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FORECASTING VOLATILITY – EVIDENCE FROM INDIAN STOCK USING ARCH AND GARCH MODELS

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ABSTRACT

This paper explores to develop alternative models from the Autoregressive Conditional Heteroscedasticity (ARCH) or its generalization, the Generalized ARCH(GARCH) family, to estimate volatility in the Indian equity market return. The different volatility estimators and model have been proposed in the literature to measure volatility returns. The ARCH effect or such influence is evidently persistent for long time periods. We have tried to capture this effect through different GARCH type models because high variability and high volatility has been seen in stock exchange rates, daily, weekly and monthly stock market returns, foreign exchange rates. The main idea underlying this study is to identify and estimate the mean and variance components of the daily closing share prices of the ARIMA-GARCH type models by explaining the volatility structure of the residuals obtained under the best suited mean fort he said series. The study concludes that there is a presence of volatility clustering, evidence of asymmetric effect on volatility of risk premium in the stock market.

Keywords: *ARIMA (Autoregressive Integrated Moving Average), EARCH (Exponential Autoregressive Conditional (Heteroscedasticity), TARCH (Threshold Autoregressive Conditional Heteroscedasticity).*

Introduction

Forecasting procedures are widely used in financial market to evaluate companies and their stocks The investment decisions by investors may under go changes due to high volatility, which may lead to a fall in the long-term capital flows from foreign as well as domestic investors. This paper explores to develop alternative models from the Autoregressive Conditional Heteroscedasticity (ARCH) family to explain the Indian equity markets. For this purpose, we have selected two indices from each of the two main stock exchanges in India – the Bombay Stock Exchange (BSE) and the National Stock Exchange (NSE). Over the past few years, modeling and forecasting volatility of a financial time series has become a popular area of research and has gained a great deal of attention from academicians, researchers and others, this is because volatility is considered as an important concept for many economic and financial applications, like risk management, portfolio optimization and asset pricing. Volatility refers to the amount of risk or uncertainty about the size of changes in a security's value. The main aim of building these models was to make a good forecast of future volatility that would be helpful in obtaining a more efficient portfolio location, having a better risk management and more precise derivative prices of a certain financial instrument.

A generalized Arch model extended by Bollerslev (1986) is another popular model for estimating stochastic volatility. These models are generally used in various branches of econometrics, especially in financial time series analysis. Besides, with the introduction of models of ARCH and GARCH, there have been number of empirical applications of modeling variance (volatility) of financial time series.

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The existing literature describes that GARCH type models are the better models in describing return series having the property of changing variance level It has been tested statistically and empirically.

Literature Review

Tripathy, Rao and Kanagaraj (2009) He has investigated the impact of introduction of the derivative instruments and leverage and asymmetric effect on spot market volatility using NSE Nifty as a proxy for Indian stock market during the period October 1995 to December 2006 by using EGARCH, TARCH, GARCH, and component ARCH model. The research study has also reported that asymmetric GARCH models provide better fit than the symmetric GARCH models.

Srinivasan and Ibrahim (2010) Attempted to model and forecast the volatility of the SENSEX Index returns of Indian stock market. Results showed that the symmetric GARCH model performed better in forecasting conditional variance of the SENSEX Index return rather than the asymmetric GARCH models, despite the presence of leverage effect.

Ahmed and Suliman (2011) This paper try to estimate volatility (conditional variance) in the daily returns of the principal stock exchange of Sudan namely, Khartoum Stock Exchange (KSE) over the period from January 2006to November 2010. They provide evidence on the existence of risk premium for the KSE index return series which support the positive correlation hypothesis between volatility and the expected stock returns.

Goudarzi and Ramanarayanan (2011) They investigated the volatility of BSE 500 stock index and modeled two non-linear asymmetric model viz., EGARCH (1, 1) and TGARCH (1, 1) and found that TGARCH (1, 1) model was found to be the best preferred model as per Akaike Information Criterion (AIC), Schwarz Information Criterion (SBIC) and Log Likelihood (LL)criteria.

Adesina (2013) It means **s**ymmetric and asymmetric GARCH models to estimate the stock return volatility and the persistence of shocks to volatility of the Nigerian Stock Exchange (NSE). He used monthly data from January1985 to December 2011 of the NSE all share-index. His study revealed high persistent volatility for the NSE return series found no asymmetric shock phenomenon (leverage effect) for the return series.

Vijayalakshmi and Gaur (2013) This model used eight different models to forecast volatility in Indian and international stock markets. NSE and BSE index were considered as a proxy for Indian stock market and the exchange rate data for Indian rupee and foreign currency over the period from 2000 to 2013. Based on the forecast statistics the study found that TARCH and parch models lead to better volatility forecast.

Research Methodology

Sample Data and Preliminary Analysis

The daily data of S&P Sensex30 index of Bombay Stock Exchange (BSE) of India is used for analysis. The period is January 2009 to January 2022, total number of observations are 738 excluding public holidays. The S&P Sensex 30 index is a weighted index of top 30 securities that are listed equities on the BSE. The daily returns are used to generate the continuously compounded returns used in the ARCH and GARCH modeling. To analyze the asymmetric volatility of Indian Stock market taking sample of NIFTY of NSE. The data used in this study consist of the daily closing points of NIFTY for the period of ten years.

The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model

$$\boldsymbol{Mean\ Equation} \quad \boldsymbol{r_t = \mu + \varepsilon_t}$$

$$\boldsymbol{Variance\ Equation} \quad \boldsymbol{\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2}$$

$where\ \omega > 0\ and\ \alpha_1 \geq 0\ and\ \beta_1 \geq 0, and$

$r_t = return\ of\ the\ asset\ at\ time\ t$

$\mu = average\ return$

$\varepsilon_t = residual\ returns, defined\ as$:

$\varepsilon_t = \sigma_t z_t$

Heteroscedasticity Testing

One of the most important issues before applying the GARCH methodology is to first examine the residuals for the evidence of Heteroscedasticity. To test the presence of Heteroscedasticity in residual of the return series of Nifty index returns, Lagrange Multiplier (LM) test for Autoregressive conditional Heteroscedasticity (ARCH) is used. The test procedure is performed by first obtaining the residuals from the ordinary least squares regression of the conditional mean equation which might be an autoregressive (AR) process, moving average(MA) processor a combination of AR and MA processes (ARMA)process (Suliman, 2012).

The conditional mean equation is as:

$$R_t = \emptyset_1 R_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1}$$

It is compute the Engle(1982) test for Arch effect to ensure that here is no Arch effect.

Volatility Measurement Technique

GARCH models represent the main methodologies that are applied in modeling the stock market volatility. The present study employed GARCH (1, 1) and GARCH-M (1, 1) for modeling conditional volatility and for modeling asymmetric volatility EGARCH (1,1) and TGARCH (1, 1) were applied. The following GARCH techniques are applied to capture the volatility in the return series.

Symmetric Measurement

To study the relation between asymmetric volatility and return, the GARCH (1, 1) and GARCH-M (1, 1) models are used in the study.

The Generalized ARCH Model (GARCH)

The GARCH model (Bollerslev[1] 1986), which allows the conditional variance to be dependent upon previous own lags; conform to the conditional variance question in the simplest form as:

$\sigma^2_t = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \beta_1 \sigma^2_{t-1}$

where $\alpha_0 > 0$, $\alpha_1 \geq 0$ and $\beta_1 \geq 0$

The size of parameters α_1 and determine the short-run dynamics of the volatility time series. If the sum of the coefficient is equal to one, then any shock will lead to a permanent change in all future values. Hence, shock to the conditional variance is 'persistence.'

The GARCH-in-Mean (GARCH-M Model)

In GARCH model, the conditional variance enters the mean equation directly, which is generally known as a GARCH-M model. The return of a security may depend on its volatility and hence a simple GARCH-M (1, 1) model can be written as:

Mean Equation $R_t = \mu + \lambda_1 \sigma_t^2 + \varepsilon_t$

where, rt is the return of the asset at time *t*, μ is the average return, and ε*t* is the residual return.

Variance Equation $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$

The parameter λ in the mean equation is called the risk premium. A positive λ indicates that the return is positively related to its volatility, i.e. a rise in mean return is caused by an increase in conditional

variance as a proxy of increased risk, The main drawback of symmetric GARCH is that the conditional variance is not able to respond asymmetrically to rise and fall in the stock returns. Hence, a number of models have been introduced to deal with the issue and are called asymmetric models viz., EGARCH, TGARCH and PGARCH, which are used for capturing the asymmetric phenomena. To study the relation between asymmetric volatility and return, the EGARCH (1, 1) and TGARCH(1, 1) models are used in the study.

The Exponential GARCH Model

This model is based on the logarithmic expression of the conditional variability. The presence of leverage effect can be tested and this model enables to find out the best model, which capture the symmetries of the Indian stock market (Nelson1991) and hence the following equation:

$$Ln(\sigma_t^2) = \alpha_0 + \beta_1 Ln(\sigma_{t-1}^2) + \alpha_1 \left\{ \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$$

The left-hand side is the log of the conditional variance. The coefficient ϒ is known as the asymmetry or leverage term. The term ϒ accounts for the presence of the leverage effects, which makes the model asymmetric if ϒ =0 then the model is symmetric. If ϒ is negative and statistically different from zero, it indicates the existence of the leverage effect.

Threshold GARCH Model

The generalized specification of the threshold GARCH for the conditional variance (Zakoian1994) is given by:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

The γ is known as the asymmetry leverage parameter.

Good news has an impact of α_1 while bad news has impaction $\alpha_i + \Upsilon_i$ is α significant and positive, negative shocks have a larger effect on σ_t^2 than the positive shocks. The criteria to accept the null hypothesis of no leverage effect in TGARCH model is that ϒ coefficient must be negative. In other words, if the ϒ coefficient is not negative ($\Upsilon \neq 0$) the news impact is asymmetric.

Results and Discussion

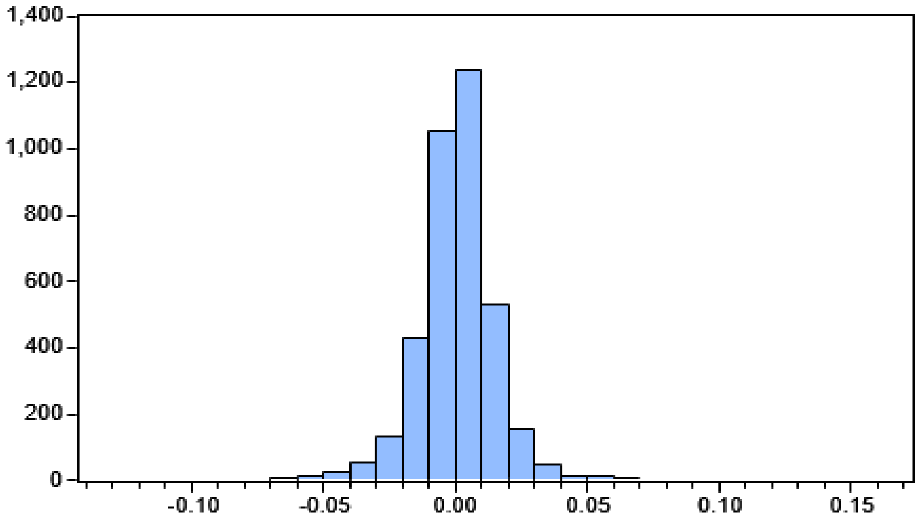


Fig.1: Descriptive Statistics

Series: RET
Sample 3/30/2001
3/31/2016Observations
3734

Mean	0.000511
Median	0.000934
Maximum	0.163343
Minimum	-0.130539
Std.Dev.	0.014936
Skewness	-0.272266
Kurtosis	12.46677
Jarque-Bera	13989.47
Probability	0.000000

In order to evaluate the series, observe extreme values, temporal clustering, and fat-tail (leptokurtic) in the graph and descriptive statistics. Examination of the values of kutosis, skewness and Jarque-Bera test statistics, which is significantat1% level and hence the null hypothesis of normality is rejected. To make the series stationary, the closing price of the Nifty index is converted into daily natural logarithm turn series. Figure 2 shows volatility clustering of return series of the S&P CNX Nifty for the study period from January 2009 to January 2022. From the figure 2, it can be inferred that the period of low volatility tends to be followed by period of low volatility for a prolonged period and the period of high volatility is followed by period of high volatility for a prolonged period, which means the volatility is clustering and the return series vary around the constant mean but the variance is changing with time

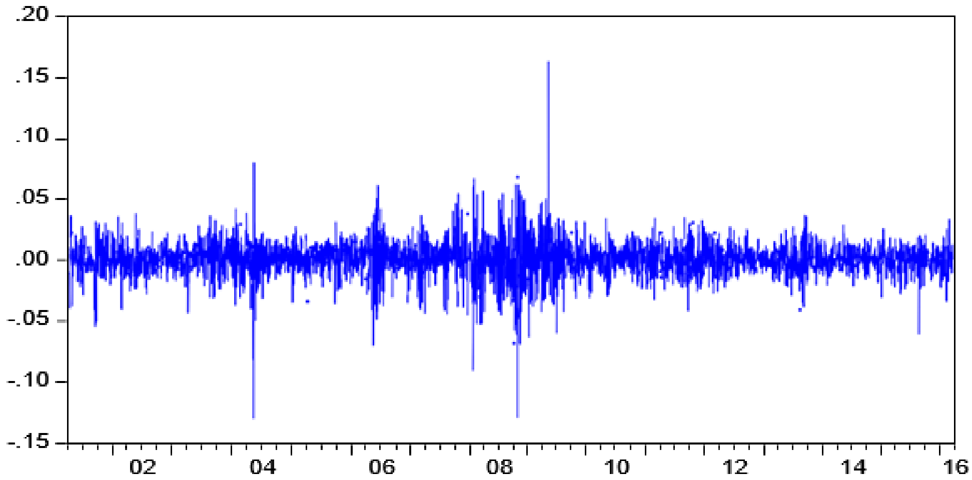


Fig. 2: Nifty Returns

Table 1 shows the presence of unit root in the series tested using ADF and PP tests. Both the ADF and PP test statistics reported in table 1 reject the hypothesis at 1% level as the critical value of 3.43 for both ADF and PP tests of a unit root in the return series. Also, the p values of ADF and PP are less than 0.05. Hence, the results of both the tests confirm that the series are stationary.

Table 1: Stationary Test

Value	ADF	PP
t- Statistic	-56.69278	-56.70007
Prob*	0.0001	0.0001
Critical Value		
1 %	-3.431916	-3.431916
5 %	-2.862117	-2.862117
10 %	-2.567121	-2.567121

As a prior step for estimating ARCH family model equation, a mean equation needs to be formulated. The mean equation for ARCH family model has been formulated as ARMA (1, 1) model using Box Jenkins methodology. The results for mean equation have been unremunerated in the table below

Table 2: Mean Equation ARMA (1,1)

Probability	Variable	Coefficients	Std. Error	t-Statistics
0.0468	C	0.000513	0.000258	1.988394
0.0266	AR(1)	-0.352298	0.158833	-2.218035
0.0048	MA(1)	0.432098	0.153069	2.822905

The coefficients of constant, AR&MA terms are significant at 5% level. After obtaining the residuals from the ARMA (1, 1) model the ARCH-LM test is applied to find out the presence of arch effect in the residuals of the Nifty return series. From the table 3, it is inferred that the ARCH-LM test statistics is highly significant. Since p value is less than 0.05, the null hypothesis of 'no ARCH effect' isr ejected at 1% level, which confirms the presence of ARCH effects in the residuals of time series models in the Nifty returns.

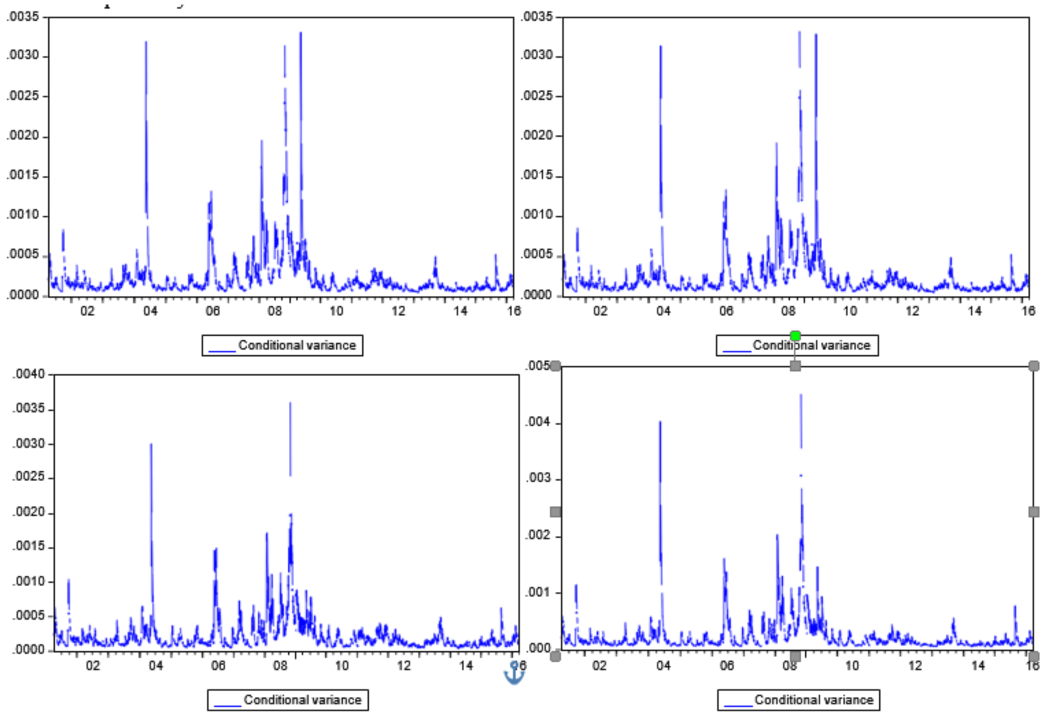
Table 3: ARCH-LM Test

Heteroskedasticity Test: ARCH

F-statistic	188.9328	Prob.F(1,3730)
Obs*R-squared	179.9207	Prob.Chi-Square(1)

The validity of autoregressive conditional heteroskedasticity (ARCH) in the residuals. If there is no ARCH in the residuals, the autocorrelations and partial autocorrelations should be zero the Q-statistics should not be significant, there is clear evidence that the return series exhibit ARCH effect. The squared residuals of Nifty returns revealed significant correlation among the error terms with all F statistics being significant as is evident from low p values.

The GARCH-M(1,1) model is estimated by allowing he mean equation of the return series to depend on a function of the conditional variance. The constant in mean equation is significant 5% level, indicating that there is and normal return for the market, it is inferred that the coefficient of conditional variance (λ) in them equation value is positive however, it statistically insignificant, which implies that there is no significant impact of volatility on the expected return, Indicating lack of risk-return tradeoff overtime. This outcome was he previous findings of Goudarziand Ramanarayanan (2010). In the variance equation of GARCH-M (1, 1), the parameters viz., constant (α0), ARCH term (α1) and GARCH term (β1) are highly significant 1%level. The sum of α1 and β1 is 0.9783, which infers that's hocks will persist in the future period. The ARCH-LM test was applied on Nifty residuals to check the presence of additional Arch effect and the results showed that the test statistics do not exhibit additional Arch effect for the whole study period indicating that the variance equation is well specified. The best fitted models both in symmetric as well as in asymmetric effect are selected based on the minimum AIC and SIC value and the highest log likelihood value. Hence GARCH-M(1, 1) model is found to be the best fitted model for this study. This outcome was not in consensus with the previous studies, as per Goudarzi and Ramanarayanan (2010), Mittal, Arora, and Goyal (2012) and Banumathy and Azhagaiah (2015) GARCH(1,1) model is best fitted model to describe the symmetric volatility process.



Conclusion

In this study, volatility of Nifty index return has been tested by using the symmetric and asymmetric GARCH models. The daily closing prices of Nifty index for fifteen years are collected and modeled using four different GARCH models that capture the volatility clustering and leverage effect for the study period. This paper examined the volatility of returns on the National Stock Exchange index S&P SENSEX 30. The preliminary analysis of data used reveals the non -stationary, normal distribution and variables show white noise process which shows serial correlation. Weak evidence of ARCH effects in BSE return series are shown by ARCH effect test. To capture the volatility, GARCH (1, 1), EGARCH (1, 1) and ARMA models are used. The ARCH effect (a1) is significantly positive. The EGARCH(1,1) model at 5% is showing that news about previous volatility has an explanatory power on current volatility for other models it was not found. i.e. from January GARCH (1,1), GARCH-M (1,1), EGARCH(1,1), and TGARCH(1,1) model shave been employed for this study after confirming the unit root rest, volatility clustering and arch effect. The results show that the leverage coefficient has the expected sign in both the models i.e. EGARCH (negative and significant) and TARCH (positive and significant). To identify the best fitted model among the different specifications of GARCH models.

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