VOLATILITY GUESSTIMATION IN INFORMATION TECHNOLOGY ENABLED SERVICES BASED ON INDIAN STOCK MARKET: AN EMPIRICAL APPROACH WITH ECONOMETRIC MODELS

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Abstract
Understanding and predicting volatility is important for investors, policy makers and market regulators in financial markets. This study focuses on volatility estimation in the IT enabled services (ITES) industry, which plays an important role in Indian banking This study uses the methodology of financial modelling to assess volatility, which will help with risk management and investment decisions
The methodology collects information on the historical share prices of ITES companies listed on Indian stock exchanges. Several different statistical methods, including ARCH, GARCH, and EGARCH models, are used to model volatility in the industry. Additionally, the study includes other variables that can influence volatility such as macroeconomic indicators.
Keywords: Volatility, ITES, ARCH, GARCH, EGARCH, TARCH, PARCH

Introduction
In the dynamic landscape of the global economy, the Information Technology Enabled Services (ITES) sector stands out as a catalyst for innovation, efficiency, and growth. With its profound impact on various industries and facets of daily life, understanding the volatility within this sector is of paramount importance for investors, policymakers, and stakeholders alike. In the context of the Indian economy, where ITES plays a pivotal role, assessing and predicting its volatility becomes even more critical. This study embarks on an empirical journey to delve into the volatility of the ITES sector within the Indian stock market. By employing econometric models, we aim to provide valuable insights into the fluctuations and dynamics of this sector. Volatility, as a measure of the dispersion of returns for a given security or market index, serves as a fundamental metric for risk assessment and investment decision-making. Understanding the factors influencing ITES volatility can guide investors in devising robust strategies and policymakers in formulating effective regulations to foster a stable and conducive economic environment. The Indian ITES sector has witnessed rapid evolution over the years, driven by technological advancements, globalization, and changing consumer behaviours. From software development and IT consulting to business process outsourcing (BPO) and knowledge process outsourcing (KPO), the sector encompasses a wide array of services, each with its unique

characteristics and market dynamics. Such diversity necessitates a nuanced analysis of volatility, considering the underlying factors specific to each segment and their interplay with broader market forces. Econometric modelling offers a systematic framework for dissecting the complexities of volatility and uncovering the underlying drivers. By leveraging historical data and statistical techniques, we endeavour to discern patterns, relationships, and causality within the ITES sector. Through this empirical approach, we seek to contribute to the existing body of knowledge surrounding ITES volatility and provide practical implications for investors, policymakers, and industry stakeholders. This study is structured as follows: following this introduction, we provide a comprehensive review of relevant literature, highlighting previous research endeavours and theoretical foundations. Subsequently, we outline the methodology employed in our empirical analysis, elucidating the data sources, variables, and econometric techniques utilized. We then present our findings, accompanied by detailed discussions and interpretations. Finally, we offer concluding remarks, summarizing key insights and avenues for future research. In essence, this study endeavours to shed light on the volatility of ITES within the Indian stock market, offering valuable perspectives for stakeholders navigating the dynamic landscape of the global economy. Understanding the volatility of the ITES sector is crucial due to its significant impact on economic growth, employment, and innovation. The Indian ITES industry, in particular, has emerged as a global leader, contributing substantially to the country's GDP and employment generation. However, the sector is not immune to market fluctuations and external shocks, which can have far-reaching implications for businesses, investors, and policymakers. By analysing the volatility of ITES stocks in the Indian market, we aim to provide insights that can inform investment decisions, risk management strategies, and policy interventions. Through the application of econometric models, we seek to identify the key determinants of ITES volatility, including internal factors such as firm-level characteristics and external factors such as market sentiment and macroeconomic conditions.

ARCH Family models have been used to guesstimate the Volatility. HCL Technologies one of n the biggest ITES company has been taken into consideration from Indian Stock Market for further analysis. The data has been collected from Yahoo Finance from 1st April 2013 to 28th June 2023 for analysis.

Literature Survey

Several studies have investigated volatility estimation in the Indian stock market, with a specific focus on ITES companies. "Mishra and Mathur (2018) employed the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to estimate volatility in a sample of ITES firms listed on the National Stock Exchange of India (NSE)". Their findings revealed significant volatility clustering and persistence in ITES stock returns, indicating the presence of time-varying volatility dynamics in the sector.

In a similar vein, "Gupta et al. (2020) conducted a comparative analysis of volatility estimation techniques for ITES stocks, including GARCH, EGARCH (Exponential GARCH), and TGARCH (Threshold GARCH) models". Using daily stock price data from the Bombay Stock Exchange (BSE), they found that the EGARCH model outperformed other models in capturing the asymmetric volatility patterns observed in ITES stock returns.

Furthermore, "Jain and Singh (2019) explored the impact of macroeconomic factors on the volatility of ITES stocks in the Indian market. Employing a multivariate GARCH framework, they examined the effects of variables such as exchange rates, interest rates, and GDP growth on ITES stock volatility". Their results indicated that macroeconomic factors significantly influence the volatility dynamics of ITES companies, highlighting the interconnectedness between the ITES sector and the broader economy.

Other empirical studies have focused on specific aspects of volatility estimation in ITES companies. For instance, "Sharma and Chaudhary (2017) investigated the role of investor sentiment in driving volatility in ITES stocks. Using sentiment analysis techniques on social media data, they demonstrated that investor sentiment has a significant impact on the volatility of ITES companies, particularly during periods of market uncertainty".

Methodology

Historical price data for a selected set of stocks from the Indian Equity market has been collected**.** Several econometric models were employed to estimate volatility in ITES stocks, with a focus on capturing time-varying volatility patterns and asymmetries in stock returns. The primary models used in the analysis include:

'Generalized Autoregressive Conditional Heteroskedasticity (GARCH)' Models: GARCH models are widely used for modelling volatility dynamics in financial time series data. The basic GARCH model specifies that volatility is a function of lagged squared residuals, capturing the persistence and clustering of volatility.

Exponential 'GARCH (EGARCH) Models': EGARCH models extend the basic GARCH framework by allowing for asymmetric effects of positive and negative shocks on volatility. This model is particularly suitable for capturing the leverage effect observed in stock returns, where negative shocks tend to have a stronger impact on volatility than positive shocks.

'Threshold GARCH (TGARCH) Models': TGARCH models incorporate threshold effects, where the impact of past shocks on volatility depends on the sign and magnitude of the shocks. This model is useful for capturing regime-switching behaviour in volatility dynamics, which is prevalent in financial markets.

The 'Fractionally Integrated GARCH (FIGARCH) model is an extension of the standard GARCH model that allows for long memory in volatility'. Unlike traditional GARCH models, which assume that the volatility process is stationary, the 'FIGARCH model relaxes this assumption by allowing the volatility process to be fractionally integrated'.

The 'Fractionally Integrated Exponential GARCH (FIEGARCH) model is a combination of the FIGARCH model and the EGARCH model'. It incorporates both the long memory properties of volatility and the asymmetry in the impact of positive and negative shocks on volatility. The 'FIEGARCH (1,1) model, in particular, specifies a first-order fractional integration term and a first-order asymmetric term'.

The parameters of the econometric models were estimated using maximum likelihood estimation techniques. The adequacy of the model specifications was assessed using diagnostic tests such as the Ljung-Box test for autocorrelation in residuals and the 'ARCH-LM test for ARCH effects'.

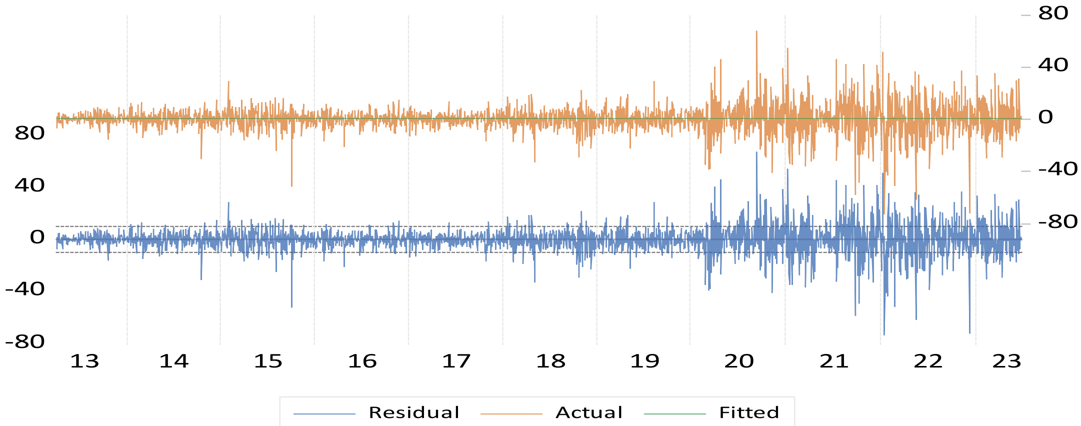
To ensure the robustness of the results, sensitivity analyses were conducted by varying model specifications and sample periods. Alternative volatility estimation techniques, such as rolling window approaches and weighted averages, were also employed to compare the performance of different models.

Results and Analysis

ARCH Family Models for HCL Technologies.

After fitting the regression model with constant, we get the residuals as in the below mentioned diagram: -

Figure 1



'From the above diagram it has been found that the periods of low volatility are tend to be followed by prolonged period of low volatility and same for the high volatility. When this happens, we have all the justifications to run the ARCH family model for volatility guesstimation. But we should cross validate the same by ARCH test that whether we should run the ARCH family model or not'. The 'ARCH Test result' is as follows: -

Table 1

Heteroskedasticity Test: ARCH

F-statistic	53.17703	Prob. F(1,2521)	0.0000
Obs*R-squared	52.11982	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 02/21/24 Time: 19:32
Sample (adjusted): 4/03/2013 6/28/2023
Included observations: 2523 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	88.93495	6.431286	13.82849	0.0000
RESID^2(-1)	0.143729	0.019710	7.292258	0.0000

R-squared	0.020658	Mean dependent var	103.8631
Adjusted R-squared	0.020269	S.D. dependent var	309.3897
S.E. of regression	306.2381	Akaike info criterion	14.28740
Sum squared resid	2.36E+08	Schwarz criterion	14.29202

Log likelihood	-18021.55	Hannan-Quinn criter.	14.28907
F-statistic	53.17703	Durbin-Watson stat	2.027413
Prob(F-statistic)	0.000000		

'From the above test result we can see that p value is 0 and is less than 0.05 i.e 5 percent. So we can reject null hypothesis and accept the alternative hypothesis,. The null and alternative hypothesis is as follows: -
"Null Hypothesis: There is no ARCH effect"
"Alternative Hypothesis: There is ARCH effect"
"So we can go for ARCH family models i.e ARCH, GARCH, TARCH, EGARCH and FGARCH".
Let us start with **ARCH (5)** model. But all the models should be tested with normal distribution. The result is as hereunder:
Dependent Variable: DHCLTECH
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 02/21/24 Time: 19:42
Sample (adjusted): 4/02/2013 6/28/2023
Included observations: 2524 after adjustments
Convergence achieved after 23 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-2)^2 + C(5)*RESID(
-3)^2 + C(6)*RESID(-4)^2 + C(7)*RESID(-5)^2

Table 2

Mean Equation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.498157	0.120987	4.117437	0.0000
	Variance Equation			
C	17.65563	0.905145	19.50584	0.0000
RESID(-1)^2	0.262776	0.021095	12.45661	0.0000
RESID(-2)^2	0.241525	0.014687	16.44469	0.0000
RESID(-3)^2	0.199276	0.020671	9.640542	0.0000
RESID(-4)^2	0.239999	0.012418	19.32644	0.0000
RESID(-5)^2	0.112876	0.018773	6.012839	0.0000

R-squared	-0.000090	Mean dependent var	0.401291
Adjusted R-squared	-0.000090	S.D. dependent var	10.19135

S.E. of regression	10.19181	Akaike info criterion	7.138571
Sum squared resid	262071.4	Schwarz criterion	7.154750
Log likelihood	-9001.876	Hannan-Quinn criter.	7.144442
Durbin-Watson stat	2.015030		

From the mean equation in the above table the variance equation is estimated. ARCH models has two parts 1. Mean Equation and 2. Variance equation. In the above equation there are 5 ARCH and there is no GARCH. Now AIC and SIC value is 7.1385 and 7.1547. The model can be taken based on AIC and SIC value. The criterion for the best model is lower the value of AIC and SIC better is the model.

So, for further analysis we have to find the AIC and SIC values of other models. The lowest value of AIC and SIC will be taken into consideration.

GARCH (1,1) Model

The result is as here under:

Table 3

Dependent Variable: DHCLTECH

Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 02/21/24 Time: 20:43

Sample (adjusted): 4/02/2013 6/28/2023

Included observations: 2524 after adjustments

Convergence achieved after 32 iterations

Coefficient covariance computed using outer product of gradients

Presample variance: backcast (parameter = 0.7)

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Mean equation

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.271384	0.130721	2.076052	0.0379
	Variance Equation			
C	0.122667	0.040618	3.020028	0.0025
RESID(-1)^2	0.038422	0.003246	11.83523	0.0000
GARCH(-1)	0.962747	0.002659	362.0742	0.0000

R-squared	-0.000163	Mean dependent var	0.401291
Adjusted R-squared	-0.000163	S.D. dependent var	10.19135
S.E. of regression	10.19217	Akaike info criterion	7.026041
Sum squared resid	262090.3	Schwarz criterion	7.035286
Log likelihood	-8862.864	Hannan-Quinn criter.	7.029396
Durbin-Watson stat	2.014884		

The AIC and SIC for GARCH (1, 1) values are 7.026 and 7.035.

TARCH(GJR-GARCH)

The result is as follows:

Table 4

Dependent Variable: DHCLTECH
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 02/21/24 Time: 20:48
Sample (adjusted): 4/02/2013 6/28/2023
Included observations: 2524 after adjustments
Convergence achieved after 39 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-1)^2*(RESID(-1)<0) +
C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.345810	0.130259	2.654793	0.0079
	Variance Equation			
C	0.154539	0.055038	2.807870	0.0050
RESID(-1)^2	0.069066	0.008121	8.504116	0.0000
RESID(-1)^2*(RESID(-1)<0)	-0.047716	0.008555	-5.577372	0.0000
GARCH(-1)	0.957022	0.003738	256.0412	0.0000

R-squared	-0.000030	Mean dependent var	0.401291
Adjusted R-squared	-0.000030	S.D. dependent var	10.19135
S.E. of regression	10.19150	Akaike info criterion	7.016023
Sum squared resid	262055.5	Schwarz criterion	7.027579
Log likelihood	-8849.220	Hannan-Quinn criter.	7.020216
Durbin-Watson stat	2.015152		

The AIC and SIC values are 7.016 and 7.027.

EGARCH

The following table shows the result of EGARCH

Table 5

Dependent Variable: DHCLTECH
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 02/21/24 Time: 20:49
Sample (adjusted): 4/02/2013 6/28/2023

Included observations: 2524 after adjustments
Convergence achieved after 44 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.450333	0.129948	3.465493	0.0005
	Variance Equation			
C(2)	-0.062228	0.006931	-8.978649	0.0000
C(3)	0.105271	0.008205	12.83058	0.0000
C(4)	0.035628	0.007243	4.919032	0.0000
C(5)	0.996630	0.001019	977.6645	0.0000

R-squared	-0.000023	Mean dependent var	0.401291
Adjusted R-squared	-0.000023	S.D. dependent var	10.19135
S.E. of regression	10.19146	Akaike info criterion	7.010511
Sum squared resid	262053.8	Schwarz criterion	7.022067
Log likelihood	-8842.264	Hannan-Quinn criter.	7.014704
Durbin-Watson stat	2.015165		

The AIC and SIC values are 7.01 and 7.02.

PARCH Model

Following table shows the result:

Table 6

Dependent Variable: DHCLTECH
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 02/21/24 Time: 21:00
Sample (adjusted): 4/02/2013 6/28/2023
Included observations: 2524 after adjustments
Convergence achieved after 54 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(6) = C(2) + C(3)*(ABS(RESID(-1)) - C(4)*RESID(
-1))^C(6) + C(5)*@SQRT(GARCH(-1))^C(6)

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Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.416985	0.130579	3.193348	0.0014
	Variance Equation			
C(2)	0.036424	0.019426	1.875055	0.0608
C(3)	0.053891	0.004519	11.92567	0.0000
C(4)	-0.326205	0.062924	-5.184146	0.0000
C(5)	0.957258	0.003464	276.3645	0.0000
C(6)	1.229095	0.175689	6.995855	0.0000

R-squared	-0.000002	Mean dependent var	0.401291
Adjusted R-squared	-0.000002	S.D. dependent var	10.19135
S.E. of regression	10.19136	Akaike info criterion	7.011109
Sum squared resid	262048.3	Schwarz criterion	7.024976
Log likelihood	-8842.019	Hannan-Quinn criter.	7.016141
Durbin-Watson stat	2.015207		

The AIC and SIC values are 7.01 and 7.02.

Component ARCH (1, 1) model

Results are show in the below table:

Table 7

Dependent Variable: DHCLTECH
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 02/21/24 Time: 21:00
Sample (adjusted): 4/02/2013 6/28/2023
Included observations: 2524 after adjustments
Convergence achieved after 54 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(6) = C(2) + C(3)*(ABS(RESID(-1)) - C(4)*RESID(
-1))^C(6) + C(5)*@SQRT(GARCH(-1))^C(6)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.416985	0.130579	3.193348	0.0014
	Variance Equation			
C(2)	0.036424	0.019426	1.875055	0.0608
C(3)	0.053891	0.004519	11.92567	0.0000

C(4)	-0.326205	0.062924	-5.184146	0.0000
C(5)	0.957258	0.003464	276.3645	0.0000
C(6)	1.229095	0.175689	6.995855	0.0000

R-squared	-0.000002	Mean dependent var	0.401291
Adjusted R-squared	-0.000002	S.D. dependent var	10.19135
S.E. of regression	10.19136	Akaike info criterion	7.011109
Sum squared resid	262048.3	Schwarz criterion	7.024976
Log likelihood	-8842.019	Hannan-Quinn criter.	7.016141
Durbin-Watson stat	2.015207		

The AIC and SIC values are 7.01 and 7.02.

FIGARCH Model

The table below shows the result of the model

Table 8

Dependent Variable: DHCLTECH
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 02/21/24 Time: 21:04
Sample (adjusted): 4/02/2013 6/28/2023
Included observations: 2524 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.350584	0.125480	2.793943	0.0052
	Variance Equation			
C(2)	1.417397	0.320261	4.425760	0.0000
RESID(-1)^2	0.421670	0.035519	11.87157	0.0000
GARCH(-1)	0.738214	0.032243	22.89559	0.0000
D	0.458687	0.052089	8.805884	0.0000

R-squared	-0.000025	Mean dependent var	0.401291
Adjusted R-squared	-0.000025	S.D. dependent var	10.19135
S.E. of regression	10.19147	Akaike info criterion	7.016535
Sum squared resid	262054.2	Schwarz criterion	7.028092
Log likelihood	-8849.868	Hannan-Quinn criter.	7.020729
Durbin-Watson stat	2.015162		

The AIC and SIC values are 7.02 and 7.03.

FIEGARCH (1, 1) model

The model result is shown in the following table:

Table 9

Dependent Variable: DHCLTECH
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 02/21/24 Time: 21:05
Sample (adjusted): 4/02/2013 6/28/2023
Included observations: 2524 after adjustments
Failure to improve likelihood (non-zero gradients) after 144 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.353298	0.124466	2.838517	0.0045
	Variance Equation			
OMEGA	3.387205	0.029366	115.3450	0.0000
ALPHA	-1.004301	6.54E-05	-15352.75	0.0000
BETA	0.996808	1.54E-05	64759.07	0.0000
THETA1	0.262190	0.020378	12.86600	0.0000
THETA2	-0.003589	0.011623	-0.308767	0.7575
D	0.567112	0.103450	5.481968	0.0000

R-squared	-0.000022	Mean dependent var	0.401291
Adjusted R-squared	-0.000022	S.D. dependent var	10.19135
S.E. of regression	10.19146	Akaike info criterion	6.994823
Sum squared resid	262053.5	Schwarz criterion	7.011002
Log likelihood	-8820.467	Hannan-Quinn criter.	7.000694

The AIC and SIC values are 6.99 and 7.01.
From the above analysis the minimum value of AIC and SIC is for FIEGARCH (1,1) model which is 6.99 and 7.01. So as per criterion the best model fitted is FIEGARCH (1, 1).

Though the **FIEGARCH (1, 1)** model is the best model but we have to go for diagnostic checking. So we have to estimate the model firstly by checking whether there is any serial correlation present in the model?

Let's start with correlogram of squared residuals. The results are taken with 36 lags which are displayed below.

Table 10

Date: 02/21/24 Time: 21:13
Sample (adjusted): 4/02/2013 6/28/2023
Included observations: 2524 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.006	0.006	0.0870	0.768
		2	-0.014	-0.015	0.6181	0.734
		3	-0.006	-0.006	0.7053	0.872
		4	0.011	0.011	1.0351	0.904
		5	0.007	0.007	1.1753	0.947
		6	-0.017	-0.016	1.8692	0.931
		7	0.010	0.010	2.0996	0.954
		8	0.028	0.027	4.0720	0.851
		9	-0.005	-0.005	4.1234	0.903
		10	-0.019	-0.018	5.0555	0.887
		11	-0.012	-0.011	5.3985	0.910
		12	-0.024	-0.026	6.8611	0.867
		13	-0.001	-0.001	6.8620	0.909
		14	0.001	0.001	6.8632	0.940
		15	-0.004	-0.004	6.8982	0.960
		16	0.003	0.002	6.9159	0.975
		17	-0.009	-0.008	7.1186	0.982
		18	-0.016	-0.016	7.8037	0.981
		19	-0.011	-0.010	8.1001	0.986
		20	0.015	0.016	8.7047	0.986
		21	-0.013	-0.014	9.1052	0.988
		22	0.014	0.014	9.6098	0.990
		23	-0.004	-0.005	9.6527	0.993
		24	0.000	-0.001	9.6532	0.996
		25	-0.002	-0.001	9.6598	0.997
		26	0.043	0.044	14.293	0.969
		27	-0.004	-0.005	14.334	0.978
		28	-0.002	-0.002	14.345	0.985
		29	0.000	-0.000	14.345	0.989
		30	-0.023	-0.025	15.673	0.985
		31	0.019	0.019	16.600	0.984
		32	-0.009	-0.007	16.799	0.987
		33	-0.013	-0.014	17.238	0.989
		34	-0.006	-0.007	17.317	0.992
		35	-0.028	-0.028	19.345	0.985
		36	0.008	0.008	19.512	0.989

*Probabilities may not be valid for this equation specification.

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From the above result we got Q Statistics and the respective probability value. The null and alternative hypothesis are :-

Null Hypothesis: There is no serial correlation in the residuals

Alternative Hypothesis: There is serial correlation in the residuals.

The above p values shows that null hypothesis is true as p>0.05 for all Q statistics. So, there is no serial correlation.

Next, we have to check whether there is ARCH effect or not. For that ARCH-LM test is performed for which the result is as follows:-

Table 11

Heteroskedasticity Test: ARCH

F-statistic	0.086816	Prob. F(1,2521)	0.7683
Obs*R-squared	0.086882	Prob. Chi-Square(1)	0.7682

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 02/21/24 Time: 21:20
Sample (adjusted): 4/03/2013 6/28/2023
Included observations: 2523 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.018988	0.051503	19.78519	0.0000
WGT_RESID^2(-1)	0.005868	0.019916	0.294646	0.7683

R-squared	0.000034	Mean dependent var	1.025004
Adjusted R-squared	-0.000362	S.D. dependent var	2.374603
S.E. of regression	2.375033	Akaike info criterion	4.568692
Sum squared resid	14220.41	Schwarz criterion	4.573316
Log likelihood	-5761.405	Hannan-Quinn criter.	4.570370
F-statistic	0.086816	Durbin-Watson stat	1.999762
Prob(F-statistic)	0.768289		

The Null hypothesis and Alternative hypothesis are :-

Null Hypothesis: There is no ARCH effect

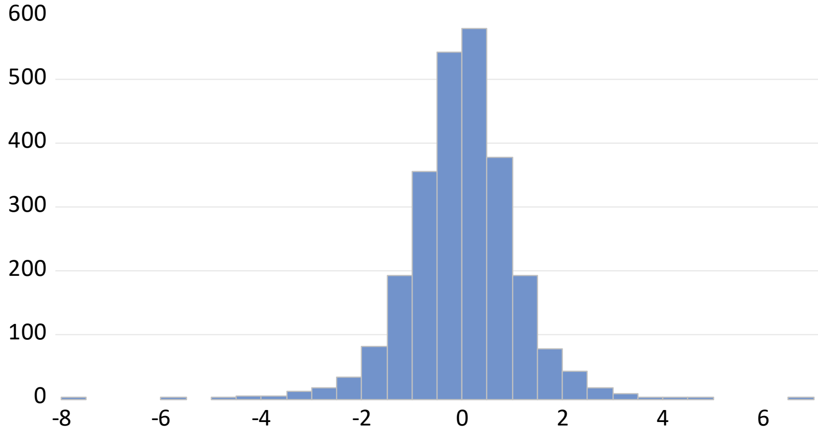
Alternative Hypothesis: There is ARCH effect.

As p values are > 0.05 so we have to accept the null hypothesis and conclude that there is no ARCH effect in the model.

Lastly, we have to check whether the residuals are normally distributed or not?

Let's check it with Histogram – Normality test.

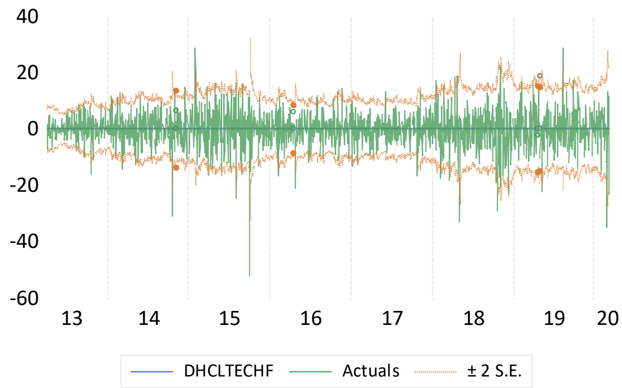
Figure 2



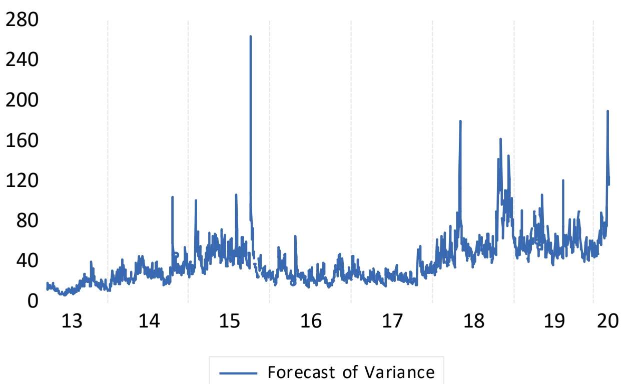
Series: Standardized Residuals	
Sample 4/02/2013 6/28/2023	
Observations 2524	
Mean	0.001775
Median	0.022051
Maximum	6.537967
Minimum	-7.557393
Std. Dev.	1.012441
Skewness	-0.210642
Kurtosis	6.368442
Jarque-Bera	1211.928
Probability	0.000000

The Jarque – Bera statistic value is 1211.928. And the corresponding p value is 0.
The Null Hypothesis: The residuals are normally distributed and the Alternative Hypothesis: The residuals are not normally distributed.
As $p<0.05$ we have to reject the null hypothesis. And accept the alternative hypothesis which is not desirable. But as this model has no serial correlation and ARCH effect so according to economists, we can accept the model.
Now with the help of above model we will proceed to forecast volatility whose diagram and results are described below. The data is segregated into pre covid and post covid for forecasting the same as covid is one of the factors which effected the entire stock market.
1st Segregation - Data from 1st April 2013 to 10th March 2020.

Figure 3

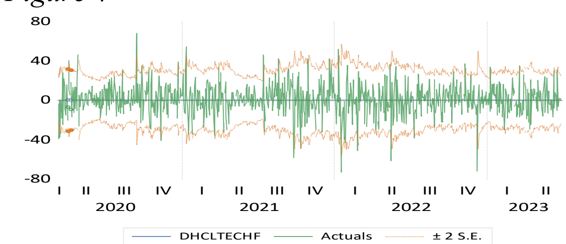


Forecast: DHCLTECHF	
Actual: DHCLTECH	
Forecast sample: 4/01/2013 3/09/2020	
Adjusted sample: 4/02/2013 3/09/2020	
Included observations: 1705	
Root Mean Squared Error	6.211990
Mean Absolute Error	4.469398
Mean Abs. Percent Error	NA
Theil Inequality Coef.	0.946066
Bias Proportion	0.000680
Variance Proportion	0.999274
Covariance Proportion	0.000047
Theil U2 Coefficient	NA
Symmetric MAPE	170.0977

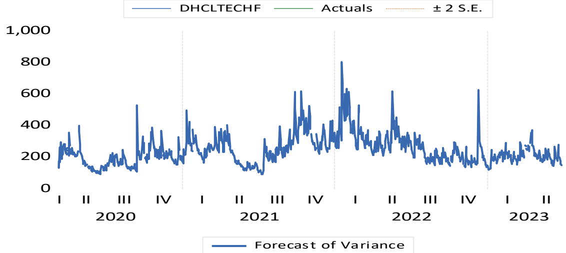


2nd Segregation - Data from 10th March 2020 to 28th June 2023

Figure 4



Forecast: DHCLTECHF	
Actual: DHCLTECH	
Forecast sample: 3/11/2020 6/28/2023	
Included observations: 819	
Root Mean Squared Error	15.48009
Mean Absolute Error	11.40282
Mean Abs. Percent Error	NA
Theil Inequality Coef.	0.976755
Bias Proportion	0.000982
Variance Proportion	NA
Covariance Proportion	NA
Theil U2 Coefficient	NA
Symmetric MAPE	184.7092



Finally, from granger causality test it was found that volatility of HCL Technologies granger cause the movement of NIFTY 50 and SENSEX.

Conclusion

In this empirical study, the ARCH family model is used to guesstimate the volatility fo HCL Technologies stock price, and the unit root test is utilized to determine whether time series data are stationary. ARCH family models are used to predict the volatility and Granger Causality Test is performed to find out whether the Volatility Index is highly effecting the stock price of HCL technologies or not. Daily data from April 1, 2013 to June 28, 2023 is taken as sample data. The below table shows the values of AIC and SIC of ARCH Family models.

ARCH Family Model (AIC and SIC Values)

Model	AIC	SIC
ARCH (5)	7.1385	7.1547
GARCH (1, 1)	7.026	7.035
TARCH (GJR-GARCH)	7.016	7.027
EGARCH	7.01	7.02
PARCH	7.01	7.02
Component ARCH (1, 1)	7.01	7.02
FIGARCH	7.02	7.03
FIEGARCH (1, 1)	6.99	7.01

As per the analysis there is no serial correlation in the residuals. And after ARCH-LM test it was found that there is no ARCH effect. So, the FIEGARCH (1, 1) model is the best model. Guesstimating the volatility, we found after segregating into per covid and post covid there is a constant periodic volatility which has been forecasted and a good return can be expected from HCL Technologies. Similarly, it has been that from Granger Causality Test it was found that volatility of HCL Technologies granger cause the movement of NIFTY 50 and SENSEX. But Volatility Index has no effect on stock price of HCL Technologies. So, the same stock may be taken into consideration for investment by the Rational Investors.

And as per the study the values of all the models which are used in above analysis are totally statistically significant.

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