FORECASTING THE STOCK MARKET VOLATILITY OF NIFTY50 INDEX OF NSE USING BY ARCH MODEL

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Abstract.

The stock market is unpredictable and subjected to significant movements. Stock prices are going to fluctuate as the consequence of rapid investment and information flow, which ultimately impacts the market. This is a process which can be mutually advantageous and beneficial. Following it was established, the Indian stock market has experienced significant ups and downs, which makes it a particularly fluctuating market. This study chooses to execute an empirical investigation and describe the distinguishing characteristics of the Nifty50 Index of the NSE in India utilizing econometrics.

It also recommends particular things are contingent upon the volatility that the Nifty50 Index was at the moment.Secondary sources including publications, journals, and NSE websites have supplied im portant and required data.Were the fiveyear period of data obtained by the daily closing price of the NSE's nifty50 index in India from the second of June, 2018 to the 30th of May, 2023.Using time serie s data, the study was analysed and investigated using a descriptive method.Were the expected marke t volatility of the NSE's nifty50 indexes determined by a widenrange of methodologies, included the u nit root test, the ARCH (1) as well as ARCH (2) models.

Keywords: NSE, Stock Market, Volatility, Stationarity, Unit root test, ARCH Model,

1. Introduction

The National Stock Exchange (NSE) stock market has been crucial to the Indian economy ever since it was initially founded in 1992 and began trading in 1994. While it is now very volatile and has a low level of normalization in terms of monitoring or institutions. The whole market is high-risk and poses significant problems to both institutions and ordinary investors because of the erratic stock market, unscientific investments, and the sporadic occurrence of malignant investments. Many overseas institutional investors who were permitted to do so under the SEBI Acts have entered the investing community. The climate for financing and investments has grown more complex as a result of the uncertainties and swift international capital movements. The Indian stock market has recently been characterized by both possibilities and threats. In this scenario, it has become a hot topic in academics and the financial industry to accurately describe how stock prices vary and how to predict the stock market's future rate of return. The study of volatility therefore has a great theoretical relevance and practical usefulness. The variance is typically assumed to be constant in traditional econometric models as regression analysis and time series analysis when attempting to explain the volatility of stock market return. Financial time series data are inherently unstable; the volatility clustering phenomenon causes larger variations to congregate during one period of time while smaller fluctuations congregate during another. The homoscedasticity assumption appears to not be met for time series with "sharp peak," "fat tail," and volatility clustering features. Few writers were capable of conducting modelling using typical econometric methods, which frequently led to extremely substantial deviation. Economic researchers have worked hard to update the conventional econometric models in order to increase the prediction model accuracy. This paper aims to investigate and analyze the market volatility and market fluctuation for nifty50 index of NSE in India by using econometric models of ARCH (1), ARCH (2).

2. Review of literature

The following are the important studies which facilitate to develop the present study of forecasting the stock market volatility of Nifty50 Index of NSE Using by ARCH Model. Abroad have been carried out over the last few decades and which that are being summarized below:

Sutheebanjard and Premchaiswadi (2010). Research on the stock market revealed that it is a highly dynamic, nonlinear system whose performance is affected by a variety of variables, including interest rates, inflation, the state of the economy, political unrest, and so on.

Panait and Slavescu (2012). The variance coefficient from the model's mean equation is not statistically significant for the majority of the time series examined and on the majority of frequencies, which makes the GARCH-in-mean model ineffective at validating the theoretical claim that there is a positive relationship between volatility and future returns.

Torben et al. (2009). Volatility forecasting is a critical and pressing financial issue that has drawn a lot of attention. Although returns on financial assets are generally acknowledged to be more or less unpredictable on a daily as well as monthly basis, return volatility is a phenomenon that can be predicted and serves as a key indicator for financial economics and risk management.

Leung et al (2000). Index trading vehicles provide investors with a useful means of hedging against potential market risks as well as new chances for market arbitragers and speculators to make profits. As a result, it is equally crucial to scholars and practitioners to be able to anticipate stock indices correctly.

Chang et al. (2009). Using the right forecasting model may yield enormous returns through exceptionally precise forecasts, but the volatile nature of the stock market makes forecasting a challenging task. Therefore, predicting accuracy is a major issue for many investors, emphasizing the need of designing a more suitable forecasting model.

Islam et al. (2012). In research on predicting the volatility of the Dhaka stock market using both linear and non-linear models, the moving average model came out on top when measured by the root mean square error, mean absolute error, Theil-U, and linex loss function. On the basis of numerous error measurement criteria, they also discover that moving average models perform the best and do not outperform linear models.

MCMillan, Speight and Apgwilym (2000). Demonstrate that the random walk model provides significantly better monthly volatility forecasts, while the GARCH, moving average, and smoothing models generate somewhat better daily forecasts. Random walk, moving average, and recursive smoothing models present considerably better weekly volatility forecasts.

Ederington and Guan (2005). For traders, investors, financial analysts, and researchers who are interested in understanding stock market dynamics, accurate volatility projections are crucial.

Engle (1982). has put out the ARCH model and any necessary augmentations. The ARCH model family has been widely used in research on a variety of financial markets, including stocks, foreign exchange, futures, and currency market, since it has a special benefit in driving variance of financial time series. The 2003 Nobel Prize in Economics was given to Engle and Granger in honor of their exceptional contributions to the time series model.

Wang, Dai and Zhang (2010). Discovered that a time series is a collection of numbers created by repeated observations made at various moments in the same event (for instance, the occurrence of stock market volatility). This type of chronological series is sensitive to different dependent circumstances, therefore from a statistical standpoint, it looks to have some unpredictability.

Bollerslev (1986). Has developed the GARCH model and expanded the parameters impacting conditional variance to two aspects: mean square error and conditional variance of prior periods.

Tong (2009). ARMA (1, 1) - GARCH (1, 1) model better matches the long-term volatility of the stock market, according to his conclusions. has utilized the ARCH conditional mean equation to dynamically examine the CSI 300 Index.

Chen and Han (2009). Revealed that using an ARCH type model to perform empirical research on the CSI 300 Index and examine the Chinese stock market's fluctuation characteristics. The findings demonstrated that the CSI 300 Index's daily return volatility had apparent clustering and continuity, but not asymmetry, and that its data series distribution exhibited characteristics of a "sharp peak" and "fat tail."

3. Objectives of the study

- ✓ To study the volatility of stock market in NSE of Nifty50 Index.
- ✓ To analyze and forecasting the volatility fluctuation using by Unit root test and ARCH Models.

4. Background of NSE

In 1992, India's National Stock Exchange (NSE) was founded with the mission of modernizing the nation's capital markets and offering a productive trading environment for securities. The NSE launched the Nifty index on April 22, 1996 as part of its goal. The index was created to accurately reflect the performance of the Indian equities market and provide investors with a trustworthy indication. The National Stock Exchange's Nifty index consists of fifty actively traded equities from different industries. These stocks are chosen according to predetermined standards including market capitalization, liquidity, and trading volume. The index aims to reflect the overall performance of the Indian stock market by representing a diverse array of businesses. The free-float market capitalization-weighted approach is the basis for the Nifty's computation process. This indicates that the index is determined using the aggregate market value of the component companies after taking into account the percentage of shares that are available for public trading (free float). The Nifty has changed throughout time to reflect adjustments to the Indian economy and market dynamics. To guarantee its applicability and representativeness, the index has undergone several adjustments and alterations. To track the performance of the next fifty most liquid equities, the NSE introduced the Nifty Junior index in 2009, which consists of firms beyond the Nifty 50. Furthermore, the Nifty family has grown to include industry-specific indexes like Nifty Pharma, Nifty IT, and others. Investors may learn more about the performance of particular industries inside the larger equities market.

4.1 ARCH Models

Professor Engle, an American economist, initially developed the ARCH (Auto-Regressive Conditional Heterogeneous) model to characterize variation. The ARCH model, that challenges the linear conception of a relationship between risk and returns, challenges traditional thinking to the test. With attributes of a "fat tail" and a "sharp reach their highest," this model accurately describes the financial data. It accomplishes this by developing a function connected to the earlier volatilities using the fluctuating variance. Since it provides an effective research instrument for the heteroscedasticity problem, academics have embraced this approach from the start. However, it was steadily demonstrated that in ordering to more accurately are expecting conditional heteroscedasticity, an extensive order q must be used when modelling specific time series using the ARCH model. Bollerslev (1986) applied the ARCH model as his foundation that incorporated lag phase to conditional variance to develop the GARCH (broadened autoregressive conditional heteroscedasticity) model. In the meantime, additional investigators developed the IGARCH, EGARCH, GARCH-M, and VGARCH models, and they together established the GARCH model family. All of these models had characteristics comparable to the GARCH model.

The structure that follows provides an illustration of the foundational ARCH(p) model: Where:

$\sigma t2=\alpha 0+\sum pi\text{-}1\alpha i\epsilon 2t\text{-}i$

The conditional variance of the error term at time t can be expressed by σt2, the lag order of the model demonstrates that all past squared error terms are considered to account, The α0 is a constant term, and ∑pi is the model's parameters that indicate its effect of past squared error terms (ϵ2t-i) on the current conditional variance. In real terms, maximum likelihood estimation is employed to estimate the parameters α0, α1..., αp based on the data that is currently seen.

To be able to take into account greater complexity in volatility, the ARCH model is able to enhanced through the addition of lagged conditional variances to the equation. A particular variation is the Extended Autoregressive Conditional Heteroskedasticity (GARCH) model.

5. Data and Methodology

Secondary sources like publications, journals, and NSE websites provided important and required data. Was the five-year period of data obtained by the closing price on a given day of the NSE's nifty50 index in India from the second of June, 2018 to May 30, 2023. Using time series data, the study was analyzed and examined using a descriptive method. Were the expected market volatility of the NSE's nifty50 indexes estimated through the application of a selection of methods, comprising the unit root test, the ARCH (1), ARCH (2), and ARCH-M Models.

Compound returns were the unit of measurement of stock market returns.

Ri was equivalent to ln (Pi/Pi-1).

where Pi-1 is the index at day t-1 and days is the daily closing price of the nifty50 index. In addition, during this article, each disposal the procedure is investigated applying the statistical application of EViews 12 YV.

6. Result and Analysis

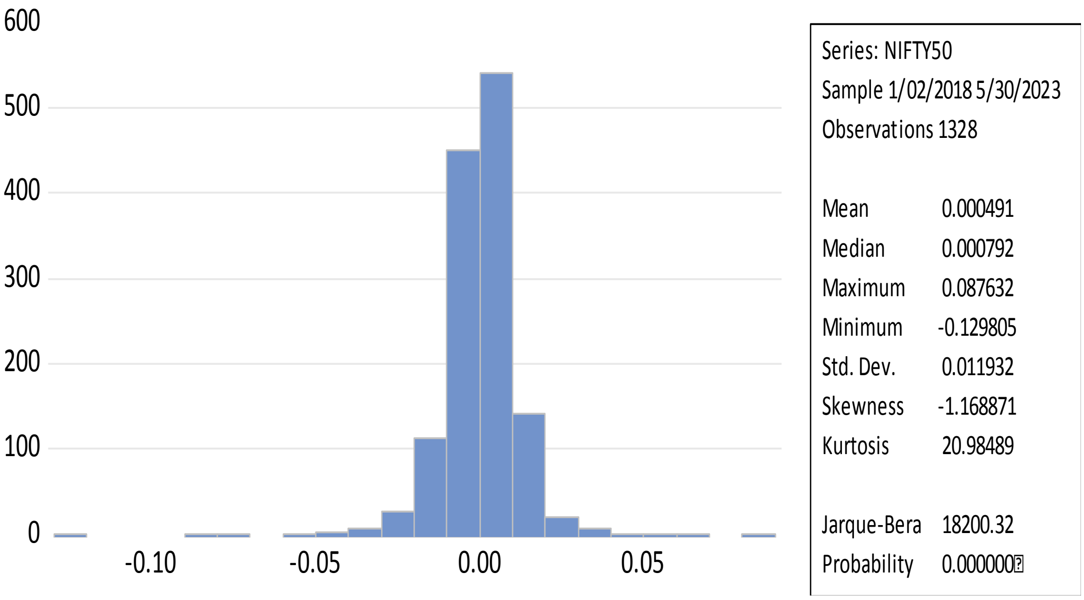
The result of nifty50 Index has demonstrate the following methods of ARCH tools and forecasting the stock market volatility.

6.1. Descriptive Statistical Analysis

The statistical table-1, indicates were can see that the mean of return series is 0.000491%, nearly 0, which is not surprising, since stock return series usually have a regressive tendency towards a long - term value. And the gap between the maximum and minimum value is 0.2174, and standard deviation has a value around 1.2%, both of these implies relatively high volatility in a stock market during sample period. The negative value of skewness may due to the negative inclination of the asymmetric tail. The Kurtosis value (20.98489) is much greater than the standard normal distribution value (+3), this reveals that the distribution of nifty50 has characteristics of 'sharp peak' and 'fat tail'. And its J-B statistic is 18200.32, which is much higher than the J-B value of standard normal distribution (5.8825), therefore we reject the null hypothesis that return series is subject to normal distribution, namely, it obeys the skewed distribution.

Table- 1.

Descriptive statistic.



6.2. Stationarity

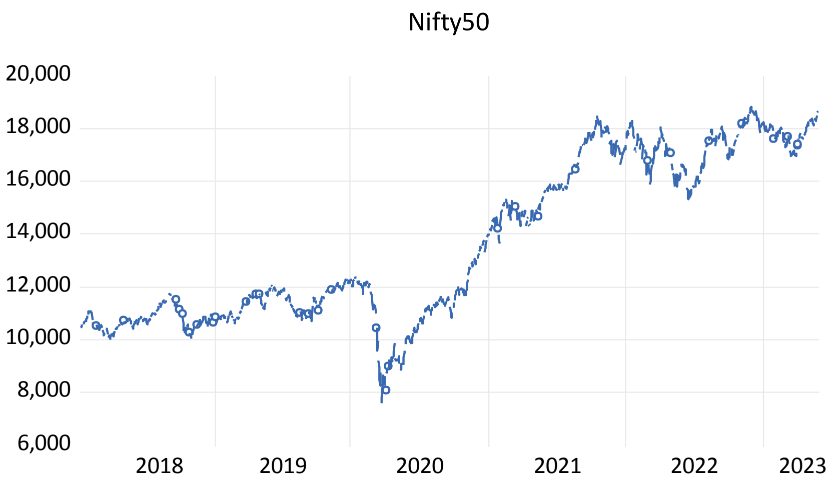


Figure-1. Time plot of change in the log of closing prices of nifty50 Index.

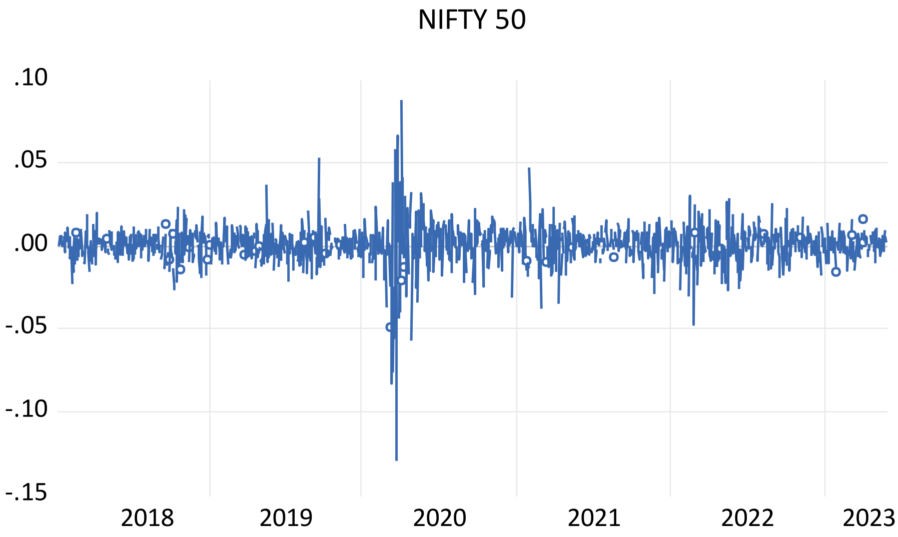


Figure -2.

Time plot of change in the log returns of closing prices of nifty50 Index**.**

Figure -1 above is a draw of the daily closing price of nifty50 index of NSE, rest of this article, the statistical software EViews 12 YN is applied to each disposal step.

The figure -2 has explained that a slight presence of time trend in the return series and its shows that apparent features of time varying variance clustering. Hence, the traditional variance model with assumption of homoscedasticity is no longer suitable for fitting volatility of the nifty50 index. Thus, which seems is not constant and volatility of this model is non stationarity series. Next move on study the stationarity of return series, and were can start from the auto correlogram and q static, which are shown in the below table.

Table -2. Autocorrelation and partial correlation of return series

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.047	-0.047	2.9246	0.087
		2	0.025	0.022	3.7284	0.155
		3	0.010	0.012	3.8538	0.278
		4	0.009	0.010	3.9674	0.410
		5	0.127	0.128	25.488	0.000
		6	-0.140	-0.132	51.828	0.000
		7	0.088	0.074	62.160	0.000
		8	0.006	0.014	62.203	0.000
		9	-0.025	-0.030	63.072	0.000
		10	0.081	0.070	71.912	0.000
		11	-0.093	-0.061	83.522	0.000
		12	0.071	0.029	90.380	0.000
		13	-0.025	-0.001	91.226	0.000
		14	-0.030	-0.035	92.448	0.000
		15	0.042	0.021	94.850	0.000
		16	-0.053	-0.014	98.652	0.000
		17	0.052	0.009	102.27	0.000
		18	-0.040	-0.011	104.38	0.000
		19	-0.018	-0.022	104.81	0.000
		20	0.038	0.019	106.76	0.000
		21	-0.003	0.031	106.78	0.000
		22	0.017	-0.015	107.17	0.000
		23	-0.035	-0.010	108.84	0.000
		24	-0.055	-0.066	112.97	0.000
		25	0.048	0.031	116.09	0.000
		26	-0.020	0.004	116.62	0.000
		27	-0.002	-0.018	116.63	0.000
		28	0.039	0.058	118.68	0.000
		29	-0.033	-0.031	120.14	0.000
		30	0.001	-0.027	120.14	0.000
		31	-0.025	0.004	121.03	0.000
		32	-0.027	-0.046	122.03	0.000
		33	-0.010	-0.018	122.17	0.000
		34	0.008	0.040	122.26	0.000
		35	0.075	0.054	129.96	0.000
		36	-0.023	-0.003	130.70	0.000

From the above table it has indicates the accompanying p values of every Q statistic are larger than 5% significance level, (only first four lags less than the 0.05), Thus, we can judge that the return series has no problem of autocorrelation, and then it may possess a problem of white noise, which means return series is currently no suit for Auto regressive model. Therefore, we take the first-order difference on it, and define a new series DR=d (R) to describe the fluctuations. Then, by drawing its correlogram, we can further determine the stationarity of the differenced series.

Table -3. Autocorrelation and partial correlation of DR series

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.534	-0.534	377.88	0.000
		2	0.041	-0.341	380.11	0.000
		3	-0.007	-0.253	380.18	0.000
		4	-0.056	-0.297	384.36	0.000
		5	0.184	-0.016	429.37	0.000
		6	-0.237	-0.208	503.89	0.000
		7	0.149	-0.122	533.41	0.000
		8	-0.024	-0.067	534.20	0.000
		9	-0.066	-0.154	540.08	0.000
		10	0.134	-0.015	564.18	0.000
		11	-0.162	-0.103	599.40	0.000
		12	0.125	-0.066	620.31	0.000
		13	-0.044	-0.030	622.89	0.000
		14	-0.038	-0.085	624.81	0.000
		15	0.081	-0.045	633.65	0.000
		16	-0.095	-0.065	645.88	0.000
		17	0.093	-0.044	657.45	0.000
		18	-0.053	-0.030	661.20	0.000
		19	-0.017	-0.068	661.58	0.000
		20	0.047	-0.074	664.52	0.000
		21	-0.029	-0.024	665.69	0.000
		22	0.035	-0.027	667.31	0.000
		23	-0.016	0.025	667.66	0.000
		24	-0.058	-0.070	672.21	0.000
		25	0.081	-0.040	681.03	0.000
		26	-0.041	-0.019	683.31	0.000
		27	-0.011	-0.091	683.46	0.000
		28	0.054	0.000	687.41	0.000
		29	-0.050	-0.005	690.83	0.000
		30	0.028	-0.036	691.92	0.000
		31	-0.012	0.013	692.12	0.000
		32	-0.008	-0.016	692.21	0.000
		33	-0.000	-0.071	692.21	0.000
		34	-0.024	-0.080	692.98	0.000
		35	0.080	-0.019	701.61	0.000
		36	-0.037	0.027	703.48	0.000

Above the Table-3, which has notice that the rate on which the autocorrelation function of series DR decays is relatively fast, it approaches 0. Therefore, it can be initially judged that series DR is stationary, and it does not possess white noise. We can further confirm the stationarity of series DR by unit root test.

6.3. Unit root Test

In the tests for stationarity, the most commonly used method is the unit root test proposed by two American statistician D.A Dickey and W.A. Fuller in the 1970s, which judges whether the autocorrelation coefficient is equal to 1. After nearly 30 years' research, this approach was eventually summarized as the Augmented Dickey-Fuller (ADF) Test. Here we use the ADF test to examine the stationarity of DR series and result are given below (Original result from EViews is attached in Appendix Table 2).

Table- 4.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.67753	0.0000
Test critical values:	1% level	-3.435169	
	5% level	-2.863556	
	10% level	-2.567893	

Notes: '*'denotes significance at 1% level.

As shown in the Table - 4, the ADF value of series DR is -12.67753, which is much smaller than 1% critical value, and the accompanying P value is 0, which also indicates a significance in 1% level. Therefore, we reject the null hypothesis that series DR has a unit root, namely, DR is stationary. Now we can use series DR to build the ARCH models.

6.4. ARCH (1) Model effects

Table- 5.

Output of the ARCH (1) Model on Nifty50 Index Return.

Heteroskedasticity Test: ARCH

F-statistic	55.98813	Prob. F(1,1322)	0.0000
Obs*R-squared	53.79457	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 09/28/23 Time: 01:04
Sample (adjusted): 1/04/2018 5/30/2023
Included observations: 1324 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000114	1.71E-05	6.634354	0.0000
RESID^2(-1)	0.201576	0.026940	7.482522	0.0000

R-squared	0.040630	Mean dependent var	0.000142
Adjusted R-squared	0.039905	S.D. dependent var	0.000619
S.E. of regression	0.000607	Akaike info criterion	-11.97528
Sum squared resid	0.000487	Schwarz criterion	-11.96744
Log likelihood	7929.634	Hannan-Quinn criter.	-11.97234
F-statistic	55.98813	Durbin-Watson stat	2.148763
Prob(F-statistic)	0.000000		

The ARCH Model's conclusion, that was made public regarding the Nifty50 Index, demonstrates that the probabilities of a constant is 0.000. At the one percent (%) level of significance, a heteroskedasticity test indicates the mathematical significance of RESID^2(-1). It suggests that the preceding square residual terms had an impact on risk volatility. As therefore, it is pertinent to point out that the Nifty50 Index's recent volatility has had an important effect on today's volatility.

6.5. ARCH (2) Model effects

Table- 6. Output of the ARCH (2) Model on Nifty50 Index Return.

Heteroskedasticity Test: ARCH

F-statistic	128.2881	Prob. F(2,1317)	0.0000
Obs*R-squared	215.2298	Prob. Chi-Square(2)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 09/28/23 Time: 01:08
Sample (adjusted): 1/05/2018 5/30/2023
Included observations: 1320 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.30E-05	1.63E-05	4.478844	0.0000
RESID^2(-1)	0.129562	0.025738	5.033982	0.0000
RESID^2(-2)	0.357250	0.025738	13.88043	0.0000

R-squared	0.163053	Mean dependent var	0.000142
Adjusted R-squared	0.161782	S.D. dependent var	0.000620
S.E. of regression	0.000568	Akaike info criterion	-12.10734
Sum squared resid	0.000425	Schwarz criterion	-12.09555
Log likelihood	7993.843	Hannan-Quinn criter.	-12.10292
F-statistic	128.2881	Durbin-Watson stat	2.122802
Prob(F-statistic)	0.000000		

The output ARCH (2) model of Table – 6. Revealed the output of ARCH (2) Model on Nifty50 Index shows that the probability of constant is equal to 0.000. An heteroskedasticity test illustrate that RESID^2(-2) term is also statistically significant at 1% level of significance. Which is implies the volatility of risk is influenced by past square residual terms. Therefore, it can be mention that the ARCH (2) model also influenced past volatility of the Nifty50 Index. The ARCH (2) model is appropriately significant and influencing the current volatility.

7. Discussion and Conclusion

ARCH (1) Model:

F-Statistics = 55.98813: P value = 0.0000

Hypothesis $H_{0:}$ Rejected at significance level of 0.01%

Therefore, ARCH (1) model is effects presently.

ARCH (2) Model:

F-Statistics = 128.2881: P value = 0.0000

Hypothesis $H_{0:}$ Rejected at significance level of 0.01%

Therefore, ARCH (2) model is effects presently.

After analyzing the both models we can be conclude that ARCH (1) and ARCH (2) are affected on Nifty50 Index of NSE and estimate on AFCH models for batter results.

In this study has explores the analysis of market volatility of nifty50 Index of NSE. Notably, which is estimated risk and volatility markets through the applied different methods as autocorrelation, partial autocorrelation and Unit root test for identified the model is stationarity or non-stationarity, whereas it can be result revealed that the data has been stationarity at the significance level of 0.01%, also applied the ARCH models for forecasting market volatility of Nifty50 Index. Thus, the residuals terms of RESID^2(-1) and RESID^2(-2) of ARCH models were affects to the current scenario in the National Stock Exchange (NSE) in India.

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