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Volatility Modelling of the BSE SENSEX Using the ARCH Model: An Empirical Study of Select Large-Cap Constituent Stocks (2021–2026)

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Abstract
Stock market volatility is of continuing interest to investors, portfolio managers, corporates and policymakers because it directly influences risk assessment, asset pricing and capital allocation decisions. This paper examines the return-generating and volatility process of the Bombay Stock Exchange Sensitive Index (BSE SENSEX) using the Autoregressive Conditional Heteroskedasticity (ARCH) model of Engle (1982), estimated separately for five consecutive financial years spanning April 2021 to January 2026. Daily closing prices of the SENSEX and ten actively traded, large-capitalisation constituent stocks were employed as explanatory variables in the mean equation, while the conditional variance was modelled as a GARCH(1,1)-type specification and estimated through Maximum Likelihood in EViews. The results show that the ARCH coefficient is positive and statistically significant in four of the five years, confirming the presence of volatility clustering in SENSEX returns, whereas the GARCH persistence term is small and, in three of the five years, negative, implying that shocks to variance die out quickly rather than persisting. The explanatory power of the mean equation ranged between 0.69 and 0.81 across the five years, and descriptive statistics of daily returns confirm negative skewness and excess kurtosis, validating the use of an ARCH-family model over ordinary least squares. The findings carry implications for risk management, portfolio diversification and short-horizon volatility forecasting in the Indian equity market.

Keywords: *ARCH model; BSE; GARCH; SENSEX; Volatility clustering*

1. Introduction

The Indian equity market has grown, over the last three decades, into one of the largest and most closely watched emerging markets in the world, with the BSE SENSEX serving as its principal barometer. Because stock prices absorb a continuous stream of economic, political and firm-specific information, they rarely move smoothly; instead, periods of relative calm are interspersed with episodes of sharp, clustered price swings. This tendency for large changes to be followed by large changes, and small changes by small changes — commonly referred to as volatility clustering — was first documented by Mandelbrot (1963) and later formalised econometrically by Engle (1982) through the Autoregressive Conditional Heteroskedasticity (ARCH) model, which allows the conditional variance of a time series to depend on its own past squared residuals rather than assuming a constant variance as ordinary least squares (OLS) does. Understanding and, where possible, forecasting this volatility is of practical importance to a wide set of market participants. For investors and portfolio managers, volatility measures the risk attached to expected returns and therefore underlies asset-allocation and hedging decisions. For derivative pricing, an accurate estimate of the conditional variance of the underlying asset is a direct input into option-pricing models. For regulators and policymakers, sudden or persistent increases in volatility can signal building systemic stress in the financial system. Ordinary least squares regression, which assumes homoskedastic (constant-variance) errors, is poorly suited to capturing this behaviour; the ARCH family of models was designed specifically to address this limitation. This study applies the ARCH model to daily closing values of

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the BSE SENSEX over five consecutive financial years — 2021–22, 2022–23, 2023–24, 2024–25 and 2025–26 — treating the daily closing prices of ten actively traded, large-capitalisation constituent stocks drawn from the defence, information technology, banking, logistics, energy and infrastructure sectors as explanatory variables in the mean equation, and modelling the residual variance using a GARCH(1,1)-type ARCH specification estimated by Maximum Likelihood in EViews. Estimating the model separately, year by year, rather than pooling the full period, allows the study to examine whether the strength of the ARCH effect, the persistence of volatility, and the explanatory power of the selected stocks have remained stable or have shifted across a period that includes the post-pandemic recovery, a global monetary tightening cycle, and more recent phases of the Indian market cycle. The remainder of the paper is organised as follows. Section 1.1 reviews the relevant literature on ARCH/GARCH modelling of stock market volatility, with particular reference to the Indian market. Section 2 sets out the research methodology, including the objectives, data sources, variable definitions and model specification. Section 3 presents the data, descriptive statistics, year-wise ARCH model estimates and discussion of outcomes. The paper concludes with the key findings, implications and limitations of the study.

1.1.Review of Literature

The theoretical foundation for modelling time-varying volatility was laid by Engle (1982), who introduced the ARCH model to describe the variance of United Kingdom inflation forecast errors as a function of past squared residuals. Bollerslev (1986) generalised this framework to the Generalised ARCH (GARCH) model by additionally allowing the conditional variance to depend on its own lagged values, substantially reducing the number of parameters required to capture volatility persistence. These two contributions remain the foundation of nearly all subsequent empirical work on financial market volatility, including the present study. Within the Indian context, Srivastava (2008) applied GARCH-class models to the BSE SENSEX and the NSE NIFTY and found significant ARCH effects together with evidence of a leverage effect. Vasudevan and Vetrivel (2016) modelled and forecast SENSEX return volatility using symmetric GARCH(1,1) as well as asymmetric EGARCH(1,1) and TGARCH(1,1) specifications over a long sample (1997–2015) and reported that the asymmetric specifications outperformed the symmetric GARCH(1,1) model in out-of-sample forecasting. More recent studies have extended this literature along several dimensions. Mamilla et al. (2023) used GARCH models to examine the impact of the COVID-19 pandemic on the volatility of several NSE sectoral indices. Acharya, Kaliyaperumal and Mahapatra (2024) documented a statistically significant month-of-the-year calendar anomaly in Indian stock returns using SENSEX and NIFTY data from 1996 to 2021. Bhardwaj, Garima, Lemma and Refera (2024) found that the introduction of index options trading altered the volatility structure of the NIFTY index. Firdous and Ray (2025) found that the SENSEX, the Singapore Straits Times Index and the Dow Jones Industrial Average all exhibited a strong and persistent GARCH effect around the COVID-19 period. Ali and Dembo (2025) compared GARCH(1,1), EGARCH, TGARCH and FIGARCH specifications for the SENSEX and NIFTY 50 over 2001–2025 and found that the asymmetric EGARCH and TGARCH models outperformed the symmetric GARCH(1,1) model in forecast accuracy. A parallel body of Indian work has estimated ARCH/GARCH-family models directly on the SENSEX, the NIFTY, and individual sectoral or firm-level series over varying sample periods, including Pandey (2005), Banerjee and Sarkar (2006), Karmakar (2005), Hansda and Ray (2002), Srinivasan and Ibrahim (2010), Joshi and Vidyanagar (2014) and Banumathy and Azhagaiah (2015). A second strand looks at volatility transmission between Indian equities and other asset classes, including crude oil and exchange rates (Singhal & Ghosh, 2016; Lakshmanasamy, 2022; Mahalwala, 2022). A third strand documents calendar and event-driven anomalies in Indian stock return volatility (Elangovan, Irudayasamy & Parayitam, 2022; Banu & Shibu, 2022). Taken together with the foundational econometric contributions of Engle (1982), Bollerslev (1986),

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Nelson (1991), Glosten, Jagannathan and Runkle (1993), Zakoian (1994), Baillie, Bollerslev and Mikkelsen (1996) and Ding, Granger and Engle (1993), this literature establishes three points of broad consensus: (i) Indian equity returns display significant ARCH/GARCH effects and volatility clustering; (ii) volatility in the Indian market is frequently asymmetric, reacting more strongly to negative than to positive shocks; and (iii) the strength and persistence of the ARCH/GARCH effect is not constant over time. However, most existing Indian studies estimate the model on the SENSEX or NIFTY return series alone over a single long sample period, with relatively little attention paid to a year-by-year comparison. The present study addresses this gap.

2. Method

2.1. Objectives of the Study

- To examine whether the daily returns of the BSE SENSEX exhibit a significant ARCH (volatility-clustering) effect during each of the five financial years from 2021–22 to 2025–26.
- To estimate the relationship between the SENSEX and ten select large-cap constituent stocks within an ARCH mean-equation framework.
- To compare the strength and persistence of the estimated ARCH and GARCH coefficients, and the overall explanatory power of the model, across the five years under study.
- To draw out the implications of the year-wise volatility pattern for investors, risk managers and policymakers.

2.2. Data Source and Study Period

The study is based entirely on secondary data comprising the daily Open, High, Low and Close (Close taken as the SENSEX value) of the BSE SENSEX, together with the daily closing prices of ten select constituent stocks, for five separate financial-year sub-periods running from 1 April 2021 to 19 January 2026 (Table 1). Each financial year is treated as an independent estimation window so that the ARCH model is re-estimated five times rather than once over the pooled period, allowing the volatility process to be compared across years. As shown in Table 1 Sample Periods and Number of Observations Used in the ARCH Model Estimation.

Table 1 Sample Periods and Number of Observations Used in the ARCH Model Estimation

Financial Year	Sample Period (as estimated in EViews)	Observations
2021–22	01/04/2021 – 31/03/2022	248
2022–23	01/04/2022 – 17/01/2023 (adjusted)	199
2023–24	03/04/2023 – 19/01/2024 (adjusted)	199
2024–25	01/04/2024 – 16/01/2025 (adjusted)	199
2025–26	01/04/2025 – 19/01/2026 (adjusted)	199

2.3. Variables of the Study

The dependent variable in the mean equation is the daily closing value of the BSE SENSEX. The independent variables[1 – 10] are the daily closing prices of ten large-cap constituent stocks spanning the defence, information technology, banking, logistics, port infrastructure, energy and oil-marketing sectors (Table 2). As shown in Table 2 Variables Used in the Study.

Table 2 Variables Used in the Study

Code	Company / Constituent	Sector
SENSEX	BSE Sensitive Index (dependent variable)	Broad market index
HAL	Hindustan Aeronautics Limited	Aerospace & Defence
BEL	Bharat Electronics Limited	Defence Electronics
TCS	Tata Consultancy	Information

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	Services Limited	Technology
INFL / INSL	Infosys Limited	Information Technology
HDFC	HDFC Bank Limited	Banking
ICICI	ICICI Bank Limited	Banking
CCIL / CCIL	Container Corporation of India Limited (CONCOR)	Logistics / Port Infrastructure
APSEZ	Adani Ports and Special Economic Zone Limited	Port Infrastructure
RIL	Reliance Industries Limited	Energy / Conglomerate
IOCL	Indian Oil Corporation Limited	Oil Marketing

2.4.Model Specification

The mean (return-generating) equation is specified as an ordinary linear regression of the SENSEX on the ten selected stock prices: SENSEXt = β0 + β1HALt + β2BELt + β3TCSt + β4INFYt + β5HDFCt + β6ICICIt + β7CCIt + β8APSEZt + β9RILt + β10IOCLt + εt, where εt is the error term. Rather than assuming εt has constant variance, the ARCH(1)-GARCH(1) specification models the conditional variance of εt, denoted ht, as a function of the previous period's squared residual and the previous period's conditional variance: $ht = C + \alpha \cdot \varepsilon t{-}1^2 + \beta \cdot ht{-}1$. Here, C is the constant term in the variance equation, α (the coefficient on RESID(−1)²) measures the ARCH effect, and β (the coefficient on GARCH(−1)) measures the persistence of past conditional variance into the present. Non-negativity of the estimated conditional variance and $(\alpha + \beta) < 1$ are the standard conditions for a well-behaved, non-explosive GARCH process; where these conditions are not met, or where the coefficient covariance matrix is singular, this is noted explicitly against the relevant year's results[11 – 20].

2.5.Estimation Software and Diagnostics

All models were estimated in EViews using the ML ARCH – Normal distribution estimation method (BFGS/Marquardt algorithm). For each year, the paper reports the estimated mean-equation and variance-equation coefficients and the standard set of overall diagnostics: R-squared, Adjusted R-squared, Standard Error of the regression, Log-likelihood, Akaike Information Criterion (AIC), Schwarz Criterion (SC), Hannan–Quinn criterion, and the Durbin–Watson statistic.

3. Results And Discussion

3.1.Results

The return series shows negative skewness in four of the five years, indicating a longer left tail (larger negative daily moves than positive ones), and excess kurtosis in every year, most markedly in 2024–25 (Table 3). Fat-tailed, negatively skewed return distributions of this kind are inconsistent with the assumption of constant-variance, normally distributed errors underlying OLS, and are precisely the stylised facts that the ARCH family of models is designed to accommodate. As shown in Table 3 Descriptive Statistics of SENSEX Daily Return Series, by Financial Year[51 – 54].

Table 3 Descriptive Statistics of SENSEX Daily Return Series, by Financial Year

Financial Year	Mean Return (%)	Std. Dev. (%)	Skewness	Excess Kurtosis
2021–22	0.069	1.007	−0.798	2.652
2022–23	0.002	0.932	0.079	0.551
2023–24	0.092	0.625	−0.259	0.620
2024–25	0.022	0.883	−0.758	8.248
2025–26	−0.019	0.843	−0.112	2.833

In two years (2021–22 and 2024–25) the EViews estimation reported a singular coefficient-covariance matrix, so standard errors, z-statistics and probability values are not available for the mean-equation coefficients in those two years; the point estimates remain informative about direction and relative magnitude but formal significance testing is not

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possible for those years. Table 4 summarises the estimated variance-equation coefficients and overall diagnostics across all five years.

Table 4 Comparative Summary of the ARCH Model Variance Equation and Diagnostics, 2021–22 to 2025–26

FY	ARCH (α)	GARCH (β)	α + β	R^2	Adj. R^2
2021–22	0.8894	−0.1052	0.7842	0.7723	0.7602
2022–23	1.0648	−0.0397	1.0251	0.6907	0.6743
2023–24	1.2632	0.0184	1.2816	0.8119	0.8019
2024–25	0.8579	−0.1535	0.7044	0.7723	0.7602
2025–26	1.0084	0.0317	1.0401	0.7942	0.7832

The year-wise plots of the daily percentage change (@PC()) in the SENSEX and each of the ten constituent stocks serve as a preliminary, purely visual diagnostic for volatility clustering ahead of the formal ARCH estimation. The FY 2025–26 charts, for example, show HDFC Bank recording an isolated spike of over +100% while the remaining series show a comparatively contained range of daily percentage changes relative to earlier years, consistent with the lower return standard deviation reported for that year in Table 3.

3.2.Discussion

The ARCH coefficient (α), which captures the sensitivity of today's conditional variance to yesterday's squared shock, is positive in all five years and is statistically significant at conventional levels in the three years for which standard errors could be estimated (2022–23, 2023–24 and 2025–26), with point estimates ranging from 0.86 to 1.26. This provides consistent evidence of a genuine ARCH effect in SENSEX returns: large shocks to the index are systematically followed by periods of elevated variance, rather than variance behaving as a constant, as OLS would assume. The GARCH coefficient (β), which captures the extent to which last period's conditional variance carries over into the present, is comparatively weak throughout, and is negative in three of the five years (2021–22, 2022–23 and 2024–25). A negative or near-zero GARCH term, combined with a relatively large ARCH term, suggests that in the Indian market over this period[20 -30], volatility shocks were absorbed and dissipated quite quickly rather than persisting for an extended run of days — a pattern that differs from the high, positive GARCH persistence (often above 0.85) more typically reported for mature developed markets and for some of the longer-sample Indian studies reviewed in Section 1.1 (e.g., Vasudevan & Vetrivel, 2016; Firdous & Ray, 2025). One plausible explanation is the presence of a small number of extreme single-day percentage changes in individual constituent stocks — most likely reflecting unadjusted corporate actions such as bonus issues or stock splits rather than genuine market volatility — which can distort short-sample ARCH/GARCH estimates, particularly the persistence parameter. Across the mean equation, HDFC Bank, ICICI Bank, BEL and RIL are consistently significant explanatory variables of the SENSEX level wherever standard errors are available (2022–23, 2023–24 and 2025–26), while TCS and CONCOR alternate between significance and non-significance across years, and IOCL enters with a positive and significant coefficient in 2022–23, is insignificant in 2023–24, and becomes strongly significant with a much larger magnitude in 2025–26. This year-to-year instability in the coefficient pattern is consistent with the changing sectoral composition of SENSEX gains and losses across the study period, and reinforces the value of estimating the model separately by year rather than relying on a single pooled estimate. The overall explanatory power of the mean equation, measured by R^2, is highest in 2023–24 (0.812) and lowest in 2022–23 (0.691), while the 2025–26 model shows the lowest (best) information-criterion values alongside the lowest S.E. of regression, consistent with the comparatively lower return volatility observed for that year.

3.3.Findings

- SENSEX daily returns display negative

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skewness in four of the five financial years studied and excess kurtosis (fat tails) in every year, confirming[30-40] that the return distribution departs from normality and that an ARCH-family model is more appropriate than OLS for this data.

- The ARCH coefficient (α) is positive in all five years and statistically significant in the three years where standard errors could be estimated, confirming the presence of a genuine volatility-clustering effect in SENSEX returns throughout the study period.
- The GARCH persistence coefficient (β) is weak and, in three of the five years, negative, indicating that volatility shocks in the Indian market over this period dissipated relatively quickly rather than persisting strongly from one day to the next.
- HDFC Bank, ICICI Bank, BEL and RIL are the most consistently significant explanatory stocks in the SENSEX mean equation across the years for which significance testing was possible.
- Two of the five years (2021–22 and 2024–25) produced a singular coefficient-covariance matrix, most likely reflecting near-multicollinearity among the ten explanatory stocks or extreme single-day outlier observations, limiting formal inference for those years.
- The graphical analysis identifies a small number of extreme single-day spikes in individual constituent stocks (BEL in 2022–23, HAL in 2023–24, RIL in 2024–25, and HDFC Bank in 2025–26) consistent with unadjusted corporate actions.
- The model's explanatory power (R^2) ranges from 0.69 to 0.81 across the five years, indicating that the ten select stocks jointly explain a substantial, though not complete, share of the year-to-year variation in the SENSEX level.

Conclusion

This study set out to examine whether the BSE SENSEX exhibits a significant ARCH (volatility-clustering) effect and to estimate its relationship with ten select large-cap constituent stocks, separately, for each of five recent financial years. The evidence confirms the presence of a consistent and, in most years, statistically significant ARCH effect, together with descriptive statistics (negative skewness and excess kurtosis of returns) that independently support the use of an ARCH-family specification over ordinary least squares. At the same time, the persistence of volatility, as captured by the GARCH coefficient, is found to be weak and inconsistent across years, suggesting that shocks to SENSEX variance over 2021–2026 have tended to be absorbed relatively quickly rather than compounding over an extended run of trading days. For investors and portfolio managers, the findings imply that short-horizon risk management approaches — which respond promptly to a volatility shock without assuming that elevated volatility will persist for an extended period — may be more appropriate for the Indian market over this period than approaches calibrated to the high-persistence GARCH processes typically associated with mature markets. For policymakers and market regulators, the year-to-year instability in both the ARCH/GARCH parameters and the significance of individual constituent stocks underscores the value of continuously re-estimating, rather than assuming a static, volatility model for the Indian market. Limitations and Scope for Further Research: The study uses unadjusted daily closing prices for the ten select constituent stocks; the extreme single-day percentage changes identified suggest that some of these series may contain corporate-action-related discontinuities that have not been adjusted for, which could affect the precision of individual coefficient estimates, particularly in years with a singular covariance matrix[40 – 50]. The mean equation also uses price levels rather than log-returns for the explanatory stocks, which may itself contribute to the weak and unstable GARCH persistence term reported here. Future work could usefully re-estimate the model on split/bonus-adjusted, log-differenced data; extend the ARCH(1,1) specification to asymmetric variants such as EGARCH or TGARCH to test directly for a leverage effect; and incorporate macroeconomic explanatory variables (for example, inflation, interest

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rates or crude oil prices) alongside the firm-level stock prices used here.

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