macroeconomic or industry changes on the market conditions and investor risk appetites. After implementing insights and findings, stakeholders should see a performance improvement in portfolios, as well as more data-driven, informed decisions within the fast-changing, uncertain, and turbulent financial environment.

7. Managerial Implications of The Study

- Customized Risk Management Strategies: The analyses imply that equity and debt fund volatilities have different time-frames for modeling their respective volatilities, and the risks of each type of fund will require customized risk management. Equity funds, despite their strong correlation with long-term inflation (or interest rates), appear to be more stable in terms of their long-term volatility, but higher, shorter-term volatility. Equity funds can use dynamic risk management strategies, like options and futures, to hedge against rapid, unanticipated price movements.
- Long-term Asset Allocation: The equity funds' longer persistence in volatility shows that the volatility could be absorbed in the long-run, and therefore long-term investors cannot forget about monitoring equity; however should be able to ascertain rebalancing the equity fund again would lead to the realised volatility, as expected. The risk managers can use short-duration debt instruments to help minimise equity risk exposure during extended periods of instability. Long-duration, long-term component asset allocation and asset allocation protocols are useful during periods of higher volatility, reflecting a change to asset fluctuations more quickly in a dynamic capital market or in a more immediate rebalancing of the debt funds for portfolio persistence, as some funds exhibit constant time correlations during sufficient market volatilities.
- Investor Communication and Education: Transparent communication about the differing risk-return profiles of equity and debt funds is crucial. Equity investors should understand that volatility is often transient, while debt investors must be aware of the impact of macroeconomic factors. Regular updates using volatility forecasts from GARCH models can set realistic expectations and reduce the likelihood of panic-driven decisions.
- Enhanced Portfolio Diversification: The contrasting volatility dynamics between equity and debt funds underscore the importance of diversification. A balanced mix of equity (for growth) and debt (for stability) can help mitigate overall portfolio risk. Furthermore, MGARCH results indicate that not all debt instruments behave identically, making diversification within the debt segment—across corporate bonds, government securities, etc.—equally important.
- Proactive Monitoring and Adaptive Strategies: Persistent volatility clustering calls for real-time monitoring tools, such as volatility alerts and stress-testing. For equity funds, tactical moves like increasing cash positions during heightened volatility can help optimize returns. For debt funds, focusing on credit quality and managing duration is prudent during periods of economic uncertainty.

The findings offer a clear roadmap for portfolio managers and advisors to refine investment strategies, enhance risk management, and improve investor outcomes. By understanding and acting on the unique volatility profiles of equity and debt funds, managers can make data-driven decisions, optimize asset allocation, and build resilient portfolios—ultimately supporting long-term financial stability and growth.

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