CHAPTER 7

STOCK MARKET RISK: AN EMPIRICAL INVESTIGATION (II)

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7.1 INTRODUCTION

Markowitz's theory of portfolio selection, which he developed in 1952, provides the cornerstone for many of today's financial market activities. He incorporated the basic principle of economics ["to get something, we must give up something else"] into finance theory, implying that there is a risk-return trade-off. To put it another way, if an investor wants a larger return on a project, he must be willing to take on more risk. Because risk is quantifiable in terms of a benchmark, the investor defines his utility function in terms of his risk tolerance. The dispersion of distinct results is one measure that is quickly brought in while doing so. As a result, the concept of risk is linked to variance.

Variance is a well-known statistic that can be calculated based on previous observations (returns). It is utilised as a surrogate for variability in practically all financial models. We can calculate the variability using past prices that are as close to the current variability as possible. Therefore, in the financial market, this has been conceived as 'VOLATILITY.' As a result, volatility can be thought of as a synonym for variability in general or variation in particular. Many empirical studies have been undertaken around the world to quantify stock market volatility. According to studies, the emergence of "New Economy" equities, which are valued higher than their "Old Economy" counterparts on the expectation of giving very high returns in the future, has made stock markets more volatile in recent years. As a result of this high expectation, prices have fluctuated widely, making the markets volatile.

In other words, volatility is generally benign in and of itself. What counts is the outcome of the volatility. Stock prices can move swiftly, especially in today's networked economy, when investors' fundamental ideas about stocks change. The market is merely reacting to fundamental overvaluations, which accounts for much of today's volatility.

There are two types of elements that affect volatility: those that effect long-term volatility and those that affect short-term volatility. Several economic factors can create gradual changes in stock market volatility, which might take months or years to see. These are referred to as long-term factors, and include things like business leverage, personal leverage, and the state of the economy. In recent years, many surges in stock volatility in various markets throughout the world have sparked investors' interest in stock volatility. The development and subsequent collapse of the Indian stock market in 1992 and 2001, as well as the stock market disasters in the United States in October 1987 and October 1989 The Mexican currency crises of 1994, the Asian currency crises of 1997, the Russian currency crises of 1998, the Brazilian currency crises of 1999, the 2001 Argentinean crisis, the 2002 Turkish crisis, the subprime financial crisis of 2008, and the European Debt Crisis of 2009 are all notable examples.

These spikes in volatility are difficult to link to longer-term events like recessions or leverage. Rather, the majority of people have attempted to connect them to the structure of securities trading. Trade volume, trading halts (circuit breakers and circuit filters), computerised trading, noisy trading, international linkages, market makers, takeovers, supply of equities, the press are just a few of the elements that might generate short-term volatility.

Volatility is not abnormal or undesirable in and of itself. However, excessive volatility induced by traders' and investors' irrational or speculative conduct, trading system flaws, and a lack of information transparency is undesirable. If stock market volatility rises, investors and policymakers may face serious implications. Investors may associate more volatility with greater risk, and as a result, their investing decisions may be affected. Policymakers may be afraid that stock market volatility would spread to the actual economy, causing economic performance to suffer. Alternatively, policymakers may believe that rising stock volatility endangers financial institutions' viability and smooth operation of financial markets.

Stock return volatility hurts consumer spending and hurts business investment spending (Garner 1988), since investors perceive a rise in stock market volatility as an increase in the risk of equity investments. As a result, investors may opt for less risky items to invest in. This decision could cause a rise in the cost of capital for firms (Arestis et al 2001). According to Bekaert (1995), a country's volatility is a significant component in the cost of capital in segmented capital markets. The best assets give the highest return per unit of risk, therefore volatility can be used as a criterion for investment.

Furthermore, significant stock return volatility could disrupt the financial system's smooth operation and result in structural or regulatory adjustments. Extreme price fluctuations may overwhelm systems that perform well with regular return volatility. Changes in market rules or regulations may be required to improve the market's resiliency in the face of increased volatility.

However, an increase in volatility, on the other hand, cannot be blamed in and of itself. Volatility may simply be a product of fundamental economic factors, as well as information and expectations about them. Indeed, the more quickly and precisely prices reflect new information, the more efficient securities pricing and, as a result, resource allocation will be. A market is said to be "efficient" if share prices move randomly about their "intrinsic" values and prices always "fully represent" available information.

The stock market's allocative efficiencies, which operate as a barometer of a country's health, are crucial to a country's industrial development. Despite its long history, the Indian stock market has only a few outstanding moments to its credit as a growth agent. A variety of committees were formed to examine the stock market's operation, and they offered a slew of recommendations to reduce speculative activities and, as a result, share price fluctuations. Ironically, all of these attempts have mostly failed to manage a logical share price movement, which has hampered the market's ability to function for a long time.

7.2 OBJECTIVES OF THE CHAPTER:

The aim of this chapter is to use the BSE and NSE benchmark indexes, sectoral indexes, and thematic indexes to analyse and evaluate the volatility behaviour and levels in the Indian stock market. The chapter's sub-objectives, on the other hand, are listed as follows:

1. To investigate the presence of below mentioned stylized facts in the benchmark indices, sectoral indices and thematic indices of BSE and NSE.

2. To model the same ARCH, SGARCH, EGARCH, GJR GARCH, APARCH and FIEGARCH methods are being used.

The stylized properties considered in the study for analysis are:

1. Distribution properties: Heavy tails.
2. Dependence properties: Absence of autocorrelation in linear function, Slow decay of autocorrelation in absolute returns, Volatility clustering.
3. Other properties: Leverage effect, Gain/loss asymmetry, Volatility persistence, Long memory.

7.3 ARCH AND GARCH MODEL ANALYSIS – BROAD MARKET INDEX

The econometric issue is to define how the data is utilised to forecast the mean and variation of the return based on previous data. The assumption that the disturbance term in a model has a constant conditional variance over time is the basic constraint of the ARIMA model. Mandelbrot (1963) and Fama (1965) research have shown that such an assumption is false when studying stock returns. As a result, a more flexible model is needed to represent the data's volatility.

The variance of the disturbance terms is assumed to be constant across time in traditional econometric analysis. Because of volatility clustering, the assumption is particularly limiting when evaluating financial series. It is necessary therefore to use models that can deal with series variance. Further, autocorrelation in the variance at a time with values lagged one or more periods was found by researchers forecasting time series such as stock prices and foreign exchange rates. Autocorrelation is characterised as autoregressive conditional heteroskedasticity when the error variance is related to the squared error term in the prior term (ARCH).

While numerous specifications for the mean return have been developed and applied in attempts to estimate future returns, there were essentially no methodologies for the variance before the emergence of ARCH models. The rolling standard deviation was used as the primary descriptive tool. This is a standard deviation calculated from a predetermined number of recent observations. It is assumed that the variance of tomorrow's return is an equally weighted average of the previous days' squared residuals. The premise of equal weights appears to be undesirable, as current events appear to be more relevant and hence should be given higher weights. Furthermore, using zero weights for observations older than one month is undesirable (Engle, 2001).

Engle (1982) proposed the ARCH model, which allows data to determine the right weights to use in variance forecasting. The GARCH model of Bollerslev is a useful generalisation of this paradigm (1986). The weights are falling and never reach zero in this model, which is likewise a weighted average of prior squared residuals. It produces models that are simple to estimate and has been shown to accurately forecast conditional variances (Engle and Patton, 2001).

Stock market returns are characterised by statistical probability distributions. The majority of high frequency financial time series are found to be non-normal. The variance of the errors in a return series is constant across the sample, which is known as homoskedasticity, which is one of the main assumptions of ordinary regression. When this assumption is broken, it implies that there is a problem with heteroskedasticity. Fama (1965), Engle (1982), and Bollerslev (1986) all found heteroskedasticity in stock returns (1986).

The ARCH model's key flaws are:

a. Because volatility is dependent on the square of the prior shock, the model assumes that positive and negative shocks have the same influence on volatility.

b. Because it responds slowly to big single shocks in time series data, it overpredicts volatility (Tsay, 2005).

c. The ARCH model offers no new insight into the causes of changes in a financial time series. It merely provides
a mechanical technique of expressing the conditional variance's behaviour.

d. The ARCH model is somewhat limited. If a 12 in an ARCH(1) model is to have a finite fourth moment, it must be in the interval [0, 1/3]. For whatever reason, the constraint becomes more difficult for higher order ARCH models.

ARCH models can represent and capture many of the stylized elements of volatility behaviour typically observed in financial time series, such as time changing volatility or volatility clustering (Zivot and Wang, 2006). The assumptions of ARCH models state that the mean equation does not have autocorrelation; while, the variance equation have autocorrelation.

Before applying the ARCH models, there are a few conditions that need to be satisfied which are:

1. The series need to be stationary. The stationarity of the series is tested with the help of Unit root test - Augmented Dickey Fuller test and Philips-Perron test. The difference of the S&P BSE Sensex and Nifty50 index are taken in order to make them stationary. The results of which are stated as below:

Table 7.1: Unit root test

INDICES	ADF		Philips - Perron	
	I(0)	I(1)	I(0)	I(1)
BSE Sensex	-3.06	-22.2*	-3.104	-59.7*
NSE Nifty50	-3.175	-21.9*	-3.22	-59.6*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The table shows that both the market indices are significant at I(1) level of significance indicating that they are non-stationary at level and must be converted using logarithmic differencing.

2. The model should also have an ARCH effect in the residual. The model is unnecessary and mis-specified if there is absence of ARCH effect.

ARCH effect refers to auto correlation in squared residuals. The null hypothesis argues that there is no ARCH effect, while the alternative hypothesis claims that there is. The ARCH model's order is α_1 and the GARCH model's order is β_1.

ARCH LM TEST

Table 7.2 ARCH LM test

ARCH LM-Test	Chi-squared	df	p-value	a0 (coefficients)	a1 (coefficients)	b1 (coefficients)
BSE - Sensex	567.24	12	< 2.2e-16	0.000165	0.05	0.05
NSE – Nifty50	493.05	12	< 2.2e-16	0.000165	0.05	0.05

Source – Author's estimation

The results demonstrate that the ARCH LM test probability values for the S&P BSE Sensex and the Nifty50 are both less than 5%, indicating that the null hypothesis will be rejected and the alternative hypothesis will be accepted. The ARCH effect is evident in the return series, according to this. In addition, the fifth chapter of data analysis displays the graph of prices and returns of Sensex and Nifty50 which also confirms the presence of volatility clustering.

GARCH Models

The non-negativity restriction on the coefficient parameters of $\beta_i's$ to ensure the positivity of the conditional variance is a challenge when using the original ARCH model. When a model requires a significant number of lags to accurately mimic a process, however, non-negativity may be broken. To avoid lag structure that is too long predicted by Engle, Bollerslev (1986) modified the ARCH model, the so-called GARCH, by incorporating the conditional variance values with lags (1982). The conditional variance in the GARCH (p,q) model is defined as a linear combination of the conditional return equations q lags of the squared residuals (ε_{t-1}^2) and the conditional variance equation's p lags (σ_{t-1}^2). To ensure that the conditional variance σ_t^2 is always positive, all of the coefficients are assumed to be positive. The generalised ARCH or GARCH(p,q) model is the name given to this model. When q = 0, the GARCH model is reduced to the ARCH model. A

GARCH (1, 1) model with only three parameters in the conditional variance equation is usually sufficient for financial time series (Zivot and Wang, 2006).

Following that, many variations of the GARCH model were proposed in the literature, including the following which are used for the study:

1. GARCH (the standard GARCH)
2. E-GARCH (Exponential GARCH)
3. GJR-GARCH (Glosten, Jagannathan and Runkle)
4. APARCH (Asymmetric Power GARCH)
5. FIEGARCH (Fractionally Integrated Exponential GARCH)

Conditional heteroskedasticity with homoscedastic unconditional error variance is assumed in the ARCH and GARCH models, implying that the changes represent a random and transient departure from a constant unconditional variance.

The GARCH model has the advantage of capturing the trend for volatility clustering in financial data. As a result, it allows us to make the link between information and volatility clear, because any change in the rate at which information arrives in the market affects market volatility. As a result, unless information remains constant, which is unlikely, volatility must vary with time, even on a daily basis.

Unexpected returns of the same magnitude (regardless of sign) cause the same level of volatility in the GARCH process. However, Engle and Ng (1993) suggest that the GARCH model underpredicts volatility after bad news and overpredicts volatility after good news if a negative return shock creates larger volatility than a positive return shock of equal magnitude.

The GARCH (p,q) is considered stationary when $\{(\alpha_1 + \alpha_2 + \cdots + \alpha_q) + (\beta_1 + \beta_2 + \cdots + \beta_p)\}$. The significant GARCH lag coefficients β_p demonstrate that conditional variance shocks take a long time to fade away, indicating that volatility is ‘persistent'. When the GARCH error coefficient α_q is large, volatility reacts substantially to market swings; therefore if α_q is quite high and / or α_q is relatively low, volatility tends to be ‘spiky.'

If $(\alpha + \beta)$ is close to unity, a shock at time t will last for many periods in the future. It has a high value, which indicates that it has a ‘long memory.' Non-negativity requirements on α_q, β_p, and α_0 can make GARCH model estimation challenging. Furthermore, due to the non-negative constraints, increasing ε_{t-1}^2 in any period raises h_{t+m} for all, excluding random oscillatory activity in the process.

After determining the presence of clustering volatility and the ARCH effect on the log return series, the GARCH model was used. The model was run separately with a "normal distribution" and a "student's t" error distribution function, with the results compared to see which one best fit the model. The results are shown in the tables below. To determine the best fit, the Akaike information criterion (AIC) is utilized, with the function with the lowest absolute value of AIC being chosen as the best fitted model (1978).

1. Standard GARCH - Normal distribution

The standard GARCH model is estimated first using normal distribution and then using skewed student t distribution for both the benchmark indices of Bombay stock exchange and National stock exchange. The table below represents standard GARCH model using normal distribution of BSE Sensex.

Table 7.3: Standard GARCH (BSE) – Normal distribution

Parameters	Estimates
mu	0.000772*
ar1	0.033688
ma1	0.031365
omega	0.000002*
alpha1	0.10107*
beta1	0.891443*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The results of standard GARCH estimates of Sensex using normal distribution state that the overall mean (mu) is significant as its probability is less than 5%; whereas other statistics such as AR(1), MA(1) are insignificant in explaining the volatility. The alpha and beta terms are non-negative, significant and the addition of their estimates is greater than one. This shows the persistence of the volatility. The AIC criteria here is -6.1209 and Hannan Quinn is -6.1172.

Table 7.4: Standard GARCH (NSE) – Normal distribution

Parameters	Estimate
mu	0.000758*
ar1	0.088978
ma1	-0.027947
omega	0.000002*
alpha1	0.105437*
beta1	0.888058*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The results of standard GARCH estimates of Nifty50 using normal distribution state that the overall mean (mu) is significant as its probability is less than 5%; whereas other statistics such as AR(1), MA(1) are insignificant in explaining the volatility. The alpha and beta terms are non-negative, significant and the addition of their estimates is greater than one. This shows the persistence of the volatility. The AIC criteria here is -6.0906 and Hannan Quinn is -6.0972. Further, skewed student t distribution is used to estimate the five GARCH models namely – standard GARCH, exponential GARCH, GJR GARCH, APARCH and FIEGARCH. We use skew t distribution because it has a larger likelihood and smaller errors compared to other distribution.

2. Standard GARCH - Skewed student t distribution

First, we start with the standard GARCH model studied with the help of skewed student t distribution which is shown in table 7.5 for Sensex and table 7.6 for Nifty50.

Table 7.5 Standard GARCH (BSE) – Skewed t distribution

Parameters	Estimate
mu	0.00067*
ar1	-0.192911
ma1	0.252649
omega	0.000002
alpha1	0.092009*
beta1	0.898734*
skew	0.940982*
shape	6.919321*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The specification of the model states that it is a standard GARCH model of S&P BSE Sensex with ARMA (1,1) model. The factor integration here is zero and the distribution is that of a skewed student t distribution.

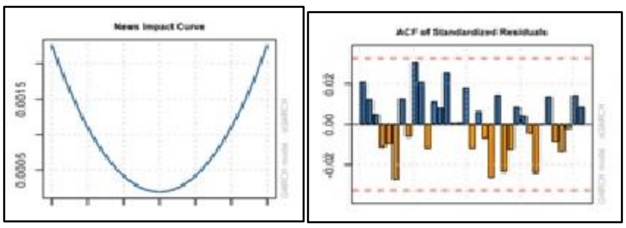
The overall mean (mu) is significant; while, the AR(1) and MA(1) shows no persistence since it is not significant. Volatility model specifications are the alpha (1) and beta (1) which are coefficient to the squared residuals i.e., squared lagged coefficients and squared variance. Alpha (1) is the ARCH term (past errors) and beta (1) is the GARCH term (past GARCH) both of which are positive and significant. The α_1 reflects the news impact captured in the returns; while, β_1 represents the persistence of volatility. Omega which is the variance parameter is not significant.

Here, the α_1 is 0.092 and β_1 is 0.90, therefore the sum of them i.e., $\alpha_1 + \beta_1$ is 0.992 which is less than 1. Hence the model follows a stationary process and also as time passes risk will fall down. It can also be called decay in volatility persistence. Also $\beta_1 > \alpha_1$. In case if, $\alpha_1 + \beta_1$ is greater than or equal to one or negative it means that the GARCH model is asymmetric.

Further, the skewness value is positive and between 0.5 and 1 which means that the series is positively moderately skewed. In addition, the shape estimates which is based on the degrees of freedom is significant and shows thick tails.

Finally, the information criterion is -6.1531 (AIC), -6.1619 (Hannan Quinn) which is lower than that of standard GARCH model with normal distribution. This means that this model with skewed student t distribution is a better model. Further the goodness of fit values of the residuals are over 0.05 i.e., higher than 95% confidence level. Therefore, we accept the null hypothesis and conclude that model is better choice (Table B3).

Figure 7.1: Standard GARCH graphs (BSE)



Source – Author's estimation

The plots shown above represents the news impact curve and autocorrelation function (ACF). The GARCH model does not cover the news impact curve. Therefore, it doesn't reflect the impact of good news or bad news on the volatility. The autocorrelation function of standardized residual lies within the confidence interval represented by the red line confirming absence of autocorrelation in returns.

Table 7.6: Standard GARCH (NSE) – Skewed t distribution

Parameters	Estimate
mu	0.000638*
ar1	-0.252085
ma1	0.303473
omega	0.000002
alpha1	0.09309*
beta1	0.897309*
skew	0.926316*
shape	6.991732*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The specification of the model states that it is a standard GARCH model of Nifty50 with ARMA (1,1) model. The factor integration here is zero and the distribution is that of a skewed student t distribution.

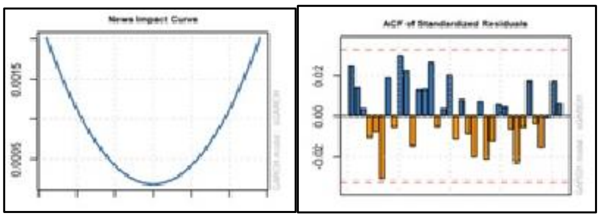
The overall mean (mu) is significant; while, the AR(1) and MA(1) shows no persistence since it is not significant. Volatility model specifications are the alpha (1) and beta (1) which are coefficient to the squared residuals i.e., squared lagged coefficients and squared variance. Alpha (1) is the ARCH term (past errors) and beta (1) is the GARCH term (past GARCH) both of which are positive and significant. . The α_1 reflects the news impact captured in the returns; while, β_1 represents the persistence of volatility. Omega which is the variance parameter is not significant.

Here, the α_1 is 0.093 and β_1 is 0.90, therefore the sum of them i.e., $\alpha_1 + \beta_1$ is 0.993 which is less than 1. Hence the model follows a stationary process and also as time passes risk will fall down. It can also be called decay in volatility persistence. Also $\beta_1 > \alpha_1$. In case if, $\alpha_1 + \beta_1$ is greater than or equal to one or negative it means that the GARCH model is asymmetric.

Further, the skewness value (0.93) is positive and between 0.5 and 1 which means that the series is positively moderately skewed. In addition, the shape estimates based on the degrees of freedom is significant and shows thick tails.

Finally, the information criterion for the GARCH model with normal distribution is -6.1496 (AIC) and -6.1447 (Hannan Quinn), which is lower than the ordinary GARCH model (normal distribution). This implies that the skewed student t distribution model is superior. Furthermore, the residuals' goodness of fit values are greater than 0.05, indicating a confidence level greater than 95%. As a result, we are unable to reject the null hypothesis and conclude that model is the preferable option (Table B4).

Figure 7.2: Standard GARCH graphs (NSE)



Source – Author's estimation

The plots shown above represents the news impact curve and autocorrelation function (ACF). The GARCH model does not cover the news impact curve. Therefore, it doesn't reflect the impact of good news or bad news on the volatility. The autocorrelation function of standardized residual lies within the confidence interval represented by the red line confirming absence of autocorrelation in returns.

3. Exponential GARCH – Skewed student t distribution

The exponential GARCH model estimates studied with the help of skewed student t distribution which is shown in table 7.7 for Sensex and table 7.8 for Nifty50.

Table 7.7: EGARCH (BSE)

Parameters	Estimate
mu	0.00037*
ar1	-0.017262
ma1	0.087182
omega	-0.164075*
alpha1	-0.112095*
beta1	0.981759*
gamma1	0.170494*
skew	0.932897*
shape	7.130731*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The specification of the model states that it is an exponential GARCH model of S&P BSE Sensex with ARMA (1,1) model. The factor integration here is zero and the distribution is that of a skewed student t distribution.

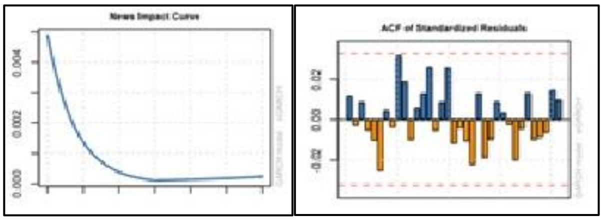
The overall mean (mu) is significant; while, the AR(1) and MA(1) shows no persistence since it is not significant. Volatility model specifications are the alpha (1) and beta (1) which are coefficient to the squared residuals i.e., squared lagged coefficients and squared variance. Alpha (1) is the ARCH term (past errors) and beta (1) is the GARCH term (past GARCH) both of which are significant. However, the ARCH term estimate is negative which implies that the model is not symmetric and insignificant . The α_1 reflects the news impact captured in the returns; while, β_1 represents the persistence of volatility.

Here, the α_1 is -0.11 and β_1 is 0.98, therefore the sum of them i.e., $\alpha_1 + \beta_1$ is 0.87 which is less than 1. Hence the model follows a stationary process and also as time passes risk will fall down. It can also be called decay in volatility persistence. Also $\beta_1 > \alpha_1$. In case if, $\alpha_1 + \beta_1$ is greater than or equal to one or negative it means that the GARCH model is asymmetric. The gamma coefficient which represents the leverage effect, is positive and significant which confirms the asymmetry in the information. It means bad news has a larger impact than good news.

Further, the skewness value (0.93) is positive and between 0.5 and 1 which means that the series is positively moderately skewed. In addition, the shape estimates which is based on the degrees of freedom is significant and shows thick tails.

Finally, the information criterion is -6.191 (AIC), -6.1855 (Hannan Quinn) which is lower than that of standard GARCH with student t distribution. Further the goodness of fit values of the residuals are over 0.05 i.e., higher than 95% confidence level (Table B3). Therefore we cannot reject the null hypothesis and conclude that model seems to be a better choice. However, since the value of the ARCH term is negative we conclude that the exponential GARCH model does not reflect the characteristics of returns distribution appropriately and therefore we exclude the model from the analysis.

Figure 7.3: EGARCH graphs (BSE)



Source – Author's estimation

The plots shown above represents the news impact curve and autocorrelation function (ACF). The news impact accounts for the impact of good news or the impact of bad news on volatility. It depicts a better picture of gain/loss asymmetry than the standard GARCH. The autocorrelation function of standardized residual lies within the confidence interval represented by the red line confirming absence of autocorrelation in returns.

Table 7.8: EGARCH (NSE)

Parameters	Estimate
mu	0.000361*
ar1	0.076735
ma1	-0.011069
omega	-0.168841*
alpha1	-0.114467*
beta1	0.981173*
gamma1	0.17288*
skew	0.923694*
shape	7.173784*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

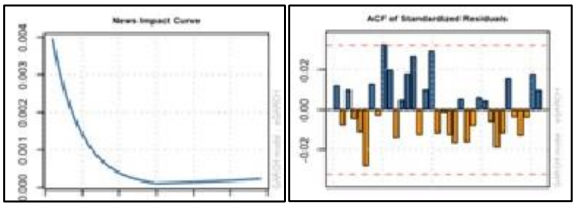
The specification of the model states that it is an exponential GARCH model of Nifty50 with ARMA (1,1) model. The factor integration here is zero and the distribution is that of a skewed student t distribution.
The overall mean (mu), AR(1) and MA(1) shows no persistence since it is not significant. Volatility model specifications are the alpha (1) and beta (1) which are coefficient to the squared residuals i.e., squared lagged coefficients and squared variance. Alpha (1) is the ARCH term (past errors) and beta (1) is the GARCH term (past GARCH) both of which are significant. However, the ARCH term estimate is negative which implies that the model is not symmetric and insignificant . The α_1 reflects the news impact captured in the returns; while, β_1 represents the persistence of volatility. The gamma coefficient which represents the leverage effect, is positive and significant which confirms the asymmetry in the information. It means bad news has a larger impact than good news.

Here, the α_1 is -0.11 and β_1 is 0.98, therefore the sum of them i.e., $\alpha_1 + \beta_1$ is 0.87 which is less than 1. Hence the model follows a stationary process and also as time passes risk will fall down. It can also be called decay in volatility persistence. Also $\beta_1 > \alpha_1$. In case if, $\alpha_1 + \beta_1$ is greater than or equal to one or negative it means that the GARCH model is asymmetric.

Furthermore, the skewness value (0.92) is positive and between 0.5 and 1, indicating that the series is strongly skewed positively. Furthermore, the shape estimations based on degrees of freedom are significant, with thick tails.

Finally, the information criterion is -6.1745 (AIC), -6.169 (Hannan Quinn) which is lower than that of standard GARCH model following student t distribution. Further the goodness of fit values of the residuals are over 0.05 i.e., higher than 95% confidence level (Table B4). Therefore, we accept the null hypothesis and conclude that model seems to be a better choice. However, since the value of the ARCH term is negative we conclude that the exponential GARCH model does not reflect the characteristics of returns distribution appropriately and therefore we exclude the model from the analysis.

Figure 7.4: EGARCH graphs (NSE)



Source – Author's estimation

The plots shown above represents the news impact curve and autocorrelation function (ACF). The news impact accounts for the impact of good news or the impact of bad news on volatility. It depicts a better picture of gain/loss asymmetry than the standard GARCH. The autocorrelation function of standardized residual lies within the confidence interval represented by the red line confirming absence of autocorrelation in returns.

4. GJR GARCH – Skewed student t distribution

The GJR GARCH model, proposed by Glosten et al. (1993), asymmetrically models positive and negative shocks on conditional variance.

Table 7.9: GJR GARCH (BSE)

Parameters	Estimate
mu	0.000383*
ar1	-0.169542
ma1	0.234275
omega	0.000002*
alpha1	0.01613*
beta1	0.894982*
gamma1	0.152923*
skew	0.929313*
shape	7.210118*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The specification of the model states that it is a GJR GARCH model of S&P BSE Sensex with ARMA (1,1) model. The factor integration here is zero and the distribution is that of a skewed student t distribution.

The overall mean (mu) is significant; while, the AR(1) and MA(1) shows no persistence since it is not significant. Volatility model specifications are the alpha (1) and beta (1) which are coefficient to the squared residuals i.e., squared lagged coefficients and squared variance. Alpha (1) is the ARCH term (past errors) and beta (1) is the GARCH term (past GARCH) both of which are positive and significant. The α_1 reflects the news impact captured in the returns; while, β_1 represents the persistence of volatility. Further, the gamma (1) coefficient which represents the leverage effect, is also positive and significant which confirms the asymmetry in the information. It means bad news has a larger impact than good news.

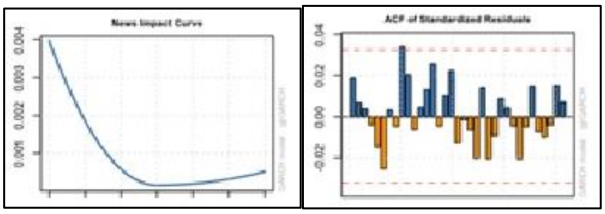
Here, the α_1 is 0.016 and β_1 is 0.895, therefore the sum of them i.e., $\alpha_1 + \beta_1$ is 0.911 which is less than 1. Hence the model follows a stationary process and also as time passes risk will fall down. It can also be called decay in volatility persistence. Also $\beta_1 > \alpha_1$. In case if, $\alpha_1 + \beta_1$ is greater than or equal to one or negative it means that the GARCH model is asymmetric.

Further, the skewness value (0.93) is positive and between 0.5 and 1 which means that the series is positively moderately skewed. In addition, the shape estimates which is based on the degrees of freedom is significant and shows thick tails.

Finally, the information criterion is -6.1916 (AIC), -6.1861 (Hannan Quinn) which is quite similar to the exponential GARCH model. However, since the value of the ARCH term in the exponential GARCH model is negative the model does not reflect the characteristics of returns distribution appropriately and is excluded from the analysis. Hence, the GJR GARCH model is a better fit.

Further the goodness of fit values of the residuals are over 0.05 i.e., higher than 95% confidence level (Table B3). Therefore we cannot reject the null hypothesis and conclude that model is better choice.

Figure 7.5: GJR GARCH graphs (BSE)



Source – Author's estimation

The plots shown above represents the news impact curve and autocorrelation function (ACF). The news impact accounts for the impact of good news or the impact of bad news on volatility. It depicts a better picture of gain/loss asymmetry than the standard GARCH. The autocorrelation function of standardized residual lies within the confidence interval represented by the red line confirming absence of autocorrelation in returns.

Table 7.10: GJR GARCH (NSE)

Parameters	Estimate
mu	0.000361*
ar1	-0.184725
ma1	0.243245
omega	0.000003*
alpha1	0.017491*
beta1	0.893582*
gamma1	0.152167*
skew	0.917976*
shape	7.229916*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The specification of the model states that it is a GJR GARCH model of Nifty50 with ARMA (1,1) model. The factor integration here is zero and the distribution is that of a skewed student t distribution.

The overall mean (mu) is significant; while, the AR(1) and MA(1) shows no persistence since it is not significant. Volatility model specifications are the alpha (1) and beta (1) which are coefficient to the squared residuals i.e., squared lagged coefficients and squared variance. Alpha (1) is the ARCH term (past errors) and beta (1) is the GARCH term (past GARCH) both of which are positive and significant. The α_1 reflects the news impact captured in the returns; while, β_1 represents the persistence of volatility. Further, the gamma (1) coefficient which represents the leverage effect, is also positive and significant which confirms the asymmetry in the information. It means bad news has a larger impact than good news.

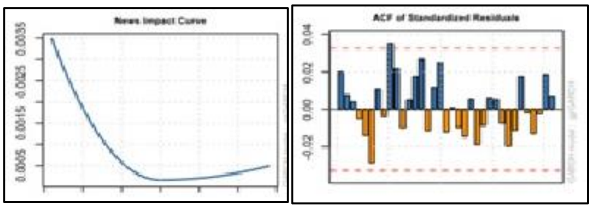
Here, the α_1 is 0.017 and β_1 is 0.893, therefore the sum of them i.e., $\alpha_1 + \beta_1$ is 0.91 which is less than 1. Hence the model follows a stationary process and also as time passes risk will fall down. It can also be called decay in volatility persistence. Also $\beta_1 > \alpha_1$. In case if, $\alpha_1 + \beta_1$ is greater than or equal to one or negative it means that the GARCH model is asymmetric.

Further, the skewness value (0.92) is positive and between 0.5 and 1 which means that the series is positively moderately skewed. In addition, the shape estimates which is based on the degrees of freedom is significant and shows thick tails.

Finally, the information criterion is -6.1741 (AIC), -6.1687 (Hannan Quinn) which is quite similar to that of the exponential GARCH model. However, since the value of the ARCH term in the exponential GARCH model is negative the model does not reflect the characteristics of returns distribution appropriately and is excluded from the analysis. Hence, the GJR GARCH model is a better fit.

Further the goodness of fit values of the residuals are over 0.05 i.e., higher than 95% confidence level (Table B4). Therefore we cannot reject the null hypothesis and conclude that model is better choice.

Figure 7.6: GJRGARCH graphs (NSE)



Source – Author's estimation

The plots shown above represents the news impact curve and autocorrelation function (ACF). The news impact accounts for the impact of good news or the impact of bad news on volatility. It depicts a better picture of gain/loss asymmetry than the standard GARCH. The autocorrelation function of standardized residual lies within the confidence interval represented by the red line confirming absence of autocorrelation in returns.

5. Asymmetry Power GARCH – Skewed student t distribution

The APARCH model satisfies Ding, Granger, and Engle's long-term memory condition of returns (1993). In addition to the GJR-GARCH model, the APARCH model captures asymmetry in return volatility. That is, when returns are negative, volatility tends to rise greater than when returns are positive of the same size.

Table 7.11: APARCH (BSE)

Parameters	Estimate
mu	0.00036*
ar1	-0.097449
ma1	0.166296
omega	0.00003
alpha1	0.086221*
beta1	0.902565*
gamma1	0.62077*
delta	1.454522*
skew	0.930301*
shape	7.235564*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The specification of the model states that it is a APARCH model of S&P BSE Sensex with ARMA (1,1) model. The factor integration here is zero and the distribution is that of a skewed student t distribution.

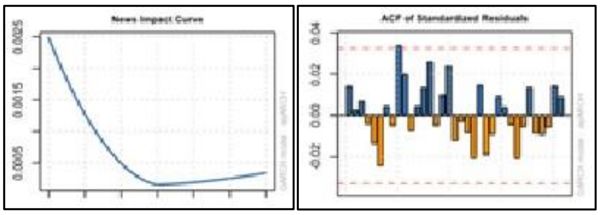
The overall mean (mu) is significant; while, the AR(1) and MA(1) shows no persistence since it is not significant. Omega, the variance parameter is insignificant in the model. Volatility model specifications are the alpha (1) and beta (1) which are coefficient to the squared residuals i.e., squared lagged coefficients and squared variance. Alpha (1) is the ARCH term (past errors) and beta (1) is the GARCH term (past GARCH) both of which are positive and significant. The α_1 reflects the news impact captured in the returns; while, β_1 represents the persistence of volatility. Further, the gamma (1) coefficient which represents the leverage effect, is also positive and significant which confirms the asymmetry in the information. It means bad news has a larger impact than good news. This model also determines the power coefficient represented by delta which is also significant.

Here, the α_1 is 0.086 and β_1 is 0.90, therefore the sum of them i.e., $\alpha_1 + \beta_1$ is 0.986 which is less than 1. Hence the model follows a stationary process and also as time passes risk will fall down. It can also be called decay in volatility persistence. Also $\beta_1 > \alpha_1$. In case if, $\alpha_1 + \beta_1$ is greater than or equal to one or negative it means that the GARCH model is asymmetric.

Further, the skewness value (0.93) is positive and between 0.5 and 1 which means that the series is positively moderately skewed. In addition, the shape estimates which is based on the degrees of freedom is significant and shows thick tails.

Finally, the information criterion is -6.193 (AIC), -6.1868 (Hannan Quinn) which is lower than all the GARCH family models with student t distribution. Therefore, the results suggests that the asymmetric power GARCH is model is a superior model. Further the goodness of fit values of the residuals are over 0.05 i.e., higher than 95% confidence level (Table B3). Therefore, we accept the null hypothesis and conclude that model is better choice.

Figure 7.7: APARCH graphs (BSE)



Source – Author's estimation

The plots shown above represents the news impact curve and autocorrelation function (ACF). The news impact accounts for the impact of good news or the impact of bad news on volatility. It depicts a better picture of gain/loss asymmetry than the standard GARCH. The autocorrelation function of standardized residual lies within the confidence interval represented by the red line confirming absence of autocorrelation in returns.

Table 7.12: APARCH (NSE)

Parameters	Estimate
mu	0.000342*
ar1	-0.062039
ma1	0.125014
omega	0.000035
alpha1	0.088625*
beta1	0.901923*
gamma1	0.607824*
delta	1.425385*
skew	0.919937*
shape	7.257916*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The specification of the model states that it is a APARCH model of S&P BSE Sensex with ARMA (1,1) model. The factor integration here is zero and the distribution is that of a skewed student t distribution.

The overall mean (mu) is significant; while, the AR(1) and MA(1) shows no persistence since it is not significant. Omega, the variance parameter is insignificant in the model. Volatility model specifications are the alpha (1) and beta (1) which are coefficient to the squared residuals i.e., squared lagged coefficients and squared variance. Alpha (1) is the ARCH term (past errors) and beta (1) is the GARCH term (past GARCH) both of which are positive and significant. The α_1 reflects the news impact captured in the returns; while, β_1 represents the persistence of volatility. Further, the gamma (1) coefficient which represents the leverage effect, is also positive and significant which confirms the asymmetry in the information. It means bad/negative news has a larger impact than good/positive news. This model also determines the power coefficient represented by delta which is also significant.

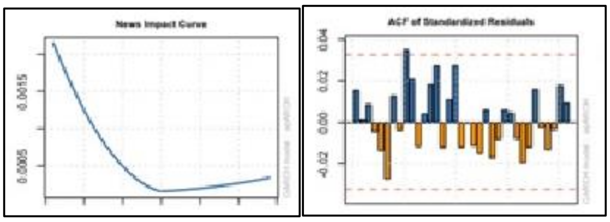
Here, the α_1 is 0.088 and β_1 is 0.90, therefore the sum of them i.e., $\alpha_1 + \beta_1$ is 0.988 which is less than 1. Hence the model follows a stationary process and also as time passes risk will fall down. It can also be called decay in volatility persistence. Also $\beta_1 > \alpha_1$. In case if, $\alpha_1 + \beta_1$ is greater than or equal to one or negative it means that the GARCH model is asymmetric.

Further, the skewness value (0.92) is positive and between 0.5 and 1 which indicates that the series is positively moderately skewed. Furthermore, the shape estimations based on degrees of freedom are significant, with thick tails.

Finally, the information criterion is -6.1756 (AIC), -6.1696 (Hannan-Quinn) which is lower than all the GARCH family models with student t distribution. Therefore, the results suggests that the asymmetric power GARCH is model is a superior model. Further the goodness of fit values of the residuals are over 0.05 i.e., higher than 95% confidence level (Table B4). Therefore, we accept the null hypothesis and conclude that the model is better choice.

According to Ding et al. (1993), the asymmetric power ARCH model accounts for both leverage and the Taylor effect. The Taylor effect was called after Taylor (1986), who established that the sample autocorrelation of absolute returns was frequently greater than that of squared returns.

Figure 7.8: APARCH graphs (NSE)



Source – Author's estimation

The plots shown above represents the news impact curve and autocorrelation function (ACF). The news impact accounts for the influence of positive or negative news on volatility. It depicts a better picture of gain/loss asymmetry than the standard GARCH. The autocorrelation function of standardized residual lies within the confidence interval represented by the red line confirming absence of autocorrelation in returns.

6. Fractionally integrated GARCH models

The FIE-GARCH model was proposed by Bollerslev and Mikkelsen (1999). Since this model has a positive conditional variance property, it was required to use it in this study in order to assess the impact of shocks on volatility and stock market deviation. The estimation is done with the help of the Maximum Likelihood ARCH (ML ARCH) – Student's t distribution (BFGS/Marguardt steps).

Table 7.13: FIEGARCH – BSE & NSE

Index	Omega	Alpha	Beta	Theta 1	Theta 2	D
BSE - Sensex	-0.000734	-0.999511*	0.999929*	0.262*	-0.158*	0.909*
NSE - Nifty50	-0.012119	-1*	0.999*	0.257*	-0.209*	0.771*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The specification of the model states that it is a FIEGARCH model of S&P BSE Sensex with ARMA (1,1) model. The factor integration here is one and the distribution is that of a normal distribution. The skewed t distribution could not be applied because of an error that showed up during computation.

The omega which is the variance parameter is insignificant in the model. Volatility model specifications are the alpha and beta which are coefficient to the squared residuals i.e., squared lagged coefficients and squared variance. Alpha is the ARCH term (past errors) is negative and beta is the GARCH term (past GARCH) which is positive and both are significant. The α_1 reflects the news impact captured in the returns; while, β_1 represents the persistence of volatility. Furthermore, the theta (2) calculated parameter is statistically significant, indicating that negative and positive shocks have asymmetric effects on the index return's conditional variance. Theta (1) is similarly statistically significant and less than zero, showing a leverage effect on the conditional variance.

Here, the α_1 is -0.999511 and β_1 0.999929 is, therefore the sum of them i.e., $\alpha_1 + \beta_1$ is 0.00048 which is less than 1. Hence the model follows a stationary process and also as time passes risk will fall down. It can also be called decay in volatility persistence. Also $\beta_1 > \alpha_1$. In case if, $\alpha_1 + \beta_1$ is greater than or equal to one or negative it means that the GARCH model is asymmetric.

Further, the D value (0.909) is significant and between 0.5 and 1 which means that the persistence of shocks in variance is adequately described by the model. It also indicates the stability of the process.

Finally, the information criterion is -6.137214 (AIC), -6.132959 (Hannan-Quinn) which is lower than the asymmetric power GARCH model. Thus, the results suggests that the asymmetric power GARCH model is a superior model.

In case of National stock exchange, the specification of the model states that it is a FIEGARCH model of Nifty50 with ARMA (1,1) model. The factor integration here is one and the distribution is that of a skewed student t distribution.

The omega which is the variance parameter is insignificant in the model. Volatility model specifications are the alpha and beta which are coefficient to the squared residuals i.e., squared lagged coefficients and squared variance. Alpha is the ARCH term (past errors) is negative and beta is the GARCH term (past GARCH) which is positive and both are significant. The α_1 reflects the news impact captured in the returns; while, β_1 represents the persistence of volatility. Furthermore, the theta (2) calculated parameter is statistically significant, indicating that negative and positive shocks have asymmetric impacts on the conditional variance of the index returns. Theta (1) is similarly statistically significant and less than zero, showing a leverage effect on the conditional variance.

Here, the α_1 is -1 and β_1 is 0.9999, therefore the sum of them i.e., $\alpha_1 + \beta_1$ is -0.0001 which is less than 1 and negative which means the GARCH model is asymmetric. Hence the model follows a stationary process and also as time passes risk will fall down. It can also be called decay in volatility persistence. Also $\beta_1 > \alpha_1$.

Further, the D value (0.771) is significant and between 0.5 and 1 which indicates that the model effectively predicts the persistence of shocks in variance. It also indicates the stability of the process. The T dist DoF is 7 and significant.

Finally, the information criterion is -6.168975 (AIC), -6.164112 (Hannan-Quinn) which is lower than the asymmetric power GARCH model. Thus, the results suggests that the asymmetric power GARCH model is a superior model.

7.4 ARCH AND GARCH MODEL ANALYSIS - SECTORAL INDICES (BSE)

To begin, all sectoral indicators are verified for non-stationarity, ensuring that the features of the timeseries are independent of the time period under study. The unit root test which are Augmented Dickey Fuller test and Philips-Perron test are used to determine the series' stationarity. At both the level and the initial difference, the unit root is checked. To make the BSE sectoral indices stationary, the difference between them is taken. The results of which are stated as below:

Table 7.14: Unit root test of sectoral indices (BSE)

UNIT ROOT TEST	ADF		PP	
SECTORS	I(0)	I(1)	I(0)	I(1)
Automobiles	-1.138	-56.62*	-1.148	-56.65*
Bank	-1.08	-57.3*	-1.133	-57.65*
Basic materials	-1.748	-55.76*	-1.92	-56.37*
Capital goods	-2.564	-53.13*	-2.574	-53.09*
Consumer discretionary	-0.777	-37.64*	-0.8427	-55.5*
Consumer durables	-0.099	-38.43*	-0.233	-58.66*
Energy	-0.15	-40.07*	-40.07	-59.106*
Finance	-1.06	-21.66*	-1.0906	-57.17*
FMCG	-0.502	-20.75*	-0.478	-60.76*
Healthcare	-0.365	-54.27*	-0.413	-54.65*
Industrials	-2.222	-52.14*	-2.299	-52.39*
IT	0.304	-62.27*	0.314	-62.24*
Metal	-2.552	-55.937*	-2.68	-56.12*
Oil & Gas	-2.3	-57.41*	-2.269	-57.34*
Power	-2.46	-53.57*	-2.477	-53.486*
Realty	-1.91	-16.52*	-1.947	-52.45*
Teck	-0.307	-61.72*	-0.263	-61.73*
Telecom	-2.647	-58.27*	-2.6	-58.27*
Utilities	-3.225	-15.83*	-3.01	-53.95*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The table reveals that all the sectors are integrated at level 1. Secondly, the model should also have an ARCH effect in the residual. If there is absence of ARCH effect than the model is unnecessary and mis-specified. ARCH effect refers to auto correlation in squared residuals. The null hypothesis indicates that there is absence of ARCH effect; whereas the alternative hypothesis represents the presence of ARCH effect. α_1 represent the ARCH model's order and β_1 represents the GARCH model's order.

Table 7.15: ARCH LM test of Sectoral indices (BSE)

Sectoral indices	Chi-squared	df	p-value	a0	a1	b1
Automobiles	391.21	12	2.20E-16	0.0001909	0.05	0.05
Bank	461.64	12	2.20E-16	0.0003039	0.05	0.05
Basic materials	627.45	12	2.20E-16	0.0002357	0.05	0.05
Capital goods	337.35	12	2.20E-16	0.0002676	0.05	0.05
Consumer discretionary	497.15	12	2.20E-16	0.0001446	0.05	0.05
Consumer durables	512.62	12	2.20E-16	0.0002418	0.05	0.05
Energy	471.55	12	2.20E-16	0.0002024	0.05	0.05
Finance	506.25	12	2.20E-16	0.0002742	0.05	0.05
FMCG	607.55	12	2.20E-16	0.000134	0.05	0.05
Healthcare	479.92	12	2.20E-16	0.000118	0.05	0.05
Industrials	425.41	12	2.20E-16	0.0002261	0.05	0.05
IT	551.48	12	2.20E-16	0.0002102	0.05	0.05
Metal	640.57	12	2.20E-16	0.0003769	0.05	0.05
Oil & Gas	400.17	12	2.20E-16	0.0002302	0.05	0.05
Power	421.93	12	2.20E-16	0.0002215	0.05	0.05
Realty	353.62	12	2.20E-16	0.0005682	0.05	0.05
Teck	619.64	12	2.20E-16	0.0001784	0.05	0.05
Telecom	465.56	12	2.20E-16	0.0003199	0.05	0.05
Utilities	570.3	12	2.20E-16	0.0002042	0.05	0.05

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The results demonstrate that the ARCH LM test probability values are less than 5% for all BSE sectoral indices, indicating that the null hypothesis will be rejected and the alternative hypothesis will be accepted. The ARCH effect is evident in the return series, according to this. Furthermore, the fifth chapter of data analysis shows a graph of all indices' prices and returns, confirming the occurrence of volatility clustering.

Therefore, on the basis of this we further move to the empirical analysis of GARCH models of all the sectoral indices of the Bombay stock exchange presented in the tabular manner below:

Table 7.16: GARCH estimates of Sectoral indices (BSE)

BSE - Sectors	GARCH Models	Omega	Alpha	Beta	Gamma	Delta	Theta 1	Theta 2	D
Automobiles	SGARCH	0.000	0.088	0.884*	-	-	-	-	-
	EGARCH	-0.228*	-0.077*	0.974*	0.160*	-	-	-	-
	GJR GARCH	0.000*	0.032*	0.884*	0.105*	-	-	-	-
	APARCH	0.000	0.088	0.901*	0.473*	1.167*	-	-	-
	FIEGARCH	-8.07E-05*	-0.99974*	0.999*	-	-	0.247*	-0.134*	0.717*
Bank	SGARCH	0.000	0.081	0.916*	-	-	-	-	-
	EGARCH	-0.095*	-0.074*	0.989*	0.141*	-	-	-	-
	GJR GARCH	0.000	0.023	0.924*	0.095	-	-	-	-
	APARCH	0.000	0.07*	0.929*	0.475*	1.414*	-	-	-
	FIEGARCH	-0.0006*	-1*	0.999*	-	-	0.194*	-0.128*	1.047*
Basic Materials	SGARCH	0.000*	0.099*	0.879*	-	-	-	-	-
	EGARCH	-0.233*	-0.082*	0.972*	0.189*	-	-	-	-
	GJR GARCH	0.000*	0.043*	0.876*	0.108*	-	-	-	-
	APARCH	0.000	0.096*	0.883*	0.356*	1.625*	-	-	-
	FIEGARCH	0.0003*	0.15*	0.6*	-	-	0.1*	0.1*	0.4*
Capital goods	SGARCH	0.000*	0.118*	0.862*	-	-	-	-	-
	EGARCH	-0.206*	-0.072*	0.975*	0.209*	-	-	-	-
	GJR GARCH	0.000	0.059*	0.866*	0.111*	-	-	-	-
	APARCH	0.000	0.118*	0.876*	0.309*	1.442*	-	-	-
	FIEGARCH	-0.0008*	-1*	0.9998*	-	-	0.307*	-0.1*	0.953*
Consumer discretionary	SGARCH	0.000004	0.1162	0.8596	-	-	-	-	-
	EGARCH	-0.304*	0.0996*	0.9658*	0.212*	-	-	-	-
	GJRGARCH	0.000005*	0.1862*	0.8549*	-0.149*	-	-	-	-
	APARCH	0.000042	0.1096*	0.8662*	-0.431*	1.528*	-	-	-
	FIEGARCH	-0.0051	-1*	0.9998*	-	-	0.28*	0.143*	0.665*
Consumer durables	SGARCH	0.000	0.083*	0.896*	-	-	-	-	-
	EGARCH	-0.206*	-0.042*	0.975*	0.174*	-	-	-	-
	GJR GARCH	0.000*	0.053*	0.882*	0.071*	-	-	-	-
	APARCH	0.000	0.096*	0.899*	0.242*	1.218*	-	-	-
	FIEGARCH	-0.0004*	-1*	0.999*	-	-	0.262*	-0.072*	0.718*
Energy	SGARCH	0.000*	0.096*	0.880*	-	-	-	-	-
	EGARCH	-0.211*	-0.066*	0.976*	0.186*	-	-	-	-
	GJR GARCH	0.000*	0.050*	0.877*	0.092*	-	-	-	-
	APARCH	0.000	0.076*	0.868*	0.201*	2.607*	-	-	-
	FIEGARCH	-0.0105*	-0.192*	1*	-	-	0.224*	-0.057*	-19.2*

Finance	SGARCH	0.000	0.086*	0.910*	-	-	-	-	-
	EGARCH	-0.115*	-0.083*	0.986*	0.154*	-	-	-	-
	GJR GARCH	0.000*	0.024*	0.915*	0.107*	-	-	-	-
	APARCH	0.000	0.076*	0.920*	0.474*	1.521*	-	-	-
	FIEGARCH	-7.981*	0.091*	0.9849*	-	-	0.145*	-0.065*	-709.7*
FMCG	SGARCH	0.000*	0.104*	0.860*	-	-	-	-	-
	EGARCH	-0.289*	-0.054*	0.967*	0.188*	-	-	-	-
	GJR GARCH	0.000*	0.063*	0.861*	0.074*	-	-	-	-
	APARCH	0.000	0.069*	0.854*	0.149*	2.831*	-	-	-
	FIEGARCH	0.003*	-1*	0.999*	-	-	0.291*	-0.067*	0.888*
Healthcare	SGARCH	0.000*	0.102*	0.851*	-	-	-	-	-
	EGARCH	-0.414*	-0.061*	0.954*	0.190*	-	-	-	-
	GJR GARCH	0.000*	0.059*	0.840*	0.085*	-	-	-	-
	APARCH	0.000	0.073*	0.841*	0.129*	2.885*	-	-	-
	FIEGARCH	-5.91E-05*	-0.999*	0.901*	-	-	0.284*	-0.059*	0.605*
Industrials	SGARCH	0.000*	0.121*	0.856*	-	-	-	-	-
	EGARCH	-0.271*	-0.082*	0.968*	0.219*	-	-	-	-
	GJR GARCH	0.000*	0.057*	0.854*	0.122*	-	-	-	-
	APARCH	0.000	0.120*	0.866*	0.351*	1.4*	-	-	-
	FIEGARCH	-0.003*	-1*	0.999*	-	-	0.3*	-0.116*	0.843*
IT	SGARCH	0.000*	0.112*	0.862*	-	-	-	-	-
	EGARCH	-0.172*	-0.051*	0.980*	0.170*	-	-	-	-
	GJR GARCH	0.000*	0.071*	0.859*	0.080*	-	-	-	-
	APARCH	0.000	0.101*	0.899*	0.343*	1.016*	-	-	-
	FIEGARCH	-0.003*	-1*	0.999*	-	-	0.249*	-0.101*	0.669*
Metal	SGARCH	0.000	0.081*	0.900*	-	-	-	-	-
	EGARCH	-0.152*	-0.060*	0.981*	0.162*	-	-	-	-
	GJR GARCH	0.000*	0.038*	0.906*	0.076*	-	-	-	-
	APARCH	0.000*	0.073*	0.906*	0.279*	1.911*	-	-	-
	FIEGARCH	-0.0015*	-1*	0.999*	-	-	0.228*	-0.086*	1.143*
Oil & Gas	SGARCH	0.000*	0.101*	0.876*	-	-	-	-	-
	EGARCH	-0.217*	-0.059*	0.974*	0.203*	-	-	-	-
	GJR GARCH	0.000*	0.061*	0.872*	0.083*	-	-	-	-
	APARCH	0.000	0.104*	0.880*	0.246*	1.649*	-	-	-
	FIEGARCH	-0.0008*	-1*	0.999*	-	-	0.287*	-0.090*	0.863*
Power	SGARCH	0.000*	0.102*	0.882*	-	-	-	-	-
	EGARCH	-0.178*	-0.058*	0.979*	0.200*	-	-	-	-
	GJR GARCH	0.000*	0.066*	0.879*	0.074*	-	-	-	-

	APARCH	0.000	0.111*	0.888*	0.252*	1.406*	-	-	-
	FIEGARCH	-0.003*	-1*	0.999*	-	-	0.274*	-0.087*	0.998*
Realty	SGARCH	0.000*	0.095*	0.886*	-	-	-	-	-
	EGARCH	-0.180*	-0.032*	0.976*	0.194*	-	-	-	-
	GJR GARCH	0.000*	0.076*	0.878*	0.044*	-	-	-	-
	APARCH	0.000	0.104*	0.887*	0.143*	1.531*	-	-	-
	FIEGARCH	-0.015*	-1*	0.999*	-	-	0.272*	-0.047*	0.846*
TECK	SGARCH	0.000*	0.097*	0.881*	-	-	-	-	-
	EGARCH	-0.186*	-0.061*	0.979*	0.171*	-	-	-	-
	GJR GARCH	0.000*	0.055*	0.869*	0.094*	-	-	-	-
	APARCH	0.000	0.098*	0.899*	0.410*	1.010*	-	-	-
	FIEGARCH	-0.00025*	-1	0.999*	-	-	0.235*	-0.108*	0.818*
Telecom	SGARCH	0.000*	0.081*	0.890*	-	-	-	-	-
	EGARCH	-0.215*	-0.040*	0.973*	0.162*	-	-	-	-
	GJR GARCH	0.000*	0.048*	0.890*	0.063*	-	-	-	-
	APARCH	0.000	0.083*	0.892*	0.214*	1.740*	-	-	-
	FIEGARCH	-0.0042*	-1*	0.999*	-	-	0.278*	-0.055*	0.682*
Utilities	SGARCH	0.000*	0.089*	0.895*	-	-	-	-	-
	EGARCH	-0.159*	-0.050*	0.982*	0.189*	-	-	-	-
	GJR GARCH	0.000*	0.057*	0.892*	0.065*	-	-	-	-
	APARCH	0.000*	0.093*	0.895*	0.209*	1.725*	-	-	-
	FIEGARCH	-7.215*	-0.997*	0.995*	-	-	0.275*	-0.606*	1.020*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The empirical findings of the selected sectors indexes of the Bombay stock market are listed in the table above. Standard GARCH, GJR GARCH, asymmetric power GARCH, and fractionally integrated GARCH models are calculated for each sector. The best model is chosen from among these based on the information criterion – AIC and Hannan – Quinn (Table B5). Following that, the best fit model to the data is interpreted using the ideal parameters chosen based on their probability values. The significant parameters falling under 95% confidence interval are marked with an asterisk (*) sign.

Based on the information criterion, the automobile sector seems to follows the EGARCH process. Here, omega represents the variance of the model, alpha which is the ARCH term refers to the extent that the magnitude of a shock to the variance affects the future volatility in the returns of an asset. The GARCH term beta provides insight into the persistence of past volatility and aids in the prediction of future volatility. Finally, the gamma term demonstrates how the sign of the shock affects the volatility of an asset's future returns. Here, alpha is negative and significant, indicating a negative relationship in absolute value between previous and current variance. The gamma component, also known as the asymmetry term, is positive and significant, implying a positive link between stock returns and conditional volatility.

Other sectors such as finance, healthcare, oil & gas, consumer durables (EGARCH) and realty follow the GJR GARCH/EGARCH as well as the APARCH model according to their information criterion. These models confirm presence of volatility clustering presented by the alpha term, volatility persistence by the beta term, leverage effect by the gamma coefficient. The power parameter presented by delta is greater than one in all the cases while in healthcare it is greater than 2. The presence of long memory can also be found in the data ranging from 1.6 in oil & gas and 1.2 in consumer durables. Since in healthcare the power term is greater than 2 it is not preferred to carry forward with the APARCH model and hence the GJR GARCH model is considered. The gamma terms in all of the models are positive and significant, implying that earlier negative shocks have a larger impact on current conditional volatility than previous positive shocks.

Bank, capital goods sector, industrials, consumer discretionary goods & services and power sector follow the APARCH model. Here, the delta parameter for all the sectors are around 1.4 which confirms the use of a model that allows for the estimation of the power term. The returns of the sectors depict clustering of volatility, volatility persistence and leverage effect. Further, the energy sector, FMCG sector, metal, telecom and utilities sector follow the GJR GARCH model. Finally, the basic materials, IT and TECK sector follows the FIE GARCH model. This not only confirms the clustering of volatility, volatility persistence and leverage effect but it also states the long-term memory process in the data. In all the sectors, theta 2 is statistically significant which means the negative and positive shocks have asymmetric effects on index returns, but theta1, which is similarly significant, reflects the leverage effect on conditional variance.

Here, the estimation of following sectors – finance, healthcare and utilities sector are done using the FIEGARCH model under normal distribution because of an estimation error. All the other sectors are estimated using the skewed t distribution for a better analysis.

7.5 ARCH AND GARCH MODEL ANALYSIS - SECTORAL & THEMATIC INDICES (NSE)

Similar exercise is carried out for the selected sectoral as well as thematic indices of the national stock exchange. These are verified for non-stationarity, ensuring that the features of the timeseries are independent of the time period under study. The unit root test which is measured by Augmented Dickey Fuller test and

Philips-Perron test are used to determine the series' stationarity. At both the level and the initial difference, the unit root is checked. To make the NSE sectoral and thematic indices stationary, the difference between them is taken. The following are the outcomes of the study:

Table 7.17: Unit root test of Sectoral and Thematic indices (NSE)

Unit Root test	ADF		PP	
Indices	I(0)	I(1)	I(0)	I(1)
Commodities	-2.449	-56.16*	-2.53	-56.33*
Financial services	-0.907	-15.41*	-0.797	-58.46*
India Consumption	-0.305	-17.92*	-0.404	-59.2*
India Manufacturing	-0.873	-26.38*	-0.68	-55.65*
Infrastructure	-3	-55.35*	-2.96	-55.22*
Media	-1.795	-57.44*	-1.836	-57.44*
Pharmaceuticals	-0.943	-55.74*	-0.969	-55.95*
Private bank	-0.9	-57.29*	-0.961	-57.66*
PSU bank	-2.424	-55.32*	-2.364	-55.22*
Service sector	-0.894	-15.81*	-0.801	-59.65*

Source – Author’s estimation

Asterisk (*) denotes significance at 5%

Furthermore, the residual in the model should have an ARCH effect. The model is unnecessary and mis-specified if there is absence of ARCH effect. Auto correlation in squared residuals is referred to as the ARCH effect. The null hypothesis argues that there is absence of ARCH effect, while the alternative hypothesis claims that there is. The ARCH model's order is 1, and the GARCH model's order is 1.

Table 7.18: ARCH LM test of Sectoral and Thematic indices (NSE)

NSE – Sectoral & Thematic indices	Chi-squared	df	p-value	a0	a1	b1
Commodities	503.53	12	2.20E-16	0.00021	0.05	0.05
Financial services	506.25	12	2.20E-16	0.00027	0.05	0.05
India Consumption	389.42	12	2.20E-16	0.00013	0.05	0.05
India Manufacturing	87.36	12	1.60e-13	0.0041	0.96	0.11
Infrastructure	447.89	12	2.20E-16	0.00023	0.05	0.05
Media	338.72	12	2.20E-16	0.00026	0.05	0.05
Pharmaceuticals	435.11	12	2.20E-16	0.00014	0.05	0.05
Private bank	530.79	12	2.20E-16	0.00032	0.05	0.05
PSU bank	51.021	12	9.23E-07	0.00043	0.05	0.05
Service sector	553.43	12	2.20E-16	0.00018	0.05	0.05

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The results show that for all NSE sectoral and thematic indexes, the ARCH LM test probability values are less than 5%, indicating that the null hypothesis will be rejected and the alternative hypothesis would be accepted. This indicates that the return series has an ARCH effect. Furthermore, the fifth chapter of data analysis shows the graph of all indices' prices and returns, confirming the occurrence of volatility clustering.

As a result, we proceed to the empirical study of GARCH models for all of the National Stock Exchange's sectoral and thematic indices, that is provided in the table below.

Table 7.19: GARCH estimates of Sectoral and Thematic indices (NSE)

NSE – Sectoral & Thematic indices	GARCH Models	Omega	Alpha	Beta	Gamma	Delta	Theta 1	Theta 2	D
Commodities	SGARCH	0.000*	0.094*	0.887*	-	-	-	-	-
	EGARCH	-0.198*	-0.079*	0.977*	0.187*	-	-	-	-
	GJR GARCH	0.000*	0.040*	0.886*	0.104*	-	-	-	-
	APARCH	0.000	0.091*	0.890*	0.347*	1.701*	-	-	-
	FIEGARCH	377.2	-0.044	1*	-	-	0.192*	-0.059*	-27.7*
Financial services	SGARCH	0.000	0.086*	0.910*	-	-	-	-	-
	EGARCH	-0.115*	-0.083*	0.986*	0.154*	-	-	-	-
	GJR GARCH	0.000*	0.024*	0.915*	0.107*	-	-	-	-
	APARCH	0.000	0.076*	0.920*	0.474*	1.521*	-	-	-
	FIEGARCH	-7.981*	-0.091	0.985*	-	-	0.145*	-0.065*	-709*
India Consumption	SGARCH	0.000*	0.1*	0.876*	-	-	-	-	-
	EGARCH	-0.251*	-0.095*	0.973*	0.180*	-	-	-	-
	GJR GARCH	0.000*	0.024*	0.878*	0.136*	-	-	-	-
	APARCH	0.000	0.060*	0.864*	0.357*	2.72*	-	-	-
	FIEGARCH	-0.003	-1*	0.9998*	-	-	0.263*	-0.137*	1*
India Manufacturing	SGARCH	0.00042*	0.737*	0.262*	-	-	-	-	-
	EGARCH	-0.793*	0.899*	0.699*	4.619*	-	-	-	-
	GJR GARCH	0.0004*	0.910*	0.261*	-0.363*	-	-	-	-
	APARCH	0.059*	0.812*	0.346*	-0.092*	0.504*	-	-	-
	FIEGARCH	-1.605	0.145*	0.633*	-	-	7.1027	-3.058	-23.654
Infrastructure	SGARCH	0.000*	0.094*	0.889*	-	-	-	-	-
	EGARCH	-0.177*	-0.075*	0.979*	0.177*	-	-	-	-
	GJR GARCH	0.000*	0.039*	0.891*	0.099*	-	-	-	-
	APARCH	0.000	0.09*	0.896*	0.355*	1.609*	-	-	-
	FIEGARCH	-0.0002	-1*	0.999*	-	-	0.251*	-0.107*	1.043*
Media	SGARCH	0.000*	0.109*	0.854*	-	-	-	-	-
	EGARCH	-0.265*	-0.048*	0.968*	0.18*	-	-	-	-
	GJR GARCH	0.000*	0.065*	0.857*	0.075*	-	-	-	-
	APARCH	0.000	0.101*	0.862*	0.198*	1.848*	-	-	-
	FIEGARCH	-0.0007	-1*	0.999*	-	-	0.256*	-0.074*	0.708*
Pharmaceuticals	SGARCH	0.000*	0.304*	0.643*	-	-	-	-	-
	EGARCH	-0.893*	0.070*	0.887*	0.605*	-	-	-	-
	GJR GARCH	0.000*	0.241*	0.637*	0.135*	-	-	-	-
	APARCH	0.001*	0.136*	0.879*	0.136*	0.688*	-	-	-
	FIEGARCH	-8.38*	-0.567*	0.989*	-	-	0.216*	-0.182*	-17.8*

Private bank	SGARCH	0.000	0.092*	0.904*	-	-	-	-	-
	EGARCH	-0.11*	-0.074*	0.987*	0.163*	-	-	-	-
	GJR GARCH	0.000*	0.029*	0.911*	0.106*	-	-	-	-
	APARCH	0.000	0.085*	0.918*	0.438*	1.325*	-	-	-
	FIEGARCH	-0.021	-0.999*	0.999*	-	-	0.249*	-0.11*	1.079*
PSU bank	SGARCH	0.000*	0.089*	0.869*	-	-	-	-	-
	EGARCH	-0.257*	-0.053*	0.967*	0.157*	-	-	-	-
	GJR GARCH	0.000*	0.04*	0.885*	0.081*	-	-	-	-
	APARCH	0.000	0.083*	0.903*	0.319*	1.227*	-	-	-
	FIEGARCH	0.006	0.999*	0.999*	-	-	0.163*	-0.084*	0..837*
Services sector	SGARCH	0.000	0.089*	0.905*	-	-	-	-	-
	EGARCH	-0.156*	-0.101*	0.982*	0.162*	-	-	-	-
	GJR GARCH	0.000*	0.018*	0.906*	0.127*	-	-	-	-
	APARCH	0.000	0.051*	0.906*	0.426*	2.488*	-	-	-
	FIEGARCH	-0.002*	-1*	0.999*	-	-	0.246*	-0.160*	-0.905*

Source – Author's estimation

Asterisk (*) denotes significance at 5%

The above table list the empirical findings of the selected sectoral and thematic indices of the National stock exchange. For each sector the GARCH models - standard GARCH, GJR GARCH, asymmetric power GARCH, and fractionally integrated GARCH are estimated. The best model is chosen from among these based on the information criterion – AIC and Hannan – Quinn (Table B6). Following that, the best fit model to the data is interpreted using the ideal parameters chosen based on their probability values. An asterisk (*) is used to indicate significant parameters that fall outside of the 95 percent confidence interval.

On the basis of the information criterion, the majority of the sectors of the national stock exchange follow the GJR GARCH model – commodities index, consumption index, media index and service sector index. The GJR-GARCH model, incorporates other stylized characteristics in financial time series, such as the clustering of volatility, in addition to leptokurtic returns. If the volatility was high at time (t), it is more likely to be high at time (t-1). The empirically documented feature that negative shocks at time (t–1) have a higher impact on the variance at time (t) than positive shocks is captured by the GJR-GARCH model, which is not considered by the GARCH model. The rise in risk was thought to be caused by higher leverage created by a negative shock, hence this imbalance was dubbed the leverage effect. In all the sectors the leverage term which is the gamma coefficient is statistically significant and positive.

Other sectoral/thematic index such as the private bank, PSU bank, and infrastructure (GJR GARCH) follow the EGARCH/GJR GARCH and the APARCH process. Apart from claiming the clustering of volatility, persistence and leverage effect the APARCH model also incorporates the power parameter. The delta ranges to 1.6 in the infrastructure sector, manufacturing index and pharmaceuticals index follow the APARCH model whose delta parameter range around 0.5 and 1.4, respectively. Finally the financial services sector follows the FIEGARCH model. This not only validates the presence of volatility clustering, volatility persistence, and the leverage effect in the data, but it also states that the data has a lengthy memory process. Theta 2 is statistically significant in all sectors, indicating that index returns have unequal effects of both negative and positive stimuli on conditional variance, whereas theta1, which is also statistically significant, reflects the leverage effect on conditional variance.

Here, the estimation of the following sectoral index – financial services, private bank and service sector are done using the FIEGARCH model under normal distribution because of an estimation error. All the other sectors are estimated using the skewed t distribution for a better analysis.

Conclusion –

Many of the financial operations of today are based on Markowitz’s portfolio selection theory which discusses at length about the risk and return trade off. Variance in return or volatility has piqued the investors curiosity, in recent years, in markets around the world. Thus this chapter empirically investigates the stylized facts of returns distribution of the benchmark indices, sectoral and thematic indices with the help of GARCH family models. The presence of these properties in the indices considered suggest valuable information about the market that can be helpful to the policymakers, portfolio managers, investors, brokers and alike.