EXAMINING EFFICIENCY OF NSE MARKET USING HIGH FREQUENCY DATA

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Abstract: Market Efficiency is the base to explain the relationship between information and stock market price. Market efficiency explains the capacity of the stock market to incorporate market information quickly. One of the primary assumptions of the Efficient Market Hypothesis is that investors are rational, but actually, investors are inefficient. Companies generate and frequently disseminate information at the intervals. The financial markets regularly process a variety of new information released at every short interval. With the advent of High-Frequency data, more information can be extracted that is not evident in low-frequency data. In this paper, the authors try to test the efficiency of the Market using ARMA and GARCH techniques and explain its implications.

***IndexTerms* -** Market Efficiency, Volatility, High Frequency data, ARMA and GARCH.

I. INTRODUCTION

Availability of reliable information, equal trade opportunities and operationally efficient markets are essential for the information dissemination in the market. Complete information about the present or potential working of the company is also required. At the same time, not all the market participants can gather information independently. Various reasons for not being able to gather information independently are a) high cost is involved, b)the place of the company's location and c)lack of necessary skills of the market participants (Avadhani 1992). Consequently, the companies generate and frequently disseminate information at the intervals. The financial markets regularly process a variety of new information released at every short interval of five minutes. Further, it takes approximately half an hour to assimilate the information adequately. After that, the market once again starts seeking new information for decision-making (Sivakumar,2010).

This information processing behaviour of financial market generates the volatility in asset prices. Three primary reasons for volatility in asset prices during trading hours are

1) Volatility caused by public information during regular trading hours
2) Volatility caused by informed traders with private information
3) Volatility caused by pricing errors occurring during the trading period (French and Roll,1986).

Prior literature has not been able to capture the intraday return or volatility dynamics through ordinary time series models (Anderson and Bollerslev, 1997). However, the advent of high-speed electronic technology has made high-quality intraday data accessible. Complete transaction book or order book data is now available across the globe. This database is given the name "High-frequency data or Tick by tick data".

High-frequency data have expected to reveal new information that is not evident in lower frequency data. However, interpretation of this data is complex due to irregular temporal spacing, periodic patterns, price discreteness and long-lived dependence (Harju and Hussain, 2018). Tick-by-tick database is expected to reveal limitations related to the efficiency of markets, thereby providing a legal way of making an excess return from trading (Goodhart and Hara, 1997).

High-frequency data set occurs at varying time intervals, as trades do not happen at an equally spaced time interval. Consequently, the presence of the intraday seasonality is observed in the volatility of prices, the volume of trade and the behaviour of spreads (Goodhart and Hara. 1997). Markets microstructure related scholastic studies acknowledged the existence of multiple intraday return patterns (Harris, 1986; Atkins and Dyl,1990; Fabozzi et al., 1995). Observance of any kind of pattern is essential for researchers to test market efficiency repeatedly.

II. RESEARCH METHOD

2.1 Need for the Study

Existing literature on financial markets had mostly used low-frequency data, especially daily data. The problem associated with the daily data is that it consists of an average of the last 30 minutes of the trade. Consequently, it is not suitable to bring out the dynamics of the complete trading session. Furthermore, most of the information that appeared during the day is absorbed before the last 30 minutes of the trade. Therefore, the present study uses high-frequency data.

2.2 Objective of the Study

To test the weak form of efficient market hypothesis using high-frequency data.

2.3 Sample

The sample used for the study is selected stocks Nifty for the period of 1st January 2019-31st December 2019. Five-minute interval data for prices are used.

2.4 Analysis

The weak form of efficiency is defined by the situation when current asset prices reflect all the information enclosed in the past price movement. Hence, future price movement cannot be predicted by examining the past price movement. This also implies that it is not possible to obtain excess returns by studying the historical data of assets prices (Ahmad, Ashraf, & Ahmed, 2006). If the financial market does not follow the weak form of efficiency, it becomes predictable (Bessembinder and Chan,1995). This predictable characteristic of the financial market provides the opportunity for investors or traders to earn abnormal profits. Various scholastic studies found that asset market is least weak-form efficient (Bessembinder and Chan, 1995; Coutts and Cheung, 2001). These studies bring out the success of technical trading strategies that produce abnormal profits to investors. Previous studies related to the weak form of efficiency have mostly used daily data.

However, the problem associated with the daily data is that it is an average of the last 30 minutes of the trade. Subsequently, it is not suitable to bring out the dynamics of the complete trading session. High-quality intraday data is available these days due to advancement in technology. High-frequency data is expected to reveal limitations related to the efficiency of markets, thereby providing a legal way of making an excess return from trading (Goodhart and Hara, 1997). Therefore, the present chapter tries to re-examine the weak form of efficiency of Indian Stock Market using the 1- minute interval intraday return data. This paper follows the methodology pattern of Hartika Arora, 2017, closely.

2.5 Efficient Market Hypothesis

2.5.1 Weak form of efficient market hypothesis:

The market is said to have a weak form of efficiency if the current market prices reveal all the information enclosed in the past price movement. Hence, future prices cannot be forecasted by examining the prices of the past. Thus, technical analysis methodology will not be able to generate surplus returns, although some forms of fundamental analysis might endow with excess returns. The weak form of EMH is supported by various researchers (Basu 1977), while others oppose its existence (Buguk and Brorsen; Malkiel 2003). Emerging electronic technology has made tick size data available to exploit a weak intraday form of efficiency.

2.5.2 Semi strong form of efficient market hypothesis:

The market is said to have a semi-strong form of efficiency if the current price reflects not only the past price but also complete publicly available information. The various studies of the semi-strong form of market efficiency put forward that investors are unable to achieve higher returns from publicly available information and announcements. Semi strong form of the efficient market has been empirically proved through the event-based methodology. With the use of high frequency data, the micro structural and immediate impact of public announcements can be observed.

2.5.3 Strong form of efficient market hypothesis:

In the strong form of an efficient market, all forms of published information, including information that is not yet published is reflected in stock prices. Hence, no one can make abnormal profits from any public and private information. However. The evidence of the strong form of EMH put on a serious doubt upon its existence in the real-world situation (Thaler 1987; Rabin and Thaler 2001).

Therefore, the efficient market hypothesis has the following implications:

1. Stock prices follow a random walk
2. As soon as new information arrives in the stock market, then prices quickly assimilate it.
3. It is impossible to attain higher returns in the stock market.

III. Features of High Frequency Data

Advancements in information technology have made it easy to source high-frequency data for financial markets. Data vendors like Reuters encapsulate all the transaction information occurred from the global market and nourish their customers with the data in real-time. Some data suppliers also provide tools to configure customized data sets. The NYSE (New York Stock Exchange) was the first exchange which made available high-frequency data-sets for every single traded price since the early 1990s. The first study based on high-frequency data from the foreign exchange market was made available by Olsen and Associates Research Group. High-Frequency data in India for capital market and derivative market segment of National Stock Exchange (NSE) is maintained by DotEx International Limited, a 100% subsidiary of NSE. The NSE trading system can make trades at a gap of 1/64th of a second.

High-Frequency data is complicated and unique, as it has the following features:

a) Distinct intraday periodicity;
b) Distinct short-lived volatility dynamics produced from information release;
c) A consistent volatility parameter at the daily frequency; and
d) Noise in the time series due to recording errors.

Time-series properties of high-frequency data can be seriously distorted by a small number of significant shocks. (Goodhart et al., 1993). This creates low-frequency dependence and extreme outliers (Anderson,2000), Engle and Russell (2002) described the various characteristics of the high-frequency data set that include:

3.1 Irregular Temporal Spacing:

High-frequency data is a complete trade book or order book database. Hence, transactions or orders placed in the stock market do not have fixed time stamps. In other words, some transactions may take place within the gap of seconds, some with the gap of a minute apart.

3.2 Discreteness:

A change in the price of a security from trade to trade is called "tick". For heavily traded stocks, it is generally not possible to have a large size of the tick. This discreteness generates a high degree of kurtosis in high-frequency data.

3.3 Diurnal Patterns

Intraday financial data usually contain very strong diurnal or periodic patterns. Most evident diurnal patterns in literature are U-shaped during the trading day.

3.4 Temporal Dependence

Tick-by-tick data strong temporal interdependence. The main cause of this temporal interdependence is the result of price discreteness. A spread between bid prices and ask prices to create auto-correlation. Another major reason for this temporal dependence is that traders usually break large trades into a sequence of small trades in order to get a better average price. Falkenberry (2002) reviewed various issues related to high-frequency data. The major problem associated with the high-frequency data is its size. For example, Microsoft (MSFT) has an average of 90,000 ticks per day, which figures around 22.6 million for a year. Normal small-cap stock trades around 2100 ticks per day, which figures around 530,000 for a year. Therefore, storage of high-frequency data under fields: date, time, price stamps and volumes for each tick requires large space up to several gigabytes. Though there is an issue related to size of the tick-by-tick database, it has a huge scope for market participants.

IV. REVIEW OF LITERATURE

Brown and Easton (1989) used London stock market's low frequency data, used techniques like Runs test, Serial correlation test and found that the market was inefficient. In the year 2000 Milionis & Moschos again studied London stock market but this time using tests like GARCH-M model, Auto correlation function and again found that the London stock market was inefficient.

In the year 2002 Abrosimova et al. studied a different country using Autocorrelation, variance ratio tests, ARIMA, GARCH techniques on Russian Stock market low frequency data and found that Russian stock market was inefficient. Robinson (2005) ran Auto-correlation test, Runs test on Jamaican stock market's low frequency data and found that the market was inefficient.

In the Indian Subcontinent Ahmad Ashraf &Ahmed (2006) ran Auto-correlation Function, GARCH model, non-parametric Kolmogrov-Smirnov test on Indian Stock market and found that there was no existence of efficiency in Indian Stock market. Hameed et al. (2006) studied Pakistan stock market's low frequency data and found that it was inefficient using Auto-correlation, GARCH (1,1) techniques.

Asiri (2008) found Bahrain Stock market as efficient using ARIMA and Exponential smoothing methods. He also used low frequency data only. His finding was quite different from other literature because it showed that market was efficient.

Ntim et al (2011) studied African Stock Market by taking low frequency data from 2000-2007 and conducted Variance-t ratio test based on ranks and signs tests and found that the market was inefficient. Mishra (2011) studied 8 emerging and developed stock markets and found that all were inefficient using Unit root and GARCH (1,1) tests. Gimba (2012), studied Nigerian stock market using low frequency data and found that the market was inefficient. He used techniques like Variance Ratio test, Auto -correlation test, Runs test.

Niarchos &Alexakis (2003) studied high frequency data of Greek Stock Market from June to September 1998 and found that the market was inefficient using ARCH test. Strawinski and Slepaczuk (2008) used Robust Regression on Warsaw Stock Market's High frequency data and found that the stock market was inefficient.

Schulmeister,S (2009) studied US spot and Future Market's High Frequency data from 1983-2007 and concluded that the it was inefficient. Shmilovici.et.al. (2009) studied foreign exchange market from January 2000 to December 2000. By analyzing foreign exchange markets' high frequency data using Universal Variable Order Markov (VOM) test he concluded that it was efficient.

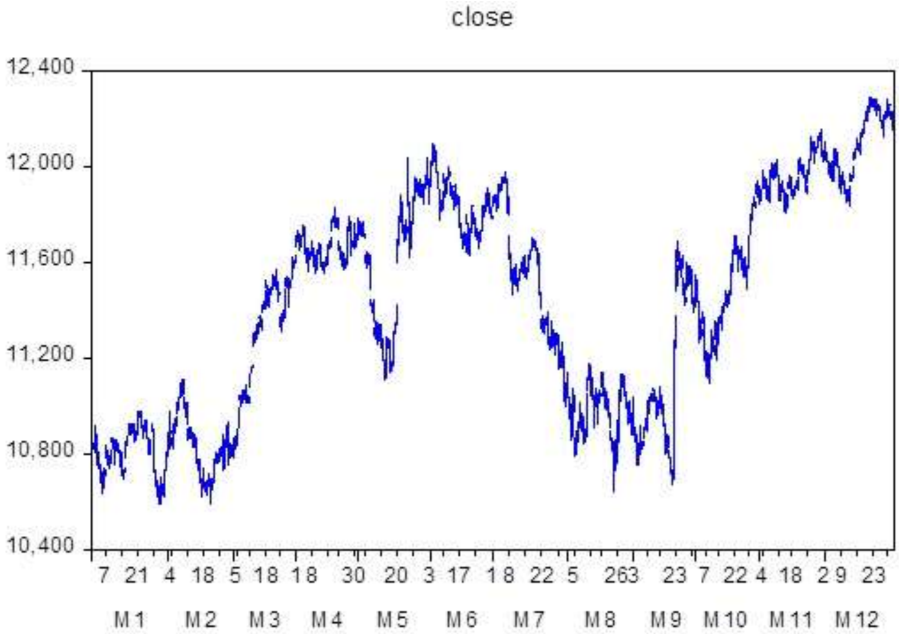
Wang and Yang (2010) studied New York Energy Futures Market's High Frequency data from 2000-2007 and concluded that Heating oil and natural gas futures were inefficient but Crude oil and Gasoline futures were efficient. He used Neural network, semi parametric functional coefficient model, non-parametric kernel regression, GARCH techniques. Reboredo et al (2012) studied US stock market for 5 months from April to August 2006 using Simple Random Walk model, Auto-regressive model, Nonlinear regression model on its high frequency data and found that it was inefficient.

Hartika Arora, 2017 studied National Stock Market (NSE) of India studied its High frequency data and concluded that it was inefficient. She used techniques like ARMA and GARCH.

V. Results and Analysis

In this paper we took 1-minute Nifty index from 1st January 2019 to 31st December 2020. Then in order to visualize the data a graph was plotted.

Figure 1: Plot of NIFTY 50 one-minute data



Since trend with many breaks is found, it can be assumed that the data is non-stationary. Thus, in becomes necessary to check presence of unit root in the data.

5.1 Unit Root Test

To find presence of the unit root, this study has used the Augmented Dickey-Fuller (ADF) test.

Table 1: ADF test on NIFTY 50 one-minute data

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-1.354534	0.6061
Test critical values:	1% level		-3.430253	
	5% level		-2.861381	
	10% level		-2.566726	
Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLOSE(-1)	-4.57E-05	3.37E-05	-1.354534	0.1756
C	0.536347	0.385686	1.390629	0.1643

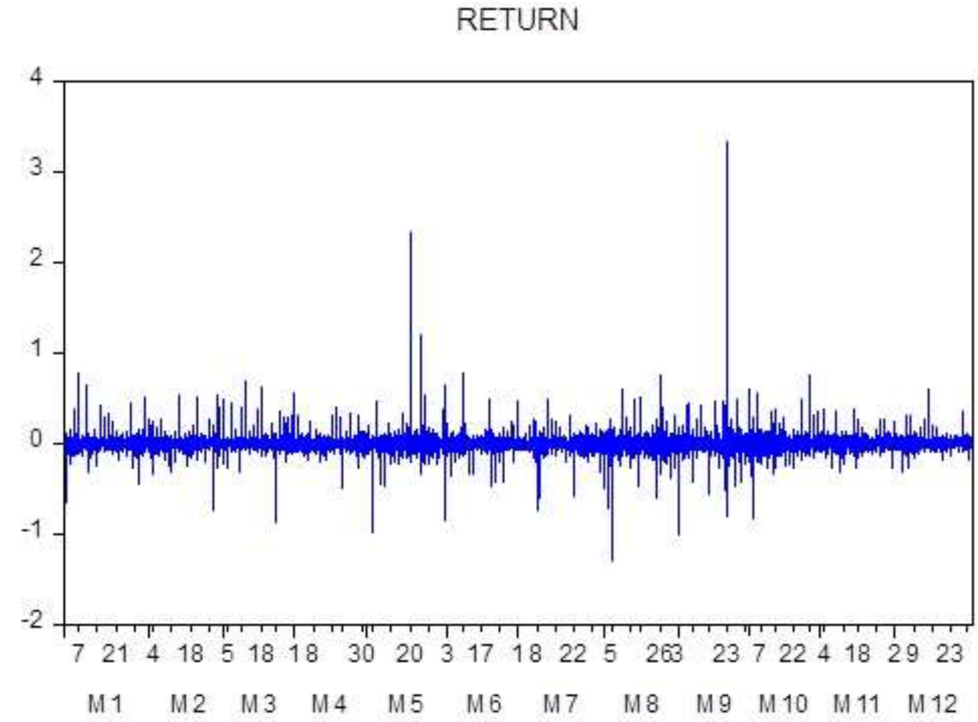
Since the p value is more than 0.05 we fail to reject the null hypothesis "The series has unit root". Hence there is a necessary to transform the series. The returns are calculated as the difference of the logarithmic price ie Return = dlog(close)*100. The new series when plotted show stationarity.

Table 2. Results of Augmented Dickey-Fuller test on transformed data

			t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic			-216.4441	0.0001
Test critical values:	1% level		-3.430253	
	5% level		-2.861381	
	10% level		-2.566726	
Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLOSE(-1)	1.009357	0.004663	-216.4441	0.0000
C	0.014010	0.003305	4.238987	0.0000

Since the p value is more than 0.05 we reject the null hypothesis "The series has unit root".

Figure 2: Plot of transformed return one-minute data

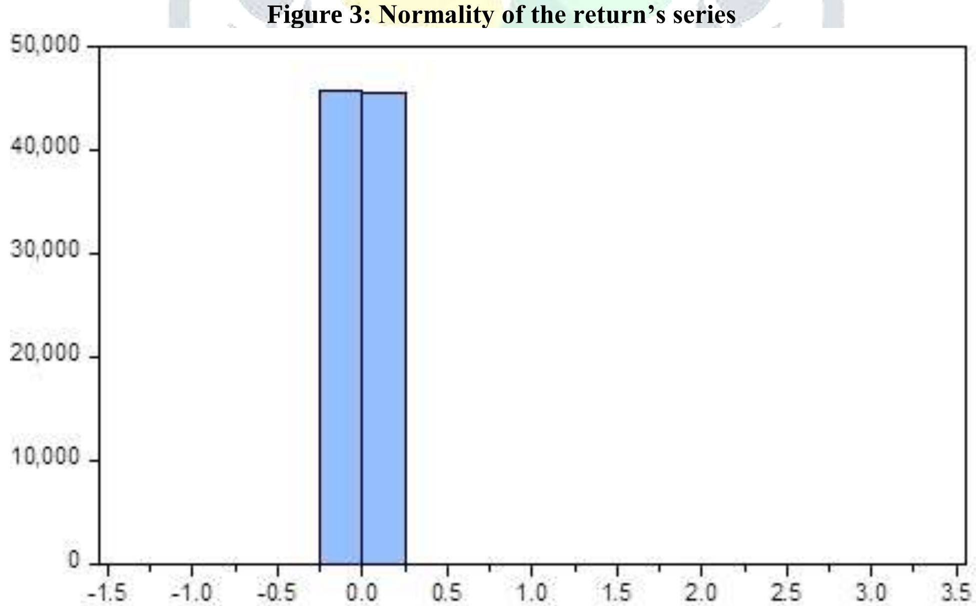


The new series when plotted shows stationarity. Hence the new series is stationary and fit for further analysis

5.2 Descriptive Statistics

Descriptive statistics for the entire sample are computed to study the distribution pattern. Descriptive statistics include analysis of mean, maximum values, minimum values, standard deviation, skewness and kurtosis. Further, normality has been checked by applying the Jarque-bera test. Skewness and kurtosis help to understand the characteristics of the distribution.

Figure 3: Normality of the return's series



From table 3, it is observed that mean returns are positive for the complete sample in the period. Mean returns are negative for Nifty. Standard deviation is a measure of the variability or dispersion of a statistical population. From descriptive statistics, it is observed that return series have a low standard deviation, which depicts that return fluctuations and around its mean (the mean-reverting behavior). The coefficient of the Jarque-bera test is significant at one per cent for the complete sample. It represents that the trading returns are asymmetric and do not have a normal distribution. Leptokurtic distribution (kurtosis>3) of trading returns are observed for Nifty.

Table 3. Descriptive Statistics of selected sample

	Mean	Median	Max	Min	Std.Dev	Skewness	Kurtosis	Jarque-Bera	p-value of Jarque-Bera
Nifty	-4.05e-09	-4.15e-05	3.329353	-1.307392	0.040855	7.731867	665.0658	1.67e+09	0.000*

5.3 Test for presence of the Autocorrelation

Now we regress 'Return' on 'C' check correlogram Q statistic. After checking the ACF and PACF we regress Return on C along with 'ar (1)'. Then we check the presence of ARCH effect in the residuals. We get the results as in Table 4.

Table 4: Results of Heteroskedasticity test

Heteroskedasticity Test: ARCH			
F-statistic	105.4288	Prob. F(2,91523)	0.0000
Obs*R-squared	210.3797	Prob. Chi-Square(2)	0.0000

Yet another essential requirement of time series data is that error terms of this developed autoregressive moving average model for stock returns should exhibit constant variance. If error terms do not exhibit constant variance, they are said to be heteroscedastic. Because the p value is significant in Table 4, we confirm the presence of ARCH effect in the series. It shows that period of high volatility is followed by the period of high volatility and the period of low volatility is followed by their period of low volatility. This suggests that the residuals are conditionally heteroscedastic, can be represented by the ARCH and GARCH model.

5.4 Test for Volatility Clustering Using GARCH (1,1)

GARCH (1,1) is employed to study the nature of the return residuals. From the GARCH model, volatility clustering can be observed. The variance equation of GARCH model depicts the nature of volatility of the return series. This variance equation of GARCH (1,1) has two terms: ARCH and GARCH. The sum of their coefficients depicts persistence in volatility clustering. If the value is very close to one, it indicates high persistence in volatility clustering. Consequently, it represents the inefficiency of the stock market (Hameed et al., 2006). Table 5 shows the sum of ARCH and GARCH coefficient are very close to one for the complete sample used in the present study. Hence high persistence of volatility clusters is observed. Similar volatility clustering was observed in the Indian stock market by Abrosimova et al. (2002) using the daily data.

Table 5. Results of Heteroskedasticity Test (ARCH) effect.

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000568	0.000581	0.977059	0.3285
AR(1)	0.044597	0.018240	2.445046	0.0145
	Variance Equation			
C	0.000851	5.47E-05	15.55869	0.0000
RESID(-1)^2	0.150000	0.013868	10.81599	0.0000
GARCH(-1)	0.599971	0.025450	23.57405	0.0000
Durbin-Watson stat	1.996420			

VI. CONCLUSION

Financial market efficiency is an essential issue for investors, researchers, analysts and regulators of emerging markets like India. Evidence of non-existence of a weak form of efficiency is an imperative signal of predictability, thus making traders earn abnormal profits. Earlier studies investigating the weak form of efficiency have used daily data. However, re-testing the weak form of efficiency using high-frequency data is required to capture the intraday predictability characteristics of the stock market. Hence this study tries to re-examine the weak form of efficiency using high-frequency data. Various statistical techniques are employed, GARCH (1,1) for the return series. GARCH (1,1) model symbolizes high persistence in volatility clustering for the three sub-periods. Hence, it provides evidence for the nonexistence of the weak form of efficiency. The results of this study do not hold by the validity of the weak form of efficiency for stock market returns of Nifty 50. Therefore, this gives an opportunity for traders to forecast future prices and earn abnormal profits. Hence, this study re-confirms the testable implications of financial market predictability for traders and investors.

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