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

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ABSTRACT

Global financial meltdowns have massive shock on different sectors as well as on scripts returns. The study empirically examines the stock returns volatility of selected NSE-listed diversified sector companies to assess their risk exposure and market behavior based on time series dataset taking into consideration of daily closing adjusted stock price from 2001-02 to 2015-16. The application of GARCH, T-GARCH and E-GARCH models provides the evidence of the persistence of time varying asymmetric volatility. The findings reveal significant variations in stock return volatility among diversified firms, influenced by market conditions, and firm-specific factors due to recent global financial meltdown which is originated from US sub-prime crisis. The study also explores the effect captured by different models show that negative shocks have significant effect on conditional volatility.

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

Introduction

Stock market volatility is a crucial area of interest for investors, analysts, and policymakers, as it significantly influences investment policy decisions, risk management strategies, and economic stability. Stock returns volatility represents the degree of variation in the price of a stocks over time, serving as an essential indicator of market uncertainty and risk. Understanding volatility patterns can help investors optimize portfolios, hedge risks, and develop effective trading strategies. This study focuses on measuring the stock returns volatility of select six diversified companies listed on the National Stock Exchange (NSE). Diversified companies operate across multiple business segments, reducing dependence on a single industry and potentially mitigating risk exposure. However, their stock performance may still be subject to market fluctuations, and firm-specific factors. Volatility is the dispersion about central tendency and traditional knowledge says return and risk positively correlated (Pandey, 2010). However, some recent theoretical works consistently assent that stock market volatility has been found to be negatively correlated with stock returns. The theoretical framework provides the foundation for understanding stock returns volatility in India by examining established financial theories and models that explain market behavior, risk factors, and volatility measurement techniques. 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: (i) Investment decision; (ii) Assets pricing; (iii) Expected returns and (iv) Risk of various assets, etc.

Past Studies and Research Gap

Fama (1970) suggests in The Efficient Market Hypothesis that stock prices fully reflect all available information, meaning that price movements should be random and unpredictable. However, empirical studies have shown that stock returns often deviate from this theory due to market inefficiencies, behavioral biases, and asymmetric information**.** Studies by **Bekaert and Harvey (1997)** indicate that emerging markets exhibit higher volatility compared to developed markets due to economic instability, policy changes, and foreign investment dynamics. **Padhi (2006)** in her research paper explains the market volatility at the individual script level and at the aggregate indices level to know how volatility changes whether volatilities show the same trend or it varies across the selected sectors. Study concluded that different ARCH coefficients are found for different indices at different lag values. Five sectors showing the same trend for persistence characteristics. **Anbukarasi & Nithya (2014)** in his research paper has investigated the returns of S&P CNX NIFTY and sectoral index and to know the level of volatility on it and various sectoral index. The study found that the correlation is significant for most of the indices except the CNX Metal index, Pharma, PSU bank index and CNX Realty index and further found that some indices have more impact on NIFTY. Kumar (2020) in his study has applied GARCH models to NSE data and found that news asymmetry (bad news affecting volatility more than good news) is a common phenomenon.

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 perception of different diversified stocks 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 study are set.

Objectives of the Study

The objectives of the current study are as follows:

- Examining the volatility characteristics of select NSE listed diversified sector companies using descriptive statistics;
- Studying the presence of volatility in select NSE listed diversified sector companies daily return series using ARCH (1) model;
- Exploring volatility in select NSE listed diversified sector companies using GARCH and T-GARCH Model;
- Measuring the volatility in sample diversified companies' daily returns series using E-GARCH Model.

Data and Methodology

The current study uses secondary data, like daily adjusted closing share price of select NSE-listed diversified sector companies collected from Capitaline corporate database and NSE official website as well, which are considered here for calculation of daily stock price return series of each company and yearly stock returns volatility (Beta value) of them. The judgment sample technique has been used based on market capitalization of sample top companies. It makes an attempt to measure volatility of diversified sector's 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 Global financial recession period covering the study period from 7th August, 2007 to 2nd April, 2009. Different statistical tools are adopted in this study, such as Descriptive statistics, Autoregressive Conditional Heteroskedasticity (ARCH) Test, Generalized Autoregressive Conditional Heteroskedasticity (GARCH) Model, Threshold Generalized Autoregressive Conditional Heteroskedasticity (T-GARCH) Model and Exponential Generalized Autoregressive Conditional Heteroskedasticity (E-GARCH) Model. Eviews8.0 has been used here.

Results and Analysis

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 (Global Recession Period)

Diversified Sector Companies	Mean	S. D.	Variance	Kurtosis	Skewness
Rel. Inds	0.0011	0.02	0.0004	9.54	0.035
Grasim	0.0016	0.021	0.0004	7.52	0.27
Castrol India	-2E-04	0.016	0.0002	15.74	0.63
Unitech	0.005	0.034	0.0011	4.12	0.45
Voltas	0.0024	0.029	0.0008	7.21	0.92
Century Textiles	0.0024	0.034	0.0011	6.79	0.54

The daily mean returns of the selected companies in Diversified Sector are majority lower and negative in four periods. In global recession period S.D. and variance gives support to the high variability of stock price changes. Skewness has been found to be lower. Kurtosis indicates high pickedness (Leptokurtic) which implies that the return series is fat tailed. Kurtosis indicates 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.

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

- **Precondition for Performing ARCH Test**
  - **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

Diversified Sector	Global Recession Period		Decision Rule	Decision on H_0	Data Series Normality
	J-B	P–Value			
Rel. Inds	66.61	0.000	P–Value<0.05	Rejected	Not normal
Grasim	135.34	0.000	P–Value<0.05	Rejected	Not normal
Castrol India	48086.34	0.000	P–Value<0.05	Rejected	Not normal
Unitech	2995.9	0.000	P–Value<0.05	Rejected	Not normal
Voltas	5.86	0.000	P–Value<0.05	Rejected	Not normal
Century Textiles	78.61	0.000	P–Value<0.05	Rejected	Not normal

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

- **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)

Diversified Sector	None		Null Hypothesis (H_0)	Data series stationarity
	t-Statistics & Prob.	C.V. (5%)		
Rel. Inds	-17.75 (0.000)	-1.94	Rejected	Stationary series
Grasim	-19.27 (0.000)	-1.94	Rejected	Stationary series
Castrol India	-22.63 (0.000)	-1.94	Rejected	Stationary series
Unitech	-19.23 (0.000)	-1.94	Rejected	Stationary series
Voltas	-13.90 (0.000)	-1.94	Rejected	Stationary series
Century Textiles	-19.80 (0.000)	-1.94	Rejected	Stationary series

It is found that H_0 is rejected for daily stock return series. 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 are stationary at level for the study period.

- **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.

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) $\sigma_t^2 = a_0 + \Sigma_{t=1}^{q} a_i U_{t-1}^2$ (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 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
Rel. Inds	9.00	0.002	8.85	0.002	Rejected	ARCH effects are present
Grasim	3.53	0.06	3.52	0.06	Accepted	No ARCH effects
Castrol India	5.32	0.05	5.28	0.05	Accepted	No ARCH effects
Unitech	126.67	0.000	96.91	0.000	Rejected	ARCH effects are present
Voltas	17.02	0.000	16.41	0.000	Rejected	ARCH effects are present
Century Textiles	10.28	0.000	10.07	0.000	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 of diversified sectors stocks during the study period. 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, 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 Diversified 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 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 $\alpha_0 > 0$, $\alpha_1 \geq 0$ & $\beta_1 \geq 0$ $\varepsilon_t = \sigma_t Z_t$ Where Z_t are standardized residual returns and σ_t^2 stands for the conditional variance. In GARCH (1, 1), constant $\alpha_1 \geq 0$ & $\beta_1 \geq 0$ 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 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)								
Diversified	α_0	α_1	β_1	$\alpha_j+\beta_i$				
Rel. Inds	5.94	0.130	0.822	0.952	-5.06	-5.05	3814.5	Comparatively low persistence value
Unitech	0.0002	0.204	0.737	0.941	-3.95	-3.93	2960.9	Comparatively low persistence value
Voltas	0.0001	0.133	0.766	0.899	-4.27	-4.25	3214.6	Comparatively low persistence value
Century Textiles	9.91	0.106	0.847	0.953	-4.01	-4	3025.9	Comparatively low persistence value

The present study has employed GARCH (1, 1) technique to capture the conditional volatility in different 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. The major inferences from the GARCH model are that during post-global financial recession period, highest and lowest ARCH and GARCH combined value are .99 and .971 in respect of this stock price returns.

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

T-GARCH model has been employed 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 Threshold GARCH (T-GATRCH) model has been proposed by Zakoian (1991). 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 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								
Diversified	**α_0**	**α_1**	**γ**	**β_1**				
Rel. Inds	5.33	0.019	0.124	0.871	-5.07	-5.05	3817	Positive γ which implies negative shocks is larger effect on volatility
Unitech	0.0002	0.012	0.267	0.784	-3.95	-3.93	2960.95	Positive γ which implies negative shocks is larger effect on volatility
Voltas	0.0001	0.067	0.106	0.779	-4.29	-4.26	3228.13	Positive γ which implies negative shocks is larger effect on volatility
Century Textiles	6.70	0.021	0.139	0.914	-4.02	-3.99	3027.78	Positive γ which implies negative shocks is larger effect on volatility

In this paper, T-GATCH model has been adopted in stock price of return series data in select stocks in six different sectors. After conducting TGARCH test during three different time period to know the asymmetric coefficient effect, the results concludes that coefficient of leverage (δ) is positive in all cases and significant at 1% level indicating negative shocks.

Measuring Volatility in select NSE listed Diversified Sector companies using E-GARCH Model

There are two pre-conditions of E-GARCH model. Firstly, the data set must have volatility. Secondly, the data set must confirm ARCH effect. The Exponential GARCH model is a GARCH variant that models the logarithm of the conditional variance process. In addition to modelling the logarithm, this model has additional leverage terms to capture asymmetry in volatility clustering.

EGARCH Model Equations	Log (σ^2) = w + $\beta . \ln(\sigma^2{}_{t-1}) + \gamma . \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \sigma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^{-2}}}$ (Where β the persistence of the GARCH is effect and γ represents the leverage effect and σ represents ARCH effect)
Test Statistics	ARCH, GARCH and E-GARCH coefficient value
Decision Rule	If γ is significant & negative, leverage effect exists in return series.

The results are as follows:

Table 7: E-GARCH Model (Global Recession Period)

Company Name/ Sector	Estimated Model with values				AIC	SIC	Log Likelihood	Decision (Decision Rule: If γ is significant & negative, then leverage effect exists in return series.)
First Period - Coefficients - GARCH (1, 1)								
Diversified	α_0	α_1	γ	β_1				
Rel. Inds	-2.06	0.416	-0.054	0.778	-5.06	-5.04	3812.02	Leverage effect exists
Grasim	-0.686	0.26	-0.01	0.937	-5	-4.98	3766.68	Leverage effect exists
Castrol India	-3.73	0.741	-0.033	0.615	-5.66	-5.61	1412.15	Leverage effect exists
Unitech	-2.7	0.337	0.01	0.64	-3.96	-3.93	2960.91	Leverage effect not exist
Voltas	-0.253	0.128	-0.02	0.977	-4.29	-4.27	3232.94	Leverage effect exists
Century Textiles	-0.872	0.305	0.035	0.906	-4.02	-4	3028.46	Leverage effect not exist

In E-GARCH model, it indicates greater the risk of volatility or variance of the firm. In conditional variance equation, this is perfectly captured by E-GARCH model. The β value (representing GARCH effect) in E-GARCH model in pre global financial meltdown period indicates high level of persistence and low level of volatility exist in case of one company. The asymmetric effect captured by parameter (γ) in E-GARCH model is negative and statistically significant at 1% level of significance that provides the presence of leverage effect. Leverage effect indicates that positive shocks have less effect on conditional variance when compared to the negative shocks. The results of all select companies daily stock returns reveal that β is close to one indicating high persistence with slow decay of volatility shocks for overall time period.

Conclusion

In GARCH model, it seems that the combined value or sum of coefficient of ARCH and GARCH value is around one, it specifies volatility clustering and persistency. However, T-GARCH model shows that negative shocks or bad news have a greater effect on the conditional variance than the positive shocks or good news, and E-GARCH model indicates that positive shocks have less effect on conditional variance when compared to the negative shocks. In global recession times its ranges from 0.899 to 0.953 in six companies returns series.

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