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INTRADAY STOCK MARKET DATA ANALYSIS: BASED ON SIMULATION AND EMPIRICAL STUDIES

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Abstract - The effect of periodic time dependence in interest rate of stock price movement is investigated. The model is based on Black – Schloes SDE time – dependent rate, whole solution is governed by lognormal process. The striking price is modeled as FPT and its behavior is analyzed by carrying out extensive Monte Carlo simulation of SDE. A new phenomenon of damped oscillatory behavior of FTP is predicted.

I. INTRODUCTION

The understanding of the stochastic dynamics of stock price is a challenging problem. During the past decades many sophisticated mathematical and computational techniques have been developed for analyzing financial markets. Many aspects related to this problem cannot be solved analytically and one has to resort to extensive simulation studies. This gave the birth of a new field called as computational finance, which requires development of computational algorithms. The solution of PDE and Monte-Carlo simulation enable us to study different aspects of financial derivatives and analysis of portfolio risks [1-5]. Monte Carlo Method is a simulation technique, which makes use of random numbers. These numbers are independent and identically uniformly distributed. Earlier data was neither helping to predict the price of the stock in future nor explored the dynamics of stock price. Computational finance models attempt to capture the randomness of a stock's price moment in future. In a fixed future time, the change in stock's price is modeled as a random variable having a normal distribution. The standard deviation of the normal variation depends on the time duration as well as the volatility of the market. When the market becomes more volatile then we look further ahead, this mean, the less likely the stock will have a price near the adjusted current price [2].

The Intraday Trend Behavior of Different Stocks

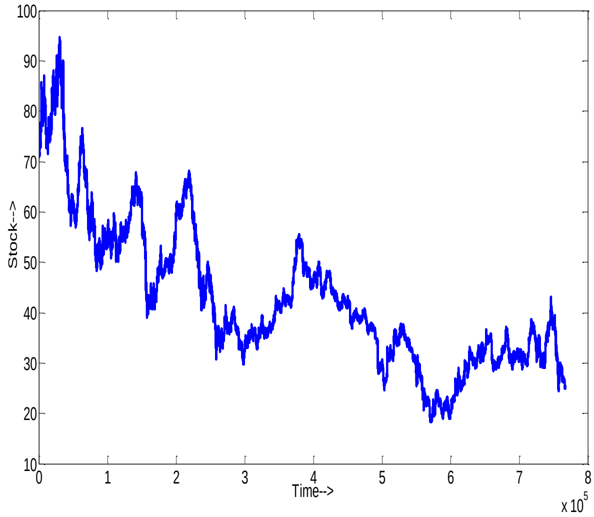

Fig 2.1: Trend behaviour of Intraday stock price of General Motors(GM) of S&P 500 index in minutes from 01/12/2004 to 31/12/2008. (source: www.futurestickdata.com).

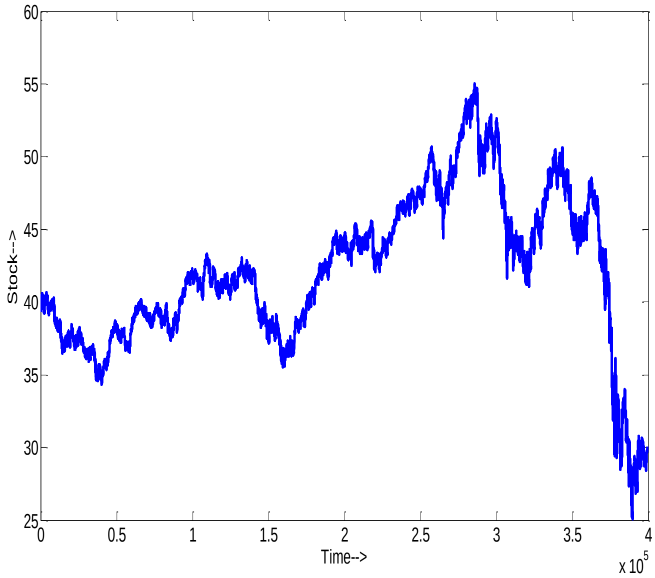

Fig 2.2: Trend behaviour of Intraday stock of Coca – Cola(KO) of NYSE index in minutes from 01/12/2004 to 31/12/2008. (source: www.futurestickdata.com).

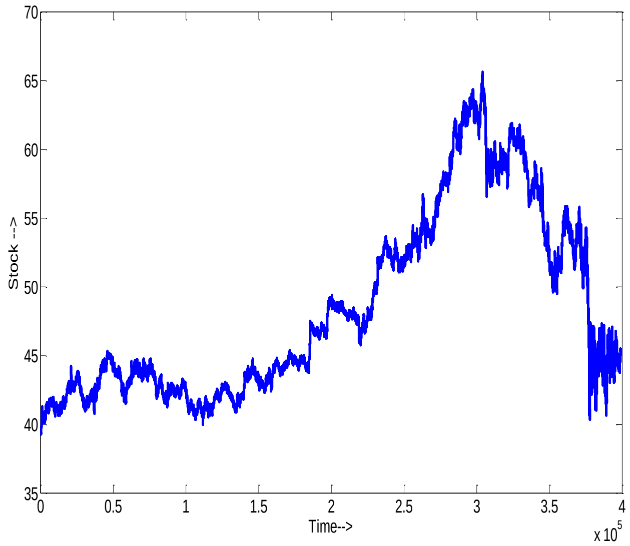

Figure 2.3: Trend behaviour of Intraday stock price of power shares QQQ of NASDAQ 100 index in minutes from 01/13.2004 to 31/12/2008. (source: www.futurestickdata.com).

The Intraday Probability Distribution Stocks

It has been found that the price of stock *S (t)* is Lognormal distributed. So *S(t)* takes value in (0, ∞). The probability density function of S (t) is given by:

$$P(S\,|\,S_0,t)=\frac{e^{-\left(\frac{\log(S/S_0)-(\mu-\sigma^2/2)t}{2\sigma^2 t}\right)^2}}{S\sigma\sqrt{2\pi t}}\text{, for s>0,}$$

Where, μ – mean parameter and σ – volatility (fluctuation about mean parameter)
The expected value, second moment and variance of S (t) are given by:

$$E(S(t)) = S_0\, e^{\mu t}$$
$$E(S(t)^2) = S_0^2\, e^{(2\mu+\sigma 2)t}$$
$$\sigma^2(t) = var(S(t)) = S_0^2\, e^{2\mu t}(e^{\sigma 2t}-1)$$

The estimated parameters and its corresponding standard errors

μ =	4.87023	0.000210841
σ =	0.133275	0.000149087

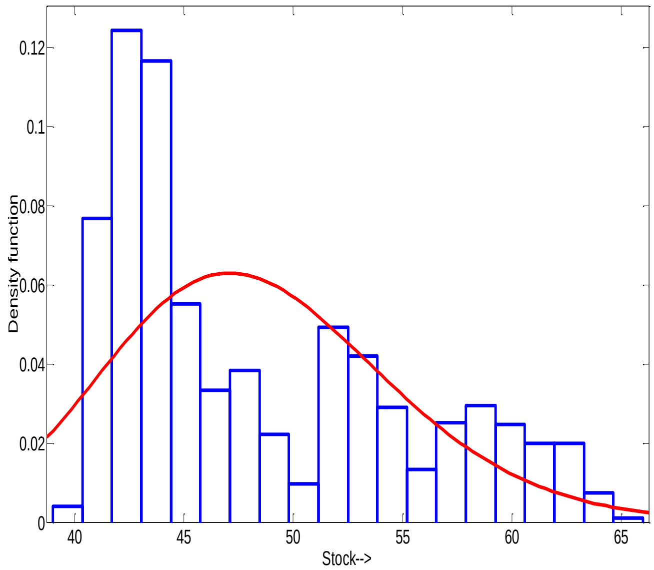

Fig 2.4: Lognormal distribution of figure-2.1 with density histogram of empirical Coca – Cola (KC) of NYSE Index. (source: www.futurestickdata.com)

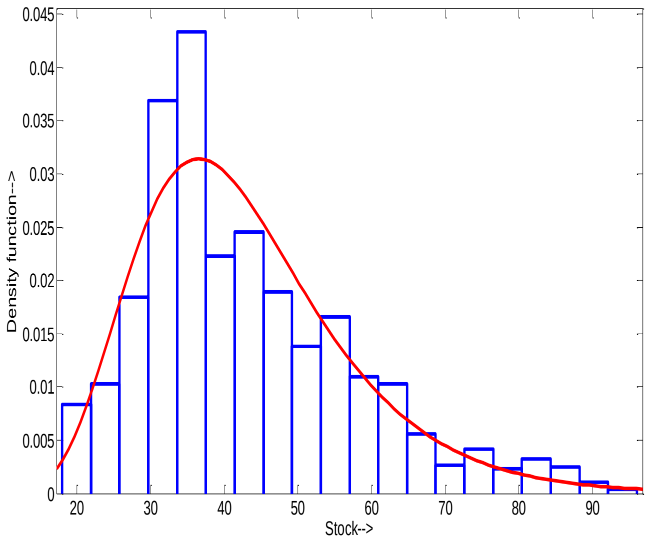

Fig 2.5: Lognormal distribution of figure-2.2 with density histogram of empirical General Motors (GM) of S&P 500 index (source: www.futurestickdata.com).

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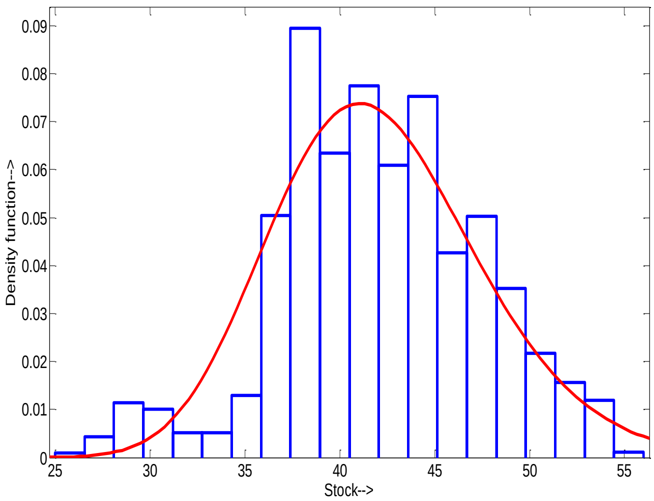

Fig 2.6: Lognormal distribution of figure-2.3with density histogram of empirical power shares QQQ of NASQ 100 index. (source: www.futurestickdata.com)

By applying log likelihood estimates the parameter long – named distribution with corresponding empirical data Parameter Estimate Std. Err.

μ = -3.2966 1.0218e-05

σ = 0.00895068 7.22519e-06

The estimation of parameters of long normal distribution from its corresponding impirical distribution by applying Log – liklihood estimation techniques.
The estimated value of μ and σ along with their estimation errors are given by Parameter Estimate Std. Err.

μ = 4.73203 0.000206708

σ = 0.130663 0.000146165

The Intraday Probability Distribution Stock Returns

The stock returns can be defined as:

$$R(t) = \log\left(\frac{S_t}{S_{t-1}}\right)$$

The normalized stock returns can be calculated as:

r(t) = R(t) – Mean(R(t))/std(R(t))

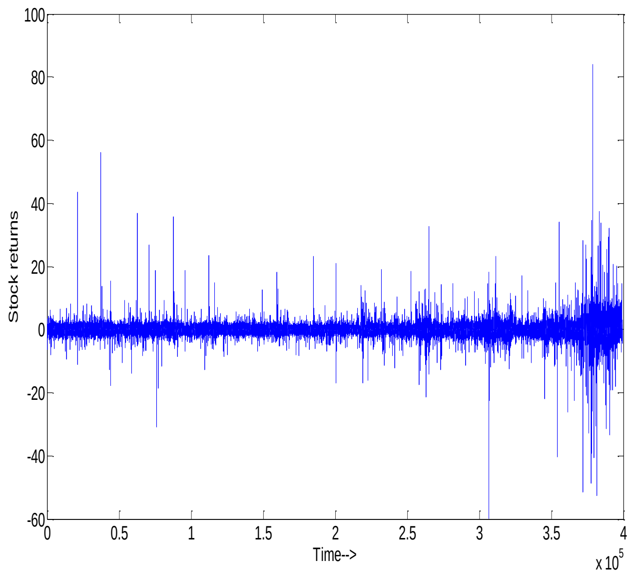

Fig 2.7: Normalized returns of data in figure –2.1 (source: www.futurestickdata.com)

It has been observed that the stock returns can be characterized by Gaussian distribution. The Gaussian distribution is defined as

$$F(r,\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(r-\mu)^2}{2\sigma^2}}$$

Where μ is the mean of the distribution and σ is the standard deviation of the distribution.

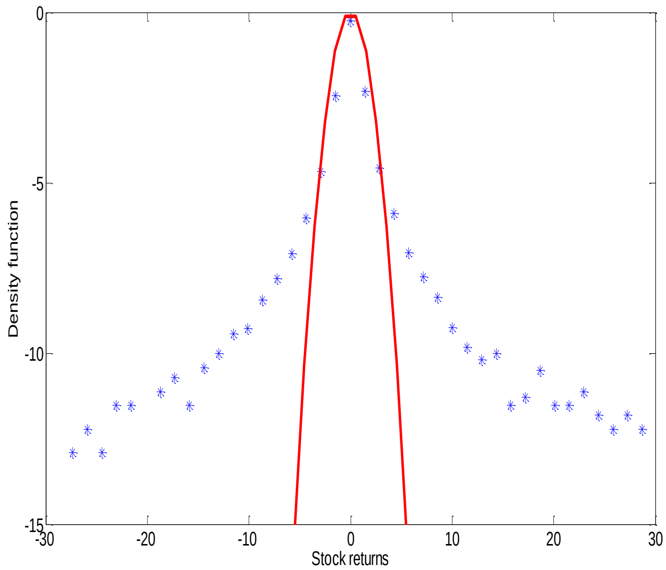

Fig 2.8: Probability density of stock returns of empirical data of figure -2.7 with standard normal probability density function (source: www.futurestickdata.com).

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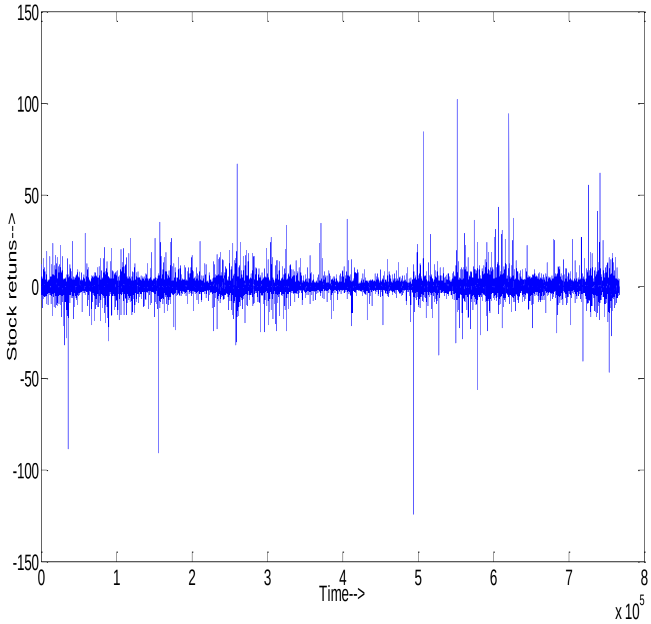

Fig 2.9: Normalized returns of data in figure– 2.2 (source: www.futurestickdata.com).

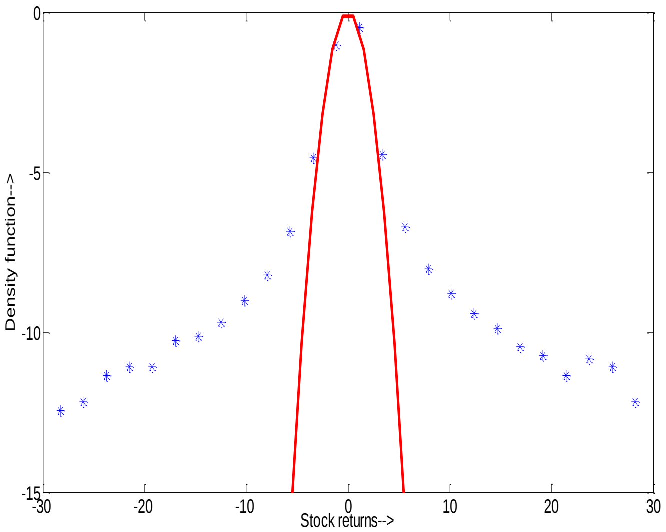

Fig 2.10: Probability density of stock returns of empirical data of figure-2.9 with standard normal probability density function. (source: www.futurestickdata.com)

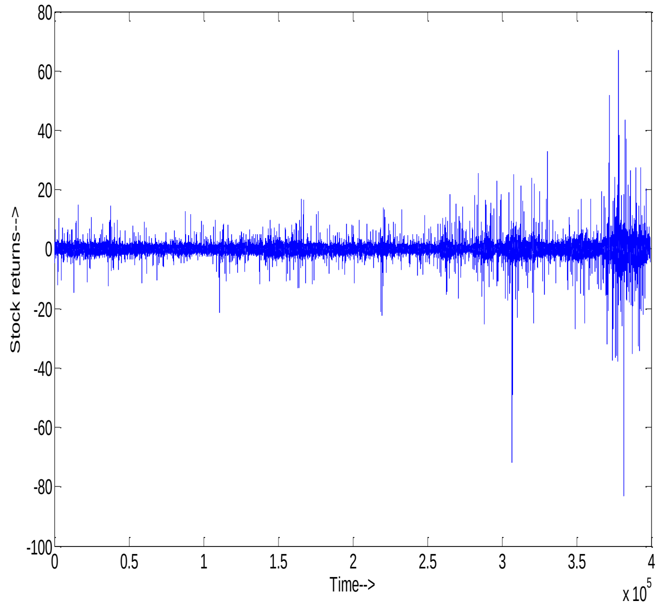

Fig 2.11: Normalized returns of data in figure–2.3 (source: www.futurestickdata.com).

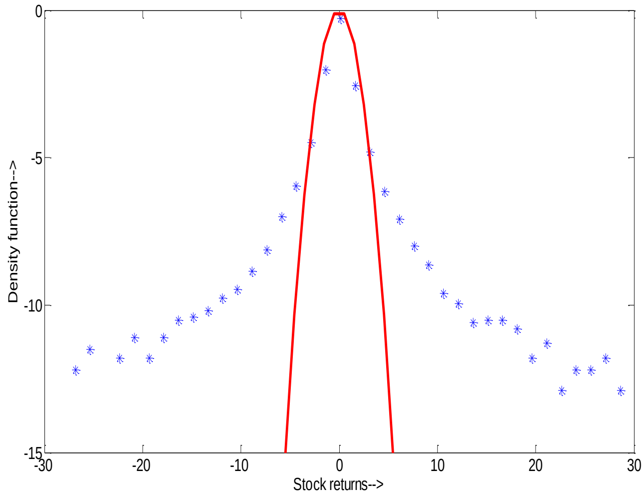

Fig 2.12: Probability density of stock returns of empirical data of figure – 2.11 with standard normal probability density function. (source: www.futurestickdata.com).

The intraday Volatility Analysis of Different Stocks

The volatility of stock returns can be calculated as:

Volatility = |Stock returns| = |R(t)|

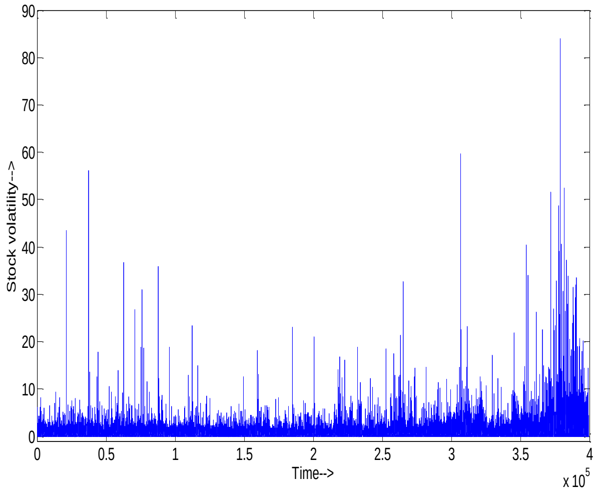

Fig 2.13: Stock volatility of stock returns in figure – 2.7 (source: www.futurestickdata.com).

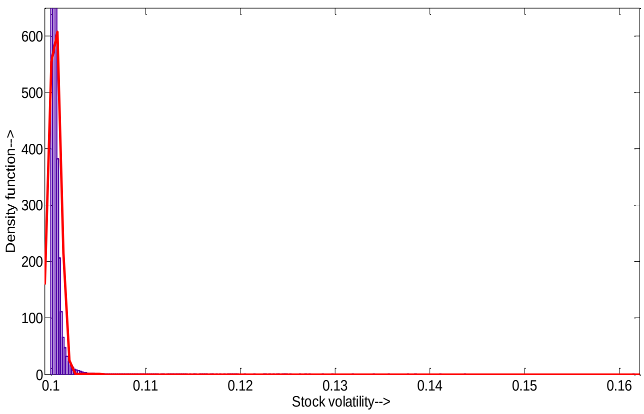

Fig 2.14: Lognormal distribution with empirical probability density of figure – 2.13. (source: www.futurestickdata.com).

Parameter Estimate	Std. Err.
μ = -3.29869	9.36885e-06
σ = 0.00592215	6.62479e-06

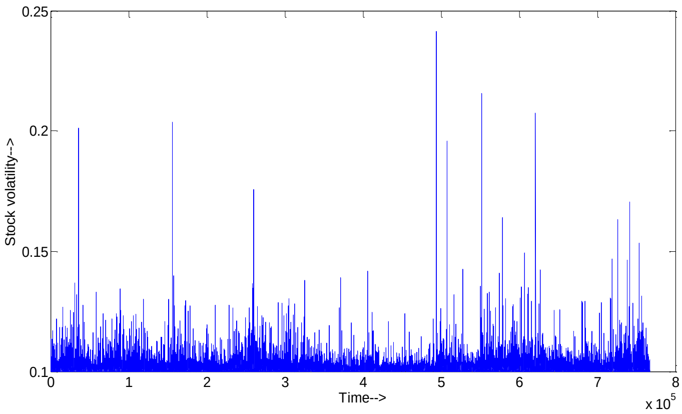

Fig 2.15: Lognormal distribution with empirical probability density of figure –2.9 (source: www.futurestickdata.com).

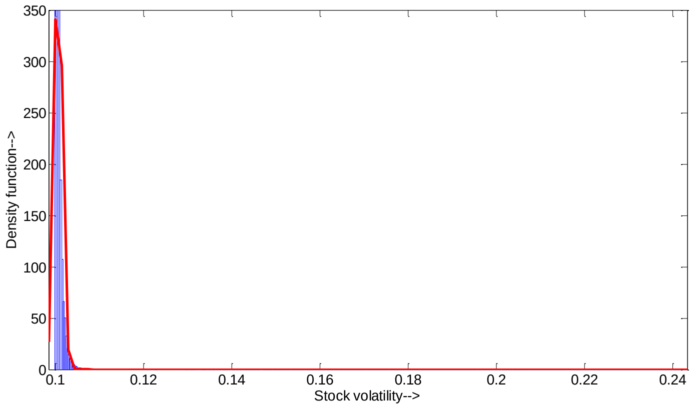

Fig 2.16: lognormal distribution with empirical probability density of figure –2. 15.

Applying log – likelihood estimates techniques, we have estimated the parameters μ & σ from the corresponding empirical data.
The estimated value of μ & σ are as given below:

Parameter Estimate	Std. Err.
μ = -3.2966	1.0218e-05
σ = 0.00895068	7.22519e – 06

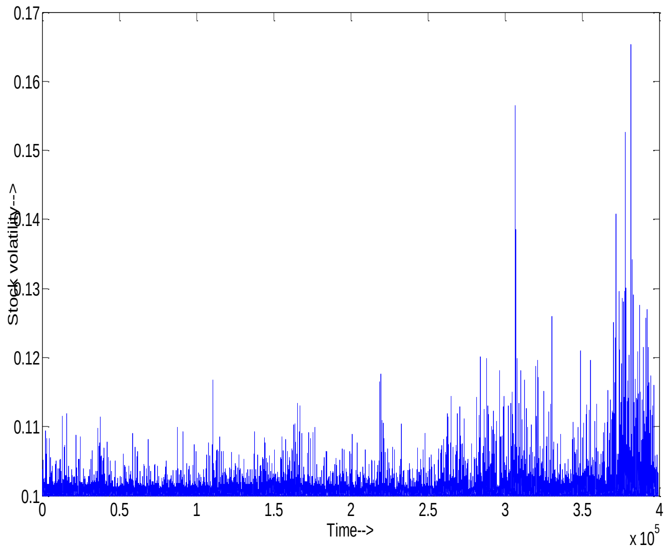

Fig 2.17: Stock volatility of stock returns in figure -2.11. (source: www.futurestickdata.com)

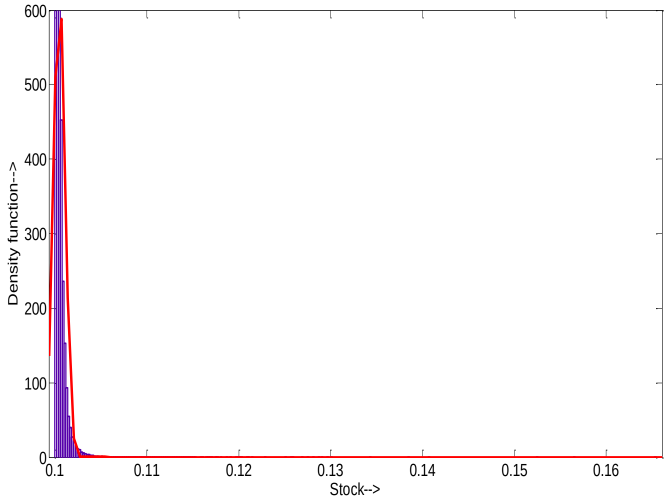

Fig 2.18: Lognormal distribution with empirical probability density of figure 2.17. (source: www.futurestickdata.com).

Applying log – likelihood estimates techniques, we have estimated the parameters μ & σ from the corresponding empirical data.
The estimated value of μ & σ are as given below

Parameter Estimate	Std. Err.
$\mu = -3.29818$	9.84077e-06
$\sigma = 0.00622046$	6.95849e-06

II. AIM AND SCOPE OF ANALYSIS

The interesting find out in this chapter after it has been analyzed from the three empirical data sets, that the price fluctuation of stock and its volatility distribution are well captured by lognormal distribution. But stock returns distributions are not characterized by the well–known Gaussian distribution. So there is deep underlying mechanism is needed to analyze the non – Gaussian behavior of Intra day high frequency stock returns.

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