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Application of Statistical Methods in the Analysis of Daily Stock Exchange Data

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ABSTRACT:
Forecasting is a necessity of human life and a common problem in all branches of learning. Financial and economic problems are domains in which forecasting is of major importance. In the field of stock exchange, the basic goal of market participants is to predict the future trends of stock price and determine the best time to execute transactions in order to optimize investment decisions. A stock, also known as equity of share is a portion of the ownership in a corporate sector by an individual. Hence, a stock of a company entitles its holder a share in its profit. Only by issuing shares a corporate company can mobilize huge capitals. The stock market is a field of financial game and it can fetch bigger financial benefits compared to fixed deposits with banks and for other such investments. The stability as well as the inflation of the economy of a country is swiftly and better reflected by the trend in the stock market. So the study of the fluctuations in the stock market becomes important. There are many approaches to know the depth of an analysis of stock price variation. So we have arrived to propose applicability of forecasting methods such as Time Series Analysis and Factor Analysis to provide better accuracy in forecasting as compared to traditional methods.

Keywords:
Time Series Analysis, Factor Analysis.

1. Introduction:
Stock market analysts have adopted many statistical techniques likes Auto Regressive Moving Average(ARMA) , Auto Regressive Integrated Moving Average (ARIMA), Auto Regressive Conditional Heteroscedasticity(ARCH),Generalized Auto Regressive Conditional Heteroscadasticity(GARCH), ARMA-EGARCH, Box and Jenkins approach along with various soft computing and evolutionary computing methods.

What is the most I can lose on this investment?
This is the question that almost every Investor who has invested or is considering for making investment in a risky asset at some point of time. The Value at risk measures the potential loss in value of a risky asset or portfolio over a defined period for a given confidence interval.

2. Review of Literatures :
• Chan et.al (2014) [13]:
They examine the intraday relationship between returns and returns volatility in the stock index and stock index futures markets. There results indicate a strong inter market dependence in the volatility of the cash and futures returns. Price innovations that originate in either the stock or futures markets can predict the future volatility in the other market. They show that this relationship persists even during periods in which the dependence in the returns themselves appears to weaken. The findings are robust to controlling for potential market frictions such as asynchronous trading in the stock index. There results have implications for understanding the pattern of information flows between the two markets.

• Axel Groß-Klußmann (2012)[3]:
In this work, the authors present econometric models and empirical features of intra-daily (high frequency) stock market data. They focus on the measurement of news impacts on stock market activity, forecasts of bid-ask spreads and the modeling of volatility measures on intraday intervals. First, the authors quantify market reactions to an intraday stock-specific news flow. Using pre-processed data from an automated news analytics tool they analyze relevance, novelty and direction signals and indicators for company-specific news. Employing a high-frequency VAR model based on 20 second data of a cross-section of stocks traded at the London Stock Exchange.

They find distinct responses in returns, volatility, trading volumes and bid-ask spreads due to new arrivals.In a second analysis author introduce a long memory autoregressive conditional Poisson(LMACP) model to highly persistent time series of counts. The model is applied to forecast quoted bid-ask spreads, a key parameter in stock trading operations. They discuss theoretical properties of LMACP models and evaluate rolling window forecasts of quoted bid-ask spreads for stocks traded at NYSE and NASDAQ. They show that Poisson time series models significantly outperform forecasts from ARMA, ARFIMA, ACD and FIACD models in this context. Finally, they address the problem of measuring volatility on small 20 second to 5 minute intra-daily intervals in an optimal way. In addition to the standard realized volatility approaches they construct volatility measures by integrating spot volatility estimates that include information on observations outside of the intra-daily intervals of interest. Comparing the alternative volatility measures in a simulation study we find that spot volatility-based measures minimize the RMSE in the case of small intervals.

• Puspanjali et.al (2012)[14] :

In this,Authors presents a scheme using Differential Evolution based Functional Link Artificial Neural Network (FLANN) to predict the Indian Stock Market Indices. The Model uses Back-Propagation (BP) algorithm and Differential Evolution(DE) algorithm respectively for predicting the Stock Price Indices for one day, one week, two weeks and one month in advance. The Indian stock prices i.e. BSE (Bombay Stock Exchange), NSE, INFY etc. with few technical indicators are considered as input for the experimental data. In all the cases, DE outperforms the BP algorithm. The Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) are calculated for performance evaluation. The MAPE and RMSE in case of DE are found to be very less in comparison to BP method. The simulation study has been done using Java-6 and Net Beans within this. Accurate stock prediction is always a very challenging task. They proposed FLANN model trained with back propagation is giving good result as per the recorded RMSE, and MAPE values during testing for one day, one week, two weeks and one month ahead respectively. The DE optimized FLANN is proving it's superiority as far as RMSE and MAPE are concerned. Further they predict for further work on performance of DE is to be compared with Particle Swarm Optimization (PSO).

• Preethi et.al (2012)[7] :

Author predicted surveys on recent literature in the area of Neural Network, Data Mining, Hidden Markov Model and Neuro-Fuzzy system used to predict the stock market fluctuation. Neural Networks and Neuro-Fuzzy systems are identified to be the leading machine learning techniques in stock market index prediction area. The Traditional techniques are not cover all the possible relation of the stock price fluctuations. There are new approaches to known in-depth of an analysis of stock price variations. NN and Markov Model can be used exclusively in the finance markets and forecasting of stock price. In this paper, they propose a forecasting method to provide better an accuracy rather traditional method. Further, authors predicted the future work as Neural Network and Markov model can also explore for other applications and comparative study with other time series analysis and forecasting models.

• D Men et.al (2008)[6]:

In their work the authors predicted the fluctuations of stock prices and trade volumes are investigated by the method of Zipf plot, where Zipf plot technique is frequently used in physics science. Author discuss the statistical properties of fat tails phenomena and the power law distributions for the daily stocks prices and trade volumes. In the second part, they consider the fat tails phenomena and the power law distributions of Shanghai Stock Exchange Index and Shenzhen Stock Exchange Index during the years 2001-2006 by Zipf plot method.

• Wang et.al (2008)[12]:

Here the authors predicted the data of Chinese stock markets is analyzed by the statistical methods and computer sciences. The fluctuations of stock prices and trade volumes are investigated by the method of Zipf plot, where Zipf plot technique is frequently used in physics science. The objective of this research is to investigate the power law behavior and the fat tails phenomena of Chinese stock markets. Some research work has been done for Chinese stock markets. In this paper, they (Jun Wang, Bingli Fan and Dongping) continue the research work by Zipf plot method. The work they have done during the period between 2002-2007.

• For our proposed research, we got the required data from website: www.yahoo.com and nseindia.com.

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3. DATA :

The data series we study are daily frequency observation on closing prices of companies and are going to take from nseindia.com, the National Stock Exchange of India. We consider the data for companies: ICICI, HDFC, IDBI, TCS, INFOSYS, SATYAM, CIPLA , DR .REDDY, SUNPHARMA, ZEEL, NDTV, CINEVISTA and ONGC. The observations run from 1st January 2013 to 31st May 2016 for ONGC and from 1st March 2016 to 31st May 2016 for the remaining companies.

3.1. DATA COLLECTION :

The analysis was conducted based on closing prices of the data from 1st January 2013 to 31st May 2016 expressed in Rupees and did not include dividends. Table 1 presents the names of the companies and sample of dataset. The required data was obtained from www.yahoo.com & nseindia.com, the National Stock Exchange of India Limited or S & P CNX NIFTY (NSE), is a Mumbai-based stock exchange. It is the largest stock exchange in India in terms of the daily turnover and the volume of equities and derivatives method. Sample of data is given in table-1, 2.

TABLE1: sample of the data set

DATE	NDTV	ZEELTV	ICICI	IDBI	INFOSYS	SATYAM	CIPLA	SUNPHARMA
02-May-16	99.05	416.4	226.75	68.6	1,201.05	314.85	540.65	811.79999
03-May-16	98.8	419.75	221.1	67.8	1,177.80	309.6	536.85	798.25
04-May-16	97.9	404.55	214.45	66.9	1,188.85	307.65	533.2	804.20001
05-May-16	97.6	400.45	214.65	66.2	1,192.45	315.35	541.8	810.45001
06-May-16	97.55	403.1	218.6	67.75	1,181.50	315.85	537.35	804.40002
09-May-16	98.55	420.7	225.3	69.3	1,199.05	317	536.55	805.29999
10-May-16	97.95	417.6	225.5	69.15	1,212.80	313.65	537.05	802.15002
11-May-16	96.45	447.95	223.95	67.75	1,201.85	314.75	536.6	796.29999
12-May-16	96.3	447.5	231.8	68.3	1,210.00	312.05	536.3	803.54999
13-May-16	97.4	448.85	226.5	65.6	1,207.25	304.9	531.7	795.04999
16-May-16	99.3	447.1	223.75	63.8	1,215.00	308.45	521.8	797.84998
17-May-16	98.1	445.2	225.95	64.6	1,214.25	310.7	523.75	799.90002
18-May-16	98.75	435.75	226.45	65.55	1,209.85	306.95	524.55	795.29999
19-May-16	97.3	438.15	225.55	64.35	1,205.75	306.45	512.7	792.5
20-May-16	96.35	434.4	220.1	64.1	1,201.60	303.55	507.1	791.34998
23-May-16	96.15	435.65	221.1	64.45	1,188.00	311.5	497.4	784.54999
24-May-16	93.35	439.1	224.55	64.2	1,187.75	320	494.05	772.29999
25-May-16	94.3	442.6	235	65.4	1,208.65	342.5	469.8	785.45001
26-May-16	93.5	444.45	241.15	65.6	1,234.15	336.1	467.95	779.34998
27-May-16	94.4	453.4	243.15	67.45	1,247.50	339.1	473.45	824.95001
31-May-16	93.85	443.35	244.65	67.9	1,248.65	369.2	472.65	762.75

TABLE-2 : QUARTERLY DATA FOR ONGC COMPANY

YEAR	QUARTER	QUARTERLYAVERAGE
MAR-2013	1	314.884375
JUNE-2013	2	320.6938462
SEP-2013	3	284.3606061
DEC-2013	4	281.869697
MAR-2014	1	291.884375
JUNE-2014	2	373.4184615
SEP-2014	3	415.0333333
DEC-2014	4	381.5181818
MAR-2015	1	333.3578125
JUNE-2015	2	314.8623077
SEP-2015	3	259.8439394
DEC-2015	4	239.5727273
MAR-2016	1	214.0253846

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3.2. DATA PREPARATION :

Relative return is calculated for the above data i.e., the return that an asset achieves over a period of time compared to a benchmark. The relative return is the difference between the absolute return achieved by the asset and the return achieved by the benchmark. The daily return on the portfolio was calculated using the formula

$$R_t = \frac{S_t - S_{t-1}}{S_{t-1}},$$

Where, S_t : Value of stock at the close of day t

& S_{t-1} : Value of portfolio at the close of day t-1.

Why is relative return so important?

Because it is a way to measure the performance of actively managed funds, which should get a return greater than that of the market. Relative return can also be used within a context smaller than the entire market. The bottom line is that absolute return does not say much on its own. You need to look at the relative return to see how an investment's return compares to other similar investments. Once you have a comparable benchmark in which to measure your investment's return, you can then make a decision of whether your investment is doing well or poorly and act accordingly.

The following TABLE -3 gives a sample of computed relative returns for different days of May-2016.

DATE	NDTV	ZEELTV	ICICI	IDBI	INFOSYS	SATYAM	CIPLA	SUNPHARMA
03-May-16	-0.00911	0.008045	-0.03008	-0.01166	0.00938	-0.01667	-0.0068	0.007453
04-May-16	-0.00306	-0.03621	0.00093	-0.01327	0.00302	-0.0063	0.01612	0.007771
05-May-16	-0.00051	-0.01013	0.0184	-0.01046	-0.00918	0.025028	-0.00821	-0.007464
06-May-16	0.01025	0.006618	0.03065	0.023414	0.01485	0.001586	-0.00149	0.001118
09-May-16	-0.00609	0.043662	0.00088	0.022878	0.01146	0.003641	0.000932	-0.003911
10-May-16	-0.01531	-0.00737	-0.00687	-0.00216	-0.00903	-0.01057	-0.00084	-0.00729
11-May-16	-0.00156	0.072677	0.03505	-0.02025	0.00678	0.003507	-0.00056	0.009104
12-May-16	0.01142	-0.001	-0.02286	0.008118	-0.00227	-0.00858	-0.00858	-0.010578
13-May-16	0.0195	0.003017	-0.01214	-0.03953	0.00642	-0.02291	-0.01862	0.003521
16-May-16	-0.01208	-0.0039	0.00983	-0.02744	-0.00062	0.011643	0.00373	0.002569
17-May-16	0.00662	-0.00425	0.00221	0.012539	-0.00362	0.007295	0.00152	-0.00575
18-May-16	-0.01468	-0.02123	-0.00397	0.014706	-0.00339	-0.01207	-0.02259	-0.00352
19-May-16	-0.00976	0.005508	-0.02416	-0.01831	-0.00344	-0.00163	-0.01092	-0.001451
20-May-16	-0.00208	-0.00856	0.00454	-0.00389	-0.01132	-0.00946	-0.01913	-0.0085929
23-May-16	-0.02912	0.002878	0.0156	0.00546	-0.00021	0.02619	-0.00674	-0.015614
24-May-16	0.010177	0.007919	0.04653	-0.00388	0.01759	0.027287	-0.04908	0.017027
25-May-16	-0.00848	0.007971	0.02617	0.018692	0.02109	0.070313	-0.00394	-0.007766
26-May-16	0.00962	0.00418	0.00829	0.003058	0.01081	-0.01869	0.01175	0.05851
27-May-16	0.00105	0.020137	0.00555	0.028201	0.01611	0.008926	0.000211	-0.015576
30-May-16	-0.00688	-0.02095	0.00061	0.0001	-0.01495	0.032144	-0.0019	-0.060768

4. STATISTICAL TOOLS SUGGESTED:

4.1. FACTOR ANALYSIS:

Factor analysis is a statistical method used to describe variability among observed variables in terms of fewer unobserved variables called factors. The observed variables are modeled as linear combinations of the factors, plus "error" terms. The information gained about the interdependencies can be used later to reduce the set of variables in a dataset. Basically, the factor model is motivated by the following argument. Suppose variables can be grouped by their correlations. That is, all the variables within a particular group are highly correlated among themselves but have relatively small correlations with variables in a different group. It is conceivable that each group of variables represents a single underlying construct or factor that is responsible for the observed correlation. In particular, the factor analysis model is given by:

$X - \mu = L F + \varepsilon$, where X: observable random vectors ; μ: common mean ;

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L: loading matrix ; ε: Specific factors.
Now based on the principle of Factor Analysis, asset selection could be completed in the following steps:
Step 1: Estimation of parameter.
Step 2: Extract the optimal number of factors.

4.2. TIME SERIES ANALYSIS :

A time series is a set of observations taken sequentially in time. In statistics, a time series is a sequence of data points, measured typically at successive times, spaced at time intervals. Time series analysis comprises methods that attempt to understand such time series, often either to understand the underlying context of the data or to make forecasts (predictions). Time series forecasting is the use of a model to forecast future events based on known past events: to forecast future data points before they are measured. A time series model will generally reflect the fact that observations close together in time will be more closely related than observations further apart. In addition, time series models will often make use of the natural one-way ordering of time so that values in a series for a given time will be expressed as deriving in some way from past values, rather than from future values. As shown by Box and Jenkins[17], models for time series data can have many forms and represent different stochastic processes. When modeling variations in the level of a process, three broad classes of practical importance are the autoregressive (AR) models, the integrated (I) models, and the moving average (MA) models. These three classes depend linearlyon previous data points. Combinations of these ideas produce autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) models.

Autoregressive process:

The AR (p) model is given by

$$x_t = \mu + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \phi_3 X_{t-3} + \ldots\ldots + \phi_p X_{t-p} + \varepsilon_t \ ;$$

where: μ is a constant ; $\phi_1, \phi_2, \phi_3, \ldots\ldots\ldots, \phi_p$

are the autoregressive parameters.

Assumption:

Here the term εt is the source of randomness and is called white noise. It is assumed to have the following characteristics:

$$E[\varepsilon_t] = 0$$
$$E[\varepsilon_t^2] = \sigma^2$$
$$E[\varepsilon_t \varepsilon_s] = 0 \quad \forall t \neq s$$

Moving average process:

Independent from the autoregressive process, each element in the series can also be affected by the past error (or random shock) that cannot be accounted for by the autoregressive component.

That is: $x_t = \mu + \varepsilon_t - \theta_1 * \varepsilon_{t-1} - \theta_2 * \varepsilon_{t-2} - \theta_3 * \varepsilon_{t-3} - \ldots - \theta_q * \varepsilon_{t-q}$;

where: μ is a constant, $\theta_1, \theta_2, \theta_3, \ldots\ldots \theta_q$

are the moving average parameters.

Assumption:

Here the term is the source of randomness and is called white noise. It is assumed to have the following characteristics:

$$E[\varepsilon_t] = 0$$
$$E[\varepsilon_t^2] = \sigma^2$$
$$E[\varepsilon_t \varepsilon_s] = 0 \quad \forall t \neq s$$

Autoregressive moving average model:

The general model introduced by Box and Jenkins (1976) includes autoregressive as well as moving average parameters, and explicitly includes differencing in the formulation of the model. Specifically, the three types of parameters in the model are: the autoregressive parameters (p), the number of differencing passes (d), and moving average parameters (q). In the notation introduced by Box and Jenkins, models are summarized as ARIMA (p, d, q); so, for example, a model described as (0, 1, 2) means that it contains 0 (zero) autoregressive (p) parameters and 2 moving average (q) parameters which were computed for the series after it was differenced once.

The ARIMA (p, d, q) model is given by :

$$x_t = \mu + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \phi_3 X_{t-3} + \ldots\ldots + \phi_p X_{t-p}$$
$$+ \varepsilon_t - \theta_1 * \varepsilon_{t-1} - \theta_2 * \varepsilon_{t-2} - \theta_3 * \varepsilon_{t-3} - \ldots - \theta_q * \varepsilon_{t-q}$$

Where: μ is a constant; $\phi_1, \phi_2, \phi_3, \ldots\ldots\ldots, \phi_p$

are the autoregressive parameters;

$\theta_1, \theta_2, \theta_3, \ldots\ldots \theta_q$ are the moving average parameters.

There are three primary stages in building a Box-Jenkins time series model.
Model Identification
Model Estimation
Model Validation

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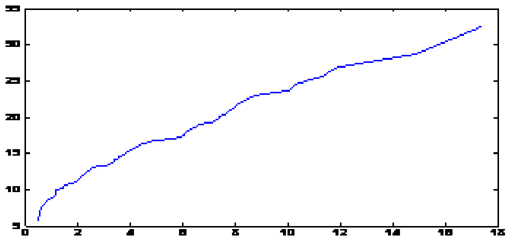
5. ANALYSIS:

5.1ASSUMPTIONS:

Assumption 1: The changes in the value of the portfolio are linearly dependent on all the changes in the value of the stocks.

Assumption 2: The stock returns follow multivariate normal distribution.



Most of the observations lie on the straight line. So from the graph, we can conclude that the data follows multi-variate normal distribution.

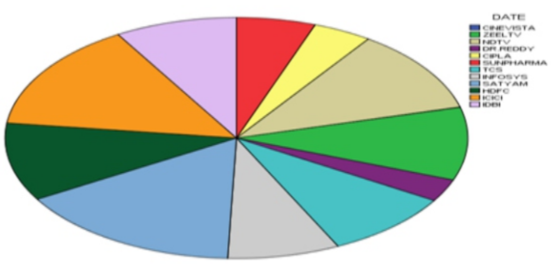
5.2.SUMMARY STATISTICS OF THE DATA:

Descriptive statistics of the daily returns for the portfolio are provided in Table- 4, 5 & 6. These daily returns were determined using relative returns.

Table-4: Descriptive Statistics

COMPANIES	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
CINEVISTA	66	-.1125	.0986	-.000016	.0439757	.206	.103
ZEELTV	66	-.0362	.0727	.002808	.0181450	1.064	3.213
NDTV	66	-.0778	.0979	-.003213	.0226225	.814	7.195
DR.REDDY	66	-.0378	.0577	.000866	.0156163	.546	2.483
CIPLA	66	-.0491	.0266	-.001184	.0135029	-.847	2.195
SUNPHARMA	66	-.0608	.0585	-.001585	.0158222	-.150	5.128
TCS	66	-.0275	.0459	.002604	.0134674	.387	1.243
INFOSYS	66	-.0305	.0563	.002250	.0147698	.854	2.124
SATYAM	66	-.0495	.1163	.004565	.0265313	1.040	4.605
HDFC	66	-.0130	.0293	.003010	.0090945	.522	.140
ICICI	66	-.0551	.0784	.004148	.0254853	.797	1.515
IDBI	66	-.0428	.0773	.002455	.0206412	.645	2.123

PIE DIAGRAM OF ALL SECTORS USING SUM



MULTIPLE LINE DIAGRAM OF ALL SECTORS

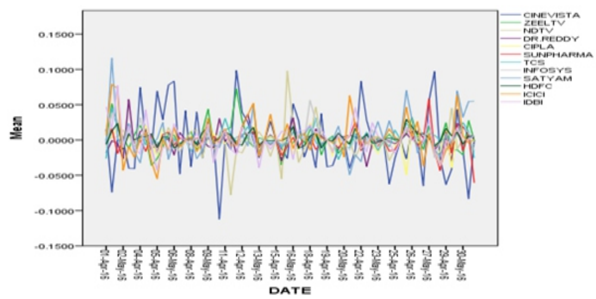


Table-5 : Descriptive Statistics of ONGC of Jan 2013- May 2016

COMPANY	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
ONGC	891	192	466	304.86	61.378	.309	-.478

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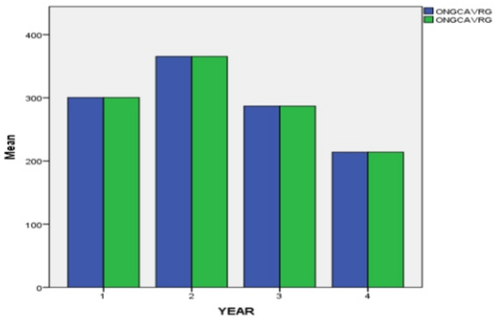
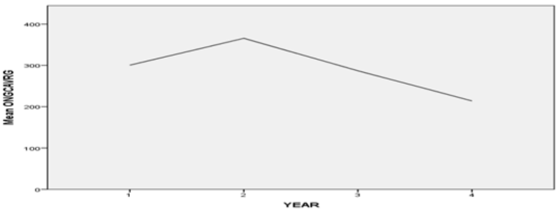
Table-6 : Descriptive Statistics of Quarterly Average ONGCof Jan 2013- May 2016

COMPANY	N	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
ONGCAVRG	13	214	415	309.64	57.255	.226	-.311

BARDIAGRAM OF ONGC AVERAGE



LINE DIAGRAM OF ONGC AVERAGE



The minimum return values, maximum return values, average returns standard, skewness and kurtosis of returns on a daily basis are presented in the table. The results show that average returns of SATYAM show high positive average returns. The results show that SATYAM has performed well overall. A common rule-of-thumb test for normality is to run descriptive statistics to get Skewness and Kurtosis. Skewness is the tilt (or lack of it) in a distribution. The more common type is right skew, where the smaller tail points to the right. Less common is left skew, where the smaller tail is points left. Skew should be within +1 to -1 range when the data are normally distributed. We observed that Skew ness for the daily returns of all the stocks are within +1 to -1 , which is an indication that the data are normally distributed. Kurtosis is the peakedness of a distribution. We observe that kurtosis of ZEELTV, NDTV, SUNPHARMA, SATYAM has high kurtosis which is an indication that data are not normally distributed (i.e., kurtosis should be within +3 to -3 range when the data are normally distributed). Negative kurtosis indicates too many cases in the tails of the distribution. Positive kurtosis indicates too few cases in the tails, but we assume in the long run the variables are normally distributed.

6. SOFTWARE USED

•R Software
•SPSS

7. SCOPE FOR FURTHER STUDY

•Removal of the outliers
•Association analysis
•Volatility and VaR

8. CONCLUSIONS:

We are looking for the factors behind the following:
•The groups of IT sector and Banking sector because the IT companies are influenced by dollar price and Banks are reflected by interest rates. So it may be possible that some of the IT companies have shares of banks or vice versa.
•The groups of TV channels so it may be possible that a pharmacy company like DR.REDDY have insurance with IDBI and advertise their products in the TV channels.
•In the other groups Pharmacy companies and TV channels are grouped respectively.
•Using Time series analysis, we fit an appropriate model namely MA(1) to forecast the future stock prices.

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