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Modeling Symmetric and Asymmetric Volatility in Nifty 50 Index Futures Market

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Abstract

Volatility in stock markets is a matter of concern for investors and policymakers across the world. Derivatives enable traders to manage risk arising out of volatility through hedging and arbitrage (Singh & Kansal, 2010). During times of high volatility, regulatory authorities step in to curb the frenzied activity in the stock market. Time series data of financial nature shows non-normality traits. Thus, it is essential to check whether distributions other than normal distribution can perfectly analyze the time series data. Therefore, it becomes important to use the appropriate methods to model volatility. This study aims to analyse both symmetric and asymmetric volatility in Nifty 50 futures markets. Different variants of GARCH models were used in the study under three probability distributions such as normal, Student's-t, and generalized error distribution (GED). EGARCH (1,1) model with Student's- t distribution proved to be the best model for capturing volatility as it had the lowest AIC value. The results detected the presence of a leverage effect and thereby confirmed that negative news created more volatility than positive news.

Keywords: Volatility persistence, Symmetric volatility, Asymmetric volatility, EGARCH, TGARCH, Nifty futures

Introduction

Volatility modeling is one of the most frequently discussed topics in financial literature (Musunuru, 2016). The fluctuating nature of returns of any instrument pertaining to financial market can be attributed to volatility (Pati & Rajib, 2010). Thus, volatility forms the undercurrent of the financial market. Stock market volatility is a major cause of concern for investors and policy makers in India and throughout the world. Derivatives enable traders to manage risk arising out of volatility through hedging and arbitrage (Singh & Kansal, 2010). The National Stock Exchange of India Ltd (NSE) is the largest derivative exchange in the world in terms of the number of contracts traded (Futures Industry Association (FIA), 2021).

Derivatives are mainly used for price discovery, hedging and portfolio diversification (Bandivadekar & Ghosh, 2003).The introduction of futures may either reduce volatility by creating an influx of more informed traders in the market or increase volatility by attracting noise traders who trade to make short-term speculative gains (Gahlot & Datta, 2011).Previous studies ignored the interrelationship of time series returns in derivative markets while analysing volatility before and after the introduction of futures (Antoniou & Holmes, 1995).

According to the US Securities and Exchange Commission, retail investors

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may find it hard to implement appropriate strategies during volatility in the stock market (Limaye, 2018).Whenever volatility soars high in the derivative market, the Securities and Exchange Board of India (SEBI) steps in to implement appropriate measures to curb the volatility and bring down the frenzied activity (Economic Bureau, 2020).Thus it becomes important to use appropriate methods to model volatility.

Though regression models have been used in the past to model volatility it is no longer the preferred model as it assumes constant variance. The GARCH models are the preferred method when it comes to volatility modeling because it best captures some of the commonly known traits of financial time series such as excess kurtosis, volatility clustering, volatility persistence, asymmetric reaction to information and volatility spillover effect (Musunuru, 2016).Since the symmetric GARCH models do not explain asymmetric effects or the leverage effect, asymmetric GARCH variants such as Exponential Generalized Autoregressive Conditional Heteroskedasticity process (EGARCH) by (Nelson, 1991) and Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) by Zakoian (1994) and Glosten et al. (1993) came into being. Asymmetric volatility or leverage effect occurs when stock returns and volatility are negatively correlated i.e. volatility tends to be high when prices are falling and vice-versa (Musunuru, 2016).

This paper focuses specifically on volatility persistence in Nifty 50 index futures markets and also detects the presence of asymmetric volatility under different distributions. This paper contributes to the existing body of literature on volatility modelling in the following aspects. First, both symmetric and asymmetric models are used for volatility estimation. Second, appropriate Autoregressive Moving Average (ARMA) model is selected to be included in the mean equation of the GARCH models. Third, due to fat tails in the data, three different distributions are used (normal, Student's-t and generalized error distribution (GED)) to model volatility of Nifty 50 index futures.

The rest of the paper is divided into the following sections. The next section throws light on the review of literature related to the volatility modelling. The second section gives description about the data selected for the study and explains the methodology behind the computation. The third section relates to the analytical overview of the study along with precise interpretation based on the results. The fourth section provides a valid conclusion for the study.

Review of Literature

Derivative products are commonly used in the stock market to facilitate price discovery, hedging and arbitrage activities (Singh & Kansal, 2010). Securities Exchange Board of India (SEBI) introduced trading in derivatives such as stock futures, index futures, stock options, index options etc to improve the efficiency of the Indian capital market (Raju & Karande, 2003). Derivative instruments are highly volatile and traders need to exercise special care while trading in them (Vo et al., 2019). Large fluctuations in price may be followed by large changes and small may be followed by small. In such cases, the most appropriate method is use to Generalized Autoregressive Conditional Heteroscedastic (GARCH) models which accounts the time varying variance in a process (Antoniou & Holmes, 1995).

Gulen and Mayhew (2000) analysed the index futures volatility in 25 international equity markets before and after index futures were introduced. Findings reported a decrease in volatility after the introduction of futures except in large markets such as United States of America and Japan. Pati and Rajib (2010) analysed the extent to which volatility persistence in National Stock Exchange S&P CRISIL NSE Index Nifty index futures was explained by trading volume. Though volume reduced the volatility in the futures market, the GARCH effect did not completely vanish. Choi et al. (2012) found there was a positive

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relationship between trading volume and volatility in the Korean stock market indicating that trading volume influenced the information flow to the market.

Antoniou and Holmes (1995) observed that futures market enabled quick information flow to spot market which increased spot market volatility. Volatility in Nifty futures market was found to be U-shaped and intraday volatility was the least between 11.00 am to 12.00 am (Singh & Gangwar, 2018). John and Amudha (2019) detected the leverage effect in NSE Nifty stocks. Both volatility clustering and persistence were present. While employing GARCH models to capture the asymmetric effect in CNX Small cap, CNX Midcap and S&P CNX Nifty, Ali and Talukdar (2017) found that both past and current news impacted volatility with negative shocks adding more to the impact than positive shocks. Musunuru (2016) examined the volatility persistence and news asymmetry in soyabean futures market and found leverage effect was absent in the market. Positive news added more to the volatility than negative news. The diagnostic test confirmed that APARCH (1,3) model with t-distribution captured the structure of volatility better than all other models.

Dutta (2014) compared symmetric and asymmetric GARCH models assuming both normal and heavy tailed distribution by using U.S.-Japan daily exchange rate series as proxy. The results revealed wherever heavy-tailed distribution was detected volatility persistence was considerably low. Srinivasan (2013) modeled and forecasted stock futures volatility by using various GARCH models. Integrated GARCH model provided accurate forecast followed by Threshold GARCH model. During the financial crisis period, BSE 500 stock index exhibited leverage effect along with volatility clustering which was analysed using EGARCH and TGARCH models respectively (Goudarzi & Ramanarayanan, 2011). While analysing the stock market volatility using GJR-GARCH model, Abounoori and Nademi (2011) found that bad news had more impact on volatility than good news. Alberg et al. (2008) observed that EGARCH model with skewed Student-t distribution is the best model for forecasting volatility in Tel Aviv stock exchange. Similar results were reported by David (2018) while measuring volatility persistence and leverage effects in Nigerian stock market.

Volatility has been analysed and studied under different scenarios using variants of the GARCH model. The literature indicates that no study has been carried out to analyse asymmetric volatility and persistence in the Nifty index futures market while assuming different probability distributions. The current study employs various symmetric and asymmetric GARCH models for modeling volatility under three different distributions such as normal or Gaussian distribution, Student's-t distribution and generalised error distribution.

Methodology

Auto-Regressive Integrated Moving Average (ARIMA) Specifications

The appropriate ARMA model is required to be chosen as the mean equation while carrying out analysis using GARCH model and its variants. Auto-Regressive Integrated Moving Average (ARIMA) model is a generalization of an Autoregressive Moving Average (ARMA) model. An ARMA model expresses the conditional mean of Y_t as a function of both past observations Y_{t-1}, $Y_{t-2,}$ Y_{t-p} and past innovations, $\varepsilon_{t-1,}$ $\varepsilon_{t-q.}$ The number of lags that Y_t depends on p is the AR degree. The number of lags that Y_t depends on p is the MA degree (Meher et al., 2021).

In general, these models are denoted by ARMA (p, q). The form of the ARMA (p, q) model is given below:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \ldots + \beta_p Y_{t-p} + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + \ldots\ldots + \phi_q \varepsilon_{t-q} \quad \textbf{(1)}$$

Where, α is the constant term,

$\beta_{1\ldots.}$ β_p is the AR non-seasonal autoregressive (AR) coefficients,

ϕ Nonseasonal Moving Average (MA) coefficients,

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Y_{t-1}….Y_{t-p} – non-seasonal AR lags corresponding to non-zero,

ε_{t-1} …… ε_{t-q} – MA lags corresponding to non-zero.

To determine the effective ARMA (p,q) model AIC values and significant coefficients were used.

GARCH Specifications

Generalised Auto Regressive Conditional Heteroskedasticity (GARCH) model consists of a conditional mean and variance equation. In a GARCH model the conditional variance is a linear function of both the squared errors and past conditional variances.

The basic GARCH model of order (p,q) can be represented as:

$$r_t = \mu + \varepsilon_t \quad (2)$$

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon^2_{t-1} + \sum_{j=1}^{q} \beta j \, h_{t-j} \quad (3)$$

where r_t is the daily return, μ is the mean value of the return and ε_t is the error term (Bollerslev, 1986) the proposed GLAD method can obtain robustly an optimal AR parameter estimation without requiring the measurement noise to be Gaussian. Moreover, the proposed GLAD method can be implemented by a cooperative neural network (NN.

In the above equation p and q are the lag lengths of squared error and conditional variance terms, respectively. The Akaike Information Criterion (AIC) and the Schwartz Information Criterion (SIC) are typically used to determine the ARCH and GARCH orders of p and q, respectively.

The conditional variance (h_t) equation of the GARCH model comprises of three parameters. ω is the coefficient of the constant in the variance equation which indicates the long-run mean volatility, α is the ARCH term in the model which is a shock from the previous period, β is the GARCH term which is the last period variance.

For the conditional variance to be positive for all t, some restrictions are imposed for the model.Accordingly,thecoefficients α_i(i=0,…,p) and β_j (j=1,…,q) are assumed to be positive in order to allow positive conditional variance (h_t). When q becomes 0, the GARCH model becomes a basic ARCH model.

The ARCH term(α) in the conditional variance equation indicates the short-run persistence of shocks whereas the GARCH term (β) represents the contribution of shocks to long-run persistence (Musunuru, 2016). However GARCH models accounts for only the symmetric impact on volatility i.e. it assumes that both positive and negative news have the same impact on volatility.

Volatility Persistence

A measure of the persistence of volatility is the "half-life" of volatility. It can be defined as the time taken for the volatility to move halfway back towards its unconditional mean following a deviation from it. Volatility persistence is calculated using the formula given below:

Half-life of volatility = log (0.5)/
log(ARCH coefficient +GARCH coefficient **(4)**

When ARCH coefficient + GARCH coefficient=1, the half-life becomes infinite (John & Amudha, 2019b). Asymmetric volatility has been studied using two different asymmetric GARCH models- (TGARCH and EGARCH). These models enable the conditional variance to respond asymmetrically to both positive and negative shocks.

EGARCH Specifications

The Exponential General Autoregressive Conditional Heteroskedastic (EGARCH) model is the asymmetric variant of GARCH model. In the EGARCH model, the mean and variance specifications are:

Mean equation: $r_t = \mu + \varepsilon_t$ (5)

Variance equation:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \frac{\varepsilon_{t-i} + \gamma_i \varepsilon_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{q} \beta j \, h_{t-j} \quad (6)$$

where $h_t = \log\sigma t^2$, ε_t can assume either positive or negative values that can have

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different impact on volatility (Nelson, 1991). Variables used in the EGARCH model are:

ω: is the intercept for the variance,

α: is the coefficient of the lagged value of the squared residual or ARCH term

β: is the coefficient for the lagged GARCH term.

γ: is the scale of the asymmetric volatility.

The asymmetric volatility or the leverage effect is captured through the variable gamma (γ). The sign of gamma decides if the asymmetric volatility is positive or negative.

If $\gamma = 0$, no asymmetric volatility.

If $\gamma < 0$, negative shocks or bad news will increase the volatility more than positive shocks or good news.

If $\gamma > 0$, positive shocks or good news will increase the volatility more than negative shocks or bad news.

Since the log of the variance (σ_t^2) is used in the model it means that even if the parameters are negative, the variance will still be positive. Therefore, the model is not subject to the non-negativity constraints (Nelson, 1991).

TGARCH Specifications

Threshold GARCH or TGARCH model accounts for asymmetric impacts by including a dummy variable.

$$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1} + \gamma N_{t-1}\varepsilon^2_{t-1} \quad \textbf{(7)}$$

where α, β, and γ are parameters and N_t is a dummy variable which takes the value of 1 if if $\varepsilon_{t-1}<0$ and zero if $\varepsilon_{t-1}>0$.The TGARCH model can be extended by including more lagged terms (Zakoian, 1994). Thus TGARCH (p,q) model can be written as :

$$h_t = \grave{u} + \sum_{i=1}^{p} \alpha_i + \tilde{a}_i N_{t-i)} \mathring{a}^2_{t-I} + \sum_{j=1}^{q} \beta j\, h_{t-j} \quad \textbf{(8)}$$

where N_{t-1} is an indicator for negative ε_{t-1} which means that N_{t-1} will be equal to 1 if, $\varepsilon_{t-1} < 0$ and 0 if $\varepsilon_{t-1} > 0$ and the parameters in the model are constrained by $\omega \geq 0$, $\alpha \geq 0$, $\beta \geq 0$ (Glosten et al., 1993) The news impact is considered as asymmetric as long as ($\gamma \neq 0$). If $\gamma > 0$, we can conclude that there is a leverage effect in the model (bad news has larger impacts on volatility).

Non-Gaussian Distributions

Often GARCH models assume that their standardized residuals are normal. However, time series data of financial nature show non-normality traits such as excess kurtosis, skewness etc (Jondeau & Rockinger, 2003).Thus it is essential to check whether distributions other than normal distribution can perfectly analyze the time series data.

Two non-normal distributions included in the study are Student's-t distribution and the Generalized Error Distribution (GED). According to Kovacic (2007), Student's-t distribution for $u_t = \varepsilon_t / \sigma_t$. The formula for standardized errors is given below:

$$f(u_t) = \frac{\frac{\Gamma(\nu+1)}{2}}{\sqrt{\Pi(\nu-2)}\,\Gamma\frac{\nu}{2}} \; \frac{1}{\left(1+\frac{u_t^2}{\nu-2}\right)^{(\nu+1)/2}} \quad \textbf{(9)}$$

Where Γ is the gamma function, and ν > 2 is the shape parameter.

The GED proposed by Nelson (1991) can be represented as the following form:

$$f(u_t) = \frac{\nu}{\lambda.2^{(\nu+1)/\nu}\,\Gamma(1/\nu)} \exp\left\{-\frac{1}{2}\left|\frac{u_t}{\lambda}\right|^{\nu}\right\}, \quad (10)$$

$$\text{where } \lambda = \frac{[2^{-2/\nu}\,\Gamma(1/\nu)]^{1/2}}{\Gamma(3/\nu)}$$

where, ν is a positive shape parameter governing the thickness of the tail behavior of the distribution. When ν =1 GED reduces to the double exponential distribution probability density function (PDF); when ν =2, the above PDF reduces to the standard normal PDF.

Data

The data is taken from the official website of National Stock Exchange (NSE) and consists of daily closing prices of Nifty futures from 4th January 2010 to 13th April, 2022. Only near-month futures contracts have been

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selected as both next-month and far-month futures contracts lack liquidity (Gupta & Singh, 2014). Log returns have been calculated using the formula:

$$R_t = \ln P_t - \ln P_{t-1} \quad \textbf{(11)}$$

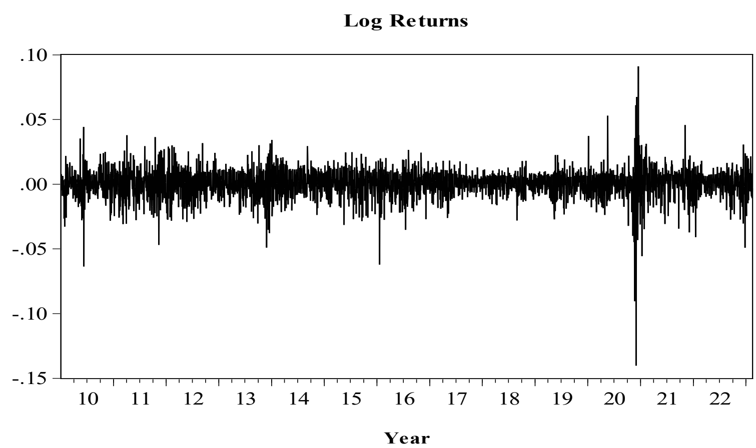
The purpose of this paper is to understand the volatility persistence and the asymmetric volatility in the futures market. At first descriptive statistics gives an overall picture of the futures market. Stationarity of the data is confirmed using both Augmented Dickey Fuller (ADF) test and Philip Perron (PP) tests. The combination of the best Autoregressive Moving Average (ARMA) is selected as per the Akaike Information Criterion (AIC) criteria to be included in the mean equation of the GARCH models. Asymmetric volatility is detected using both EGARCH and TGARCH models and the best model is selected using the Akaike Information Criteria (AIC). Diagnostic tests were carried out to determine the fitness of the model.

Empirical Analysis and Results

As part of the preliminary analysis, graph of log returns of Nifty 50 futures has been plotted to understand the structure of data series.

Figure 1

Log Returns of Nifty 50 Futures



Note. Figure shows graphical representation log returns of Nifty 50 futures from 2010 to 2022.

The graph shows that low fluctuations in log returns of Nifty 50 index futures are followed by low movements and high fluctuations are followed by high movements. This shows the possibility of GARCH effect in the data series which needs to be tested using appropriate models.

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Table 1
Descriptive Statistics of Daily Returns of Nifty 50 Futures (2010–2022)

Mean	0.0004
Median	0.0009
Maximum	0.0912
Minimum	-0.1403
Std. Dev.	0.0111
Skewness	-1.0221
Kurtosis	16.5876
Jarque-Bera	26912.20
Probability	0.000

Note. Daily returns of Nifty 50 futures (2010-2022)

The above table shows the summary of the descriptive statistics of the daily log returns of the Nifty 50 futures series. The mean returns are positive throughout the study period with low standard deviation. Negative skewness is evident which indicates that negative returns were more frequent than positive returns. The high kurtosis values indicate that the returns are leptokurtic (fat-tailed) where the mean and median are less than the mode and sharply peaked than normal distribution. However, the data series is not normally distributed as the p value of the Jarque-Bera statistic is significant (less than 5 per cent).

Table 2
Unit Root Test Results

Augmented Dickey Fuller Test		Phillips Perron Test	
Test Statistic	p value	Test Statistic	p value
–58.8013	0.0001	–58.8034	0.0001

Note. Test critical values at 10% level is -2.568054,5% level is -2.865138 and 1% level is -3.435871.

p values for all the above observations are less than 0.05, hence they are significant at 5% level.

Before conducting any further analysis, it is mandatory to see whether the return series are stationary in nature. Augmented Dickey Fuller (ADF) test and Phillips-Perron (PP) test were carried out to ensure the stationarity of the return series. The results reveal that log returns were stationary at level and had no presence of unit root.

Table 3 shows that an ARMA (4, 4) model was chosen as the mean equation for the GARCH models. The appropriate model was selected using the Akaike Information Criteria (AIC). The pre-requisite for carrying out any GARCH model is that the data series should be heteroskedastic in nature which means that log returns of the Nifty futures data should have ARCH effect. ARCH Lagrange multiplier test was used to detect the presence of ARCH effect in the data series. The ARCH LM test result reveals there is heteroscedasticity in the model as the p value is significant. This warrants the need for carrying out appropriate GARCH models to explain the volatility of the data series.

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Table 3

$ARMA_{pq}$ Model Selection Criteria

ARMA MODEL	(4,4)
C	0.0003*
	(0.000)
AR(4)	0.872*
	(0.032)
MA(4)	-0.914*
	(1.107)
SIGMASQ	0.0001*
	(0.000)
Log Likelihood	10570.94
AIC*	-6.174
BIC	-6.156
HQ	-6.168
ARCH LM	86.10533
	(0.000)

Note. * denote significance at 1 % level. Numbers in parentheses below ARMA coefficient estimates are standard errors. AIC, BIC and HQ are Akaike Information Criteria, Bayesian Information Criteria and Hannan-Quinn Criteria respectively. Numbers in parentheses below the ARCH -LM coefficients are the p-values. Model with lowest AIC value has been chosen.

Table 4

GARCH Model Results with Normal Distribution

Parameters	GARCH (1,1)	EGARCH (1,1)	TGARCH (1,1)
μ	0.0006*	0.0002*	0.0003*
	(0.0001)	(0.000)	(0.0001)
ω	2.04E-06*	-0.571*	2.85E-06*
	(0.000)	(0.051)	(0.000)
α	0.080*	0.136*	0.0012
	(0.006)	(0.013)	(0.821)
β	0.902*	0.949*	0.903*
	(0.0083)	(0.004)	(0.903)
γ		-0.117*	0.131*
		(0.007)	(0.131)
α+β	0.983	1.086	0.904
Volatility persistence	42.457	-8.400	6.902
AIC	-6.434	-6.432	-6.461
SIC	-6.412	-6.409	-6.437
$LB^2(36)$	0.8725	0.088	2.407
	(0.832)	(0.999)	(0.79)
ARCH LM	0.826	0.0086	0.605
	(0.363)	(0.925)	(0.437)

Note. * denote significance at 1 % level. Numbers in parentheses below GARCH, EGARCH and TGARCH coefficient estimates are standard errors. AIC, SIC are Akaike Information Criteria, and Schwartz Information Criteria, respectively. LB^2 (36) is the Ljung-Box statistics for the squared standardized residuals using 36 lags. Numbers in parentheses below the LB statistics and ARCH -LM coefficients are the p-values.

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μ is the mean equation coefficient which was found to be significant under all the GARCH variants. The daily mean returns ranges between 0.0002 and 0.0008 for all the symmetric and asymmetric GARCH variations. The highest return was reported under GARCH model with Student's-t and Generalised Error distribution.

Table 5
GARCH Model Results with Student's-t Distribution

Parameters	GARCH (1,1)	EGARCH (1,1)	TGARCH (1,1)
μ	0.0008* (0.0001)	0.0006* (0.0001)	0.0006* (0.0001)
ω	1.83E-06* (0.000)	-0.313* (0.044)	2.43E-06* (0.000)
α	0.069* (0.009)	0.114* (0.017)	-0.001 (0.008)
β	0.916* (0.011)	0.976* (0.0041)	0.914* (0.0101)
γ		-0.102* (0.0112)	0.119* (0.015)
α+β	0.985	1.090	0.913
Volatility persistence	45.921	0.155	7.584
AIC	-6.486	-6.510	-6.504
SIC	-6.463	-6.485	-6.479
$LB^2(36)$	6.8171 (0.448)	13.828 (0.129)	14.347 (0.111)
ARCH LM	0.155 (0.693)	0.056 (0.813)	0.121 (0.728)

Note. *denote significance at 1 % level. Numbers in parentheses below GARCH, EGARCH and TGARCH coefficient estimates are standard errors. AIC, SIC are Akaike Information Criteria, and Schwartz Information Criteria, respectively. LB^2 (36) is the Ljung-Box statistics for the squared standardized residuals using 36 lags. Numbers in parentheses below the LB statistics and ARCH -LM coefficients are the p-values.

The coefficient of the constant term in the conditional variance equation is ω , α is the coefficient of the lagged value of the squared residual (ARCH) and β is the coefficient of the lagged value of the conditional variance (GARCH).The ARCH coefficient, α is found to be in the range of 0.0012 and 0.136.The GARCH coefficient, β ranged between 0.842 and 0.975. The ARCH coefficient is significant under all the GARCH specifications except for TGARCH model with a normal and Student's-t distribution. Whereas the GARCH coefficient is significant under all the models. Strong ARCH and GARCH effects is indicated by the significance of the α and β coefficients in the conditional variance equation. The significance of the GARCH coefficient explains that past volatility has a huge impact on future volatility and therefore it affects the future returns of the Nifty futures index.

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Table 6

GARCH Model Results with Generalized Error Distribution (GED)

Parameters	GARCH (1,1)	EGARCH (1,1)	TGARCH (1,1)
μ	0.0008* (0.0001)	0.0006* (0.0001)	0.0006* (0.0001)
ω	1.95E-06* (0.000)	-0.327* (0.046)	7.34E-06* (0.000)
α	0.072* (0.0092)	0.124* (0.0174)	0.024* (0.009)
β	0.910* (0.0119)	0.975* (0.0042)	0.842* (0.0149)
γ		-0.093* (0.0098)	0.086* (0.0120)
α+β	0.983	1.099	0.866
Volatility persistence	40.602	-7.311	4.807
AIC	-6.480	-6.468	-6.423
SIC	-6.456	-6.443	-6.398
$LB^2(36)$	6.2137 (0.515)	7.3359 (0.395)	115.26 (0.250)
ARCH LM	0.379 (0.538)	0.271 (0.603)	0.655 (0.418)

Note. *denote significance at 1 % level. Numbers in parentheses below GARCH, EGARCH and TGARCH coefficient estimates are standard errors. AIC, SIC are Akaike Information Criteria, and Schwartz Information Criteria, respectively. LB^2 (36) is the Ljung-Box statistics for the squared standardized residuals using 36 lags. Numbers in parentheses below the LB statistics and ARCH -LM coefficients are the p-values.

The non-explosiveness condition is satisfied as the sum of the ARCH and GARCH coefficients is less than one for majority of the models. However, it was found to be greater than one for EGARCH model under all the distributions. High volatility persistence points out that fluctuations in price can leave longer impact on the returns. Volatility persistence was high under GARCH model with Student's-t distribution (45.921) and lowest under EGARCH model with a Generalised Error distribution. High persistence indicates that information disseminates very slowly and past news creates a long-time impact on current news. The high persistence reveals that the returns of Nifty 50 futures market have the tendency to border on past information than the current information entering the market.

Volatility is higher in a bearish market as compared to a bull market. In order to understand the true effect of positive and negative news on the volatility of nifty 50 index futures, asymmetric GARCH models such as EGARCH and TGARCH models have been used respectively. The gamma term (γ) captures the leverage effect or asymmetric volatility, i.e. the impact of news on volatility.

For a TGARCH model, if the γ is positive and significant, it indicates that negative news has higher impact on volatility. Whereas under an EGARCH model, bad news or shocks have higher impact on volatility if the leverage coefficient is negative and significant. The gamma term, γ is negative and significant under all EGARCH models and it is found to be positive and significant under all the TGARCH

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models. The results confirm the presence of leverage effect under both EGARCH and TGARCH model. Thus negative innovations have added more to the next period conditional volatility of the Nifty futures market. Thus it can be concluded that negative news have added more to the volatility in the returns of Nifty futures market than positive news. The results are in line with the findings of Ali and Talukdar (2017);Choi et al. (2012); John and Amudha (2019); Abounoori and Nademi (2011); Alberg et al. (2008) and David (2018).

Diagnostic tests were conducted to assess the overall fitness of the model and the results reveal that the models are correctly specified. If there is no auto-correlation in the model the Ljung -Box Q statistics would be insignificant. The results show that the there is no autocorrelation in the model as the Ljung-Box Q statistics are insignificant in terms of the standard residuals LB (36).The Ljung-Box Q statistics were insignificant for the squared residuals indicating that the variance equation was correctly defined under each of these periods. Heteroskedasticity in the model is checked using the ARCH -LM test. As per the results there is no heteroskedasticity in any of the models as the p values are insignificant.

AIC and SIC values help in determining the best GARCH variant for describing the model. The selection criteria showed that the model with Student's-t distribution fit the data better than the other GARCH variants. The AIC and SIC values reveal that EGARCH model performed the best as against all the other models. Thus, from the overall results, it is evident that EGARCH (1,1) model with a Student's-t distribution is best suited for Nifty 50 futures series.

Conclusion

Volatility is part and parcel of the financial market and an understanding of volatility particularly in the derivative segment is of utmost use to speculators, hedgers and investors looking for arbitrage opportunities. This paper attempted to identify the appropriate model to analyse symmetric and asymmetric volatility in the Nifty 50 futures market. Nifty futures data was taken as the sample from 4th January 2010 to 13th April, 2022. The data series showed all the peculiarities of a typical financial time series such as negative skewness, excess kurtosis and volatility persistence. Unit root results of both ADF and PP test showed the dataset was stationarity at level. The suitable ARMA model was selected for to capture the seasonal effects of the data series.

Both symmetric and asymmetric GARCH models were employed to examine volatility. Both α and β coefficients in a GARCH (1,1) model were positive and significant indicating the presence of both ARCH and GARCH effects in the model. Volatility persistence was high under GARCH model with Student's-t distribution (45.921). This shows that information decays very slowly and the Nifty 50 futures returns are influenced more by past information than current information.

The leverage effect was studied using the asymmetric GARCH variants such as EGARCH (1,1) and TGARCH (1,1) model. The gamma term (γ) of both the models confirmed the presence of asymmetric volatility or leverage effect in the futures market revealing that bad news have more impact on future volatility than positive news of the same magnitude. EGARCH (1,1) model with Student's- t distribution proved to be the best model for capturing asymmetric volatility as it had the lowest AIC value.

The diagnostic test results also reveal that model is perfectly fit and is free of both autocorrelation and heteroskedastic effects. On the whole the study revealed that Nifty 50 futures market respond differently to news shocks and negative news creates more volatility than positive news.

Volatility modelling helps in improving the accuracy of predicting asset prices which in turn will help both researchers and academicians to frame accurate models for pricing financial assets (Pati & Rajib, 2010). Information related to volatility in derivatives

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markets is of utmost interest to investors engaged in hedging, speculation and arbitrage. A similar study can be conducted by taking more indices as sample so that it would give a comprehensive picture of volatility in the futures market.

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