AN ANALYSIS OF THE EFFECTS OF ALGORITHMIC TRADING ON NATIONAL STOCK EXCHANGE

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Abstract
The Indian securities market has been growing very rapidly with a large amount of capital flowing in from the foreign institutional investors. Algorithmic trading (AT) has also gradually increased in National Stock Exchange (NSE) after the introduction of co-location trading in 2010. More than 50% percent of the trading occurs through AT in India. In this paper, we conduct an analysis of volatility for the pre-AT and the post-AT period of the leading stock indices in NSE by using various methods of volatility calculation. We also provide a compare analysis of the volatility for the pre-AT and post-AT period. Our findings indicate that the volatility has significantly reduced for the post-AT period in comparison to pre-AT period, thus making the markets more efficient. The results were corroborated through primary data collection by conducting focused interviews of people with expertise in algorithmic trading. For further research, data analysis to calculate volatility for the Pre-AT and Post-AT period can be done through more advanced models of GARCH like ARCH (q) model, NGARCH, IGARCH, QGARCH, GARCH-M, QGARCH to get more accurate estimates. Event based studes can also be conducted to analyse the volatility as they significanlty impact the stock markets. Some examples of the events can be elections, war conflicts, trade wars etc.

Keywords: Algorithmic trading, National Stock Exchange, Volatility analysis, GARCH(1,1), EWMA

1. INTRODUCTION

With the advancements in technology, many prominent technologies have emerged with the potential to revolutionize different sectors. Financial sector is no exception. Algorithmic trading(AT) has radically transformed the way in which the orders are executed worldwide. The roots of algorithmic trading dates back to 1983 when HFT based rapid fire computer was developed in USA. Gradually systems with faster processing were developed. Today algorithmic trading accounts for more than 50% trading in the US and European markets. AT was introduced in April 2008 in India and adopted by the National Stock Exchange in mid-2009. Initially, only 10-15 % of orders were executed through Algorithmic trading. After the introduction of co-location trading in January, 2010 in NSE, more than 50-55% are executed using algorithmic trading. Co-location trading places emphasis on setting up a trading platform in the vicinity of servers of the stock exchange to leverage benefits like fast execution, better information transmission which helps them to maximize profits. Prominent companies employing CLT in India are: Barclays, Motilal Oswal Securities, and Goldman Sachs etc.

Algorithmic trading has affected many aspects of the stock market such as price discovery, volatility and adjustment of prices based on the information. Volatility varies with changes in market sentiment, trading volume, order size, government policies and other events. In the research, an analysis was done to understand the impact of volatility for the Pre-AT and Post-AT period.

2. LITERATURE REVIEW

In a study by **Subrahmanyam Avanidhar (2013),** the impact of algorithmic trading on price fluctuations and liquidity in the financial markets is discussed. The Flash Crash which occurred in 2010 in NYSE and how it led to the imposition of stock-specific circuit breakers to mobilize liquidity during price swings is also covered. It also provides an analysis of the impact of circuit breakers on financial markets in the context of algorithmic trading. The findings in the paper are based on real time scenarios encountered in the stock market(NYSE) and experimental analysis on the basis of statistics cited from different papers. The key limitation is the failure to reach a definitive conclusion on whether AT improves liquidity and mitigates price swings. From the findings, it is difficult to conclude whether HFT trading should be regulated or controlled from a policy perspective. The paper provides evidence suggesting improved market quality due to AT. In a study by Chordia, Roll, and Subrahmanyam (2011), it proves that intraday volatility has declined on the NYSE due to AT. It also discusses strategies like quote stuffing Madhavan (2012) used in AT which has impacted the financial markets negatively. It also fails to state with certainty whether circuit breakers hurt or harm financial markets as they are rarely triggered and provides mixed evidence of their impact.

In a study by **Mohammad Shameem Jawed et al. (2018),** analysis of the efficiency of the Indian stock indices by measuring the speed of information adjustment (Marisetty, 2003) and change of persistence of information before and after the introduction of Co-Location Trading (CLT) which led to increased intensity in Algorithmic Trading has been conducted. The analysis was done using daily price volume data for period between 6-18 months before and after the introduction of Co-Location Trading facilities on the key indices of Indian Stock market - NSE and BSE by covering small cap, mid cap, large cap segment. The analysis of the speed and persistence of information adjustment in both the Indices was conducted through an event study approach using GARCH Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH (1,1)) model (Antoniou and Holmes, 1995). The results suggest that the speed of information adjustment into the prices increased for NSE Indices while the persistence of older information decreased after introduction of CLT. Midcap and Small cap indices showed a higher degree of improvement. The BSE indices witnessed a mixed result.

Hao Zhou et al. (2018) did a comprehensive analysis of the market environment on computerized trading in the Asia Pacific region has been conducted. Various market and regulatory characteristics that affect computerized trading were identified. Further, an analysis of on the accelerators and decelerators in computerized trading development was conducted.

Finally, the empirical studies on computerized trading were reviewed and compared with the latest theoretical and empirical studies worldwide. The paper lacked research from a statistical viewpoint. Various areas for future research were also proposed which includes the determination of optimal market design in the new trading environment. More research is needed on granular measures of HFT and its microstructure effects.

Terrence Hendershot et al. (2011) performed an analysis of whether AT improves market quality has been performed. The quote dissemination was automated in 2003 on the New York Stock Exchange. The change in market structure that led to an increase in AT is considered as an exogenous event to measure the causal effect of AT on liquidity. To analyse the effects of AT on market quality, an empirical analysis of the relation between AT and liquidity has been conducted by using a normalized measure of NYSE electronic message traffic as a proxy for AT. Further various measures of liquidity have been discussed using an instrumental variables approach. An analysis of NYSE's introduction of Autoquote in 2003 has also been conducted. It further provides sources of liquidity improvement and studies AT's relation to price discovery via trading and quote updating. Time-series data of a sample of NYSE stocks from 2001-2005 has been considered as after the period NYSE went substantial market structure changes. The data for those stocks that were present throughout the 5-year period were considered which could have induced survivorship bias as it could overestimate time-series estimates of liquidity. After analysis, it was concluded that AT narrows spreads, reduces adverse selection, and reduces trade-related price discovery.

Litzenberger Robert et al., discussed the structure of pre-electronic markets. Further, the characteristics of HFT are contrasted with pre-electronic markets. The proprietary datasets provided by NASDAQ & NYSE were analysed in order to identify algorithmic trading activities. Various evidence of improvement of market quality by using proprietary datasets of closing has been provided which includes narrowing bid-ask spreads, increasing liquidity, and reducing transitory price error and intraday volatility. After analysing the data beginning from 2006, it can be concluded that the improvement in market quality for NYSE-listed stocks was greater compared to NASDAQ which can be attributed to causal links between staggered market structure changes and market quality. Majority of the conclusions on the U.S. equity market due to HFT has relied heavily on limited samples of proprietary data provided by NYSE & NASDAQ which could have positively biased conclusions towards HFT.

Hendershott Terrence et al., studied the role of algorithmic traders on liquidity. If monitoring of algorithmic trading is not proper then it increases liquidity risk. The technological progress referring to algorithmic trading has helped in reducing the errors in the monitoring which can improve efficiency. The study aims at analysing that the decrease in monitoring cost can affect market liquidity and generate profitable trade. Lowering monitoring costs for AT will enable them to react quickly to liquidity supply and demand. ATs have a very broad scope as they help enable traders to react quickly. It reduces the friction associated with monitoring and thereby help the investors to increase their profits. In the order-driven electronic limit order book system called Xetra, orders are matched using price –time display priority. With Xetra having a dominant position, the competition authorities require the approval of all fee changes prior to implementation. The system is designed according to the specifications of the European and German regulators. So, it is quite possible that this system may not prove effective when implemented in other markets as the regulations vary from market to market. ATs monitor the market very closely and enable us to react to change in market conditions swiftly. The trading friction is reduced by AT and it also helps in finding a counterparty. The increment in ATs has effects on both regulators and trading platform designers. ATs features which are incorporated into the market mechanism can reduce infrastructure costs for investors.

3. OBJECTIVES

The objectives of this study are as follows:

1. To study the impact of algorithmic trading on volatility by taking trading date, volume and closing price as its parameters for the pre-AT period and provide a comparative analysis for different periods.
2. To study the impact of algorithmic trading on volatility by taking trading date, volume and closing price as its parameters for the post-AT period and provide a comparative analysis for different periods.

4. DATA AND CHOICES OF INDICES

NSE is one of the most prominent stock exchange among the developing countries in term of technological superiority and the trades handled by it. So, our volatility analysis will be limited to NSE and its indices. Following are the indices for which we will perform volatility analysis: NIFTY 50 , NIFTY Next 50 , NIFTY 500 .

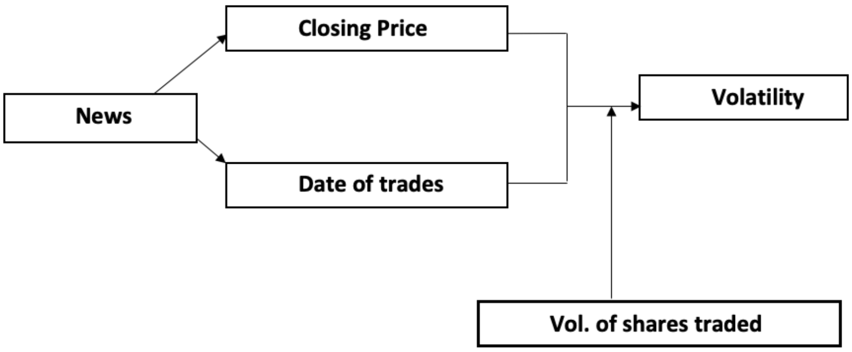
AT was introduced in 2009 in NSE. The data for analysis to be considered will be before and after introduction of AT. Our analysis will be in multiple block of 6, 12, 18, 24 calendar months before and after the introduction of AT. For the pre-AT period, the data for the period from 2007-2008 will be excluded due to sub-prime crisis. For the post-AT period, data for the period from 2009-2010 will be excluded as many regulatory changes were made during the first year of introduction of AT and co-location trading was also introduced during the same period. So for the pre-AT period the data set of the closing price for the mentioned indices will be for the period from 2005-2006 and for the post-AT period, the data set will be for the period from 2011-2012. The above-mentioned indices are chosen because NIFTY 50, NIFTY Next 50 contains the largest stocks on basis of the free float market capitalization. NIFTY500 represents the top 500 companies based on full market capitalization and represent about 87% of total trading of NSE occurs on it. Majority of the algorithmic trading happens on these indices.

Indices like NIFTY Small cap 50, NIFTY Midcap 150 were not considered because they were established on 1st April 2005 which doesn't meet our time period criteria and no volume data is available for these indices. Also, they are considered to be very risky and very less algorithmic trading occurs on these indices.

For primary data analysis, focused interviews were conducted with people having expertise in equity markets, algorithmic trading and investment banking.

5. THEORETICAL FRAMEWORK

Following are the variables under consideration:
Independent variables: Closing price, date
Dependent variables: Volatility
Intervening variable: News
Moderating variable: Volume



6. HYPOTHESIS

AT was introduced in Indian capital markets with the aim of improving the market efficiency. So, we conducted a comparative analysis of the volatility for the pre-AT and post-AT period. Thus, we proposed the following hypothesis to test the same:

H_0: The volatility has not significantly reduced after the introduction of algorithmic trading in National Stock Exchange considering external news as intervening variable and vol. of shares traded as moderating variable.
Ha: The volatility has significantly reduced after the introduction of algorithmic trading in National Stock Exchange considering news as intervening variable and vol. of shares traded as moderating variable.

7. VOLATILITY ESTIMATION METHODS

There are two primary ways to calculate volatility:

1. Historical Methods
2. Implied Methods

7.1 Historical method:

It considers past as a prologue and assumes that past is predictive and hence computes the future volatility.

7.2 Implied method:
It relies on the market data and ignores the historical data, it presumes that market is the ultimate measure and prices are the parameters to estimate volatility.
Our research is based on historical volatility and for there are three primary methods for the calculation of historical volatility Basic Volatility Method , EWMA (Exponentially Weighted Moving Average) , GARCH (1,1) analysis

7.2.1 Basic Volatility Method

1. For computing the periodic returns, we take the natural logarithm of today's price divided by yesterday's price and then computed value is squared.

$$u_i = \ln\left(\frac{S_i}{S_{i-1}}\right)$$

2. Compute the variance of the observations:

$$\text{variance} = \sigma_n^2 = \frac{1}{m}\sum_{i=1}^{m} u_{n-i}^2$$

   Here m: no of days in consideration for volatility calculation
3. Compute the standard deviation by taking the square root of variance
4. Annualize it by multiplying it with square root of 252 (as it represents number of working days in stock exchange)

7.2.2 EWMA (Exponentially Weighted Moving Average)

EWMA improves on simple method by assigning weight to the observations, i.e. the recent observations have more weight than the previous ones. It introduces a smoothing parameter 'λ' lambda which must be less than one.
Steps:
1. Assign weight to each observation (the return computed in previous method). The weight assigned to nth observation is given by: **$\lambda^* \lambda_n$.**
2. Compute the product of squared return and the weight. The square return was calculated in the simple method.
3. Now we use a recursive function for the calculation of variance such that today's variance is a function of yesterday's variance and so on. The function is given by:

$$\sigma_n^2(\text{ewma}) = \lambda\sigma_{n-1}^2 + (1-\lambda)u_{n-1}^2$$

4. The standard deviation is calculated by taking the root and further the value is annualized which represents the volatility using EMWA.

7.2.3 GARCH (1,1): Generalized Autoregressive Conditional Heteroscedasticity

GARCH analysis model adds another component, the long run variance. Long run variance is the average of daily variances.
Following is the weight assigned to each factor for computation of volatility using GARCH:

- **γ** to long run average variance
- **α** to squared return of previous day
- **β** to variance of previous day

Sum of all the weights, i.e. γ, α, β should be equal to 1.
The equation of the GARCH model to calculate volatility is as follows:

$$\sigma_n^2 = \gamma V_L + \alpha u_{n-1}^2 + \beta \sigma_{n-1}^2$$

We use a recursive function for the calculation of variance such that today's variance is a function of long run variance, yesterday's variance, and yesterday's squared return.
Further, the standard deviation is calculated by taking the root and the value is annualized which represents the volatility using GARCH.

8. FINDINGS & DISCUSSIONS

8.1 PRIMARY DATA COLLECTION RESULTS

We conducted several focused interviews with people having expertise in investment banking, algorithmic trading, equities market. The nature of the questions which we asked them was open-ended so that we can understand their views on volatility, volume of the orders in algorithmic trading, impact on arbitrage opportunities, bid-ask spread of stocks after the introduction of algorithmic trading. Following are the key insights from the interviews:

1. After the introduction of algorithmic trading in 2009, the volatility of the Indian Stock market has significantly decreased making it more efficient.
2. Volatility in the stock market depends on a number of factors like volume, news, events, price, etc. A huge amount of fluctuation occurs during events like elections or wars.
3. Volatility pre-dominantly impacts the institutional, long-term investors rather than the retail, short-terms investors.
4. After the introduction of algorithmic trading, the speed of information adjustment in the stock market has improved a lot. This has led to more intensive data analysis by the investors which has led to a significant reduction in arbitrage opportunities, making the markets more efficient.
5. The bid-ask spread has reduced in comparison to the pre-AT period but it can't be solely attributed to algorithmic trading.

6. Individual traders in India haven't adopted algorithmic trading on a large scale as they don't have capital adequacy for it. Institutional investors, large firms have widely adapted algorithmic trading in India due to capital availability.
7. The ability to exploit profit opportunities primarily depends on the quality of the algorithm.
8. Algorithmic trading will be widely adopted in the coming years and will be an integral part of the overall trading due to many factors like co-location trading, it's rapidity in exploring the arbitrage opportunities, efficient order execution, the absence of emotional factor and many other reasons.

8.2 SECONDARY DATA ANALYSIS RESULTS

Following are the key aspects for data analysis:

Indices	**Time Period**	**Tools for analysis**
	Pre-AT: 2005-2006	
1. NIFTY 50 **2.** NIFTY NEXT 50 **3.** NSE 500	**Post-AT**: 2011-2012 Time period broken down into 6, 12, 12, 24 months for analysis	1. GARCH(1,1) 2. EMWA 3. Basic Volatility Estimation

The mentioned indices were choosen because majority of the algorthimic trading in NSE occurs in them. There is very less amount of algorithmic trading in indices like NIFTY Midcap 50 etc.

Following are the results of data analysis done using various methods:

Table 1: Summary of analysis: GARCH(1,1)

INDICES	**PERIOD**	**6 months**	**12 months**	**18 months**	**24 months**
Nifty 50	**Pre-AT**	24.94%	24.94%	24.94%	24.94%
	Post-AT	19.60%	19.60%	19.60%	19.60%
Nifty Next 50	**Pre-AT**	29.08%	29.08%	29.08%	29.08%
	Post-AT	19.56%	19.56%	19.56%	19.56%
Nifty 500	**Pre-AT**	24.99%	24.99%	24.99%	24.99%
	Post-AT	19.48%	19.48%	19.48%	19.48%

Referring to table 1 which contains the summary of GARCH (1,1) analysis, following conclusions can be drawn:

1. By analysis of the volatility for the three indices for a period of 6 months, it can be concluded that the volatility has significantly reduced for the post-AT period in comparison to the pre-AT period.
2. GARCH(1,1) assigns more weight to most recent observations. Majority of the weight has been assigned to the observatons of the first 6 months and very less weight has been weight has been assigned to observations after 6 months. So, there is very less variation in volatility values of 6,12, 18, 24 months.

To plot figure 1, GARCH(1,1) volatility for the period of 24 months has been considered for the pre-AT and the post-AT period. Referring to it, it can be analysed that the volatility of post-AT period has significantly reduced in comparison to post-AT period.

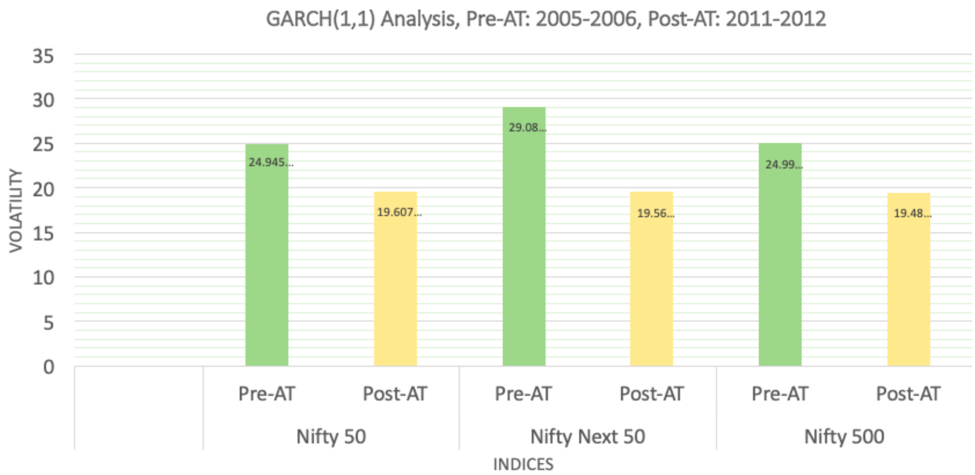


Figure 1: Graphical analysis: GARCH(1,1)

Table 2: Summary of analysis: EMWA

INDICES	PERIOD	6 months	12 months	18 months	24 months
Nifty 50	Pre-AT	31.50%	31.50%	31.50%	31.50%
	Post-AT	22.73%	22.73%	22.73%	22.73%
Nifty Next 50	Pre-AT	37.93%	37.93%	37.93%	37.93%
	Post-AT	22.66%	22.66%	22.66%	22.66%
Nifty 500	Pre-AT	31.57%	31.57%	31.57%	31.57%
	Post-AT	22.51%	22.51%	22.51%	22.51%

Referring to table 2 which contains the summary of EWMA analysis, following conclusions can be drawn:

1. By analysis the volatility using EWMA for the three indices for a period of 6 months, it can be concluded that the volatility has significantly reduced for the post-AT period in comparison to the pre-AT period.
2. EWMA assigns more weight to most recent observations. Majority of the weight has been assigned to the observatons of the first 6 months and very less weight has been weight has been assigned to observations after 6 months. So, there is very less variation in volatility of 6,12, 18, 24 months.

To plot figure 2, EWMA volatility for the period of 24 months has been considered for the pre-AT and the post-AT period. Referring to it, it can be analysed that the volatility of post-AT period has significantly reduced in comparison to post-AT period.

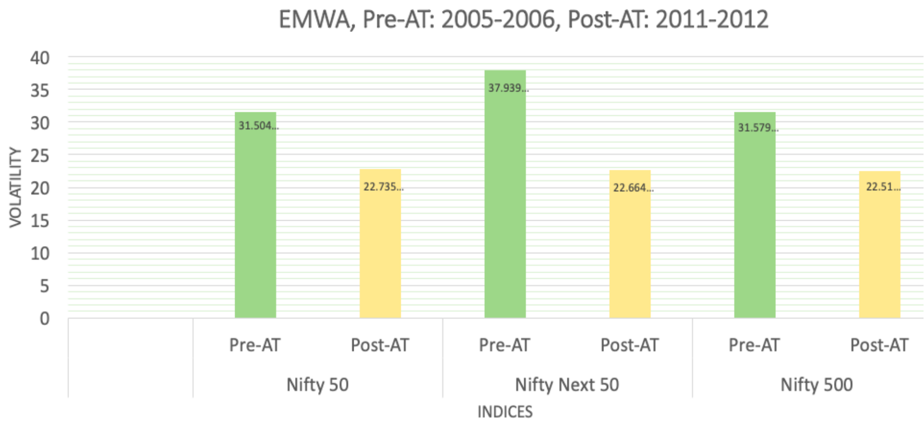


Figure 2: Graphical analysis: EMWA

Table 3: Summary of analysis: Basic Volatility Estimation

INDICES	PERIOD	6 months	12 months	18 months	24 months
Nifty 50	Pre-AT	17.32%	17.89%	23.48%	22.45%
	Post-AT	19.21%	21.11%	20.03%	18.37%
Nifty Next 50	Pre-AT	19.34%	19.76%	27.62%	26.22%
	Post-AT	18.86%	19.37%	19.62%	18.04%
Nifty 500	Pre-AT	16.38%	17.01%	22.90%	21.89%
	Post-AT	18.47%	19.71%	19.02%	17.41%

Referring to table 3 which contains the summary of basic volatility analysis, following conclusions can be drawn:

1. The results of the basic volatility estimation lack consistency to justify that the volatility for post-AT period has reduced in comparison to post-AT period.
2. For the period of 6 months, the volatility for the post-AT period increases in comparison to pre-AT period for all three indices.
3. For the period of 12 months, the volatility decreases for the post-AT period for two indices except NIFTY 500.
4. The results for period of 18 and 24 months are consistent as the volatility has reduced for the post-AT period in comparison to pre-AT for all the three indices.

To plot figure 3, basic volatility for the period of 24 months has been considered for the pre-AT and the post-AT period to remove the inconsistencies of 6 months data. Referring to it, it can be analysed that the volatility of post-AT period has significantly reduced in comparison to pre-AT period.

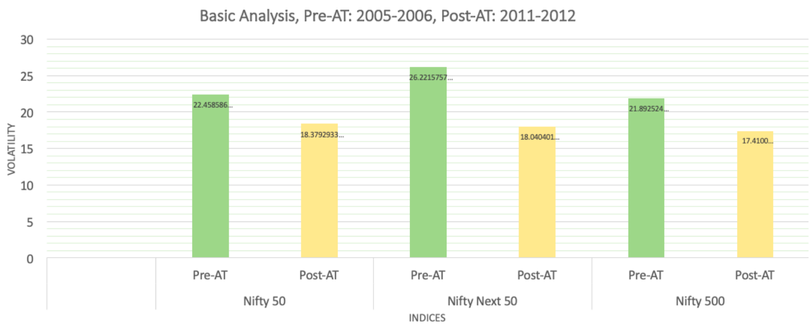


Figure 3: Graphical analysis: Basic Volatility Estimation

Table 4: Graphical Analysis: Volatility Comparison for Pre-AT Period for the Indices

INDICES	GARCH	BASIC	EMWA
Nifty 50	24.94%	22.45%	31.50%
Nifty Next 50	29.08%	26.22%	37.93%
Nifty 500	24.99%	21.89%	31.57%

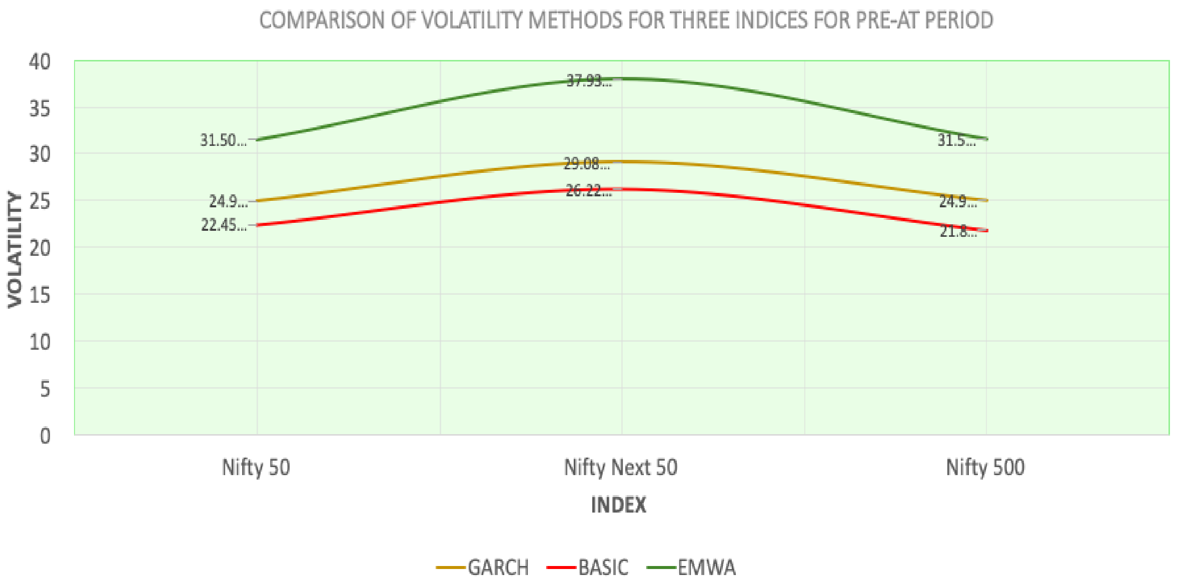


Figure 4: Graphical Analysis: Volatility Comparison for Pre-AT Period for the Indices

Referring to table 4 and figure 4 which contains the volatility comparison for Pre-AT period for the three Indices, following conclusions can be drawn:

1. It can be analysed for each index that the volatility using GARCH(1,1) and basic volatility estimation are closer whereas the EMWA value has largest deviation.
2. Basic method gives the least value of volatility followed GARCH(1,1) and EMWA. The most accurate method of volatility is GARCH(1,1).

Table 5: Graphical Analysis: Volatility comparison for Post-AT period for the indices

INDICES	GARCH	BASIC	EMWA
Nifty 50	19.60%	18.37%	22.73%
Nifty Next 50	19.56%	18.04%	22.66%
Nifty 500	19.48%	17.41%	22.51%

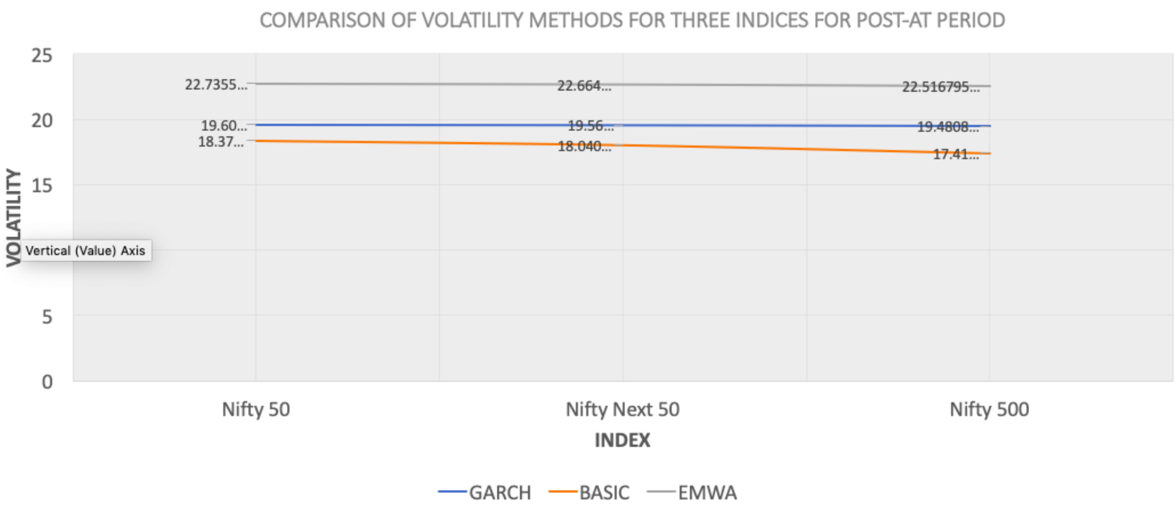


Figure 5: Graphical Analysis: Volatility comparison for Post-AT period for the indices

Referring to table 5 and figure 5 which contains the volatility comparison for Post-AT period for the three Indices, following conclusions can be drawn:

1. It can be analysed for each index that the volatility for all the indices have very less deviation.
2. Basic method is the gives the least value of volatility followed GARCH(1,1) and EMWA. The most accurate method of volatility is GARCH(1,1).

9. CONCLUSION

For estimation of volatility, three main indices of NSE were considered as the stocks included in them are the most liquid and majority of algorithmic trading occurs in those indices. After applying various methods of volatility estimation, it can be concluded that the volatility has significantly reduced for the post-AT period in comparison to pre-AT period, thus making the stock market more efficient. Though, basic volatility estimation method showed some deviation for the time horizon of 6 and 12 months. The results were corroborated through primary data collection by conducting focused interviews of people with expertise in algorithmic trading.

The most efficient method to estimate the volatility is GARCH (1, 1), followed by EMWA and basic method. EMWA analysis assigns weights to the most recent observations and GARCH (1, 1), after considering weights, also considers long run variance as a factor in order to estimate volatility whereas basic method assigns equal weights to each observation.
Through our primary data research, it can be also be concluded that the size of the orders in algorithmic trading is much larger in comparison to traditional trading and the volatility pre-dominantly impacts the institutional, long-term investors rather than the retail, short-terms investors. Majority of the algorithmic trading is done by the institutional investor as the size of the order is very large which requires a significant amount of capital.

The study holds significant importance for algorithmic traders, investors and markets as a whole as it proves that the volatility has reduced after the introduction of AT in the National Stock Exchange Market which it more efficient. As more traders will opt for algorithmic trading, it will further lead to more reduction in the volatility of the stock market and of arbitrageur opportunities, thus improving the market efficiency.

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