

Volatility Analysis in Different Intraday Time Frequencies: An Empirical Investigation

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ABSTRACT

Volatility of Futures market study is one of the most discussed and empirically explored area of stock market research across academicians, researchers and financial analysts. Many researchers have analysed the positive volatility- volume relationship and the effect of decomposed components of volume (number of transactions and average trade size) in different markets on volatility. In this study we investigate the effect of number of transactions and trade size on volatility of S&P CNX Nifty futures index using high frequency data. Three different intraday time frequencies, 1, 15 and 30 minutes have been used for the purpose. The data is sourced from NSE (National Stock Exchange). GARCH model is found to be appropriate to explain the intraday volatility behaviour. The empirical results reveal that number of trades contains more information and has more impact than trade size on volatility and different time frequency are also able to show interesting facts explaining intraday volatility. The study contributes much relevance to the investors and researchers to analyse the volatility behaviour and markets in taking appropriate investment and further research decisions respectively.

Keywords: Intraday Volatility, number of transaction, trade size, High frequency data, GARCH (Generalized AutoRegressive Conditional Heteroskedasticity).

INTRODUCTION:

The rapid development of the advanced trading system and availability of high frequency financial data, the empirical analysis of trading behaviour and the intraday volatility has become a major subject in financial econometrics. It is very important to know about market fluctuations and volatility to minimise the risks and maximise the returns. Therefore, a lot of importance is required to be given to analyse the intraday volatility behaviour to predict the direction of the stock market. Harris (2003) has explained volatility as the tendency for prices to change unexpectedly.

Volatility- volume relationship is one of the most discussed and empirically explored areas of financial research. Volume of trade represents the total quantity of futures contract bought and sold during a trading day, which further also explains the trade size per number of transaction in a particular intraday time. There are many researchers who have empirically explored the strong positive relationship between Volume and volatility in different market and time periods. Karpoff (1987) and Schwert (1989), have investigated that trading volume has positive effect on volatility of the stock market, which means trading volume plays an important role in market behaviour. Further one of the most imperative terms has been introduced to decompose volume into number of transaction and average trade size. Admati and Pfleiderer (1988) has taken this assumption that number of transaction contains more information than trade size of the market because informed traders may divide their large trades into many small size trades. On the other hand Chan and Fong (2000), confirmed that trade size plays vital role in explaining volatility- volume relation than number of trades.

Analysing volatility behaviour using high frequency financial time series data has experienced vast

development over the past several years due to the availability of advanced models and easier access to tick by tick (high frequency) data. Andersen et al. (2003) explained that for both portfolio level and asset level, high frequency data analysis provides more accurate risk assessment. High frequency data analysis is now the need of the hour to provide more robust and appropriate analysis and results. Many authors have used high frequency financial data to analyse volatility behaviour in different foreign exchange markets and index futures market and different intraday time intervals. Daigler (1997), Speight et al. (2000), Song et al. (2005), and Hatrick et al. (2011), analysed the volatility behaviour using high frequency data in 1, 5, 10, 15 and 30 minutes time intervals. The objective of this paper is to empirically gauge the role of number of transaction and trade size in explaining the intraday volatility behaviour of Indian futures market in different intraday time frequencies (1, 15 and 30 minutes). The study includes two aspects, first is to empirically analyse the explanatory power of number of trades and average trade size for return volatility, and second is to analyse the volatility behaviour in different intraday time frequencies (1, 15 and 30 minutes). High frequency (tick by tick) data has been collected from NSE (National Stock exchange) for the period December 2012 to May 2013 of trade size, number of transaction and trade price of S&P CNX Nifty futures index. Futures market is one of the most lucrative markets for volatility study because of the risk hedging and index arbitrage properties. Sometimes current volatility can be influenced by the previous period variance, GARCH – type models are primarily used to capture the effects of previous period's variances.

LITERATURE REVIEW:

Intraday analysis of volatility can be done by different combinations of the determinants of the market. There are several researchers described the foremost determinant to analyse the volatility in an accurate way.

Clark (1973) and Harris (1987) have empirically explained that the volatility-volume relationship by introducing MDH (mixture of distributions hypothesis) model. MDH assumes that return volatility and volume are positively correlated because both are related to the underlying information flow. Karpoff (1987), Chan and Fong (2000) and Yin (2010) have analysed that trading volume is positively correlated with stock return volatility. Volume – volatility relation has been explored by many researchers in different markets and time frequencies.

Jones et al. (1994) decomposed trading volume into number of trades and average trade size. Some research confirms that number of transactions has more explanatory power than trade size, Admati and Pfleiderer (1988) and Foster and Vishwanathan (1990) and Jones et al. (1994) assumed that informed traders may break large trades into smaller trade to make trading strategies, so numbers of transactions carry more information than trade size. Huang and Masulis (2003) explained that for large trades, the number of trades is the only factor which affects volatility. On the other hand Chan and Fong (2006) and Giot et al. (2010) suggest that trade size plays more important role in explaining volatility behaviour than trade size.

High frequency (tick by tick) data plays vital role to understanding and analysing stochastic behaviour of intraday volatility and helps to develop more robust models accurate explanations. Hansen and Lunde (2005) suggested that high frequency data plays a vital role to improve our understanding the stochastic behaviour of the volatility and their relative importance. Song et al. (2005), Hatrick et al. (2011) analysed the intraday volatility behaviour and volatility- volume relationship using high frequency data of volatility determinants; trade size, trade frequency, trade volume and trade prices with intraday time intervals and from different stock exchanges. Futures market is also one of the most lucrative markets to study volatility behaviour. Daigler (1997), and Speight et al. (2000) studies the volatility behaviour of futures market in different intraday time intervals using high frequency data. Alberg et al. (2008) and Shakeel and Srivastava (2017), suggested that GARCH- based models are more appropriate models to analyse volatility behaviour and measuring conditional variance of the stock market.

With all these literature reviews we can say that volume- volatility relationship with trade size and number of trades has been one of the most crucial aspects of the stock market study using high frequency data.

HYPOTHESIS OF THE STUDY:

H₀: There is no significant impact of trade Size and number of trades on price volatility.

H₀: There is no significant change in the volatility behaviour in different intraday time Frequencies.

RESEARCH METHODOLOGY:

Data:

The study includes 1, 15, and 30 minutes High frequency data of trade size, number of transaction and trade price for the period of December 2012 to May 2013. The study is conducted on S&P CNX Nifty futures index for the near month contract, as heavy trading is observed in this contract. S&P CNX Nifty futures contracts have a maximum of 3-month trading cycle - the near month (one, Latest expiry), the next month (two) and the far month (three). A new contract is introduced on the trading day following the expiry of the near month contract. The new contract will be introduced for three-month duration. The data was sourced from NSE. National stock exchange (NSE) NSE is a pure order driven market without any market maker, main motive of NSE is to bring transparency in the market for the investors. Trading is conducted on weekdays from Monday to Friday between 09:15 am to 03:30 pm. The total observations for one minute data is 45839, 3146 for fifteen minutes and 1675 for 30 minutes time intervals.

Data Characteristics:

Stock market is the one of the key source of high frequency data; these markets generate millions of data per day. High frequency data means tick by tick data. Schmid (2009) explained the increasing demand of high frequency data and how to clean and transform raw data to useful data. Whenever we receive data from any source, they provide raw data including all the information of the market. When we start analysis of any research the prime focus should be on the quality and appropriateness of the data if the available data is not fitting to the current research objectives, it is very important to clean and manipulate the data as per the requirements without changing the basic characteristics of the data. We have extracted trading price, number of trades and trade size data from the raw data for one, fifteen and thirty minute's time intervals. Further, with the help of trading price returns series has been generated. Following is the graphical representation of the return series for 1, 15 and 30 minutes time frequencies. Figure 1 does not reflect any patterns in the intraday returns and may look like a standard white noise process.

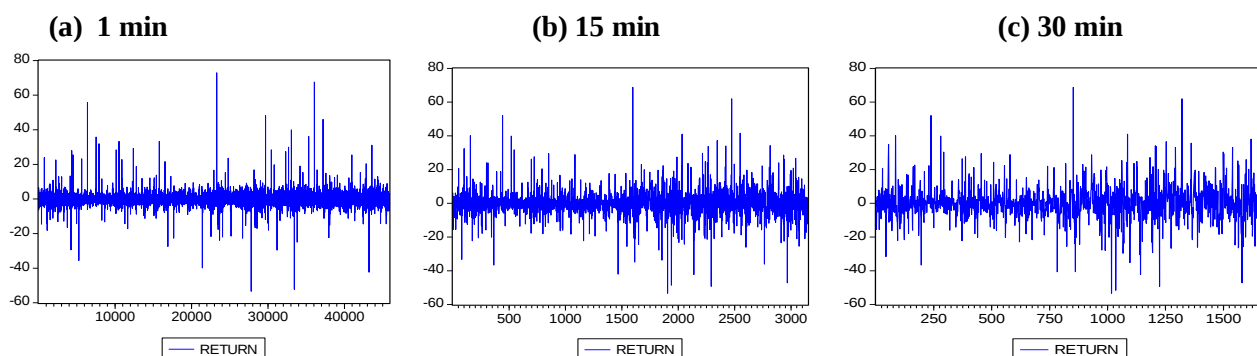


Figure 1: a, b and c represents 1, 15 and 30 minutes intraday returns respectively

The Model:

Bollerslev (1986) developed the GARCH model by allowing the conditional variance to be a function of prior period's squared errors and its past conditional variances. GARCH term is used to describe an approach to estimate volatility in financial markets. GARCH estimation involves three steps, first is to estimate a best fitting autoregressive model, second is to compute autocorrelation of the error term and third is to test for significance.

$$\text{Mean Equation: } y_t = x_t \lambda + \varepsilon_t \quad (1)$$

$$\text{Variance Equation: } \sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \quad (2)$$

The mean equation given in (1) is written as a function of exogenous variables with an error- term.

Since σ_t^2 is the one- period ahead forecast variance based on past information, it is called the conditional variance. The conditional variance equation specified in (2) is a function of three terms. α_0 is the mean, ε_{t-1}^2 represents News about volatility from the previous period, measured as the lag of the squared residual from the mean equation (the ARCH term), σ_{t-1}^2 is the last period's forecast variance (the GARCH term). As volatility is not directly observable, hence fluctuation in the index returns is used as a proxy for volatility.

In this study volume has been used in two ways; volume as number of trades and the volume as the trade size. Number of trades (NT) implies the number of transactions that occurred in a specific time frequency, while the trade size (TS) implies the number of shares traded in that time frequency. The following regression model have been used to estimate the relationship between volatility, number of trades, trade size for 1, 15 and 30 minutes

time frequencies.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 + \alpha_3 NT_{it} + \alpha_4 TS_{it} \quad (3)$$

The above regression equation has been used to analyze the impact of NT and TS on Volatility. This equation is used for all three time frequencies 1, 15 and 30 minutes. Table 3 (A) shows the results of 1 minute time frequency, Table 3 (B) represents the result of 15 minutes time frequency and table 3 (C) shows the results of 30 minutes time frequency.

DESCRIPTIVE STATISTICS:

Descriptive statistics tells about the distribution of each variable. Figure 2 (A, B and C) reports the summary statistics of the variables of the study for 1, 15 and 30 minutes time frequencies respectively. Standard deviation is the dispersion of the values from its mean; in this case we can see the positive deviation for all the variables of all the time frequencies although in case if 15 and 30 minutes, returns are showing less deviation than others. Skewness measures the degree of asymmetry around its mean; a distribution is skewed any time the median differs from its mean, all the variables are positively skewed in 1 minute case means values of the distribution are at the lower end on the other hand all the variables except returns in 15 and 30 minutes are negatively skewed, which means all the values in the distribution are at the higher end. Kurtosis is the shape of the distribution; it refers to the peakedness or flatness of a frequency distribution as compared to normal distribution. In figure (A, B and C) all the variables are showing leptokurtic (>3) distribution, all the values concentrated around the mean and thicker tails, explains high probability for extreme values. Jarque- Bera statistics tests whether the coefficient of skewness and kurtosis are jointly zero. In all the cases hypothesis of normality is rejected.

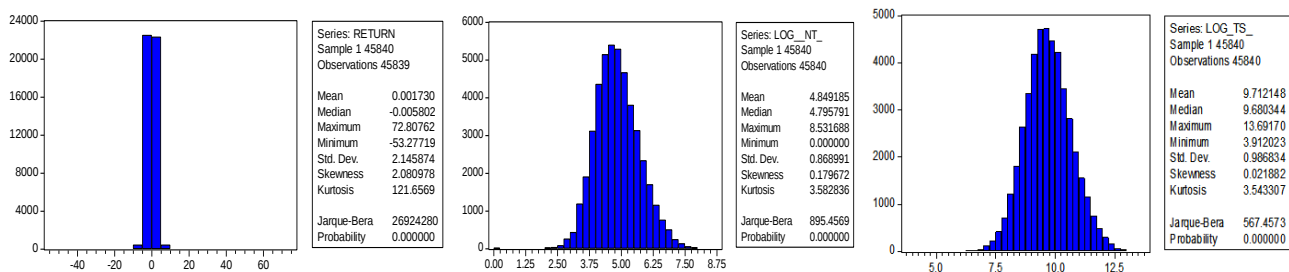


Figure2 (A): Summary statistics with Histogram of the variables Returns, NT and TS for 1 minute time frequency

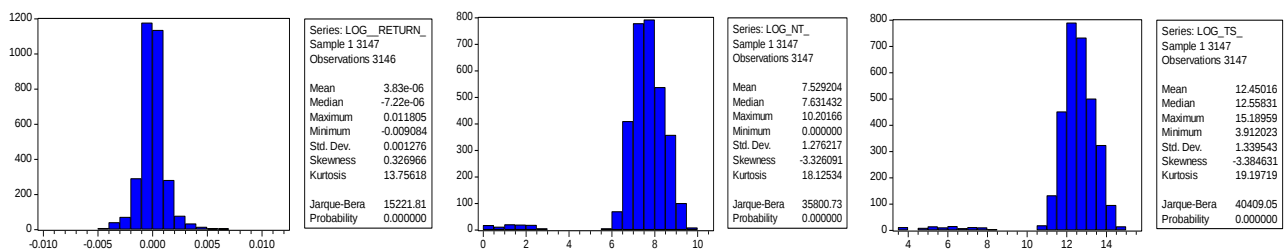


Figure2 (B): Summary statistics with Histogram of the variables Returns, NT and TS for 15 minute time frequency

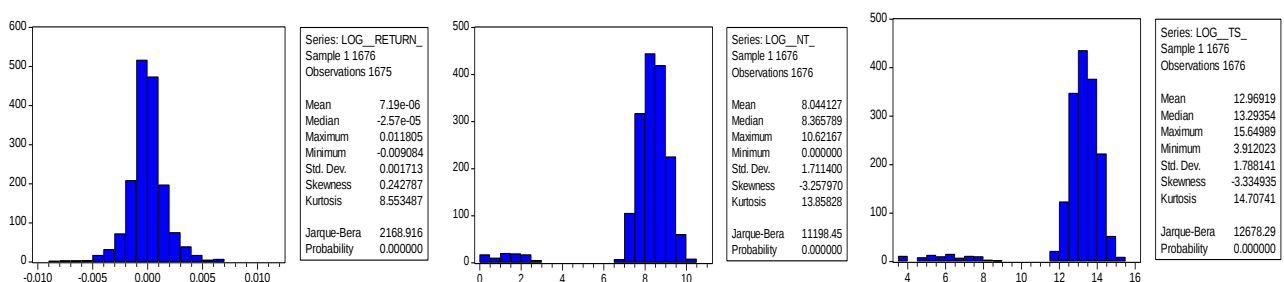


Figure2 (C): Summary statistics with Histogram of the variables Returns, NT and TS for 30 minute time frequency

Test for Stationarity:

The foundation of time series analysis is Stationarity of the data. A series is called stationary if its mean, variance and autocorrelation structure do not change over time and shows no periodic fluctuations. If the series is not stationary, it is required to transform into stationary series. Augmented Dicker- Fuller (ADF) test is used to check the unit root in a time series data. If the estimated ADF test statistics value is more than ADF critical values, explains that there is unit root in the series and the series is not stationary. But if the estimated ADF test statistics value is less than ADF critical values mean that the series is stationary. Table 1 (A, B and C) represents ADF test for Stationarity of the log values of the Return, NT and TS series for 1, 15 and 30 minutes time frequencies respectively. The ADF test value is less than the critical values at 1%, 5%, and 10% level of significance for all the series (except return series), which means there is no unit root in the series and series are stationary. Although for return series, it is significant at 5% and 10% for both 1 and 5 minutes and for 30 minutes, it is significant at 10% level of significance, which means no unit root for return series as well.

Table 1 (A) 1 Minute: Augmented Dickey Fuller test for Stationarity

	Log_Return	Log_TS	Log_NT
ADF Test Statistics	-2.681	-24.2913	-23.2455
Critical value @ 1% Level	-3.4303	-3.43032	-3.43032
Critical value @ 5% Level	-2.8614	-2.86141	-2.86141
Critical value @ 10% Level	-2.5667	-2.56674	-2.56674
Prob	0.001	0.0000	0.0000

Table 1 (B) 15 Minutes: Augmented Dickey Fuller test for Stationarity

	Log_Return	Log_TS	Log_NT
ADF Test Statistics	-2.76801	-6.381079	-5.888629
Critical value @ 1% Level	-3.43224	-3.432257	-3.432257
Critical value @ 5% Level	-2.86226	-2.862268	-2.862268
Critical value @ 10% Level	-2.5672	-2.567202	-2.567202
Prob	0.005	0.0000	0.0000

Table 1 (C) 30 Minutes: Augmented Dickey Fuller test for Stationarity

	Log_Return	Log_TS	Log_NT
ADF Test Statistics	-2.91838	-7.227062	-6.642449
Critical value @ 1% Level	-3.43406	-3.434083	-3.434083
Critical value @ 5% Level	-2.86306	-2.863076	-2.863076
Critical value @ 10% Level	-2.56763	-2.567635	-2.567635
Prob	0.0405	0.0000	0.0000

Notes: Augmented Dicker- Fuller test has been used to check the Stationarity of all the explanatory variables i.e. Return, Trade size and number of transactions to check the Stationarity of the series. Unit root of trade price is also checked because it is used to create volatility series. For all the variables 28 lags has been used.

FINDING AND DISCUSSION:

As we can see in Table 2 (A) that both ARCH and GARCH terms are statistically significant but the impact of the previous period's volatility GARCH term, is much higher than the impact of the news about volatility from the previous period (ARCH term), however the summation of ARCH and GARCH term ($0.0765 + 0.3699 = 0.4464$) is well below the value of 1, indicating lack of volatility persistence. The explanatory variables NT and TS are statistically significant. Number of trades is positively affecting intraday volatility while trade size has negative impact on the volatility. In this case NT is more able to explain volatility than trade size. There is no first order autocorrelation found in any model as D-W statistics is very close to 2, which means this model is robust and GARCH estimation is successful for this study for all the equations.

Table 2 (A): 1 minute- Number of trades and trade size

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOG_NT	0.00017	1.26E-06	135.912	0.000
LOG_TS	-0.00005	1.12E-06	-44.146	0.000
C	-0.00032	5.64E-06	-56.249	0.000

Variance Equation				
C	0.00000	2.01E-10	178.105	0.000
ARCH (1)	0.07654	0.003279	175.808	0.000
GARCH(-1)	0.36999	0.002591	142.781	0.000
Iteration	64		D-W Stat.	1.562

Notes: The result reported under volatility is estimated by equations (3). We report coefficients, iterations, Durbin- Watson, for all the explanatory variables and probability at the significance of 5%. The results reported are from the 1 minute interval log data of number of trades (NT) and trade size (TS) using GARCH Model. In Table 2 (B) also ARCH and GARCH terms are statistically significant and the previous period's volatility GARCH (1, 1) has more impact on volatility. The summation of ARCH and GARCH term ($0.0178 + 0.1979 = 0.2157$) is below the value of 1, indicating lack of volatility persistence in this case also. The explanatory variables NT and TS are statistically significant. But in 15 minutes time frequency Number of trades is negatively affecting intraday volatility while trade size has positive impact on the volatility. In this case also NT is more able to explain volatility than trade size. There is no first order autocorrelation found in any model as D-W statistics is very close to 2, which means this model is robust and GARCH estimation is successful for this study for all the equations.

Table 2 (B): 15 min - Number of trades and trade size

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOG__NT	-0.00511	0.0000	-17.1046	0.0000
LOG__TS	0.00027	0.0000	8.8913	0.0000
C	0.00053	0.0002	3.3613	0.0008
Variance Equation				
C	0.00000	0.0000	29.5166	0.0000
ARCH (1)	0.01784	0.0353	20.3263	0.0000
GARCH(-1)	0.19792	0.0146	13.5377	0.0000
Iteration	28		D-W Stat.	1.7248

Notes: The result reported under volatility is estimated by equations (3). We report coefficients, iterations, Durbin- Watson, for all the explanatory variables and probability at the significance of 5%. The results reported are from the 15 minutes interval log data of number of trades (NT) and trade size (TS) using GARCH Model. In Table 2 (C) only ARCH term is statistically significant and GARCH term is not significant. This means that only the news about volatility from the previous period (ARCH term) has impact on volatility. The explanatory variables NT and TS are statistically significant. Like 15 minutes time frequency in this case also Number of trades is negatively affecting intraday volatility while trade size has positive impact on the volatility. And NT has more explanatory power than trade size. There is no first order autocorrelation found in any model as D-W statistics is very close to 2, which means this model is robust and GARCH estimation is successful for this study for all the equations. 15 minutes results are more robust than 1 and 30 minutes.

Table 2 (C): 30 min - Number of trades and trade size

Variable	Coefficient	Std. Error	z-Statistic	Prob.
LOG__NT	-0.00066	0.0001	-14.2089	0.0000
LOG__TS	0.00068	0.0001	11.2056	0.0000
C	-0.00179	0.0003	-5.7991	0.0000
Variance Equation				
C	0.00000	0.0000	25.2611	0.0000
ARCH (1)	0.04426	0.0489	13.1870	0.0000
GARCH(-1)	0.11783	0.0141	-1.2648	0.2059
Iteration	29		D-W Stat.	1.5079

Notes: The result reported under volatility is estimated by equations (3). We report coefficients, iterations, Durbin- Watson, for all the explanatory variables and probability at the significance of 5%. The results reported are from the 30 minutes interval log data of number of trades (NT) and trade size (TS) using GARCH Model. There are plenty of researches which confirm the effect of number of transaction and trade size on volatility in

different markets and time frequencies. Admati and Pfleiderer (1988), Foster and Vishwanathan (1990), Jones et al. (1994) and Song et al. (2005) found that number of trades has greater positive effect on volatility than the trade size. But in our case we have found that number of trade has negative impact on volatility and trade size has positive impact in 15 and 30 minutes time frequencies. And NT has more explanatory power than trade size in every intraday time frequencies. As the number of trades increase it creates certainties in the market results less volatile market.

CONCLUSIONS:

The study has attempted to examine the effect of decomposed variables of Volume, number of trades and average trade size on intraday volatility of S&P CNX Nifty futures index for the 1, 15 and 30 minutes time frequencies. High frequency financial time series data has been used for this study, collected from NSE. Many authors have taken high frequency data to give robust results and to offer more realistic explanations of the volatility behaviour of different stock markets. Several studies such as Admati and Pfleiderer (1988) Foster and Vishwanathan (1990), Jones et al. (1994) and Song et al. (2005) explained the effect of trade size and number of transactions on volatility. They found that number of trades has greater positive effect on volatility than the trade size. From the results of GARCH model in this study, it has been found that number of trades contains more information and has more inverse impact than trade size on volatility. As number of trades has negative impact on volatility but trade size increases the volatility of the market. The number of trades shows the intensity of a price movement. Returns are expected to vary at the frequency of trades during the day. GARCH model has found to be appropriate for the study and able to explain that the volatility is affected by its previous own terms.

In the second part of the study, different time frequencies 1, 15 and 30 minutes has been included to gauge whether each time frequency contains same information or it varies with the different time frequencies. All the variables are statistically significant in all the time frequencies. Results explain that 15 minutes time frequencies has shown more prominent results than 1 and 30 minutes time frequencies. It is very important to know about intraday volatility behaviour in different time intervals for the short- term traders to better take the trading decisions.

We can finally add that volatility varies over different intraday time frequencies of the stock market. Number of transaction plays a vital role in describing volatility behaviour of the market. Investor should try to get appropriate information of the market to take efficient order decisions, which are the dominating components of the market, and in which time they can place the order. With this study investors can be able to cognise the behaviour of the market for taking better trading decisions.

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