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Exploring Stock Returns Volatility of Select NSE – Listed Pharmaceutical Companies: An Empirical Study

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ABSTRACT

Volatility of a financial time series has become a fertile area for research during last decades. Global financial meltdowns have massive shock on different sectors as well as on scripts returns. The current study empirically explores the volatility pattern of NSE listed pharmaceutical companies considering daily closing adjusted stock price from 2001-02 to 2015-16. The objective of the paper is to study the volatility design of daily stock returns. The application of GARCH, and T-GARCH models provides the evidence of the persistence of time varying asymmetric volatility. Main findings suggest that time varying volatility behaviour of Indian stock market may be due to recent global financial meltdown, which is originated from US sub-prime crisis. Likewise, effect captured by different models show that negative shocks have significant effect on conditional volatility.

***Keywords**: Asymmetric Volatility, Conditional Volatility, Financial Meltdown.*

Introduction

Volatility is a critical component of financial market analysis, influencing investment decisions, portfolio management, and risk assessment. It is the dispersion about central tendency and traditional knowledge says return and risk positively correlated (Pandey, 2010). The pharmaceutical sector, given its sensitivity to regulatory changes, R&D outcomes, and global healthcare trends, presents a unique case for examining stock return volatility. However, some recent theoretical works consistently assent that stock market volatility has been found to be negatively correlated with stock returns. Considering the daily log returns of stock, the daily volatility is not directly observable from the return data because there is only one observation in a trading day. It can be defined as a statistical measure of the dispersion of stock price returns for a given security or market index and it can either be measured using the standard deviation or variance between returns from that same security or market index (John, et. al., 2016). Volatility is a key parameter used in risk assets pricing. It refers to the ups and downs in the stock price returns. Stock returns are an integral part of market with bull and bear phases. Volatility is useful for superior returns. Higher volatility causes higher risk (Kumar, 2016). Estimation of stock price returns is important for several reasons, like (i) Investment decision; (ii) Assets pricing; (iii) Expected returns and (iv) Risk of various assets, etc.

Past Studies and Research Gap

Ali (2016) in his research paper 'Stock market volatility and returns: A study of NSE & BSE in India' examined relationship between returns and volatility and persistence of volatility in Indian stock market. **Anbukarasi & Nithya (2014)** in their research paper 'Return and volatility analysis of the Indian sectoral indices – with special reference to NSE' investigated the returns of S&P CNX NIFTY and sectoral index and to know the level of volatility on it and various sectoral index. **Banumathy et al. (2015)** in the research paper 'Modelling stock market volatility: Evidence from India' studied volatility pattern of Indian stock market based on index data using both symmetric and asymmetric models. **Eryilmaz (2015)**

in the research paper 'Modelling stock market volatility: The case of BIST – 100' investigated stock return volatility for BIST –100 indices. **Kumar (2009)** in the research paper 'Volatility in the Indian Stock Market: A Case of Individual Securities' investigated volatility in the individual stocks listed at NSE using daily closing prices of 29 selected companies from the S&P NIFTY from 1996- 97 to 2006 - 07.

Most of the research on the stock market volatility in India are based on broad indices. In addition to previous studies, there is a need for further study on measurement of stock returns volatility in order to have insight of different pharmaceutical companies listed in major stock exchanges in India, like NSE and to explore how volatility of individual script changes with respect to different time period in respect to different economic policies, incident, etc. and underlying different factors and shocks which can affect individual securities. Keeping in mind of this research gap, specific objectives of the current study are set.

Objectives of the Study

The objectives of the current study are as follows:

- To explore the volatility characteristics of select NSE listed pharmaceutical companies using descriptive statistics;
- To examine the presence of volatility in select NSE listed pharmaceuticals companies daily return series using ARCH (1) model;
- To analyse volatility in select NSE listed pharmaceuticals companies using GARCH and TGARCH Model.

Data and Methodology

The current study is based on secondary data. Daily adjusted closing share price of select NSE-listed pharmaceuticals companies are collected from Capitaline corporate database and NSE official website as well, are considered here for calculation of daily stock price return series of each company and yearly stock returns volatility (Beta value) of them. The sample design follows the judgment sample technique based on market capitalization of sample top companies. It makes an attempt to measure volatility of pharmaceuticals top market capitalization companies, which were listed and actively traded in NSE from 2000-01 to 2015- 2016. The study has been made considering the following 2 sub-periods and full sample period (Period I: pre-global financial recession period, which includes the study period from 1st April, 2001 to 6th August, 2007; and Period II: Post-global financial recession period, which comprises the study period from 3rd April, 2009 to 31st March, 2016. Different statistical tools are used in this study, such as Descriptive statistics, Autoregressive Conditional Heteroskedasticity (ARCH) Test, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model, and Threshold Generalized Autoregressive Conditional Heteroskedasticity (T-GARCH) Model. EViews 8.0 has been used for data analysis.

Results and Analysis

Descriptive Statistics Results

Daily mean returns of the selected companies in pharmaceutical sector are majority lower but positive except in case of Lupin Ltd where S.D. is highest in pre global financial recession period and other three time periods. Skewness has been found to be lower but positive. Kurtosis of the overall period indicate high pickedness (Leptokurtic) which indicate return distributions are not normal and clearly indicate presence of volatility in pharmaceutical stocks return.

Table 1: Descriptive Statistics Results of pharmaceutical Companies (Pre-Global Recession Period)

Company Name	Mean	S. D.	Variance	Kurtosis	Skewness
Cipla	0.0007	0.02	0.0004	8.17	-0.15
Glaxosmit Pharma	0.0008	0.01	0.0001	6.65	0.16
GlaxoSmith C H L	0.0004	0.01	0.0001	10.80	0.57
Sanofi India	0.0008	0.01	0.0001	7.22	0.72
Jubilant Life	0.002	0.022	0.0004	8.01	1.04
Dr Reddy's Labs	0.0007	0.022	0.0004	12.38	0.13
Lupin	0.0067	0.177	0.028	144	37
Ipca Labs.	0.0022	0.027	0.0004	7.01	0.5
Sun Pharma.Inds.	0.0014	0.02	0.0004	6.26	0.23
Aurobindo Pharma	0.001	0.02	0.0004	9.95	0.59
Wockhardt	0.0009	0.6	0.36	8.30	0.6

Table 2: Descriptive Statistics Results of pharmaceutical Companies (Post-Global Recession Period)

Company Name	Mean	S. D.	Variance	Kurtosis	Skewness
Cipla	0.0005	0.018	0.0003	7.28	-0.13
Glaxosmit Pharma	0.0006	0.015	0.0002	17.31	1.03
GlaxoSmith C H L	0.0012	0.019	0.0003	15.45	1.09
Sanofi India	0.0007	0.018	0.0003	11.87	0.97
Jubilant Life	0.0006	0.029	0.0008	9.14	0.91
Dr Reddy's Labs	0.0008	0.018	0.0003	7.85	-0.29
Lupin	0.0013	0.019	0.0003	6.35	-0.014
Ipca Labs.	0.0009	0.021	0.0004	8.66	0.17
Sun Pharma.Inds.	0.0011	0.02	0.0004	13.18	0.2
Aurobindo Pharma	0.0014	0.028	0.0008	8.33	-0.1
Wockhardt	0.0009	0.033	0.001	9.5	0.29

Examining the presence of volatility in select NSE listed pharmaceuticals companies daily return series using ARCH (1) model

- **Precondition for Performing ARCH Test**

(a) Assumption-1: Sample companies return series are not normal

Normality test is used to check whether the sample companies return series are distributed normally.

Hypothesis	• H_0: Return series of select stocks are normal; • H_1: Return series of select stocks are not normal.
Statistical Test	Jarque-Bera test
Test Statistic	Chi–Square
DF	n–1, where n= 2
Level of Significance	5%
Decision Rule	If P–Value is less than 0.05, H_0 is not accepted and vice versa

Table 3: Normality Test Results of Daily Adjusted Stock Price Returns

Pharmaceutical Sector	Pre-Global Recession Period		Post-Global Recession Period		Decision Rule	Decision on H_0	Data series Normality
	J-B	P–Value	J-B	P–Value			
Cipla	17.83.2	0.000	1711.2	0.000	P–Value<0.05	Rejected	Not normal
Glaxosmit Pharma	893.1	0.000	19428.2	0.000	P–Value<0.05	Rejected	Not normal
GlaxoSmith C H L	4142	0.000	14858.3	0.000	P–Value<0.05	Rejected	Not normal
Sanofi India	1323.1	0.000	10573.5	0.000	P–Value<0.05	Rejected	Not normal
Jubilant Life	1953.9	0.000	3060.7	0.000	P–Value<0.05	Rejected	Not normal
Dr Reddy's Labs	5851.9	0.000	2154.4	0.000	P–Value<0.05	Rejected	Not normal
Lupin	1.36	0.000	272.33	0.000	P–Value<0.05	Rejected	Not normal
Ipca Labs.	1139.61	0.000	2854.72	0.000	P–Value<0.05	Rejected	Not normal
Sun Pharma.Inds.	721.2	0.000	16881.7	0.000	P–Value<0.05	Rejected	Not normal
Aurobindo Pharma	3300.7	0.000	434.15	0.000	P–Value<0.05	Rejected	Not normal
Wockhardt	1960.6	0.000	3104.8	0.000	P–Value<0.05	Rejected	Not normal

It is observed that H_0 is rejected for all return series of select NSE listed pharmaceutical companies. Since, the JB test is significant at 1% level that means daily returns series are not normally distributed. J-B Test for normality is consistent with the outcome provided by both statistical results of kurtosis and Skewness.

(b) Assumption 2: Stationarity exists in Sample Companies' Daily Return Series

The Augmented Dickey Fuller (ADF) test is employed to infer the stationarity of the stock daily return series.

Unit Root Test for Stationarity Test

Hypothesis	• Null Hypothesis (H_0) : Daily stock return series has unit root; • Alternative Hypothesis (H_1): Daily stock return series has no unit root.
Test Statistics	Augmented Dickey Fuller (ADF) Test
Underlying Distribution	t- Test
Decision Rule	When t- statistics is lower than critical values and p- value <0.05, then, H_0 is rejected and vice versa.

Table 4: The Augmented Dickey-Fuller (ADF) Test results - At Level (Pre-Global Recession Period)

Pharmaceutical Sector	None		Null Hypothesis (H_0)	Data series stationarity
	t-Statistics & Prob.	C.V. (5%)		
Cipla	-36.47 (0.000)	-1.94	Rejected	Stationary series
Glaxosmit Pharma	-28.32 (0.000)	-1.94	Rejected	Stationary series
GlaxoSmith C H L	-26.46 (0.000)	-1.94	Rejected	Stationary series
Sanofi India	-15.13 (0.000)	-1.94	Rejected	Stationary series
Jubilant Life	-14.14 (0.000)	-1.94	Rejected	Stationary series
Dr Reddy's Labs	-37.45 (0.000)	-1.94	Rejected	Stationary series
Lupin	-38.16 (0.000)	-1.94	Rejected	Stationary series
Ipca Labs.	-35.51 (0.000)	-1.94	Rejected	Stationary series
Sun Pharma.Inds.	-29.43 (0.000)	-1.94	Rejected	Stationary series
Aurobindo Pharma	-14.67 (0.000)	-1.94	Rejected	Stationary series
Wockhardt	-28.46 (0.000)	-1.94	Rejected	Stationary series

Table 5: The Augmented Dickey-Fuller (ADF) Test results - At Level (Post-Global Recession Period)

Pharmaceutical Sector	None		Null Hypothesis (H_0)	Data series stationarity
	t-Statistics & Prob.	C.V. (5%)		
Cipla	-48.39 (0.000)	-1.94	Rejected	Stationary series
Glaxosmit Pharma	-20.85 (0.000)	-1.94	Rejected	Stationary series
GlaxoSmith CHL	-51.47 (0.000)	-1.94	Rejected	Stationary series
Sanofi India	-24 (0.000)	-1.94	Rejected	Stationary series
Jubilant Life	-16.26 (0.000)	-1.94	Rejected	Stationary series
Dr Reddy's Labs	11.78 (0.000)	-1.94	Rejected	Stationary series
Lupin	-28.73 (0.000)	-1.94	Rejected	Stationary series
Ipca Labs.	-31.53 (0.000)	-1.94	Rejected	Stationary series
Sun Pharma.Inds.	-28.91 (0.000)	-1.94	Rejected	Stationary series
Aurobindo Pharma	-7.15 (0.000)	-1.94	Rejected	Stationary series
Wockhardt	-30.13 (0.000)	-1.94	Rejected	Stationary series

It is found that H_0 is rejected for daily stock return series and there is no unit root in return series of select NSE listed pharmaceuticals companies for two sample periods. Since, the ADF test is performed (using neither in the test regression or none) at level is significant at 5% level i.e., it is observed that the computed all test statistics are lower than critical values. Select NSE listed companies return series for two sample periods are stationary at level.

- **ARCH Test (Test for Heteroskedasticity)**

ARCH effect has become important tools in the analysis of financial time series data, particularly in financial time series application. ARCH effect means heteroskedasticity, which is modelled as conditional variance of squared residuals obtained from mean equation as from AR (1) model.

ARCH Test for heteroskedasticity

Hypothesis	• Null Hypothesis (H_0) : Heteroskedasticity does not exists in daily stock return series; • Alternative Hypothesis (H_1): Heteroskedasticity exists in daily stock return series.
Test statistics	Autoregressive Conditional Heteroskedasticity Test (1) $\sigma_t^2 = a_0 + \sum_{t=1}^{q} a_i U_{t-1}^2$ (Where a_0 is mean and a_1 is conditional volatility and U_{t-1} is white noise representing residual of time series)
Underlying distribution	• F – test • T. R^2 Statistics (Where T is size of residuals and R^2 is coefficient of determination of regression model) or Obs* R- squared
Decision Rule	If p- value <0.05, then, H_0 is rejected and vice versa.

The results are as follows:

Table 6: Heteroskedasticity Test Results – ARCH (1) for Pre-Global Recession Period

Companies	F-statistic	Prob. F	Obs* R-squared	Prob. Chi-Square	Decision on Ho	ARCH effects are present or not
Cipla	30.51	0.000	29.97	0.000	Rejected	ARCH effects are present
Glaxosmit Pharma	60.90	0.000	58.73	0.000	Rejected	ARCH effects are present
GlaxoSmith CHL	24.11	0.000	23.78	0.000	Rejected	ARCH effects are present
Sanofi India	81.43	0.000	77.55	0.000	Rejected	ARCH effects are present
Jubilant Life	55.66	0.000	53.84	0.000	Rejected	ARCH effects are present
Dr Reddy's Labs	8.40	0.0058	8.37	0.0058	Rejected	ARCH effects are present
Lupin	0.0005	0.979	0.0005	0.979	Accepted	No ARCH effects
Ipca Labs.	88.17	0.000	83.64	0.000	Rejected	ARCH effects are present
Sun Pharma.Inds.	50.02	0.000	48.55	0.000	Rejected	ARCH effects are present
Aurobindo Pharma	164.03	0.000	148.86	0.000	Rejected	ARCH effects are present
Wockhardt	30.03	0.000	29.51	0.000	Rejected	ARCH effects are present

Table 7: Heteroskedasticity Test Results – ARCH (1) for Post-Global Recession Period

Companies	F-statistic	Prob. F	Obs* R-squared	Prob. Chi-Square	Decision on Ho	ARCH effects are present or not
Cipla	25.81	.000	25.46	.000	Rejected	ARCH effects are present
Glaxosmit Pharma	1.71	0.19	1.71	0.19	Accepted	No ARCH effects
GlaxoSmith CHL	39.10	.000	38.29	.000	Rejected	ARCH effects are present
Sanofi India	18.05	.000	17.88	.000	Rejected	ARCH effects are present
Jubilant Life	72.82	.000	69.96	.000	Rejected	ARCH effects are present
Dr Reddy's Labs	5.43	.019	5.42	.019	Rejected	ARCH effects are present
Lupin	26.73	.000	26.36	.000	Rejected	ARCH effects are present
Ipca Labs.	8.64	.003	8.59	.003	Rejected	ARCH effects are present
Sun Pharma.Inds.	130.57	.000	121.55	.000	Rejected	ARCH effects are present
Aurobindo Pharma	17.41	.000	17.26	.000	Rejected	ARCH effects are present
Wockhardt	16.57	.000	16.44	.000	Rejected	ARCH effects are present

Heteroskedasticity has been tested using ARCH (1) model in order to know whether there is ARCH effect in the residuals in select return series during two sample periods. ARCH results comprise of F value, Probability of F value, obs. R squared value and probability of χ^2 value. If p value of T. R^2 statistics is less than 0.01 or 1%, null hypothesis (H_0) is rejected. Hence, it can be stated that there is in existence of ARCH effect. However, it is found that there is in existence of ARCH effect of all sample companies excepting Lupin in pre-global recession period. SBI, Bajaj holdings, GE T & D, Apollow do not have ARCH effect in post-global recession period. During the global recession period, many stocks return is low and negative and no ARCH effect in their return series is found.

Analyzing Volatility in select NSE listed Pharmaceuticals Companies using GARCH Model

The general process for a GARCH model involves overcoming some of the drawbacks of the ARCH model**.** GARCH model represents generalized ARCH processes in the sense that the squared volatility (σ_t^2) of the concerned period is allowed to depend on previous squared volatilities, as well as previous squared values of the process. The present study has employed GARCH (1, 1) technique to capture the conditional volatility in the return series.

GARCH (1,1) Model Equations	• Mean equation: $r_t = \mu + \varepsilon_t$; • Variance equation: $\sigma_t =$ w + $\alpha\varepsilon_{t-1}^2 + \beta\alpha_{t-1}^2$ Where α $_0$ >0, α_1 ≥0 & β_1 ≥0 $\varepsilon_t = \sigma_t Z_t$ Where Z_t are standardized residual returns and σ_t^2 stands for the conditional variance. In GARCH (1, 1), constant α_1 ≥0 & β_1 ≥0 are needed to ensure that σ_t^2 is strictly positive.
Test Statistics	ARCH and GARCH coefficient value
Decision Rule	If the sum of the two estimated ARCH & GARCH coefficient ($\alpha + \beta$) is very close to one, it indicates that volatility shocks are quite persistent not explosive. If the value is larger than one, conditional variance process is explosive.

Once ARCH effect in a financial time series dataset is observed, one may further investigate GARCH effect in order to fulfill our specific objective of our research work. The study shows that maximum scripts have no ARCH effect in recession time period. There is different lag order model in GARCH and finally GARCH (1, 1) model is found. Log likelihood ratio becomes maximum, where we find minimum value of AIC, SIC, HQ value of selected empirical estimation. The results are as follows:

Table 8: GARCH Model (Pre-Global Recession Period)

Company Name/ Sectors	Estimated Model with values				AIC	SIC	Log Likelihood	Decision (Decision Rule: Volatility of shocks is highly persistence when $\alpha_i+\beta_i$=1)
First Period - Coefficients - GARCH (1, 1)								
Pharmaceuticals	α_0	α_1	β_1	$\alpha_i+\beta_i$				
Cipla	7.01	0.134	0.700	0.834	-5.03	-5.02	3791.2	Comparatively low persistence value
Glaxosmit Pharma	7.59	0.205	0.605	0.81	-5.12	-5.1	3856.9	Comparatively low persistence value
GlaxoSmith C H L	2.76	0.204	0.742	0.946	-5.29	-5.27	3984.6	Comparatively low persistence value
Sanofi India	6.41	0.182	0.638	0.82	-5.25	-5.23	3951.7	Comparatively low persistence value
Jubilant Life	2.10	0.193	0.789	0.982	-5.01	-4.99	3760.1	Very high persistence value
Dr Reddy's Labs	8.68	0.018	0.962	0.98	-4.77	-4.75	3593.7	Very high persistence value

Ipca Labs.	0.0001	0.205	0.619	0.80	-4.52	-4.5	3406.9	Comparatively low persistence value
Sun Pharma.Inds.	1.96	0.125	0.838	0.963	-5.02	-5	3777.6	Very high persistence value
Aurobindo Pharma	5.10	0.146	0.782	0.928	-4.56	-4.54	3435.5	Comparatively low persistence value
Wockhardt	2.83	0.068	0.870	0.930	-4.89	-4.87	3679.6	Comparatively low persistence value

Table 9: GARCH Model (Post-Global Recession Period)

Company Name/ Sectors	Estimated Model with values				AIC	SIC	Log Likelihood	Decision (Decision Rule: Volatility of shocks is highly persistence when $\alpha_j+\beta_i=1$)
First Period - Coefficients - GARCH (1, 1)								
Pharmaceuticals	α_0	α_1	β_1	$\alpha_j+\beta_i$				
Cipla	6.07	0.0012	0.963	0.964	-5.21	-5.2	5817.5	Very high persistence value
GlaxoSmith C H L	0.0001	0.240	0.474	0.714	-5.12	-5.1	5718.1	Comparatively low persistence value
Sanofi India	6.65	0.031	0.941	0.972	-5.27	-5.3	5884.1	Very high persistence value
Jubilant Life	6.62	0.124	0.814	0.938	-4.29	-4.3	4795.2	Comparatively low persistence value
Dr Reddy's Labs	1.67	0.021	0.972	0.993	-5.26	-5.3	5871.7	Very high persistence value
Lupin	4.06	0.034	0.953	0.987	-5.11	-5.1	5704.1	Very high persistence value
Ipca Labs.	.0001	0.088	0.650	0.738	-4.93	-4.9	5497.3	Comparatively low persistence value
Sun Pharma.Inds.	0.0001	0.225	0.330	0.555	-5.02	-5	5605.3	Comparatively low persistence value
Aurobindo Pharma	4.36	0.089	0.849	0.839	-4.38	-4.4	4892.5	Comparatively low persistence value
Wockhardt	0.0003	0.234	0.515	0.75	-4.08	-4.1	4553.7	Comparatively low persistence value

There is different lag order model in GARCH and finally GARCH (1, 1) model is found. Log likelihood ratio becomes maximum where we find minimum value of AIC, SIC, HQ value of selected empirical estimation. Table 8, and Table 9 depict values of AIC, SIC and log likelihood ratio value. Our GARCH test results found to be significant. It implies that coefficient of constant (α_0), ARCH term (α_1) and GARCH term (β_1) are highly significant at 1% level of significant. In the conditional variance equation, the estimation β_1 coefficient is considered to be greater than α_1 coefficient which resembles that the market has a memory longer than one period and volatility is highly dependable on its assumed lag values. GARCH model depicts effects of new surprise in the market values due to price sensitive information. It depicts the nature of persistence in the volatility. The sizes of parameter α_1 & β_1 determine the volatility in time series. The sum of α_1 & β_1 coefficient is close to unity. In the other words, volatility from the previous periods has a power of explaining the current volatility condition. Thus, the sum of coefficient of α_1 & β_1 in GARCH model is a measure of persistence of volatility shocks. If the results of α_1 & β_1 are close to unity (i.e. one), then the possibility of more persistent is the stock to conditional variance in return. However, it appears from the above tables of GARCH that the ($\alpha + \beta$) is around one, which indicates that the return series have both attributes, such as volatility clustering and persistent. During pre-global financial meltdown period, highest and lowest ARCH and GARCH combined values are ranges from .975 and .867 in respect of ten pharmaceuticals companies' returns series. Study shows that during post-global financial meltdown period such values of companies in pharmaceuticals sector are maximum. This clearly proves high volatility among these companies' returns series during post- global financial meltdown period.

Analyzing Volatility in select NSE listed pharmaceuticals companies using T-GARCH Model

TGARCH model has been used to know that positive and negative shocks of equal magnitude have a different impact on stock market volatility, which may be attributed to 'leverage effect'. The T-GARCH table represents α_0 is the constant in the models.

TGARCH (1,1) Model Equations	$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \gamma d_{t-1}\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$
Test statistics	ARCH and GARCH coefficient value
Decision Rule	If γ is significant and positive, negative shocks have a larger effect on σ_t^2 than the positive shocks

The results are as follows:

Table 10: T-GARCH Model (Pre-Global Recession Period)

Company Name	Estimated Model with values				AIC	SIC	Log Likelihood	Decision
First Period - Coefficients - GARCH (1, 1) with Threshold order 1								
Pharmaceuticals	α_0	α_1	γ	β_1				
Cipla	7.01	0.136	-0.004	0.700	-5.03	-5.01	3792.15	Positive γ which implies negative shocks is larger effect on volatility
Glaxosmit Pharma	9.13	0.156	0.111	0.557	-5.12	-5.1	3858.53	Positive γ which implies negative shocks is larger effect on volatility
GlaxoSmith C H L	2.57	0.164	0.083	0.749	-5.29	-5.27	3987.12	Positive γ which implies negative shocks is larger effect on volatility
Sanofi India	6.41	0.181	-0.003	0.631	-5.25	-5.22	3951.76	Positive γ which implies negative shocks is larger effect on volatility
Jubilant Life	1.92	0.159	0.061	0.799	-5.01	-4.98	3761.24	Positive γ which implies negative shocks is larger effect on volatility
Dr Reddy's Labs	0.0004	0.210	-0.003	-0.051	-4.77	-4.75	3596.34	Positive γ which implies negative shocks is larger effect on volatility
Ipca Labs.	0.0001	0.198	0.015	0.621	-4.52	-4.5	3406.97	Positive γ which implies negative shocks is larger effect on volatility
Sun Pharma.Inds.	1.83	0.128	-0.018	0.84	-5.01	-4.99	3777.7	Positive γ which implies negative shocks is larger effect on volatility
Aurobindo Pharma	4.58	0.11	0.05	0.799	-4.56	-4.54	3436.96	Positive γ which implies negative shocks is larger effect on volatility
Wockhardt	2.81	0.072	-0.013	0.87	-4.89	-4.87	3679.79	Negative γ which implies positive shocks

Table 11: T-GARCH Model (Post-Global Recession Period)

Company Name	Estimated Model with values				AIC	SIC	Log Likelihood	Decision
First Period - Coefficients - GARCH (1, 1) with Threshold order 1								
Pharmaceuticals	α_0	α_1	γ	β_1				
Cipla	2.34	0.08	0.01	0.847	-5.21	-5.19	5817.7	Positive γ which implies negative shocks is larger effect on volatility
Glaxosmit Pharma								
GlaxoSmith C H L	8.71	0.11	0.203	0.556	-5.14	-5.12	5736.97	Positive γ which implies negative shocks is larger effect on volatility
Sanofi India	7.64	0.036	-0.008	0.936	-5.27	-0.26	5884.81	Positive γ which implies negative shocks is larger effect on volatility
Jubilant Life	5.17	0.087	0.08	0.834	-4.3	-4.28	4802.16	Positive γ which implies negative shocks is larger effect on volatility
Dr Reddy's Labs	1.71	0.023	-0.003	0.973	-5.26	-5.24	5871.77	Positive γ which implies negative shocks is larger effect on volatility
Lupin	5.56	0.028	0.022	0.943	-5.11	-5.09	5706.44	Positive γ which implies negative shocks is larger effect on volatility
Ipca Labs.	0.0001	0.096	-0.039	0.672	-4.93	-4.91	5498.04	Positive γ which implies negative shocks is larger effect on volatility
Sun Pharma.Inds.	0.0001	0.281	-0.108	0.304	-5.02	-5	5605.32	Positive γ which implies negative shocks is larger effect on volatility
Aurobindo Pharma	4.92	0.045	0.112	0.834	-4.4	-4.38	4915.75	Positive γ which implies negative shocks is larger effect on volatility
Wockhardt	0.0003	0.181	0.125	0.518	-4.08	-4.06	4558.31	Positive γ which implies negative shocks is larger effect on volatility

TGARCH represents that α_0 is the constant term in the model representing a long run average; α_1 is the ARCH term, which is the lag of the squared residuals from the mean equation, representing news about volatility from previous period; γ is known as the asymmetry or leverage term. In this model, good news ($\varepsilon_{t-1} > 0$) and the bad news ($\varepsilon_{t-1} < 0$) have differential effect on the conditional variance. When $\gamma = 0$, the model collapses to the standardized GARCH forms and good news has an impact of α_i, while bad news has impact on $\alpha_i + \gamma_i$, which indicates that negative shocks or bad news have a greater effect on the conditional variance than the positive shocks or good news.

The coefficient (δ) measures TGARCH asymmetry or leverage parameter showed that only two companies (Sanofi India -.0045 and Wockhardt -.0183) under this sector during pre-global financial meltdown period and one company (Sun Pharma Inds -.003) during post-global financial meltdown period. T-GARCH results concludes that coefficient of leverage (δ) is positive in maximum cases and significant at 1% level, which led that negative shocks or bad news have a greater effect on the conditional variance than the positive shocks or good news.

Conclusion

In GARCH model, it appears that the combined value or sum of coefficient of ARCH and GARCH value is around one, it indicates volatility clustering and persistency. However, T-GARCH model indicates that negative shocks or bad news have a greater effect on the conditional variance than the positive shocks or good news.

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