



Stock returns volatility of select nse – Listed cement and chemical Stocks: an empirical study

Dr. Siddhartha Sankar Saha¹, Tapas Kumar Tripathy²

¹ Professor and Former Head, Department of Commerce, Former Dean, Faculty Council for Post Graduate Studies in Commerce, Social Welfare and Business Management, Former Director, CUCSE-CEFM & Former Director, IQAC, University of Calcutta, Kolkata, West Bengal, India

² Research Scholar, Department of Commerce, University of Calcutta and Assistant Professor of Commerce, P. K. College, Contai, West Bengal, India

Abstract

Volatility is a critical indicator of risk and is essential for investors, portfolio managers, and policymakers to make informed decisions. This study empirically examines the volatility of stock returns of select NSE-listed cement and chemical sector stocks using statistical and econometric techniques. The study employs empirical methods to analyze historical stock price data, focusing on the variability of returns over a specified period. Statistical tools such as descriptive statistics, ARCH, GARCH (Generalized Autoregressive Conditional Heteroskedasticity), and other volatility models are utilized to capture the dynamic nature of stock price movements. The findings reveal significant differences in volatility patterns between the cement and chemical sectors, influenced by industry-specific factors, and market conditions. The study contributes to a deeper understanding of sectoral risk profiles and provides insights for risk management and investment strategies in emerging markets like India. The results are particularly relevant for stakeholders seeking to optimize portfolio performance while mitigating exposure to market fluctuations.

Keywords: Asymmetric volatility, conditional volatility, financial meltdown

Introduction

Stock market volatility is a crucial area of financial research, influencing investment decisions, portfolio management, and market stability. Volatility in the Indian stock market is the basic characteristics similar to be found in major developed and emerging stock markets. While volatility can be expressed in different ways, volatility of a random variable is its standard deviation; stock return volatility is the variation of stock returns in a specified time period. Share price change due to supply and demand. Generally, volatility in the stock price return is the integral part of stock market with alternative bull and bear phases. In the bullish phase the share prices soar high and in the bearish phase market share prices fall down and these ups and downs determine the return and volatility of the stock market. It indicates a highly liquid market. Pricing of any securities depends on volatility of each asset. An increase in stock market volatility brings a large stock price change of advances or declines. Investors interpret a raise in stock market volatility as an increase in the risk of equity investment and consequently they shift their funds to less risky assets (Pandian & Jeyanthi, 2009). It has an impact on business environment and economic growth through a number of channels. Volatility is associated with unpredictability and uncertainty about the price. It is difficult to estimate about the future trend of volatility due to a large number factor including political stability, economic reasons, corporate fundamentals, government budget, policies of the government etc. However, by calculating historical volatility a prediction can be assumed about the future trend in the volatility (Kumar, 2014). The Cement and Chemical sector, a key component of the Indian economy, comprises companies engaged in the production and distribution of essential consumer goods such as food,

beverages, personal care products, and household items. Given its essential nature, the Cement and Chemical sector is often considered a defensive investment choice, relatively insulated from economic downturns compared to cyclical industries. Estimation of stock price returns becomes significant for several reasons: (i) investment decision; (ii) assets pricing; (iii) expected returns and (iv) risk of various assets, etc. By analyzing the volatility of NSE-listed stocks, the study contributes to the existing literature on financial risk management and provides practical insights for investors, regulators, and financial institutions.

Past Studies and Research Gap

Markowitz (1952) introduced the concept of risk-return trade-off, where volatility (standard deviation of returns) is a key measure of risk. Investors seek to optimize portfolios by balancing expected returns against volatility. Shiller *et al.* (1981) highlighted that investor psychology and market sentiment can lead to deviations from rational pricing, contributing to excess volatility. Andersen *et al.* (2001) introduced realized volatility, which uses intraday data to compute daily volatility. This method provides a more accurate and timely measure but requires access to high-frequency data. Bollerslev (1986) extended Engle's (1982) ARCH model to Generalized Autoregressive Conditional Heteroskedasticity (GARCH), which captures time-varying volatility and clustering effects. In emerging markets, studies by Bekaert and Harvey (1997) found that volatility levels tend to be higher compared to developed markets due to political, economic, and liquidity factors. Research on sectoral volatility has indicated that stocks in industries such as technology, finance, and commodities exhibit higher volatility than defensive sectors like utilities and consumer goods. Several studies examined how external factors impact stock volatility. While existing studies provide

insights into general market trends, there is a need for sector-specific analysis of different NSE-listed Cement and Chemical sector stocks to better understand volatility patterns in major stock exchanges in India and to explore how volatility of individual script changes with respect to different time period in respect to different economic policies, incident, etc. considering such research gap, specific objectives of the current study are set. The study aims to fill these gaps by applying different GARCH models to selected NSE-listed stocks, providing empirical insights into their risk-return dynamics.

Objectives of the Study

The objectives of the current study are as follows:

1. To explore the volatility characteristics of select NSE listed cement and chemical sector companies using descriptive statistics;
2. To examine the presence of volatility in cement and chemical sector companies daily return series using ARCH (1) model;
3. To analyse volatility in select NSE listed cement and chemical sector companies using GARCH and TGARCH Model.

Data and Methodology

This study is based on secondary data. Daily adjusted closing share prices of cement and chemical sector sample companies as well as index data have been taken from Capitaline corpoprte database and NSE official website also. The sample design follows the judgment sample technique. It tries to measure volatility of cement and chemical sector top market capitalisation companies, which are listed in National Stock Exchange (NSE) on or before 2000- 01 and actively traded in NSE upto 2016- 17. The study has been made considering the following two sample periods (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 and econometrics tools used in this study such as Descriptive statistics, Autoregressive Conditional Heteroscedasticity (ARCH) Test, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model and Threshold Generalized Autoregressive Conditional Heteroscedasticity (T-GARCH) Model, etc.

Statistical Tools used	Analysis to address stated objectives of the study
Descriptive statistics	To identify whether there is any difference in mean value, S.D., Variance, Skewness and Kurtosis of individual securities.
ARCH Test	To examine the presence of ARCH effect in sample companies daily return series using ARCH (1) model (Decision Rule: If p- value <0.05, then H ₀ is rejected and vice versa).
GARCH Model	To explain the stock market volatility (conditional variance) at the individual script level from the select sample companies (Decision Rule: If the sum of the two estimated ARCH & GARCH coefficient is equal to one, it indicates volatility shocks are quite persistent).
T-GARCH Model	To explain the stock market volatility (asymmetry or leverage effect) at the individual script level from the select sample companies (Decision Rule: If leverage term (γ) is significant and positive, negative shocks have a larger effect on conditional volatility than the positive shocks).

Results and Analysis

1. Descriptive Statistics results

To assess the distributional properties of the daily adjusted closing price of stock returns, various descriptive statistics are summarized in terms of Average Daily Returns (Mean), Standard Deviation (S.D.), Variance, Skewness, and Kurtosis is applied for all select NSE listed companies as follows:

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

Company Name	Mean	S. D.	Variance	Kurtosis	Skewness
ACC Cement	0.0012	0.023	.0004	6.56	- 0.20
Ambuja Cement	0.0013	0.02	.0004	5.22	0.55
Ramco Cement	0.0015	0.030	.0009	5.88	0.41
Shree Cement	0.0028	0.03	.0009	5.89	0.42
India Cement	0.078	3.22	10.36	6.48	0.3233
Prism Cements	0.162	3.31	10.95	7.05	0.788
Tata Chemicals	0.0014	0.02	.0004	7.51	0.21
Pidilite Inds.	0.0014	0.02	.0004	11.62	1.18

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

Company Name	Mean	S. D.	Variance	Kurtosis	Skewness
ACC Cement	0.0006	0.01	0.0001	6.55	0.47

Ambuja Cement	0.0008	0.020	0.0004	6.03	0.48
Ramco Cement	0.0011	0.02	0.0004	8.68	0.96
Shree Cement	0.0018	0.01	0.0001	6.98	0.87
India Cement	0.0003	0.02	0.0004	9.82	0.22
Prism Cements	0.165	3.44	11.83	6.61	0.52
Tata Chemicals	0.0003	0.02	0.0004	9.22	0.19
Pidilite Inds.	0.0013	0.01	0.0001	11.52	0.2

Daily adjusted closing period mean returns of Cement & Chemical Sectors companies are low in large number of cases in above tables (Table – 1 to 2). The standard deviation of return is found to be 2.5% (highest) in overall period which is comparatively lower than other periods. Skewness and Kurtosis of the overall period indicate low skewness and high wickedness (Leptokurtic) which indicates return distributions are not normal and clearly indicate presence of volatility in cement and chemical sector companies.

2. Examining the presence of volatility in select NSE listed Cement & Chemical Sector companies daily return series using ARCH (1) model

a. 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	<ul style="list-style-type: none"> ◆ H₀: Return series of select stocks are normal; ◆ H₁: Return series of select stocks are not normal.
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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 Result of Daily Adjusted Stock Price Returns

Cement & Chemical Sectors	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			
ACC Cement	990.4	0.000	981.7	0.000	P-Value<0.05	Rejected	Not normal
Ambuja Cement	328.8	0.000	674.16	0.000	P-Value<0.05	Rejected	Not normal
Ramco Cement	820.57	0.000	2609.82	0.000	P-Value<0.05	Rejected	Not normal
Shree Cement	573.6	0.000	1366.56	0.000	P-Value<0.05	Rejected	Not normal
Tata Chemicals	1363.40	0.000	3208.45	0.000	P-Value<0.05	Rejected	Not normal
India Cement	890.01	0.000	918.65	0.000	P-Value<0.05	Rejected	Not normal
Prism Cements	794.02	0.000	2114.24	0.000	P-Value<0.05	Rejected	Not normal
Pidilite Inds.	5007.5	0.000	5817.5	0.000	P-Value<0.05	Rejected	Not normal

Normality test is used to check whether the sample Cement & Chemical Sectors companies return series are distributed normally. More precisely, the test is a form of model selection and can be interpreted in several ways, depending on one’s interpretations of probability. In descriptive statistics terms, one measures a goodness of fit of a normal model to the data if the fit is poor then the data are not well modeled in that respect by a normal distribution, without making a judgment on any underlying variables. In statistics, the Jarque-Bera test is a goodness of fit test to find whether the data have the Skewness and Kurtosis matching

a normal distribution. It is observed that H₀ is rejected for all return series of select NSE listed companies. Since, the JB test is significant at 1% level that means daily returns series are not normally distributed. The majority companies return 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)

Cement & Chemical Sectors	None		Decision Rule	Null Hypothesis (H ₀)	Data series stationarity
	t-Statistics & Prob.	C.V. (5%)			
ACC Cement	-29.66 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
Ambuja Cement	-14.23 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
Ramco Cement	-39.05 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
Shree Cement	-36.71 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
India Cement	-29.49 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
Prism Cements	-28.59 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
Tata Chemicals	-9.41 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
Pidilite Inds.	-16.23 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series

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

Cement & Chemical Sectors	None		Decision Rule	Null Hypothesis (H ₀)	Data series stationarity
	t-Statistics & Prob.	C.V. (5%)			
ACC Cement	-44.39 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series

Ambuja Cement	-49.36 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
Ramco Cement	-32.19 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
Shree Cement	-43.72 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
India Cement	-47.55 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
Prism Cements	-46.05 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
Tata Chemicals	-9.48 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series
Pidilite Inds.	-17.79 (0.000)	-1.94	More negative test statistics than C.V. and P-Value<0.05	Rejected	Stationary series

A time series is said to be stationary if its mean and variance are constant and independent of time and the covariance depends only upon the distance between two time periods, but not on time periods. These conditions imply that the mean and variance of the stationary series remain constant over time. If one or more of these conditions are violated, the time series is said to be non-stationary. Hence, the Augmented Dickey Fuller (ADF) test is employed to infer the stationarity of the stock daily return series. It is found that H_0 is rejected for daily stock return series and there is no unit root in return series of NSE listed Cement &

Chemical Sectors companies for all 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.

b. ARCH Test (Test for Heteroskedasticity)

ARCH effect means heteroskedasticity, which is modelled as conditional variance of squared residuals obtained from mean equation as from AR (1) model. 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 H_0	ARCH effects are present or not
ACC Cement	69.24	0.000	66.80	0.000	Rejected	ARCH effects are present
Ambuja Cement	20.29	0.000	20.06	0.000	Rejected	ARCH effects are present
Ramco Cement	102.89	0.000	96.70	0.000	Rejected	ARCH effects are present
Shree Cement	62.76	0.000	60.36	0.000	Rejected	ARCH effects are present
India Cement	63.73	0.000	61.21	0.000	Rejected	ARCH effects are present
Prism Cements	46.38	0.000	44.99	0.000	Rejected	ARCH effects are present
Tata Chemicals	85.37	0.000	81.12	0.000	Rejected	ARCH effects are present
Pidilite Inds.	165.79	0.000	149.47	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 H_0	ARCH effects are present or not
ACC Cement	37.46	.000	36.70	.000	Rejected	ARCH effects are present
Ambuja Cement	1.68	.000	1.68	.000	Accepted	No ARCH effects
Ramco Cement	34.69	.000	34.05	.000	Rejected	ARCH effects are present
Shree Cement	32.02	.000	31.47	.000	Rejected	ARCH effects are present
India Cement	15.35	.000	15.26	.000	Rejected	ARCH effects are present
Prism Cements	25.87	.000	25.6	.000	Rejected	ARCH effects are present
Tata Chemicals	72.13	.000	69.66	.000	Rejected	ARCH effects are present
Pidilite Inds.	148.34	.000	139.20	.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 different study 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 the existence of ARCH effect of all sample Cement & Chemical Sectors companies excepting Ambuja Cement in Post-global

recession period

3. Analyzing Volatility in select NSE listed Cement & Chemical Sector 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 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 $\alpha_j+\beta_i=1$)
First Period - Coefficients - GARCH (1, 1)								
Cement & Chemical Sectors	α_0	α_1	β_1	$\alpha_j+\beta_i$				
ACC Cement	2.18	0.128	0.83	0.958	-4.78	-4.77	4413.3	Very high persistence value
Ambuja Cement	1.53	0.087	0.879	0.966	-4.97	-4.95	3960.6	Very high persistence value
Ramco Cement	5.54	0.112	0.782	0.894	-4.77	-4.76	3563.1	Comparatively low persistence value
Shree Cement	9.25	0.127	0.776	0.903	-4.21	-4.19	3042.8	Comparatively low persistence value
India Cement	0.467	0.085	0.87	0.955	-5.08	-5.08	9482	Very high persistence value
Prism Cements	0.842	0.109	0.83	0.939	-5.33	-5.35	3838.57	Comparatively low persistence value
Tata Chemicals	8.56	0.181	0.664	0.845	-4.81	-4.80	3837.10	Comparatively low persistence value
Pidilite Inds.	0.0001	0.225	0.363	0.588	-5.04	-5.02	3788.9	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)								
Cement & Chemical Sectors	α_0	α_1	β_1	$\alpha_j+\beta_i$				
ACC Cement	6.19	0.034	0.944	0.978	-5.31	-5.30	4616	Very high persistence value
Ambuja Cement								
Ramco Cement	1.40	0.032	0.936	0.936	-4.74	-4.7	5295.9	Comparatively low persistence value
Shree Cement	9.05	0.117	0.629	0.746	-4.91	-4.9	5484.6	Comparatively low persistence value
India Cement	0.814	0.143	0.791	0.934	-5.16	-5.2	3873.7	Comparatively low persistence value
Prism Cements	0.249	0.051	0.921	0.972	-4.96	-5	5532.7	Very high persistence value
Tata Chemicals	6.96	0.065	0.918	0.983	-5.00	-4.99	4953.4	Very high persistence value
Pidilite Inds.	6.32	0.155	0.689	0.844	-5.08	-5.1	5676.6	Comparatively low persistence value

The present study has employed GARCH (1, 1) technique to capture the conditional volatility in the return series. 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. 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. During recession times this value ranges from 0.588 to 0.995 in respect of all cement and chemical sector stock price returns. The study shows that volatility in post-financial recession period is more than its pre-counterpart.

4. Analyzing Volatility in select NSE listed Cement and Chemical Sector companies using T-GARCH Model

T-GARCH 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 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								
Cement & Chemical Sectors	α_0	α_1	γ	β_1				
ACC Cement	2.33	0.102	0.058	0.833	-4.78	-4.77	4416.39	Positive γ which implies

								negative shocks is larger effect on volatility
Ambuja Cement	1.65	0.071	0.034	0.875	-4.97	-4.95	3961.73	Positive γ which implies negative shocks is larger effect on volatility
Ramco Cement	5.88	0.089	0.057	0.772	-4.78	-4.75	3564.98	Positive γ which implies negative shocks is larger effect on volatility
Shree Cement	9.42	0.124	0.006	0.773	-4.21	-4.19	3042.91	Positive γ which implies negative shocks is larger effect on volatility
India Cement	0.113	0.033	0.006	0.952	-5.02	-5.03	5595.1	Positive γ which implies negative shocks is larger effect on volatility
Prism Cements	0.767	0.113	0.003	0.844	-5.33	-5.35	3838.11	Positive γ which implies negative shocks is larger effect on volatility
Tata Chemicals	9.65	0.130	0.137	0.632	-4.8	-4.78	3615.24	Positive γ which implies negative shocks is larger effect on volatility
Pidilite Inds.	0.001	0.289	-0.121	0.342	-5.04	-5.02	3790.72	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								
Cement & Chemical Sectors	α_0	α_1	γ	β_1				
ACC Cement	6.55	0.03	0.005	0.941	-5.07	-5.06	5670.02	Positive γ which implies negative shocks is larger effect on volatility
Ramco Cement	1.39	0.031	0.001	0.936	-4.74	-4.73	5298.61	Positive γ which implies negative shocks is larger effect on volatility
Shree Cement	8.84	0.093	0.056	0.634	-4.92	-4.9	5492.23	Positive γ which implies negative shocks is larger effect on volatility
India Cement	0.865	0.117	0.067	0.783	-5.15	-5.18	3871.33	Positive γ which implies negative shocks is larger effect on volatility
Prism Cements	0.25	0.046	0.014	0.92	-4.96	-4.98	5532.03	Positive γ which implies negative shocks is larger effect on volatility
Tata Chemicals	7.72	0.051	0.040	0.911	-5.00	-4.99	4957.07	Positive γ which implies negative shocks is larger effect on volatility
Pidilite Inds.	6.31	0.145	0.98	0.691	-5.08	-5.07	5676.83	Positive γ which implies negative shocks is larger effect on volatility

T-GARCH 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’. In ARCH model, return series represent hetroskedasticity for different period. GARCH model generally used the conditional variance as a linear function of lagged conditional variances and squared past returns. The T-GARCH table results (Table no- 10 and 11) clearly prove that good news has an impact of ARCH term (α_1), while bad news has impact on ARCH as well as leverage. The results of TGARCH value suggest that there is a possibility of positive shock observes for all cement and chemical sector companies except Pidilite Industries during the pre-global financial meltdown period. Pidilite Industries

has shown negative δ value (-.1218) during the pre-global financial meltdown period.

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 has a greater effect on the conditional variance than the positive shocks or good news. Again, GARCH term results in TGARCH test found that in case of pre global financial recession period are lower than post global financial recession period and overall study period. In two study periods combined values (except recession time

period) of ARCH and GARCH ($\alpha + \beta$) of three scripts were found to be closed to one. During recession times this value ranges from 0.588 to 0.995 in respect of all cement and chemical sector stock price returns. The study shows that volatility in post-financial recession period is more than its pre-counterpart. This is also true when we compare cement and chemical sectors stock price returns series results of overall period with that of its pre-counterpart. The analysis reveals that stock return volatility varies significantly across different sectors and companies, with some stocks exhibiting high fluctuations due to macroeconomic conditions, investor sentiment, and market dynamics. Furthermore, the GARCH model confirmed the presence of volatility clustering, indicating that stock markets experience periods of high and low volatility in cycles rather than remaining constant over time.

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