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Modelling and Forecasting of Stock Price Volatility – an Analysis

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Abstract— The current study uses the daily adjusted closing price for the period from 1 April 2011 to 31 March 2021 to model and forecast the price volatility of the NIFTY 50 companies listed on the Indian stock market using the GARCH family of models. Analytical research design is the method employed for the study. Purposive sampling was employed for the study's sample design, and the researcher chose one significant sector from the NIFTY 50 index that was listed on March 31, 2021. According to sector weightage, key sectors like financial services were chosen. In this study, several combinations of GARCH and ARCH lags were utilised, and high-order models were generally examined to determine which model was most appropriate. The study took into account the forecasting models Generalized Autoregressive Conditional Heteroscedasticity-symmetric GARCH (2,1), Exponential GARCH-EGARCH (2,1), and Threshold GARCH-TGARCH (2,1). Heteroscedasticity tests, such as the Lagrange Multiplier (LM) test for ARCH, were employed to determine the presence of heteroscedasticity in the return series' residual in order to observe the ARCH effect. We can employ ARCH/GARCH models if the ARCH effect is present. To determine whether the return series are stationary, tests for stationarity such the Augmented Dicky-Fuller test were done. To determine if the return series were normally distributed, tests for normality such as the Jarque-Bera test were applied. Using the Mean Absolute Error and Root Mean Square Error error statistics, the effectiveness of these GARCH models was assessed. TGARCH scored well based on these evaluations and it aids in capturing the leverage impact, volatility clustering, forecasting accuracy, and differentiating the asymmetric influence between good and negative news.

Keywords — *Price Volatility; Modelling and Forecasting; NIFTY 50; GARCH Family Models.*

1. Introduction

Investments in the stock market are typically thought to be dangerous due to their higher volatility. When macroeconomic factors have an impact on the stock markets, there is volatility in the stock market. The degree to which the security price, market, or commodity grows or drops for a specific period of time is known as volatility.

Volatility is a measure of how much uncertainty there is about how much a security's value will change. Volatility in the financial markets refers to peaks and valleys that might result in profit or loss. Volatility is a quantitative measure of price or rate of return variations based on percentage price adjustments. For people who deal in cash or trade stocks or other financial instruments, volatility is a difficulty and a big problem. Volatility issues have recently taken on a lot of significance for analysts, market players, institutional investors, regulators, and financial professionals.

While assessing volatility, stock returns are used instead of stock values, hence mean must be constant at the specific period when computing the dispersion around an average value. In many financial market-related applications, including derivative valuation and risk management, the modelling and forecasting of asset return volatility is essential. Volatility must be taken into account before making any stock market investments. In developing nations, numerous studies are being conducted to gauge volatility. As numerous parameters to calculate volatility, various variables including market rate, trading procedure, dividend distribution, and data arrival have been chosen.

2. Review of Literature

In earlier research, the GARCH family of models were used to explore the modelling and forecasting of the stock market by Abdalla and Winker (2012) and Babatunde (2013). According to their research, GARCH models were superior and the best fitting models for predicting stock price volatility. Godfrey (2020) used symmetric and asymmetric GARCH type models to study the stock market volatility modelling for the accuracy in forecasting. By comparing non-linear GARCH type models, Fauzia (2018), Dohyunchun (2019), and Huthaifa (2020) examined the volatility of stock prices and determined which model was better at capturing the leverage effect, volatility clustering, conditional variance, leptokurtosis, and skewness.

Through empirical analysis, Hussainy and Khanh (2009) and Narayan and Reddy (2020) looked at how macroeconomic variables affect the performance of the stock market and discovered a correlation between stock market development and returns by taking into account a number of macroeconomic parameters.

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Liu (2010) investigated the leverage effect in time series investigations (asymmetric). It might occur when volatility changes negatively correlate with stock returns. i.e., the volatility is anticipated to rise in response to the bad news and fall in response to the positive news. The ARCH/GARCH models were employed by Phich and Henghan (2011) and Dana (2016) to predict and forecast the volatility of stock prices, and their findings showed which model is more effective at doing so.

3. Research Methodology

Research is defined as "the pursuit of new information or the imaginative application of current knowledge to generate novel concepts, theories, and hypotheses." The study employed an analytical research design and "Purposive Sampling" as the sampling strategy. As of March 31, 2021, 10 companies that are listed on the National Stock Exchange of India and are indexed under the NIFTY 50 comprise the sampling unit for this study.

Based on the sector weighting, a list of businesses in the financial services sector was chosen. The National Stock Exchange of India's financial data was used to determine these companies' daily adjusted closing prices (source: Yahoo! Finance). Because it gives investors a more up-to-date and accurate understanding of the stock price, the adjusted closing price. Finding the best GARCH family models for predicting stock price volatility among the chosen NIFTY 50 Indian companies is the main goal.

The data were analyzed using statistical tools such as descriptive analysis, test of normality, enhanced Dickey-Fuller test, heteroscedasticity test, and models from the GARCH family such as generalized autoregressive conditional heteroscedasticity (GARCH), exponential GARCH (E-GARCH), and threshold GARCH (T-GARCH).

4. Empirical Results

According to the financial services sector's descriptive statistics, all of the selected companies' mean values are positive, which suggests that prices have gone up over time. The return series' standard deviation showed how volatile the chosen companies are. The skewness should be zero if it is normal. The likelihood of receiving positive returns is higher if the skewness values are positive or long right tailed. Similar to this, there is a larger likelihood of receiving negative returns if the value of skewness is negative or long left-tailed. Kurtosis values for each of the chosen companies are all higher than 3. It suggests that the return series were not regularly distributed and have fat tails. To determine whether the return series were normally distributed, use the Jarque-Bera test. The P-value for the test statistic ranges from 0 to 1.

Table1: Test of Normality

S.No.	Name	J-B	Probability
1	HDFC Bank	5413.60	0.000
2	HDFC	5719.20	0.000
3	ICICI Bank	2322.63	0.000
4	KOTAK Bank	2101.72	0.000
5	AXIS Bank	13210.33	0.000
6	SBI	6151.02	0.000
7	Bajaj Finance	10360.48	0.000
8	Bajaj Finserv	13646.25	0.000
9	IndusInd Bank	15610.21	0.000
10	SBI	16140.13	0.000

Source: *Computed from Eviews*

The leptokurtic distribution with a positive peaked curve, which was inferred from the null hypothesis being rejected at the 1% level of significance, suggests that the hypothesis that the return series were distributed normally was not accepted. ADF tests were used to verify the stationarity of the return series. It is useful to determine if the time series contains a unit root. The null hypothesis that the return series has a unit root, i.e. (the return series are non-stationary), is rejected at 1% significant level at the level difference itself because the (t-statistic) values of the ADF test are more negative than the test critical values.

It is necessary to evaluate the ARCH effect in the re4turn series before using the ARCH/GARCH model. As a result, the Lagrange Multiplier (LM) approach was applied, and the test's P-Value is almost zero. The chi-square (1) at 1% has a critical value of 6.645. For all of the chosen companies, the null hypothesis is thus disproved at a 1% significance level. This demonstrates the ARCH effect's presence in the return series. GARCH family models can therefore be used. The GARCH (2,1) model shows the coefficient estimation for all the chosen companies, according to the results of the GARCH (2,1), EGARCH (2,1), and TGARCH (2,1) models for the financial services sector.

The value of (1) makes it evident that the majority of the information was gathered in the past. The significance of the new information is lessened. The variance over the long term is very low. Because asymmetric volatility is not captured by the GARCH (2,1) model. For the purpose of estimating the volatility of stock return, an EGARCH (2,1) model was adopted. The ARCH and GARCH terms should

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both be smaller than 1 to satisfy the criterion of stationarity. As a result, the stationarity requirement for the chosen companies utilizing the return series under the EGARCH model was not satisfied. The fact that the Gamma value is non-zero indicates the existence of volatility asymmetry, but this model does not offer useful insight into how well or bad news affects volatility.

4. Conclusion

The in-depth analysis demonstrates the capacity to predict, estimate, and forecast stock market volatility for the return series of the chosen NIFTY 50 financial services companies for the time period from 1 April 2011 to 31 March 2021. Based on the evaluation of predicting performance using two distinct error statistics, such as Root Mean Square Error and Mean Absolute Error, the TGARCH model outperforms and is regarded as the best-fitted model. As a result, the TGARCH (2, 1) model aids in capturing the leverage effect, predicting accuracy, and differentiating the asymmetric influence between good and bad news.

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