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Stock Returns Volatility of Select NSE – Listed Iron & Still Sector Stocks: An Empirical Study

Professor (Dr.) Siddhartha Sankar Saha[1], Tapas Kumar Tripathy[2]

[1]Professor of Commerce, 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
This research paper investigates the measurement of stock return volatility for select companies listed on the National Stock Exchange (NSE) within the Iron & Steel sector. Volatility is a critical indicator of risk and is essential for investors, portfolio managers, and policymakers to make informed decisions. The study employs empirical methods to analyze historical stock price data from 2001-02 to 2015-16, focusing on the variability of returns. The application of GARCH, and T-GARCH models provides the evidence of the persistence of time varying asymmetric volatility. The findings reveal insights into the volatility patterns of Iron & Steel sector stocks, highlighting the impact of market conditions, and sector-specific events. The results contribute to a deeper understanding of risk assessment in this sector and provide valuable implications for investment strategies and practical implications for risk management and investment decision-making in the Indian equity market. The study also provides valuable insights for investors, policymakers, and market participants in assessing risk exposure and making informed investment choices.

Keywords: Asymmetric Volatility, Conditional Volatility, Financial Meltdown.

1.0 The Background of the Study

Stock market volatility is an innovative factor influencing investment decisions, risk management, and financial stability. Investors and financial analysts closely monitor volatility to assess market risk and make informed investment choices. The Iron and Steel sector, a key component of the Indian economy, comprises companies engaged in the production and distribution of iron and steel products. Given its essential nature, the Iron and Steel sector is often considered a defensive investment choice, relatively insulated from economic downturns compared to cyclical industries. However, market fluctuations, macroeconomic conditions, and sector-specific events can still impact stock return volatility. The National Stock Exchange (NSE) of India hosts some of the country's leading Iron and Steel companies, like Tata steel, SAIL (Steel Authority of India Ltd.), Bhusan Steel, JSW Steel and Jindal Steel, etc. Despite their perceived stability, the stock prices of these companies exhibit varying levels of volatility due to factors such as inflation, changes in consumer demand, raw material costs, regulatory policies, and global economic trends. Understanding the volatility of Iron and Steel stocks is crucial for investors, portfolio managers, and policymakers in assessing risk exposure and making strategic investment decisions. 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). Understanding stock return volatility is crucial for financial market participants, as it influences investment strategies, asset allocation, and risk assessment. A highly volatile stock may present opportunities for short-term traders but poses risks for long-term investors. Conversely, less volatile stocks may provide stability but offer lower returns. Volatility is useful for superior returns. Higher volatility causes higher risk (Kumar, 2016). Estimation of stock price returns is important 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 academic literature on financial risk management and provides practical insights for investors, regulators, and financial institutions.

2.0 Past Studies and Research Gap

Fama (1970) suggested the stock prices fully reflect all available information. According to efficient market hypothesis (EMH), stock price movements follow a random walk**,** implying that predicting future price movements based on past trends is not possible. However, real-world stock markets exhibit fluctuations due to investor sentiment, macroeconomic events, and market inefficiencies, leading to deviations from the EMH. **Engle (1982)** introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model**,** which was later extended by Bollerslev (1986) into the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. These models capture time-varying volatility and help in forecasting stock market fluctuations. The GARCH model is widely applied in stock return volatility studies due to its ability to model persistence and clustering of volatility. Sector-specific studies have provided insights into the unique volatility characteristics of different industries. Research study by **Reddy and Sebastin (2009)** on the banking sector and by **Mishra and Rahman (2016)** on the IT sector in India revealed that sectoral volatility is influenced by both global and domestic factors. These studies underscore the importance of considering industry-specific dynamics when analyzing stock return volatility. **Sehgal and Tripathi (2007)** studied the volatility behavior of Indian stock indices and found that Indian markets exhibit asymmetric volatility, meaning negative market shocks lead to higher volatility than positive shocks. **Goyal and Aggarwal (2020)** analyzed sectoral volatility patterns on the NSE and reported that sectors such as IT and banking experience higher volatility compared to defensive sectors, like FMCG. **Padhi (2006)** investigated that market volatility at the individual script level and at the indices level to know how volatility changes in the same trend or it varies across the sectors and conducted that LM test is using to confirm the presence of ARCH effect. Different ARCH coefficients are found for different indices at different lag values and argued that many sectors showing the same trend for volatility characteristics.

While existing studies provide insights into general market trends, there is a need for sector-specific analysis of different NSE-listed Iron & Steel 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. Keeping in mind of this research gap, specific objectives of the current study are set. This study aims to fill these gaps by applying different GARCH models to selected NSE-listed stocks, providing empirical insights into their risk-return dynamics.

3.0 Objectives of the Study

The objectives of the current study are as follows:

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

4.0 Data and Methodology

This study is based on secondary data. Daily adjusted closing share prices of Iron and Steel sector sample companies as well as index data have been taken from Capitaline corporate database and NSE official website also. The sample design follows the judgment sample technique. It makes an attempt to measure volatility of Iron and Steel 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 **Global financial recession period**, which includes the study period from 7th August, 2007 to 2nd April, 2009. Different statistical and econometrics tools used in this study such as Descriptive statistics, Autoregressive Conditional Heteroscedasticity (ARCH) Test, and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) Model.sive Conditional Heteroscedasticity (T-GARCH) Model.

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).

5.0 Results and Analysis

5.1 Descriptive Statistics results

To assess the distributional properties of the daily adjusted closing price of stock returns, various descrip tive 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 (Global Recession Period)

Company Name	Mean	S. D.	Variance	Kurtosis	Skewness
Tata steel	0.0014	0.024	0.0005	4.99	-0.046
SAIL	0.0026	0.035	0.0012	11.08	1.009
Bhusan steel	0.0039	0.061	0.0036	489.03	17.78
JSW steel	0.0289	0.69	0.476	774.2	27.03
Jindal steel	0.0026	0.029	0.0008	7.09	0.25

In recession period, the daily mean returns of the selected companies in Iron & Steel sectors are majority lower but positive return in global financial meltdown period. Skewness has been found to be negative and lower. Kurtosis of this period indicate high pickedness (Leptokurtic) which implies that the return series is fat tailed and does not follow a normal distribution and clearly indicate presence of volatility in this sector daily adjusted stock price return series. Skewness has been found to be lower during the global meltdown period. Kurtosis indicate high pickedness (Leptokurtic) which implies that the return series is fat tailed and does not follow a normal distribution and clearly indicate presence of volatility in this sector daily adjusted stock price return series.

5.2 Examining the presence of volatility in select NSE listed Metal & Aluminum Sector companies daily return series using ARCH (1) model

5.2.1 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 - 2: Normality Test Result of Daily Adjusted Stock Price Returns

Iron & Steel Sector	Second Period		Decision Rule	Decision on H_0	Data series Normality
	J-B	P-Value			
Tata steel	29.56	0.000	P–Value<0.05	Rejected	Not normal
SAIL	15.85	0.000	P–Value<0.05	Rejected	Not normal
Bhusan steel	12630.6	0.000	P–Value<0.05	Rejected	Not normal

JSW steel	679.1	0.000	P–Value<0.05	Rejected	Not normal
Jindal steel	270.2	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 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- 3: The Augmented Dickey-Fuller (ADF) Test results – At Level (Global Recession Period)

Iron & Steel Sector	**None**		**Decision Rule**	**Null Hypothesis (H_0)**	**Data series stationarity**
	t-Statistics & Prob.	**C.V. (5%)**			
Tata steel	-18.05 (0.000)	-1.94	More negative test statistics than C.V. and P–Value<0.05	Rejected	Stationary series
SAIL	-18.60 (0.000)	-1.94	More negative test statistics than C.V. and P–Value<0.05	Rejected	Stationary series
Bhusan steel	-19.32 (0.000)	-1.94	More negative test statistics than C.V. and P–Value<0.05	Rejected	Stationary series
JSW steel	-16.33 (0.000)	-1.94	More negative test statistics than C.V. and P–Value<0.05	Rejected	Stationary series
Jindal steel	-17.04 (0.000)	-1.94	More negative test statistics than C.V. and P–Value<0.05	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 NSE listed Iron and still companies for sample period. 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.

5.2.2 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. The results are as follows:

Table-4: Heteroskedasticity Test Results – ARCH (1) for Global Recession Period

Companies	F-statistic	Prob. F	Obs* R-squared	Prob. Chi-Square	Decision on Ho	ARCH effects are present or not
Tata steel	52.82	0.000	46.94	0.000	Rejected	ARCH effects are present
SAIL	8.43	0.003	8.30	0.003	Rejected	ARCH effects are present
Bhusan steel	5.24	0.04	5.20	0.04	Accepted	No ARCH effects
JSW steel	1.96	0.16	1.94	0.16	Accepted	No ARCH effects
Jindal steel	6.97	0.008	6.97	0.008	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 four 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.

5.3 Analyzing Volatility in select NSE listed Iron and Steel Sector Companies using GARCH 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-5: GARCH Model (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)								
Iron and Steel	α_0	α_1	β_1	$\alpha_j+\beta_i$				
Tata steel	0.0001	0.208	0.690	0.898	-4.7	-4.69	3542.9	Comparatively low persistence value
SAIL	0.0001	0.122	0.821	0.943	-4.1	-4.09	3092.7	Very high persistence value
Jindal steel	0.0002	0.223	0.705	0.928	-4.37	-4.35	3292.5	Comparatively low persistence value

The study shows that out of five companies, two companies do not have ARCH effect during the global recession period. During the global financial recession period, ARCH and GARCH combined value of five scripts return series are ranges from 0.898 to 0.943.

5.4 Analyzing Volatility in select NSE listed Iron & Still Sector companies using T-GARCH Model

The Threshold GARCH (T-GATRCH) model has been proposed by Zakoian (1991). In this section, T-GATCH model has been adopted in stock price of return series data in select stocks. The main target of this is to capture asymmetry in terms of negative and positive stocks and multiplicative dummy variable to check whether there are statistically significant differences when shocks are positive and negative. The results are as follows:

Table-6: T-GARCH Model (Global Recession Period)

Company Name	**Estimated Model with values**				**AIC**	**SIC**	**Log Likelihood**	**Decision**
First Period - Coefficients - GARCH (1, 1) with Threshold order 1								
Iron and Steel	α_0	α_1	γ	β_1				
Tata steel	0.0001	0.083	0.119	0.802	-4.7	-4.68	3544.15	Positive γ which implies negative shocks is larger effect on volatility
SAIL	9.95	0.063	0.091	0.845	-4.1	-4.08	3093.66	Positive γ which implies negative shocks is larger effect on volatility
Jindal steel	0.0002	0.123	0.146	0.743	-4.37	-4.35	3293.58	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 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 show that coefficient of leverage (δ) is positive in all cases and significant at 1% level representing negative shocks or bad news.

6.0 Conclusion

The finding aligns with previous research suggesting that market shocks, economic policy changes, and external factors such as global financial events significantly impact stock return volatility. This study contributes to the existing body of knowledge by providing sector-specific insights and enhancing risk assessment frameworks for market participants.

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