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Conditional volatility modelling with specific reference to select stocks of Nifty 50

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Abstract
This paper models conditional volatility of select stocks from NIFTY 50 basket. Since volatility is the most important indicator in terms of measuring of risk of any assets, it is proposed to measure volatility of financial assets through four different techniques; sGARCH, gjrGARCH, eGARCH and APARCH. We empirically examined the closing prices of five sample stocks; Reliance, HDFC bank, ICICI bank, Infosys and TCS from 1st January 2019 to 31st May 2024 covering both covid and non-covid period. A total of 1335 data points were used after converting raw closing price data into return series which were finally input into the models. All the models were found statistically stable with APARCH (1,1) as the best one to capture volatility. With respect to other parameters, return series of TCS has highest non-linearity followed by Reliance with lowest that of Infosys. Similarly, HDFC stock has shown highest asymmetry followed by TCS. Overall, it can be said all the sample stocks show volatility clustering along with certain degree of leverage effect.

Keywords: NIFTY 50, APARCH, leverage, volatility, non-linearity

1. Introduction

Globalisation benefits economies to expand in terms of increasing economic growth, employment creation along with a heightened chance of risk spillover in terms of spreading of geo political tensions across borders and economic contagion. This has particularly increased post financial crisis and Covid 19 scenario. This causes an unprecedented rise of risk in the market which in turn leads to unnecessary fluctuations in asset prices. This will also affect the investment behaviour of enterprises and individuals. For instance, individuals with comparatively a lesser investment would like to switch from trading to investing. Further, from portfolio management perspective, it will increase the cost of portfolio revision particularly in case of active portfolio management strategies [Moreira & Muir (2017); Cederberg et al. (2020)]. This apart, this makes difficult for hedgers to predict the price behaviour and hence make the hedging cost to rise. Therefore, a study of volatility of asset price has become the core issues in finance which is often described as variance of rate of return over a time period.

However, measuring and forecasting market volatility has become very difficult and despite availability of so many models and techniques, its almost impossible to perfectly capture it. The reasons are primarily twofold. First, models are primarily formulae that are based on certain theories and assumptions which may differ from reality. Second, even though models are built under certain assumptions, they are static in the sense that different datasets when applied to same model may not yield the similar results which we call as model fit error. Broadly, there are two types of models to capture volatility; rule-based models which are primarily statistical models and data-based models that are machine learning models. Empirical evidences confirm that ARCH type models are suitable to estimate short term conditional volatilities but there exists mixed evidence with respect to capturing long memory [Wang et al. (2011); Huang et al. (2016)]. On the other hand, data driven approaches are recent developments which challenges to capture non-linearity and noise in data compared to statistical models. The basic assumption here is to obtain an optimal fit to input data without having any prior knowledge about their pattern.There exists a mixed evidence of model superiority so far as comparison between these two types is concerned [Zhenghong (1999); Zhang (2003); Majumder et al. (2019)].Even though machine learning models claim to outperform traditional statistical models, they lack result interpretability which makes them less appealing so far as presentation and decision making is concerned. In comparison, statistical models are based on sound theory and can well be interpreted. This motivates us to select ARCH based models in this study.

In this study, we use variants of ARCH to capture particularly measure volatility in select stocks. GARCH (p, q) has been selected since evidences confirm in favour of this model in measuring conditional volatility. Along with this,gjrGARCH, eGARCH and APARCH have been used to capture asymmetry in information which may affect volatility over a time period.

Rest of the paper contains the followings. Section 2 provides a review of literatures followed by understanding of methodologies employed in section 3. Section 4 gives data with descriptive analysis. Section 5 discusses empirical results followed by implications, future research scope and conclusion in section 6.

2. Literature review

Engle (1982)first proposed an autoregressive conditional heteroscedasticity model to capture possible correlations of the conditional variance between successive prediction error terms. Bollerslev (1986) has been extended it to form a generalized autoregressive conditional heteroskedastic model. Later on, varieties of GARCH family were developed in order to accommodate different features of time series such as non-linearity, asymmetry, changing regimes etc. In fact, there exists a strong literature that advocate use of ARCH and GARCH family models in both measuring and forecasting volatility. Is quite a strong body of literature advocating the use of the GARCH family of models to forecast volatility.

Initial evidences confirm that GARCH (p,q) is the most suitable model to capture volatility in returns of financial assets with a significantly bigger volumes of data [Engle (1982); Bollerslev (1986); Scott (1991); Glosten (1993); Zakoian (1994); Leung et al.(2000); Hussain et al. (2019)].Wang et al. (2019) studied surge and turmoil of Chinese stock market using GARCH family models and concluded that market movement is more driven by Government's policy compared to economic factors. Andersen & Bollerslev (1998) claimed that the GARCH models provide the most accurate forecasts. Later on, the efficacy of models was examined and established by taking different types of data. For example, Akgiray (1989), Schwert (1990), Brailsford and Faff (1996), Brooks (1998) used stock market data from USA and found that the GARCH models outperformed most competitors. Using European stock market data from major economies such as Germany, France, Italy and the UK, Corhay&Rad (1994) found that the GARCH (1, 1) model generally outperformed the other GARCH models. In the similar line, Tse (1991); Tong &Tse (2002) found exponentially weighted average autoregressive models were good at better forecasting than plain vanilla GARCH model. Though, in most cases the GARCH family models were known to be leading in estimation and forecasting variations in financial data, but they failed to capture one of important aspects of time series data i.e., leveraging effect. This asymmetry of information affecting stock returns may hinder the robustness of output of plain vanilla GARCH models. Nelson (1991) proposed an alternative exponential GARCH model based on a logarithmic expression of the conditional variance. At later point in time, a number of modifications were made to EGARCH model. Zakoian (1994) proposed Threshold GARCH (TGARCH). In the similar line, the model developed by Glosten, Jagannathan and Runkle, known as GJR GARCH has been considered better in terms of examining the impact of shocks (positive and negative shocks) on volatility. Bhowmik et al. (2017) examined study on volatility on Bangladesh stock market and found asymmetry GARCH models are suitable to better capture returns. In the similar lines, Liu & Hung (2010); Li & Wang (2013); Banumathy &Azhagaiah (2015) favours asymmetry GARCH models. Trivedi et al. (2021) favours asymmetry GARCH models in examining volatility behaviour of BSE. With respect to Indian market, few recent papers where authors use GARCH models in volatility estimation and forecasting are by Dixit & Agrawal (2020); Mathur et al. (2021); Dixit et al. (2022); Khera et al. (2022); Mahalwala (2022); Raju (2022); Valavan et al. (2023); Bhat et al. (2024). Sharma et al. (2021) compared between linear and non-linear GARCH family models in forecasting volatility in selected emerging economies.Mahajan et al. (2022) compared the volatility of NIFTY 50 stocks using GARCH and a machine learning model RNN.Granger & Poon (2001) provides excellent review on forecasting the volatility in financial markets by comparing across different asset classes.

One thing is clear from the above cited papers that GARCH family models are predominantly used to model volatility in financial market due to their inherent advantage of capturing 'clustering effect'. This, apart, while measuring volatility, authors under the assumption of 'normal distribution'measured and forecasted volatility.

However, in reality, time series especially the financial series hardly possess this characteristic. Rather, financial series depicts leptokurtic behaviour therefore fitting a model under the assumption of normal distribution leads to incorrect estimation of results. Hence, in this study, the authors propose to use student's t distribution for precise estimation and comparing its result with normal distribution [see Afuecheta etal. (2020)].Further, varieties of ARCH models were developed to cater to requirement of different aspects of time series modelling. For instance, plain vanilla GARCH assumes volatility to be affected equally across different time periods. However, evidences show volatility tends to be affected more by negative shocks than positive shocks each of equal magnitude. For instance, leverage effect can better be captured through including asymmetry term γ into the conditional variance equation of sGARCH. Further, non-linearity in financial time series is a unique issue which measures particularly the tail distribution of data. Hence some power parameter can better gauge such characteristic. Therefore, applying only the GARCH (p,q) will not be sufficientandinferring result based on any one model is neitherdesirable nor adequate.Therefore, in this study it is proposed to compare result of sample stocks using a similar set ofGARCH based models. In this study we used four comparable models; standard GARCH, gjrGARCH, eGARCH and APARCH.

This paper contributes to existing literatures in the following way. To the best of our knowledge, there is a lack of sufficient empirical evidence of measuring volatility in Indian context especially post covid scenario in a comprehensive manner.Most researchers either used single GARCH (1,1) to measure and forecast volatility as empirical evidence depicts superiority of this model. This paper is an attempt to further examine the assertion. A comparison will show superiority of model simultaneously allowing to capture two specific features, which are leverage and non-linearity.

With this, the following objective is selected for the study.

'To measure different aspects of volatility behaviour of select stocks from NSE'

3. Methodologies

3.1 sGARCH (1,1)

Standard GARCH or GARCH (1,1) model is intended to capture auto regressive nature of volatility. Under GARCH framework as developed by Bollerslev (1986), the conditional variance is a function of both its own lagged values and past squared errors. This is described as

$$\sigma t^2 = \omega + \alpha(\varepsilon t - 1^2) + \beta(\sigma t - 1^2)$$

where α≥0, β≥0 guarantees non-negativity of ARCH and GARCH parameters and α+β<1 indicates stationarity of conditional variance.

GARCH assumes the impact of past errors on current volatility to be constant over time. Though asset returns are assumed to follow i.i.d. process in a speculative market, but returns tend to be dependent through time due to temporal bursts of volatility. Following development of ARCH by Engle (1982) there were notable works about presence of extreme degree of volatility persistence.

3.2 GJR GARCH

General representation of GJR GARCH is given below.

$$\sigma t^2 = \omega + \alpha(ut - 1^2) + \gamma[ut - 1^2 I(ut - 1 < 0)] + \beta(\sigma t - 1^2)$$

ω represents a constant term, α measures symmetric effect of past shocks on volatility, γ captures asymmetric effect of negative shocks and β measures volatility persistence. σt^2 is the conditional variance term which depends on past squared return, I (ut-1 < 0) is an indicator function implying that its value is 1 if ut-1 < 0 or 0 otherwise.

So far as capturing the asymmetries in time series it is often compared with the Exponential GARCH. This model includes an additional term to account for negative shocks apart from maintaining a linear structure, whereas EGARCH uses a logarithmic formulation.

3.3 Exponential GARCH (eGARCH)

Asymmetry assumes information to have either positive or negative impact. Therefore, both positive and negative shocks are believed to have different effect on return. This means volatility varies with time and hence different under rising and falling market situations.

Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) is a model used to describe the volatility of financial time series data. Typical version of EGARCH is given below.

$$lo\,g(\sigma t^2) = \omega + \beta log(\sigma t - 1^2) + \gamma\left(\frac{ut-1}{\sigma t-1}\right) + \alpha\left(\left|\frac{ut-1}{\sigma t-1}\right| - E\left[\left|\frac{ut-1}{\sigma t-1}\right|\right]\right)$$

ω is constant term, β measures volatility persistence, γ captures asymmetry or leverage effect, and α represents reaction of volatility to shocks. The model uses logarithm of conditional variance [log (σt^2)] which ensures that variance is always positive without imposing any non-negativity constraints on parameters. Parameters are estimated using MLE.

3.4 APARCH

APARCH stands for asymmetric power ARCH model which captures both the power effects and asymmetry. This ensures a better generalisation and overall framework of presenting two important aspects of volatility in addition to α and β; power parameter (⋋) and asymmetry (η). The model presented below provides flexibility in estimation of power parameter (⋋) which specifically can be able to capture skewness and heavy tails if any present in distribution of returns. In addition to this, ita (η) parameter captures the asymmetry which measures leverage effect; i.e., whether negative shocks have significantly larger impact on volatility compared to positive shocks.
The general expression of APARCH (1,1) is given below.

$$\sigma t^{\lambda} = \omega + \alpha(|\varepsilon_{t-1}| - \eta\varepsilon_{t-1})^{\lambda} + \beta\sigma_{t-1}^{\lambda}$$

σt^{λ} refers to conditional standard deviation raised to power lambda (⋋)
ω is a constant term
α is coefficient of lagged absolute residual
β represents coefficient of lagged conditional standard deviation to the power lambda (⋋)
Lambda (⋋) is the power parameter
Ita (η) captures asymmetry feature of data.

4. Data

The dataset comprises of companies listed in NSE and among the top constituents of NIFTY 50. The rationale of choosing Nifty 50 is that it is a well-diversifiedindex comprising of 50 companies that reflect the overall market condition.Second, impact cost of trading in NIFTY 50 is very low. It is the best measure of liquidity of a stock since it implies the cost borne by traders while trading in an asset. For instance, for a portfolio size of 50 lakhs, the impact cost is 0.02% in March 2024. Accordingly for a possible inclusion of a stock into NIFTY 50, a market impact cost of less than 0.50% is required. Third, the index, computed using free float capitalisation method, is used for benchmarking a variety of assets performances such as mutual funds' portfolios, index funds, structured products like derivatives and exchange traded funds. This makes it easier to select stocks.

Out of 50 companies, the author picks five companies closing prices based on proportionate weightage (see Table-1 below). Weights refers to percentage representation of company's stock being traded in a market. Total weight in terms of trading value of select five companies is 39.47%.This implies around 40% of the entire cash segment of NSE is being represented by only five companies which is a significant number. This suggests that any change in trading volumes and values definitely affects the overall performance. In other words, on a rough basis, we can also infer around 40% of total volatility is related to behaviour of these five stocks only. This makes it impelling to measure conditional volatilities of these stocks.
Timestamp data were directly imported into RStudio for these five stocks individually using 'quantmod' package (refer to appendix for code details) from 1-1-2019 till the starting of actual work i.e., 31-05-2024 with a 1335 datapoints. All further computations were made in RStudio. The reason for selecting such period is to examine volatility pattern from pre to post covid scenario. All data were converted into logarithm returns which are used as inputs for further calculation. The return is calculated as follows. Return (R_t) =$ln\left(\frac{Pt}{Pt-1}\right)$.

Table-1: Top constituents by weightage:

Company	Weight (%)
HDFC Bank Ltd	10.97
Reliance Industries Ltd	10.28
ICICI Bank Ltd	7.68
Infosys Ltd	6.22

Tata Consultancy Services Ltd	4.32

Source: NSE Indexogram

Fig.-1: closing prices of select stocks (all in one plot)

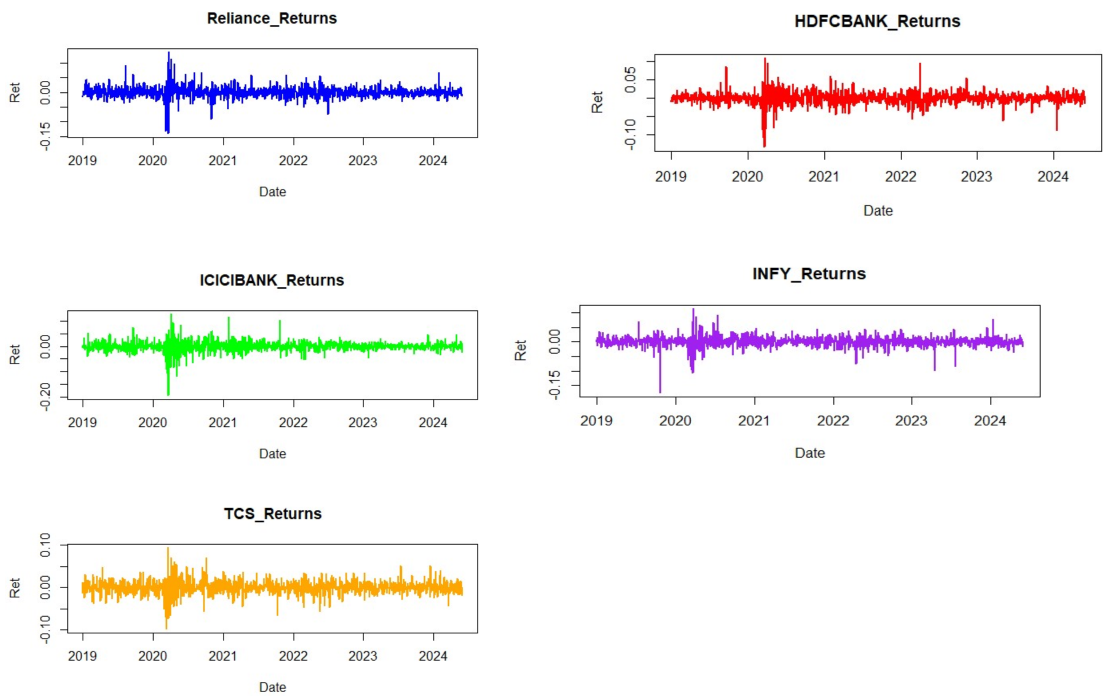

Fig.-2: Log returns of select stocks

Preliminary plotting of daily closing prices (Fig.-1) indicating presence of disruptions across sample period especially post 2020 indicating breaks which may be due to emergence of covid 19. TCS price has jumped highest since 2020 break followed by Reliance. Other three stocks depict a flatter growth over the same period. Return series (Fig.-2) show clustering of return in all the five stocks justifying use of ARCH based models for capturing the volatility dynamics. Before parameters estimation, all return data are tested for stationarity using ADF, PP, KPSS tests, ARCH effect and JB test for normality along with descriptive statistics.

Table 2: Descriptive Statistics and Unit root tests

Panel A: Descriptive statistics

Parameters	**Reliance**	**HDFCBANK**	**ICICI**	**INFY**	**TCS**
Mean	0.0007665	0.0002578	0.0008388	0.0005726	0.000505
St. Deviation	0.0187	0.0168	0.0202	0.0179	0.0154
Skewness	0.1503	-0.3347	-0.6487	-0.7924	-0.1794

Kurtosis	9.9025	9.5663	12.0731	12.3170	4.5308
JB (X^2)	5477[0.000]	5132[0.000]	8226[0.000]	8604[0.000]	1153[0.000]
ARCH (X^2)	388[0.000]	336[0.000]	268[0.000]	86.75[0.000]	234 [0.000]

JB is Jarque-Bera test of normality, p values are in brackets.

Panel B: Unit root tests

Parameter	Reliance	HDFCBANK	ICICI	INFY	TCS
ADF	-10.366[0.01]	-11.262[0.00]	-9.7969[0.00]	-10.959[0.00]	-10.944[0.01]
PP	-1447.7[0.01]	-1229.9[0.01]	-1352.9[0.01]	-1368.4[0.01]	-1360.3[0.01]
KPSS	0.0585[0.1]	0.0454[0.1]	0.0391[0.1]	0.1957[0.1]	0.0783[0.1]

In KPSS, null hypothesis is "data does not have unit root".

The mean of all series is positive, highest in case of ICICI Bank and the standard deviation representing daily unconditional volatility is also highest for ICICI Bank (0.0202) and lowest for TCS (0.0154). Skewness of all stocks except Reliance Industries Ltd comes to be negative. A negative skewness may imply most of times, return is frequently above average with a significant occasional drop in values which pull the average down. All the series are found to be highly leptokurtic except TCS (4.5308) indicating presence of heavy tail. This implies returns often exhibit extreme deviations from mean, suggesting a volatile situation. So far as JB statistic is concerned, none of the series were found normal as evident from chi-squared statistic which is significant a 1%. ARCH test for all the chosen stocks is significant suggesting that variance is heteroscedastic. This confirms application of GARCH type models. In this paper, it is proposed to use student's t distribution in modelling return data for all the stocks since it appears to fit all the above characteristics like leptokurtic feature and volatility clustering.

Panel B shows results of unit roots test of stationarity. The statistic of ADF and PP tests is significant at 1% significance level, hence we can reject null hypothesis of presence of unit root. KPSS test shows acceptance of null hypothesis which confirms that all return series are stationary hence suitable for further analysis.

5. Empirical Results

Table 3: Estimated coefficients &Diagnostic tests

Panel A: Estimated coefficients

	Optimal parameters	sGARCH(1,1)	gjrGARCH(1,1)	eGARCH(1,1)	APARCH(1,1)
Reliance	mu (μ)	0.004(0.318)	0.000(0.495)	0.000(0.451)	0.000(0.476)
	ar1	0.0902(0.814)	0.115(0.807)	0.144(0.000)	0.120(0.546)
	ma1	-0.060(0.875)	-0.088(0.851)	-0.116(0.002)	-0.092(0.645)
	omega (ω)	0.000 (0.000)	0.000(0.000)	-0.158(0.000)	0.000(0.513)
	α1	0.057(0.000)	0.018(0.002)	-0.051(0.002)	0.072(0.000)
	β1	0.917(0.000)	0.928(0.000)	0.980(0.000)	0.920(0.000)
	γ		0.065(0.002)	0.132(0.000)	
	η				0.377(0.006)
	⋋				1.244(0.000)
	Shape (t dist.)	5.129(0.000)	5.418(0.000)	5.528(0.000)	5.512(0.000)
HDFC	mu (μ)	0.000(0.288)	0.000(0.384)	0.000(0.449)	0.000(0.503)
	ar1	-0.818(0.000)	-0.812(0.000)	-0.819(0.000)	-0.821(0.000)
	ma1	0.859(0.000)	0.854(0.000)	0.856(0.000)	0.857(0.000)
	omega (ω)	0.000(0.001)	0.000(0.000)	-0.173(0.000)	0.000(0.375)
	α1	0.083(0.000)	0.055(0.000)	-0.037(0.058)	0.088(0.000)
	β1	0.888(0.000)	0.889(0.000)	0.979(0.000)	0.912(0.000)
	γ		0.052(0.092)	0.166(0.000)	
	η				0.280(0.062)
	⋋				1.033(0.000)
	Shape (t dist.)	4.421(0.000)	4.465(0.000)	4.441(0.000)	4.573(0.000)
	mu (μ)	0.000(0.000)	0.000(0.033)	0.000(0.121)	0.000(0.054)

	ar1	0.985(0.000)	0.843(0.000)	0.868(0.000)	0.868(0.000)
	ma1	-1.000(0.000)	-0.870(0.000)	-0.892(0.000)	-0.891(0.000)
	omega (ω)	0.000(0.562)	0.000(0.433)	-0.082(0.000)	0.000(0.407)
	α1	0.067(0.058)	0.018(0.154)	-0.081(0.000)	0.078(0.000)
ICICI	β1	0.925(0.000)	0.925(0.000)	0.989(0.000)	0.932(0.000)
	γ		0.108(0.002)	0.141(0.000)	
	η				0.577(0.000)
	⋋				1.005(0.000)
	Shape (t dist.)	4.759(0.000)	5.189(0.000)	5.347(0.000)	5.335(0.000)
	mu (μ)	0.000(0.086)	0.000(0.137)	0.000(0.214)	0.000(0.142)
	ar1	-0.836(0.000)	-0.841(0.000)	0.843(0.000)	-0.843(0.000)
	ma1	0.854(0.000)	0.861(0.000)	0.862(0.000)	0.861(0.000)
	omega (ω)	0.000(0.013)	0.000(0.008)	-0.310(0.000)	0.001(0.273)
	α1	0.073(0.003)	0.042(0.070)	-0.049(0.037)	0.075(0.000)
	β1	0.838(0.000)	0.832(0.000)	0.962(0.000)	0.903(0.000)
	γ		0.066(0.102)	0.126(0.313)	
INFY	η				0.456(0.012)
	⋋				0.883(0.000)
	Shape (t dist.)	4.287(0.000)	4.319(0.000)	4.373(0.000)	4.472(0.000)
	mu (μ)	0.000(0.000)	0.000(0.000)	0.000(0.126)	0.000(0.078)
	ar1	0.936(0.000)	0.936(0.000)	0.937(0.000)	0.470(0.492)
	ma1	-0.960(0.000)	-0.959(0.000)	-0.960(0.000)	-0.501(0.468)
	omega (ω)	0.000(0.000)	0.000(0.000)	-0.236(0.000)	0.000(0.552)
	α1	0.051(0.000)	0.021(0.008)	-0.023(0.228)	0.019(0.091)
	β1	0.905(0.000)	0.903(0.000)	0.971(0.000)	0.908(0.000)
	γ		0.055(0.006)	0.121(0.009)	
TCS	η				0.334(0.120)
	⋋				2.940(0.000)
	Shape (t dist.)	5.134(0.000)	5.141(0.000)	5.011(0.000)	5.184(0.000)*

** Figures in brackets are p values.*

Interpretations

In Panel A, μ representing long run conditional mean of the series which is around zero for all the sample stocks. AR(1) and MA(1) measures both first order autoregressive and moving average term. AR term shows whether current return can be partly predicted its past values or not, on the other hand, MA term captures whether current value is affected by past error term. In case of Reliance stock, except under eGARCH(1,1), none other models' AR(1) and MA(1) are statistically significant. On the other hand, for AR and MA term for TCS stock under APARCH (1,1) model are not significant.ω is constant term in conditional mean equation. The parameters α1 and β1 represent ARCH and GARCH effect respectively. For all the models, sum of α1 and β1 is less than or equal to zero, thus satisfying the condition for model stability. α1 term is not significant for few stocks; ICICI under sGARCH (p value 0.058), HDFC (p value 0.058) and TCS (0.228) under eGARCH, for ICICI (0.154) and INFY(0.070) under gjrGARCH and TCS (0.091) under APARCH(1,1). Further for eGARCH model, all the α1 are negative indicating inverse relation of past shocks to current log conditional variance. In other words, everthing else remain equal, past shocks decreased current volatility. In case of gjrGARCH and eGARCH, γ captures leverage effect which distinguishes the effect of positive and negative shocks on current volatility. Almost all γ terms are significant except for HDFC and INFY. The asymmetry parameter (η) of APARCH measures leverage effect on future volatility. Except for HDFC and TCS, for all other cases, η is significant indicating that effects of shocks on current volatility are different so far as positive (good news) and negative shocks (bad news) are concerned.⋋, the power parameter in APARCH, implying the power to which absolute residual is raised in conditional variance measures the non-linearity that might be present in data. In other way, it captures the volatility clustering in a better way especially the tail distribution of residuals. This parameter is found significant in all the cases implying that volatility clustering is well captured for the sample stocks. This can further be checked with a very high value of β1 for all the stocks.P-value of shape parameter is found significant for all indicating the data fits well into student's t distribution.

Panel B: Diagnostic tests

Model	Parameters	Reliance	HDFC	ICICI	INFY	TCS
sGARCH(1,1)	Log Likelihood (LL)	3636.257	3828.025	3642.735	3680.014	3801.436
	AIC	-5.44	-5.72	-5.45	-5.50	-5.68
	BIC	-5.41	-5.70	-5.42	-5.47	-5.66
	Shibata	-5.44	-5.72	-5.45	-5.50	-5.68
	HQIC	-5.43	-5.71	-5.44	-5.49	-5.67
	t value of joint effect of sign bias test	1.2638(0.737)	1.414(0.702)	0.226(0.973)	2.954(0.398)	1.629(0.652)
	Ljung-Box test statistic on standardised squared residuals	1.033(0.852)	0.7939(0.904)	1.285(0.792)	0.630(0.935)	0.079(0.015)
gjrGARCH(1,1)	Log Likelihood (LL)	3641.524	3829.438	3651.575	3681.743	3804.266
	AIC	-5.44	-5.72	-5.46	-5.50	-5.69
	BIC	-5.41	-5.69	-5.43	-5.47	-5.66
	Shibata	-5.44	-5.72	-5.46	-5.50	-5.69
	HQIC	-5.43	-5.71	-5.45	-5.49	-5.67
	t value of joint effect of sign bias test	0.566(0.904)	2.295(0.513)	0.621(0.891)	2.964(0.397)	1.164(0.761)
	Ljung-Box test statistic on standardised squared residuals	0.096(0.998)	0.727(0.917)	1.461(0.749)	0.944(0.872)	5.002(0.152)
eGARCH(1,1)	Log Likelihood (LL)	3643.017	3831.009	3655.187	3686.038	3802.032
	AIC	-5.44	-5.73	-5.46	-5.51	-5.68
	BIC	-5.41	-5.70	-5.43	-5.48	-5.65
	Shibata	-5.44	-5.73	-5.46	-5.51	-5.68
	HQIC	-5.43	-5.72	-5.45	-5.50	-5.67
	t value of joint effect of sign bias test	0.841(0.839)	2.108(0.550)	0.672(0.879)	3.368(0.338)	1.243(0.742)
	Ljung-Box	0.208(0.991)	2.186(0.575)	2.460(0.514	0.924(0.876	9.067(0.015

	test statistic on standardised squared residuals			)	)	)
APARCH(1,1)	Log Likelihood (LL)	3643.123	3834.013	3655.799	3688.267	3800.925
	AIC	-5.44	-5.73	-5.46	-5.51	-5.68
	BIC	-5.41	-5.69	-5.43	-5.48	-5.65
	Shibata	-5.44	-5.73	-5.46	-5.51	-5.68
	HQIC	-5.43	-5.72	-5.45	-5.50	-5.67
	t value of joint effect of sign bias test	0.614(0.893)	2.920(0.404)	0.810(0.846)	2.595(0.458)	1.363(0.714)
	Ljung-Box test statistic on standardised squared residuals**	0.106(0.997)	2.922(0.421)	2.414(0.524)	0.922(0.876)	3.990(0.255)

*Figures in brackets are p values. **at lag 5*

Interpretations

Diagnostic test results in Panel B, reports log-likelihood, information criteria, joint effect of sign bias test and Ljung-Box test statistic of weighted standardised squared residuals. Higher the log-likelihood, the better it is the overall performance of model. Log likelihood result suggest that APARCH (1,1) is marginally better for all the stocks except for TCS in which case, gjrGARCH shows highest value. Information criteria (IC) for all the models are nearly same implying all fit data equally well. In fact, all are negative, lower the value of IC, the better it is from the viewpoint of model performance. Result of sign bias test depicts confirmation of acceptance of null hypothesis. This implies no asymmetry present in the residuals of the model. In other words, a high p-value of t statistic of joint effect of sign bias test for all the models implies absence of asymmetry in residuals after taking asymmetry directly into the model through asymmetry coefficient γ. This shows, good performance of all the models. Absence of ARCH effect is further confirmed with Ljung-Box test statistic in standardised squared residuals which are not significant for all the models except for sGARCH and eGARCH in TCS stock. This means, models have adequately captured conditional heteroscedasticity present in return series.

6. Discussions

The objective of the present work is twofold; to propose a model that can capture volatility in datasets and to zero in on best model capturing volatility dynamics. In this context, four different models were selected based on characteristics of data and literatures. The work started with collecting raw stock price details from Nifty 50 for the chosen sample period. From raw data only closing prices of select stocks were considered which were converted into daily log return, which became the basis for further analysis. Initial plotting gave clue about present of clustering phenomenon but to further confirm the same, additional tests like JB, Arch and Unit root test were applied. After a concrete confirmation, Arch based models were undertaken from literatures. Since our objective was to additionally test for presence of non-linearity and asymmetry effect, we chose to consider it on comparative mode by applying four models. Coefficients of four models in tables above, suggested presence of high volatility clustering with β coefficient as higher around 0.9. All the models for all sample stocks were found stable with APARCH (1,1) outperforming the rest three as evident from log likelihood value. To further stress test, t statistic of joint effect of sign bias test and Ljung-Box test statistic of weighted standardised squared residuals were considered denoting absence of asymmetry and heteroscedasticity in models' residuals. This confirms that the models were successful in capturing the stylised features. The paper in the last section discussed the implications for managers, particularly focusing on its importance in risk management and asset pricing. Finally, it was ended with mentioning of future scope of the paper and conclusion.

7. Managerial implication

Study of this kind has immense managerial implications particularly in the field of risk management, asset pricing and portfolio management. Autoregressive models are based on regression which effectively can capture the effect of past errors on current volatilities. Knowledge of this helps managers to estimate future volatility having an important bearing on risk assessment of financial assets. This leads to design effective hedging strategies that protect value of assets against any adverse movements. Second, optimum capital allocation to portfolio is a major challenge especially in sudden dynamic environment. Correct measuring and forecasting volatility can help to ward off this challenge to certain extent for them who employ active trading strategies. Third, pricing of assets depends on time varying volatility. For instance, unlike BSOPM used in option pricing with standard deviation assumed as constant, managers can use time varying volatility to obtain real time option prices that better help in affecting option trading strategies to book profit. Fourth, volatility has a direct implication on cost of capital which in turn has a bearing on RoE of an enterprise. Hence, managers involving in routine task in corporate finance of raising capital can get better insight from knowledge of volatility estimation and forecasting. Finally, volatility estimation has indirect impact on business operation, particularly in assessing operational risk. Getting around of operational risk can help managers optimising inventory decisions.

8. Future scope

Any research adds to existing literatures by contributing an incremental knowledge to fulfil certain gaps. Study of this kind claims to fulfil the existing gap in a comprehensive manner by including four variants of autoregressive models. However, this work has its own limitations. This study only tries to examine whether standard GARCH is superior to other variants. This apart, the paper additionally tries to model asymmetry and non-linearity along with both short- and long-term (volatility persistence) autoregressive terms. Other aspects such as forecasting of volatility has not been covered which may be an interest of researchers to carry forward the same and test whether same result can be validated further from forecasted values. This apart, study of this type can be further advanced under different regimes to see whether volatility is persistent across regime. Moreover, recent literatures provide evidence against GARCH based models especially when compared to ML models. Under these circumstances, it would be of interesting to see whether ML models outperform traditional statistical models like GARCH.

9. Conclusion

This paper has been undertaken under the assumption of volatility persistence for financial assets in markets. With liberalisation, market microstructure has becoming more complex with more trading instruments available to investors. But simultaneously it comes with a bane in the form of optimising the ‘investment decision’ of investors. Moreover, with increasing integration of world markets, it is common for volatility transmission from one to another which makes it difficult to predict future risk in asset. Therefore, this study is an attempt to generalise conditional volatility of select stocks from NSE NIFTY 50. It is found the presence of ‘clustering phenomenon’ in all the sample stocks with additional information about asymmetry and non-linearity. The results show that APARCH (1,1) is the best among other variants with its superior performance measured in terms of log likelihood value.

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11. **Appendix**

```
library(quantmod)
library(rugarch)
library(FinTS)
library(tseries)
library(e1071)
library(fbasics)
#Import data from yahoo finance
getSymbols("RELIANCE.NS", src = "yahoo", from = "2019-01-01", to = "2024-05-31")
getSymbols("HDFCBANK.NS", src = "yahoo", from = "2019-01-01", to = "2024-05-31")
getSymbols("ICICIBANK.NS", src = "yahoo", from = "2019-01-01", to = "2024-05-31")
getSymbols("INFY.NS", src = "yahoo", from = "2019-01-01", to = "2024-05-31")
getSymbols("TCS.NS", src = "yahoo", from = "2019-01-01", to = "2024-05-31")

# Extract Close price for each stock

RELIANCE_Close<- RELIANCE.NS[, "RELIANCE.NS.Close"]
HDFC_Close<- HDFCBANK.NS[, "HDFCBANK.NS.Close"]
ICICI_Close<- ICICIBANK.NS[,"ICICIBANK.NS.Close"]
INFY_Close<- INFY.NS[,"INFY.NS.Close"]
TCS_Close<- TCS.NS[,"TCS.NS.Close"]

#Merge Close price into one object
combined_data= merge(RELIANCE_Close,HDFC_Close, ICICI_Close,INFY_Close,TCS_Close, all = FALSE)
#Calculate log returns for each column in the combined_data
log_returns<- diff(log(combined_data))
log_returns<- log_returns[-1, ]

#Plot of closing price
```

```
colnames(combined_data) <- c("RELIANCE", "HDFC", "ICICI", "INFY", "TCS")
plot.zoo(combined_data,
    screens = 1,
    col = c("blue", "red", "green", "purple", "orange"),
lwd = 2,
xlab = "Date",
ylab = "Closing Price",
    main = "Stock Closing Prices")
legend("topleft",
   legend = c("RELIANCE", "HDFC", "ICICI", "INFY", "TCS"),
   col = c("blue", "red", "green", "purple", "orange"),
lwd = 2,
cex = 0.4)
```

sGARCH(1,1) for Reliance stock

```
#Specify the model

Rel_sgarch=ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(1,1),
mean.model=list(armaOrder=c(0,0))),distribution.model= "std")

# Fit the model into data
Rel_sgarch_fit=ugarchfit(Rel_sgarch,data=log_returns$RELIANCE)

#Summary of model
Rel_sgarch_fit
```

Similarly for other stocks, same code was run with different model specification.