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Sector wise stock market volatility estimation

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ABSTRACT: *Price fluctuation is a natural phenomenon of stocks; prices are always changing due to a variety of factors like supply and demand. High levels of liquidity in a large stock market also influence volatility, and this in turn influences stock pricing. Significant swings in stock prices, either up or down, contribute to an increase in stock market volatility. Most investors believe that an increase in variation indicates a greater risk of stock price volatility, and vice versa. There are many reasons why stock prices fluctuate, from macroeconomic factors to changes in the industry or individual stocks. It is common to observe that falls in prices are more volatile than rises in prices, as evidenced by volatility behavior.*

GARCH models, which also handle the problem of volatility clustering (where periods of high returns are followed by periods of low returns), represent the dynamic aspect of volatility.The leverage effect, which argues that volatility is higher in a decreasing market than in a rising one, is another factor they take into account. It has been observed that the distribution of stock return series contains "fat tails," or large fluctuations that happen more frequently than a normal distribution would suggest. These fat tails can be explained with GARCH models.

This study has also developed sector-specific volatility models to predict investment risk. To derive relevant results, the data has been evaluated using a variety of time series models and other statistical techniques. According to the survey, the IT sector is more volatile than other sectors. Estimation becomes more difficult when data variety is great. It is feasible to estimate the sectors that show higher degrees of volatility by using the developed models. The efficacy and applicability of the volatility estimation models are demonstrated by the categorical analysis. The various measured association coefficients also reveal strong correlations between estimated and actual volatility, highlighting the efficacy of the volatility estimation models developed for various sectors. Investment decisions can be made based on the discovered risk once a sector's risk has been evaluated using the suggested estimating models.

KEY WORD*: estimation, GARCH, sector, sensex, stock market, volatility*

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I. Introduction

The volatility of financial instruments has to be studied by academics, decision-makers, and players in the financial market for several reasons. Before measuring risk exposure, economic agents need to be able to predict how volatile the financial markets will be. Second, because a volatile stock market increases uncertainty, which lowers growth expectations, policymakers are quite concerned about it. Recent studies suggest that investors may be deterred from investing if they believe that markets are extremely uncertain. The last effect of stock market volatility is a decrease in consumer expenditure (Garner, 1990).

Volatility can be simply described as a variable's rate of change. Increased volatility increases ambiguity about the value of the underlying asset and, hence, serves as a gauge of risk. Statistical techniques for calculating return dispersion can be applied to financial assets to calculate volatility, whereby larger dispersion is indicative of increased risk and vice versa. It follows that any uncertainty about the future is known to cause a significant increase in the underlying's volatility.

The correlation between investment risk and stock market volatility is strong. A stock is said to have low volatility when its price remains stable in spite of erratic market conditions. Conversely, equities that experience significant fluctuations in value during these periods are considered highly volatile. The price stability of large-cap firm stocks is generally achieved by their decreased volatility. For this reason, they are regarded as low-risk investment choices. Large-cap stocks are less volatile and less risky than mid-cap ones. The significant price fluctuations and high volatility of small-cap companies raise the risk for investors.

Additionally, studies have demonstrated that volatility is essentially an unobserved random variable that varies over time. It's also crucial to note that some volatility has a sticky effect, meaning that the underlying instrument's volatility will fluctuate after a period of high volatility. It is necessary to forecast and anticipate future volatility since the variability of returns affects the value of the underlying asset. This volatility forecast aids in successful risk management. As a result, scientists have developed a number of models to precisely predict the anticipated volatility.

1.2 Literature review and research gap

The current literature examines the corpus of information regarding different volatility forecasting models. Brandt and Kinlay (2005) undertook an investigation of a varied range of statistical measures of volatility, ranging from the usual variance meter to less common range-based metrics. This study demonstrates that variables including process drift, sample size and frequency, gap opening, and time-varying volatility impact techniques' efficacy.

In contrast to other methods, this demonstrates that extreme value estimators get best results; yet, even these methods have low performance at ultra high frequencies. The performance of these estimators worsens yet further when other exceptions such as opening gaps and market volatility are introduced. Of all the estimators, not a single one approaches the efficiency levels found in simulated experiments or expected by theory. Another conclusion is that all of the competing estimators perform much better than the classical estimator on every criterion. No model outperforms the benchmark consistently. Observation that researchers tend to choose simpler models—like constant volatility—over more intricate models—like GARCH—is made clear by this.

It shows that extreme value estimators get best results when compared to other methods; yet, even these methods have problems at extremely high frequencies. The performance of these estimators further degrades in the presence of additional exceptions such as opening gaps and market volatility. Not even one estimate Kumar (2006) attempted to investigate the relative accuracy of forecasting models for volatility in Indian markets, particularly the stock and foreign exchange markets. Based on observations made from out-of-sample forecasts and the number of evaluation measures that rank a particular method as superior, it was concluded that EWMA would improve the forecast of volatility within securities market, and that GARCH would attain a similar outcome within the FOREX market. Ajay (2005) compared the results of several unconditional and conditional volatility models in an effort to forecast and measure volatility in the New Delhi markets. He worked with Nifty series daily data from 1999 to 2001.

Since the initial research on volatility by Engle (1982) and Bollerslev (1986), the majority of its properties have been found through the widespread application of GARCH family models in the studies. One of these is the volatility of stock returns, which changes over time. The majority of study was carried out in the mature markets of wealthy countries, however some researchers (Bekaert and Harvey (1997), Mookerjee and Yu (1999), etc.) looked at time-varying volatility in developing economies. Both Lee et al. (2001) and Wei (2002) studied Chinese markets; the former concentrated on daily data, while the latter studied weekly data in greater detail.

Olowe (2009) examined volatility in Nigerian stock markets, whereas Kaur (2004) concentrated on Indian stock markets. Many scholars examined market volatility, but few in developing economies could provide meaningful data.

Aggarwal et al. (1999) found that changes in market return variances, rather than foreign events, were the cause of the increased volatility in stock market volatility in several developing economies when they utilized GARCH models to evaluate the volatility.

Kumar, Mohan, and Pappu (2002) concentrated their research on volatility analysis even as index futures were introduced for the NSE. Speculative behavior among market participants destabilized the volatility in the early phases of index futures inception, leading to a considerably faster movement of accessible market information, as per the GARCH model used to study the volatility changes.

Bandivakar and Ghosh (2003) looked into the spot market volatility of the Sensex and Nifty to promote index futures. They concluded that there had been a considerable decrease in volatility during the research period after applying GARCH type models to daily data collected over a six-year period. Index futures, it was concluded, should be implemented since they increased traders' awareness of current events compared to what would have happened had they relied on older, less clear news. This research study looked at two additional junior indexes in an effort to extrapolate the outcome in favor of index futures.

Deb et al. (2003) examined eight different GARCH family type models—symmetric and asymmetric—based on varying lags for the Indian stock market. The results of the investigation indicated that the ARCH (9,1) model outperformed the GARCH (1,1) model in scenarios involving forecasts for investors that place a higher value on overpredictions than underpredictions.

Raju and Karande (2003) investigated how index futures caused volatility and swings in the Nifty price. To focus on price discovery, they used GARCH models to study co-integration and volatility. Researchers found that the adoption of index futures decreased volatility, price discovery was possible in both the spot and futures markets, and the futures markets respond to equilibrium deviations.

Zhou and Zhou (2005) conducted a study that looked at the volatility of the Chinese stock market both before and after Hong Kong was returned to China. Using a different approach, they chose to run cointegration in numerous Chinese stock markets.

1.3 Objective of study and methodology

The target of current research project is to create a robust and efficient volatility estimation model. Because it is assumed that the values of more volatile equities will be less predictable, they are often riskier than less volatile ones. It is crucial to estimate stock price volatility while minimizing the estimation error since increased stock market volatility raises the risk associated with investments.

GARCH models address the issue of volatility clustering, which occurs when periods of low returns are preceded by periods of high returns. They represent dynamic nature of volatility also. Additionally, they account for leverage effect, which states that volatility is stronger during declining markets than in rising ones. The fat tails—large fluctuations that happen more frequently than a normal distribution would suggest—that are shown in the distribution of stock return series can be taken into account by GARCH models. These GARCH class models are generally formulated as follows:

$$\sigma_t{}^2 = \omega + \sum_{1}^{q} \alpha(r_i - \bar{r})^2 + \sum_{s=1}^{p} \beta_s \, \sigma_{t-s}{}^2$$

Where, ω: constant term, α, β: coefficients of ARCH and GARCH terms respectively

Effective volatility estimates are provided by GARCH models, yet due to the computational complexity, they are not widely used.

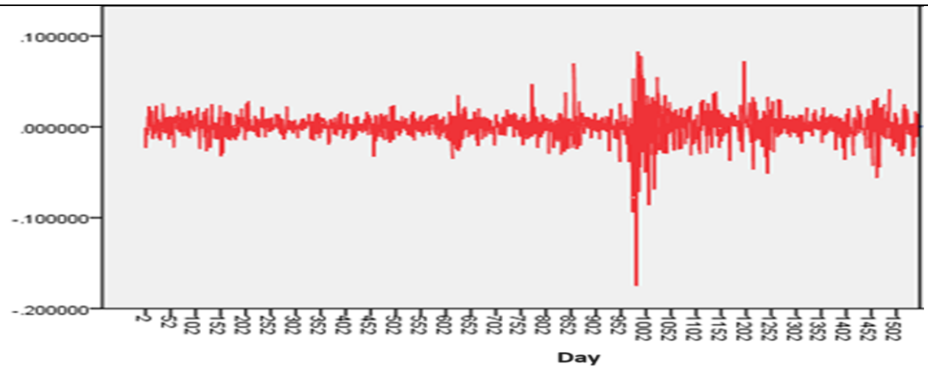
Investors are often more interested in learning the relative level of risk attached to a sector than they are in knowing the absolute magnitude of volatility. In order to evaluate the efficacy of estimating models and allay investor concerns, a categorical variable analysis of volatility is conducted. The full range of estimated and actual volatility is categorized into two groups: high risk and low risk, and the values fall into one of these groups. Next, in order to create the contingency table, the frequencies of each category are calculated. To determine the estimating model's efficiency, the classification accuracy or match % is calculated. To examine the link between actual and estimated volatility, Pearson's Chi-Squared test of independence is performed on the contingent.

The following procedures are used to analyze volatility as a categorical variable.

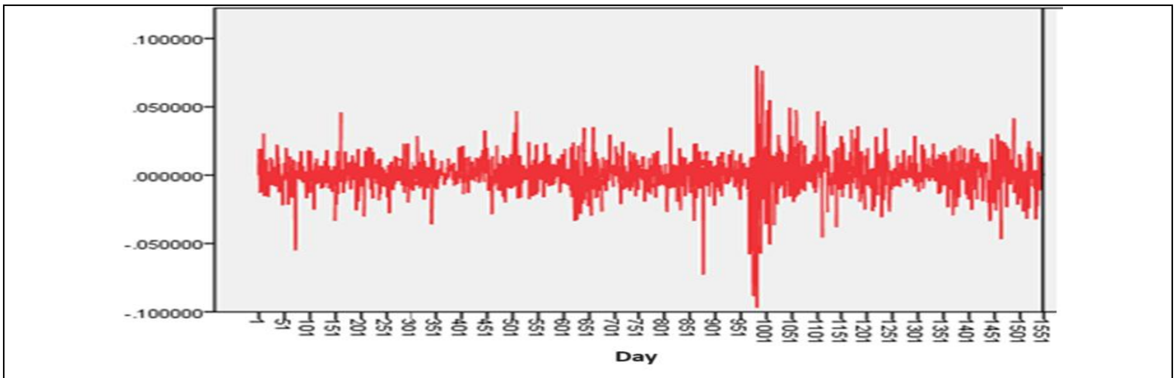
1. For categorical analysis, create a volatility contingency table for each sector.
2. Use contingency tables and the Chi-Squared Test of Independence to examine the relationship between estimated and actual volatility across all sectors.
3. Using the resulting contingency table for each sector, calculate the degree of connection between actual and estimated volatility using Cramer's V, Phi Coefficient and Gamma.
4. Analyze the Cramer's V, Phi Coefficient and Gamma values for each sector to determine how effective the various volatility estimation methods are.

1.4 Data Analysis: Results & Discussion

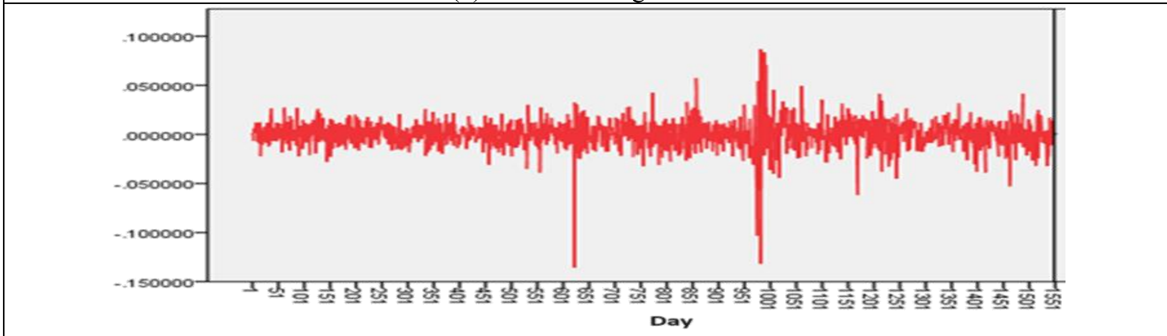
The step-wise test results for all sectors under consideration are shown below in consolidated form. Figure 1.1(a) shows the pattern of log return of Finance sector sensex. Figure 1.1(b) shows the movement of log return of IT sector sensex. Figure 1.1(c) shows the pattern of log return of Oil & Gas sector sensex.



(a) Finance Sector: Log Return



(b) IT Sector: Log Return



(c) Oil & Gas Sector: Log Return

Figure 1.1 Movement of natural log return of sector wise sensex

Table 1.1 shows the result of Augmented Dickey Fuller (ADF) test, Phillips Perron (PP) test and KPSS test. The p-values of ADF and PP test are less than 0.05 for all sectors . The p-values of KPSS test are more than 0.05 for all sectors . Hence, based on the p-value it has been inferred that log return data is stationary for all sectors .

Table 1.1 Stationarity checking results

Sector	Aug. Dickey Fuller Test		Phillips Perron Test		KPSS Test		inference
	Test Statistic	p-value	Test Statistic	p-value	Test Statistic	p-value	
Finance	-9.906922758	3.24E-17	-37.547	<0.001	0.075936255	0.1	Stationary
IT	-10.42345626	1.68E-18	-40.477	<0.001	0.31922772	0.1	Stationary
Oil & Gas	-13.78292186	9.22E-26	-38.835	<0.001	0.104904271	0.1	Stationary

Then AIC is calculated for various ARMA specifications and they are quite close to each other. Then ACF and PACF plots are also drawn to check their pattern. ARMA (1,1) is chosen based on AIC value and pattern of ACF and PACF plots.

Table 1.2 shows values of ARMA model parameters for sectors . It also shows the results of test of independence. The results include values of t statistic and corresponding p values.

Table 1.2 ARMA Model Parameters and Test of Independence results

Sector	Parameter			t statistic			p-value		
	Constant	AR	MA	Constant	AR	MA	Constant	AR	MA
Finance	0	-0.859	-0.898	1.18	-11.057	-13.411	0.238	<0.001	<0.001
IT	0.001	-0.04	0.03	2.112	-0.068	0.006	0.035	0.945	0.995
Oil & Gas	0	-0.982	-0.994	1.098	-94.73	-153.12	0.272	<0.001	<0.001

Table 1.3 shows equation of ARMA (1,1) forecasting model for selected sectors .

Table 1.3 ARMA model summary

Sector	ARMA(1,1) model
Finance	$\hat{r}_t = -0.859\, r_{t-1} + 0.898\, e_{t-1}$
IT	$\hat{r}_t = -0.04\, r_{t-1} - 0.003\, e_{t-1}$

Oil & Gas	$\hat{r}_t = -0.982\, r_{t-1} + 0.994\, e_{t-1}$

Note: ARMA (1,1) has been chosen volatility model by minimizing AIC value.

Table 1.4 shows the result of Engle's Lagrange Multiplier test to check presence of ARCH effect in residuals of ARMA model for selected sectors .

Table 1.4 Engle's Lagrange Multiplier Test results

Sector	Engle's statistic	Significance	Inference
Finance	368.88	3.88e-73	ARCH effect is present
IT	367.48	7.71e-73	ARCH effect is present
Oil & Gas	250.23	4.83e-48	ARCH effect is present

Then AIC is calculated for various GARCH specifications and they are quite close to each other. Then ACF and PACF plots are also drawn to check their pattern. GARCH (1,1) is chosen based on AIC value and pattern of ACF and PACF plots.
Table 1.5 shows the parameters of GARCH model for selected sectors .

Table 1.5 GARCH (1,1) Model Parameters

Sector	Parameter		
	ω	α	β
Finance	4.3492e-06	0.1000	0.8800
IT	3.6436e-06	0.0508	0.9278
Oil & Gas	1.2760e-05	0.1197	0.8122

Table 1.6 shows equation of GARCH (1,1) forecasting model for selected sectors .

Table 1.6 GARCH model summary

Sector	GARCH(1,1) model
Finance	$\hat{\sigma}_t^2 = 0.0000043492 + 0.1\ \varepsilon_{t-1}^2 + 0.88\,\sigma_{t-1}^2$
IT	$\hat{\sigma}_t^2 = 0.000003643 + 0.0508\ \varepsilon_{t-1}^2 + 0.9278\,\sigma_{t-1}^2$
Oil & Gas	$\hat{\sigma}_t^2 = 0.00001276 + 0.1197\ \varepsilon_{t-1}^2 + 0.8122\,\sigma_{t-1}^2$

Note: GARCH (1,1) has been chosen volatility model by minimizing AIC value.
Table 1.7 summarizes equations of ARMA (1,1) and GARCH (1,1) forecasting model for selected sectors .

Table 1.7 Volatility Model Summary

Sector	ARMA model equation	GARCH model equation
Finance	$\hat{r}_t = -0.859\, r_{t-1} + 0.898\, e_{t-1}$	$\hat{\sigma}_t^2 = 0.0000043492 + 0.1\ \varepsilon_{t-1}^2 + 0.88\,\sigma_{t-1}^2$
IT	$\hat{r}_t = -0.04\, r_{t-1} - 0.003\, e_{t-1}$	$\hat{\sigma}_t^2 = 0.000003643 + 0.0508\ \varepsilon_{t-1}^2 + 0.9278\,\sigma_{t-1}^2$
Oil & Gas	$\hat{r}_t = -0.982\, r_{t-1} + 0.994\, e_{t-1}$	$\hat{\sigma}_t^2 = 0.00001276 + 0.1197\ \varepsilon_{t-1}^2 + 0.8122\,\sigma_{t-1}^2$

Table 1.8 shows results of categorical analysis of volatility for Finance sector. It has compared category wise frequency of estimated value with that of actual value to assess the efficiency of the volatility estimation model. The proportion of match indicates the level accuracy of the estimation model. Proportion of match has come as 91% which indicates very high level of model accuracy.

Table 1.8 Finance Sector : Categorical data analysis for volatility estimation

Volatility as Categorical Variable			
Finance Sector	**Estimated Volatility**		
Actual Volatility	**High**	**Low**	**Total**
High	22	9	31
Low	7	149	156
Total	29	158	187
Proportion of Match (%)	91	Cut-off value	0.01480
Proportion of Match (%) at median (actual)	54	Median (actual) value	0.00984
Proportion of Match (%) at	89	Mid-range (actual)	0.01618

mid-range (actual)		value	

Table 1.9 Finance Sector Volatility: Chi Square Test of independence

Chi Square Test: Expected Values			
Finance Sector	**Estimated Volatility**		
Actual Volatility	**High**	**Low**	**Total**
High	4.81	26.19	31
Low	24.19	131.81	156
Total	29	158	187
Ho	Actual and estimated volatility are independent		
Ha	Actual and estimated volatility are dependent		
Chi Square Observed value	87.23	α	0.05
Chi Square Critical value	3.841	df	1
Inference	Reject Null Hypothesis		
	Actual and estimated volatility are dependent		

Table 1.9 shows the result of Chi Square test to check independence between actual and estimated volatility. As the observed value of chi square is more than critical value of chi square, therefore null hypothesis is rejected. Hence, it has been inferred that actual and estimated volatility are dependent.

Table 1.10 shows results of categorical analysis of volatility for IT sector. It has compared category wise frequency of estimated value with that of actual value to assess the efficiency of the volatility estimation model. The proportion of match indicates the level accuracy of the estimation model. Proportion of match has come as 78% which indicates high level of model accuracy.

Table 1.10 IT Sector : Categorical data analysis for volatility estimation

Volatility as Categorical Variable			
IT Sector	**Estimated Volatility**		
Actual Volatility	**High**	**Low**	**Total**
High	42	30	72
Low	12	103	115
Total	54	133	187
Proportion of Match (%)	78	Cut-off value	0.01281
Proportion of Match (%) at median (actual)	56	Median (actual) value	0.01122
Proportion of Match (%) at mid-range (actual)	61	Mid-range (actual) value	0.01292

Table 1.11 shows the result of Chi Square test to check independence between actual and estimated volatility. As the critical value of chi square is less than observed value of chi square, therefore null hypothesis gets rejected. Hence, it has been inferred that actual and estimated volatility are dependent.

Table 1.11 IT Sector Volatility: Chi Square Test of independence

Chi Square Test: Expected Values			
Finance Sector	**Estimated Volatility**		
Actual Volatility	**High**	**Low**	**Total**
High	20.79	51.21	72
Low	33.21	81.79	115
Total	54	133	187
H_0	Actual and estimated volatility are independent		
H_a	Actual and estimated volatility are dependent		

Chi Square Observed value	49.46	α	0.05
Chi Square Critical value	3.841	df	1
Inference	Reject Null Hypothesis		
	Actual and estimated volatility are dependent		

Table 1.12 shows results of categorical analysis of volatility for Oil & Gas sector. It has compared category wise frequency of estimated value with that of actual value to assess the efficiency of the volatility estimation model. The proportion of match indicates the level accuracy of the estimation model. Proportion of match has come as 90% which indicates very high level of model accuracy.

Table 1.12 Oil & Gas Sector : Categorical data analysis for volatility estimation

Volatility as Categorical Variable			
Oil & Gas Sector	**Estimated Volatility**		
Actual Volatility	**High**	**Low**	**Total**
High	19	13	32
Low	6	149	155
Total	25	162	187
Proportion of Match (%)	90	Cut-off value	0.014640030
Proportion of Match (%) at median (actual)	50	Median (actual) value	0.010450351
Proportion of Match (%) at mid-range (actual)	30	Mid-range (actual) value	0.013867003

Table 1.13 Oil & Gas Sector Volatility: Chi Square Test of independence

Chi Square Test : Expected Values			
Finance Sector	**Estimated Volatility**		
Actual Volatility	**High**	**Low**	**Total**
High	4.28	27.72	32
Low	20.72	134.28	155
Total	25	162	187
Ho	Actual and estimated volatility are independent		
Ha	Actual and estimated volatility are dependent		
Chi Square Observed value	70.55	α	0.05
Chi Square Critical value	3.841	df	1
Inference	Reject Null Hypothesis		
	Actual and estimated volatility are dependent		

Table 1.13 shows the result of Chi Square test to check independence between actual and estimated volatility. As the critical value of chi square is less than observed value of chi square, therefore null hypothesis gets rejected. Hence, it has been inferred that actual and estimated volatility are dependent.

Level of association between actual and estimated volatility indicates the efficiency of estimation models. Table 1.14 depicts various measurement of degree of association between actual & estimated volatility for all sectors under consideration. It is observed that Finance sector has the highest value of Cramer's V and Phi coefficient. Similarly, Gamma is maximum for Finance sector. All sectors have strong degree of association between actual and estimated volatility.

Table 1.14 Measurement of degree of association between actual & estimated volatility

Sector	Cramer's V	Phi Coefficient	Gamma	Strength of association
Finance	0.682983621	0.682983621	0.96228674	strong
IT	0.514298007	0.514298007	0.846350832	strong
Oil & Gas	0.61423967	0.61423967	0.946373324	strong

1.5 Conclusion

Volatility is a result of a high level of liquidity in a large stock market, where stock pricing is also influenced by the sector's volatility. Significant sensex swings, whether upwards or downwards, cause an increase in stock market volatility. Most investors associate a rise in volatility with an increase in the risk of sector volatility, and vice versa. As the variability of return causes the change in value of stocks belonging to that sector, it becomes necessary to predict and model the future volatility. This forecast of volatility helps to manage the risks effectively.

IT sector have higher volatility compared to other sectors . Estimation becomes more difficult when the data has high level of fluctuations. The sectors having higher volatility of sectors can be estimated using the developed models. The categorical analysis proves that the volatility estimation models are quite efficient and can be reasonably applied for various cases. The various measured association coefficients also indicate the strong association between actual and estimated volatility, which in turn proves high efficiency of developed volatility estimation models for sectors . The level of risk associated with a sector can be assessed by the investors using the prescribed estimation models and they can take investment decision accordingly based on associated risk level.

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