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Indian Stock Market Volatility Analysis Based on a GARCH-type Model

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Abstract
The Indian stock market, being an emerging market, exhibits significant volatility. This paper employs the returns of the top three under Nifty50 companies, i) Reliance India Ltd., ii) HDFC Bank, and iii) Bharati Airtel as per the current market capital to do an analysis utilising an Autoregressive Conditional Heteroskedasticity (ARCH) model. The Autoregressive Moving Average (ARMA) model with a t-distribution for the sample series to evaluate model performance across various distributions and orders. Conversely, it introduced threshold GARCH models to encapsulate the characteristics of the index. Furthermore, the accuracy and predictive outcomes of the models were assessed using mean squared error (MSE), mean absolute error (MAE), and root mean squared error (RMSE). The findings indicate that the ARMA model utilising Student's t-distribution surpasses alternative models in forecasting the return series of Reliance ARMA (7,7), HDFC is ARMA (1,1), and Bharti Airtel is ARMA (1,1). The GARCH model exhibits superior predictive performance for the return series of the Reliance GARCH (2,1), the HDFC is GARCH (1,1), and the Bharti Airtel is GARCH (2,1), compared to all other models. This study may serve as a valuable informational resource for governmental macro decision-making, the operations of publicly traded enterprises, and investors' investment strategies.
Keywords: Volatility, ARCH, GARCH, ARMA, Nifty50.

Introduction

The Indian stock market, with the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE), is one of the most vibrant emerging markets in the world. It has undergone a major change in structure in the recent 20 years due to liberalisation policies, technological development and entry into the market by institutional and foreign investors. Although the Indian stock market has been growing, it has been highly volatile due to the domestic and global macroeconomic factors in the country, inflation, interest rates, and geopolitical trends (Singh and Kaur, 2021)[1]. The Indian market tends to cluster volatility, in which volatile markets are followed by further turbulence, which is also in line with the results of other emerging markets. Consequently, investors are often wary of the volatility risk linked to emerging markets due to the disparities between emerging and developed markets. Certain researchers' research may assist investors in comprehending the innovation and development capabilities of firms in emerging economies, offering essential insights for management's investment decisions (Gil-Alana et al., 2020)[2]. Knowledge and prediction of such volatility based on modelling such as GARCH and its derivatives is important in portfolio risk management, derivative pricing, and policymaking in the Indian financial system (Chittedi, 2020)[3]. The Indian stock market is an emerging market that draws worldwide investors but remains in a young phase relative to its Western equivalents. Emerging markets exhibit elevated turnover rates, significant volatility, and a simultaneous presence of high risk and high returns, indicating

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pronounced speculation and instability. Concerning market standardisation, emerging markets have numerous challenges, including flawed legislation, insufficient law enforcement, and rudimentary regulatory technologies. Furthermore, insider trading, stock market manipulation, and fraud are prevalent, and the level of standardisation is inadequate. Emerging markets are typically governed by individual investors, whose trading behaviour is frequently marked by excessive activity, pronounced speculation, irrationality, and a deficiency in long-term investment strategy. In contrast, a developed stock market possesses an extensive history of evolution, with its legislative framework and market mechanics being more refined and rational. Institutional investors are a crucial component of a mature stock market, which tends to exhibit greater stability. Consequently, investors are often wary of the volatility risk linked to emerging markets due to the disparities between emerging and developed markets. Certain researchers' research may assist investors in comprehending the innovation and development capabilities of firms in emerging economies, offering essential insights for management's investment decisions.

Literature Review

The study of volatility in the financial market has attracted significant interest in the domain of financial econometrics. Bollerslev (1986)[4]. proposed a model that includes the autoregressive conditional heteroscedasticity (ARCH) model, which he designated as the generalized autoregressive conditional heteroskedasticity (GARCH) model. Tan et al. (2010)[5] employed the wavelet technique alongside the autoregressive integrated moving average (ARIMA) and the GARCH model to accurately forecast future prices. Shephard and Sheppard (2010)[6] introduced an additional expansion of the GARCH-X model, termed the high-frequency-based volatility (HEAVY) model. The multiplier methodology was expanded to include pseudo- observations by Rémillard (2012)[7], encompassing residuals of GARCH models. Klar et al. (2012)[8] indicated that the specification of error distribution significantly influences the efficiency of estimators, yet it does not affect their asymptotic normality. The GARCH model, utilising a one-parameter rational function to approximate the error density, demonstrated superior fit to the data compared to the model employing a Gaussian error density in the pursuit of a rational approximation of the GARCH model's error density explained by Chen & Takaishi (2012)[9]. Sun and Zhou (2014)[10] illustrate the analytical computation of the tail index for GARCH models. Hansen et al. (2014)[11] formulated a bivariate variant of the realised GARCH to characterise the conditional variance and conditional beta of stock returns. Hansen et al. (2015)[12] expanded this methodology to the realised EGARCH model by utilising a more adaptable leverage function and facilitating numerous realised metrics. Ismail et al. (2016)[13] have meticulously implemented their distinctive algorithm, the maximal overlap discrete wavelet transform (MODWT)-GARCH (1,1) model, and subsequently used it for comparative analysis with the typical linear GARCH (1,1) model's performance.

Employing univariate asymmetric GARCH models, Aliyev et al. (2020)[14] analysed and quantified the volatility of the Nasdaq-100, revealing enduring volatility shocks on index returns, a leveraging effect on the index, and an asymmetric response to shocks. Zivkov et al. (2021)[15] assessed the multiscale bidirectional volatility spillover impact between national stock and exchange rate markets in four African nations, utilising the MS-GARCH model. Certain scholars have examined the correlation between financial variables and social variables with the returns generated by the ESPO. Their findings indicated that the impact of social variables is less significant than that of economic variables by López-Cabarcos, (2020)[16]. Hongwiengjan and Thongtha (2021)[17] evaluated an analytical approximation of option prices employing the TGARCH model. A novel, efficient strategy

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for pricing in-the-money (ITM) options is presented for empirical practice. Kim et al. (2021)[18] employed the standard GARCH and other asymmetric GARCH models to calculate the volatility of corporate bond yield spreads. Wang et al. (2021)[19] explained about ARMA-GARCH model with t-distribution. ARMA models are still auxiliary to the modelling of stationary mean dynamics, and as mean- equation building blocks preceding the estimation of volatility, they are quite common in the literature and in ARMA-GARCH specifications by Kaur (2023)[20].

Methodology

The ARMA Model

The Autoregressive Moving Average (ARMA) model is a structural time series model, which integrates two important actions, the Autoregressive (AR) process and the Moving Average (MA) process, to understand the persistence of the previous observation and measurement and the effect that the previous shocks have on a variable. The ARMA model also lies on the assumption that the underlying time series is stationary, that is, its statistical characteristics (mean and variance) do not change with time. The overall equation of an ARMA (p, q) model is expressed as:

$$Yt = c + \sum_{i=1}^{p} \phi i\, Yt-i + \sum_{j=1}^{q} \theta j\, \epsilon t-j + \epsilon t \qquad \text{(i)}$$

Yt is the variable observed at period t, ϵt signifies the independent error term, ϕ and θ are unspecified non-zero coefficients. The ARMA model may compute variables affected by both historical states and current and future stochastic causes. This attribute renders the ARMA model appropriate for the analysis and forecasting of long-term time series. The ARMA model effectively elucidates the autoregression and trend of time series, although it is only effective for stationary time series.

The ARCH Model

Engle (1982) proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model, which aims to capture time-varying volatility in financial time series, specifically when the error term also varies over time. The traditional linear models, such as ARMA, assume constant variance (homoskedasticity). However, financial information tends to be volatile, with periods of high volatility followed by periods of low volatility, and vice versa. The basic ARCH(q) model expresses the conditional variance of the error term (ϵt) as a function of past squared residuals:

$$\sigma 2 = \alpha 0 + \sum_{i=1}^{q} \alpha i\, \varepsilon 2 \qquad \text{(ii)}$$

$t \qquad t-i$

where σ& is the conditional variance of the series at time t, $\alpha 0$ is a constant term, and αi are coefficients of the effect of past period shocks ($\varepsilon 2$) on the present volatility. The model provides that all the parameters $\alpha i > 0$ and $\alpha 0 > 0$ involve positive variance. Simply put, the ARCH model would suggest that past shocks (whether positive or negative) of large magnitude do augment the present volatility. The capability of modeling dynamics of the changing variance over time makes the ARCH model very appropriate in financial returns, interest rates, and exchange rate series, where the volatility persistence is observed.

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The GARCH Model

The GARCH model (which is an extension of the Engle ARCH model) was developed by Bollerslev (1986), and it enables volatility to rely not only on past squared errors but also on its own past, which makes it more parsimonious and flexible. The simplest model, the GARCH (1,1) model, is characterised by the conditional variance as:

$\sigma^* = \alpha \quad + \alpha \quad \varepsilon^* \quad + \beta \ \sigma^* \quad$ (iii)

) + ,)-, ,)-,

Where σ^* denotes the present conditional variance ε^* is the lagged squared error (the))-,
ARCH term), and $\sigma 2$ is the lagged variance (the GARCH term). The short-term shock effect and the long-term persistence of volatility are the measurements of the coefficients $\alpha 1$ and $\beta 1$, respectively. To be stable in the model, it should satisfy the condition $\alpha 1 + \beta 1 < 1$. The GARCH model effectively describes the empirical properties of volatility clusters, persistence and mean reversion of financial markets using fewer parameters compared to the high-order ARCH models.

Data Analysis

The concept of volatility is significant in finance, primarily in the areas of portfolio optimisation, risk management, and asset pricing. Financial information exhibits leptokurtosis, volatility clustering, long memory, volatility smiles, and leverage effects. Therefore, linear models are inadequate for predicting a variety of significant features commonly found in financial data. That is, since working with financial data, the assumption of homoscedasticity cannot be made. Here, we used the ARCH and GARCH models for the volatility. The three samples (Reliance India Ltd, HDFC Banks, and Bharti Airtel Ltd.) are of high volatility and amplitude, with a large range of volatilities realised in stock over the last three years (2022- 2024)

Reliance India Ltd.

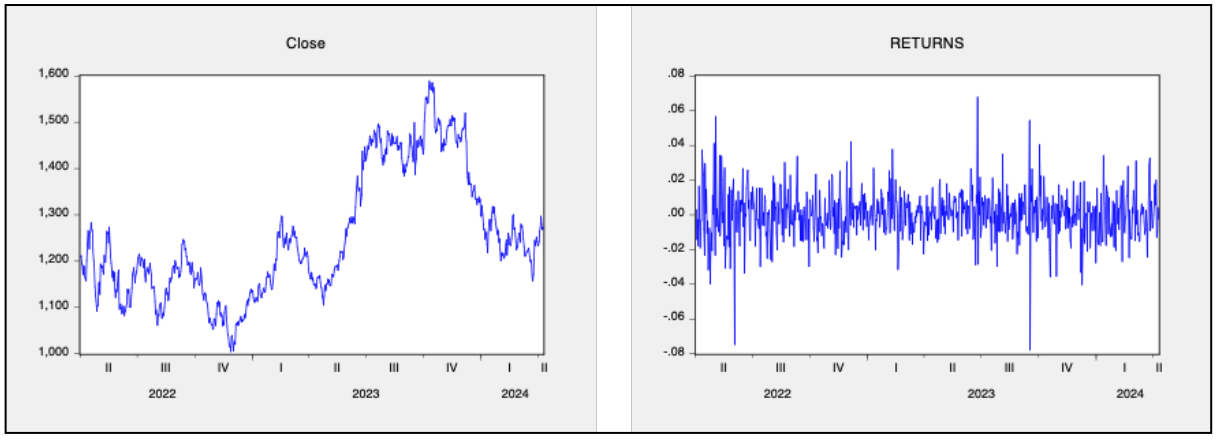

Figure 1: Reliance India Ltd. daily closing prices and returns

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HDFC Bank Ltd.

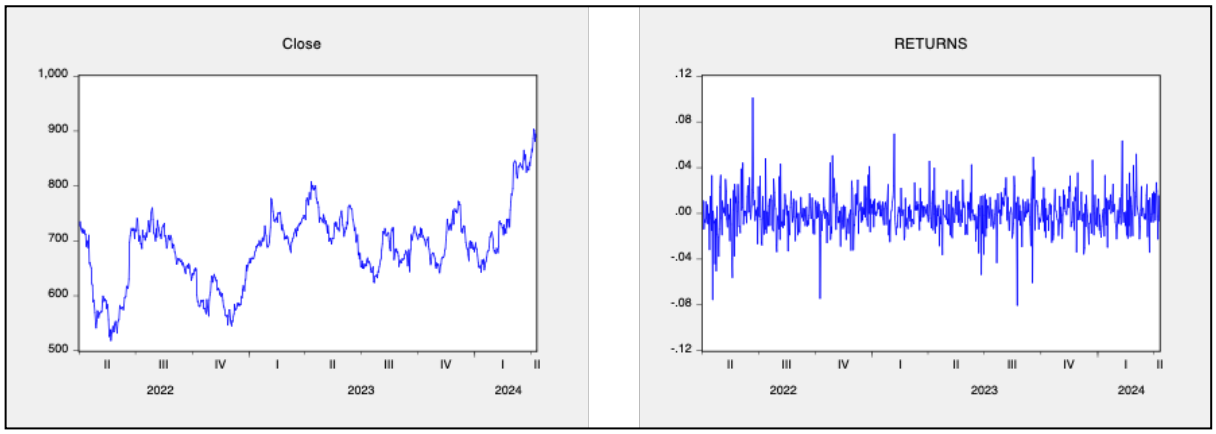

Figure 2: HDFC Bank Ltd. daily closing prices and returns

Bharati Airtel Ltd.

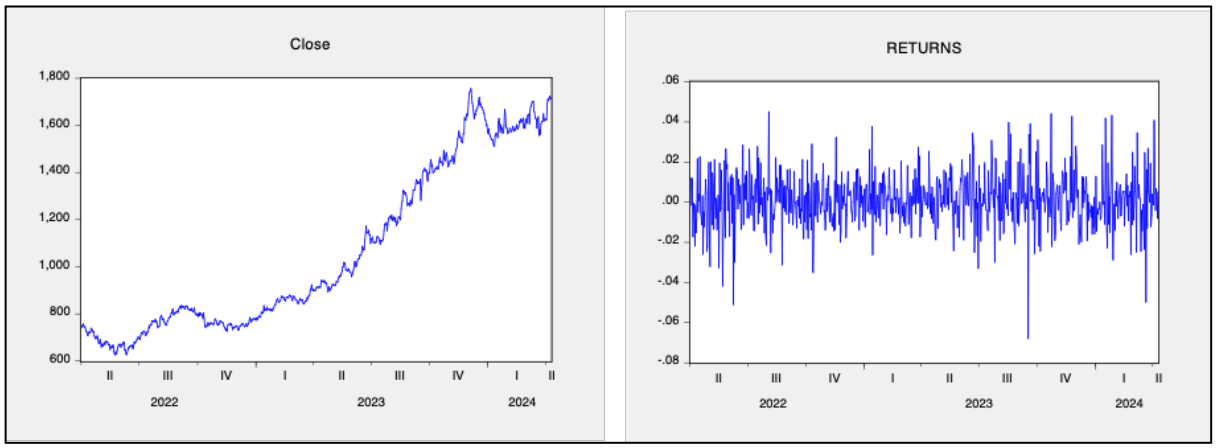

Figure 3: Bharti Airtel Ltd. daily closing prices and returns

Reliance India Ltd.

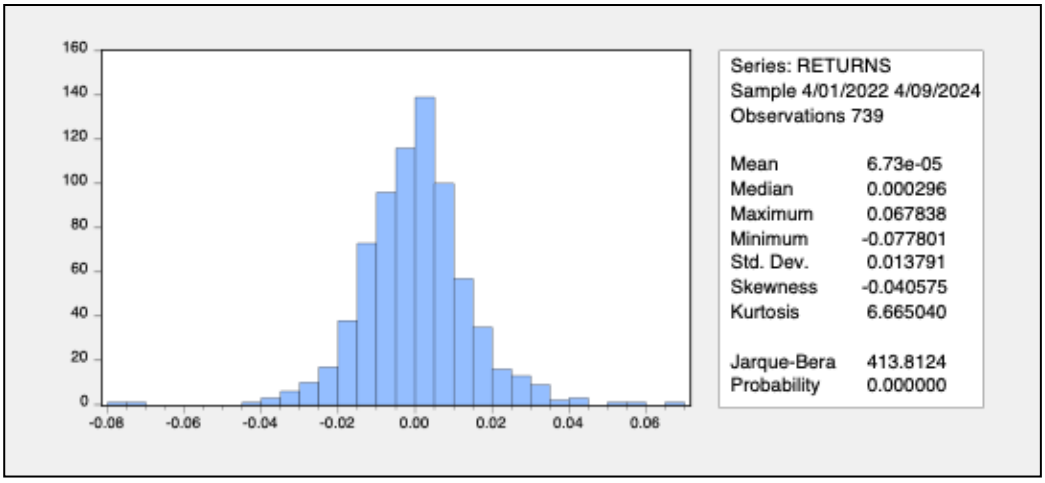

Figure 4: Descriptive Statistics of Index Returns of Reliance India Ltd.

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The stock prices of the above three figures stock price from 2022 to 2024. Among the companies, the volatility was extremely severe, characterised by large returns and risks. However, the swings in Reliance India Ltd. were relatively minor compared to the HDFC Bank Ltd. Upon comparison of the three graphs, it is evident that Reliance and HDFC exhibit nearly identical trends, albeit the volatility of the latter is significantly better. The closing price series of Bharati Airtel Ltd. shows that there is a consistent upward trend with occasional fluctuations, which are indicative of general market development with some brief instances of volatility. Conversely, the return series are moved about a zero mean, and this implies that there is stationarity in returns. Temporal changing conditional variance is indicated in the existence of volatility clustering, with a high volatility regime being succeeded by more volatility and stability-then-volatility phases. Such a behaviour justifies the adoption of ARCH and GARCH family models to model and predict stock market volatility dynamics.

HDFC Bank Ltd.

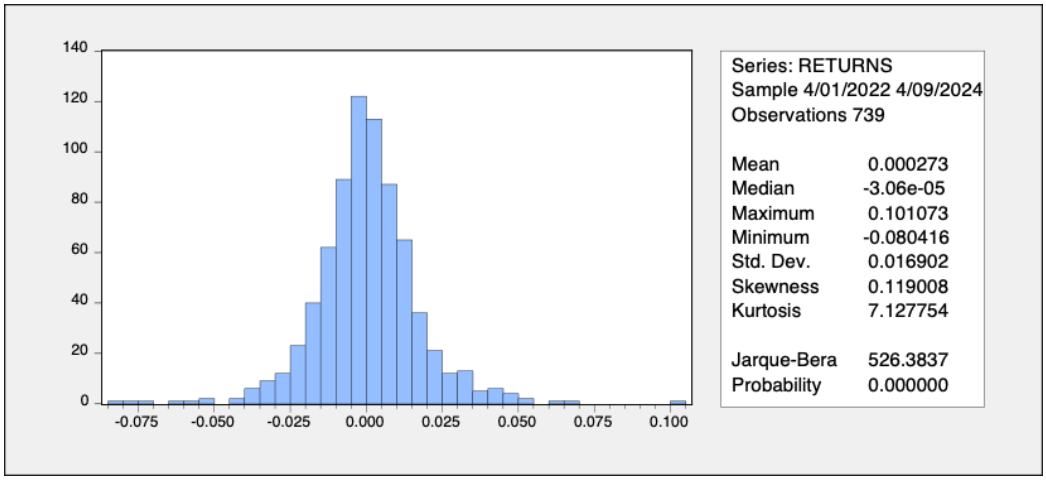

Figure 5: Descriptive Statistics of Index Returns of HDFC Bank Ltd.

Bharti Airtel Ltd.

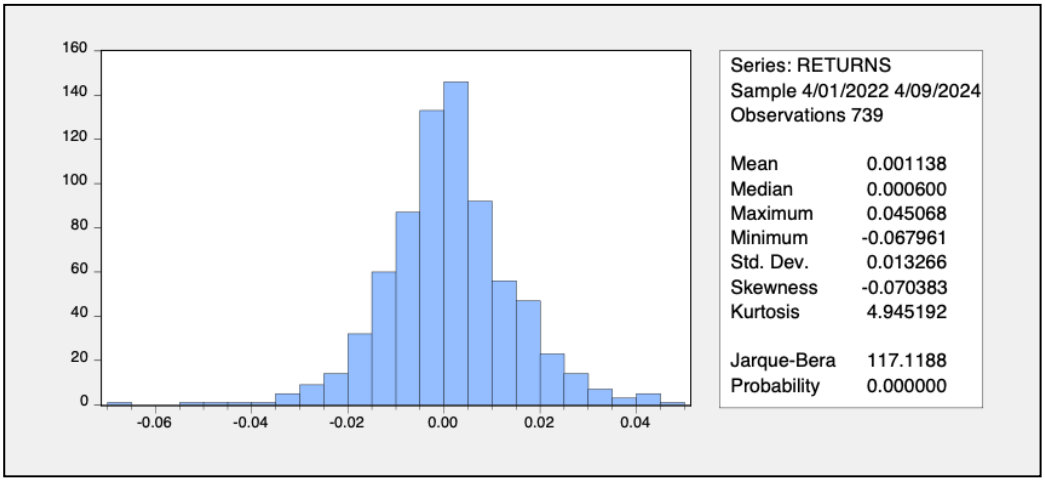

Figure 6: Descriptive Statistics of Index Returns of Bharti Airtel Ltd.

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The above three figures (4,5,6) of Descriptive statistics based on a histogram of the series of return values of the daily returns, indicating a standard deviation, the skewness of the distribution, the value of kurtosis, the Jarque-Bera statistic and p-value are shown in the following table which are highly disapproves of the null hypothesis of normality, and the result indicates that the distribution of returns is highly deviated against the normal distribution. All in all, the findings indicate that the series of returns is non-normative and heteroskedastic. Hence, it considers the ARCH or GARCH-type models to capture volatility effectively.

Descriptive Statistics.

Table 1: Descriptive Statistics

Companies	Sample size	Mean	Std.	Skewness	Kurtosis	J-B	P-value
Reliance	739	6.73e-05	0.013791	-0.040575	6.665040	413.8124	0.0000
HDFC	739	0.000273	0.016902	0.119008	7.127754	526.3837	0.0000
Bharti Airtel	739	0.001138	0.013266	-0.070383	4.945192	117.1188	0.0000

The p-values of the J–B normality test for the return series are 0, indicating that the null hypothesis of normality is rejected at the 5% significance level, and the return series of the Reliance, HDFC, and Bharti Airtel are not normally distributed. Similarly, the skewness series is negative and about 0, but the kurtosis exceeds 3, confirming that the returns of the above three companie's stock market exhibit a higher level of return. Furthermore, the standard deviation value of Reliance is 0.013791, HDFC is 0.016902, and Bharati Airtel is 0.013266, implying that the risk level of Bharti Airtel is lower than other companie's stocks and the former market is more stable than the latter.

NPS Test

Time series pre-processing is necessary before modelling. The stationarity of the sequence must be verified to prevent erroneous regression in model estimation. Subsequently, we must determine the ideal lag order of the ARMA (p, q) model via an autocorrelation test to achieve the most accurate fitting results. The correctness of the GARCH model is confirmed by assessing the ARCH effect of the sequence.

Table 2: The Nyblom Parameter Stability Test (NPS)

Companies	T-Statistics	The Significance Level of 1%	The Significance Level of 5%	The Significance Level of 10%
Reliance	0.090065	0.748	0.470	0.353
HDFC	0.065154	0.748	0.470	0.353
Bharti Airtel	0.334108	0.748	0.470	0.353

The Nyblom Parameter Stability Test (NPS) is a statistical test that is designed to test the stability of the estimated parameter of a time-series or econometric model, like an ARMA or ARCH or GARCH. The basic concept of the test is to establish whether the model parameters do not vary with time or are structurally unstable, that is, whether the relationships to be represented by the model vary throughout the sample period. A very important condition of reliable forecasting and model interpretation is parameter stability, which means that the underlying economic or financial dynamics could have changed with either some policy changes, market shocks or investor behaviour. The above Table 2 is the output of the NPS test.

The findings prove that the t-statistics of the two series are far less than critical values at the 1%,

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5% or 10% significance levels, outlining that there is no unit root in the sample series, and they are stationary time series.

Autocorrelation Test

The Ljung–Box Q (LBQ) statistics, autocorrelation (AC) plots, and partial autocorrelation (PAC) plots are used to determine the appropriate lag order for the ARMA model. The region between the dotted lines in the following Table 3,4,5 represents twice the expected standard deviation, whereas the shaded area illustrates the AC and PAC coefficients of the return series. We can ascertain that there is no substantial difference between the coefficients and 0 at the 5% significance level, given that these coefficients fall within the dotted lines. If they exceed the dotted line, autocorrelation exists in the return series. It confirms that the AC and PAC coefficients of the two-return series oscillate around 0, which can be disregarded. The probability values of Reliance, HDFC, and Bharti Airtel are below 5% when the lag order exceeds 3. Q-statistics, presented, are utilised for identifying autocorrelation and are linked to probability values. The null hypothesis is discarded if the p-value is below 0.05, and the sequence exhibits autocorrelation. The Q-statistics test findings in the tables confirm that the p-values are all below 5%, indicating that the two squared residual series exhibit autocorrelation, and the return series have a significant ARCH impact.

Table 3: Autocorrelation Test of Reliance India Ltd.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.507	-0.507	190.83	0.000
		2	0.038	-0.296	191.91	0.000
		3	-0.053	-0.263	194.02	0.000
		4	0.046	-0.172	195.62	0.000
		5	-0.055	-0.198	197.90	0.000
		6	0.043	-0.150	199.28	0.000
		7	-0.016	-0.133	199.46	0.000
		8	0.036	-0.068	200.42	0.000
		9	-0.070	-0.132	204.11	0.000
		10	0.052	-0.099	206.11	0.000

Table 4: Autocorrelation Test of HDFC Bank Ltd.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.522	-0.522	201.80	0.000
		2	0.025	-0.340	202.26	0.000
		3	-0.028	-0.292	202.84	0.000
		4	0.074	-0.148	206.89	0.000
		5	-0.049	-0.124	208.66	0.000
		6	-0.006	-0.124	208.69	0.000
		7	-0.048	-0.207	210.41	0.000
		8	0.085	-0.133	215.82	0.000
		9	-0.006	-0.062	215.84	0.000
		10	-0.048	-0.095	217.55	0.000

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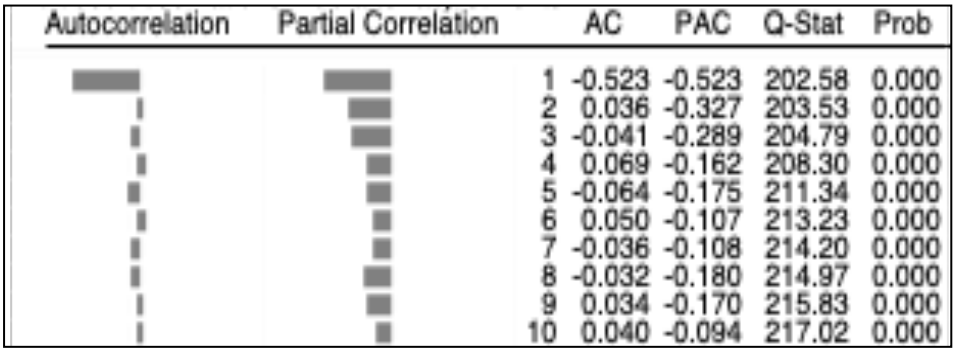
Table 5: Autocorrelation Test of Bharti Airtel Ltd.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.523	-0.523	202.58	0.000
		2	0.036	-0.327	203.53	0.000
		3	-0.041	-0.289	204.79	0.000
		4	0.069	-0.162	208.30	0.000
		5	-0.064	-0.175	211.34	0.000
		6	0.050	-0.107	213.23	0.000
		7	-0.036	-0.108	214.20	0.000
		8	-0.032	-0.180	214.97	0.000
		9	0.034	-0.170	215.83	0.000
		10	0.040	-0.094	217.02	0.000

Table 6 demonstrates that the correlation coefficients of the Reliance series are notably significant at lag orders of 1 and 7. Consequently, we developed four models for the Reliance series: ARMA (1,1), ARMA (7,1), ARMA (1,7), and ARMA (7,7). Table 7 presents the correlation coefficients of the HDFC series, which are statistically significant at delays 1 and
6. Additionally, four models are formulated based on ARMA (1,1), ARMA (6,1), ARMA (1,6), and ARMA (6,6). The lag order was associated with the model's dependability. Inadequate selection of lag order leads to the exclusion of pertinent information integration. Table 8 presents the estimation outcomes of the various ARMA models. We utilised ARMA (1,1), ARMA (4,1), ARMA (1,4), and ARMA (4,4) to model the return series, guided by the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC).

Table 6: ARMA Model estimation results of Reliance India Ltd.

	ARMA	AIC	SC	Mean
Reliance	ARMA (1,1)	-5.756461	-5.719030	-5.826210
	ARMA (7,1)	-5.762516	-5.724845	-5.739132
	ARMA (1,7)	-5.756567	-5.719137	-5.728713
	ARMA (7,7)	-5.772780	-5.735109	-5.741903

Table 7: ARMA Model estimation results of HDFC Bank Ltd.

	ARMA	AIC	SC	Mean
HDFC	ARMA (1,1)	-5.305394	-5.280440	-5.281342
	ARMA (6,1)	-5.305689	-5.280735	-5.282103
	ARMA (1,6)	-4.925801	-4.916178	-5.073516
	ARMA (6,6)	-4.604077	-4.579124	-5.023256

Table 8: ARMA Model estimation results Bharti Airtel Ltd.

	ARMA	AIC	SC	Mean
Bharti Airtel	ARMA (1,1)	-5.812627	-5.775196	-5.783412
	ARMA (4,1)	-5.808228	-5.770678	-5.784431
	ARMA (1,4)	-5.807373	-5.769942	-5.785041
	ARMA (4,4)	-5.811519	-5.773969	-5.781022

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GARCH Model

Tables 9, 10, and 11 demonstrate that the correlation coefficients of the Reliance, HDFC, and Bhatrati Airtel series are notably significant at lag orders of 1 and 2. Consequently, we developed three models of GARCH: GARCH (1,1), GARCH (1,2), and GARCH (2,1). The lag order was associated with the model's dependability. Inadequate selection of lag order leads to the exclusion of pertinent information integration. The model is the return series, guided by the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC).

Table 9: GARCH Model estimation results of Reliance India Ltd.

	GARCH	AIC	SC	Mean
Reliance	GARCH (1,1)	-5.458496	-5.451641	-5.364072
	GARCH (1,2)	-5.468556	-5.460484	-5.363012
	GARCH (2,1)	-5.477064	-5.457608	-5.423075

Table 10: GARCH Model estimation results of HDFC Bank Ltd.

	GARCH	AIC	SC	Mean
HDFC	GARCH (1,1)	-5.540749	-5.532748	-5.520735
	GARCH (1,2)	-5.537614	-5.521023	-5.524815
	GARCH (2,1)	-5.528503	-5.511095	-5.522942

Table 11: GARCH Model estimation results Bharti Airtel Ltd.

	GARCH	AIC	SC	Mean
Bharti Airtel	GARCH (1,1)	-5.549431	-5.537231	-5.515481
	GARCH (1,2)	-5.549152	-5.519843	-5.525497
	GARCH (2,1)	-5.551226	-5.539842	-5.525173

Conclusion

This study analyses the volatility characteristics of the top three companies of the Nifty50 stock Index utilising the GARCH model, which aids in comprehending the operational dynamics and price fluctuation patterns of the Indian stock market, thereby offering valuable insights for investors. GARCH-type models apply to the stock market and may accurately represent the volatility change patterns. From a time series perspective, the volatility of the Indian stock markets exhibits notable temporal variation and clustering characteristics. The Nifty50 Composite Index exhibits stationarity and a pronounced ARCH impact. Hence, the ARMA- GARCH model is well-suited for the index return series. The fitting outcomes of the models are compared by constructing ARMA-GARCH models with varying distributions and orders. The models based on the Student's t-distribution had superior fitting ability. Volatility plays a crucial role in actual economic operations and serves as an effective instrument for the government and investors to assess various risks. However, the univariate GARCH model utilised in this study struggles to elucidate the volatility spillover dynamics between financial markets and fails to account for the broader financial context adequately. Consequently, the subsequent stage should involve constructing a multivariate GARCH model to analyse the comprehensive economic system.

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