Chapter- III

RESEARCH METHODOLOGY

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3.1 INTRODUCTION

This research work is a systematic investigation which is undertaken with the specific purpose of understanding the price behaviour of selected Sensex stocks. This research work also deals with the investors' perspectives towards fundamental and technical analyses. In this direction, the present chapter describes the research methodology of the study for achieving the objectives of the study. Under each objective, a separate sample design has been structured to obtain the answers of research questions under the study.

3.2 RESEARCH DESIGN

The present research work has been carried out for fundamental and technical analyses of stocks listed in BSE Sensex to observe the effects of certain indicators on stocks behaviour. The present study is descriptive and exploratory in nature. Secondary and primary data have been used according to the objectives of the study. Research design is structured for the description of hypotheses, parameters, period of the study, data collection, and sample design under this chapter. Various analysis have been carried out for evaluation of the performance of Indian macroeconomic environment & its association with stock returns, nature of volatility of Indian stock market, financial performance of selected Indian industries & companies, effectual measure between the key variables of financial performance & stock returns, measurement of market trend of Sensex stocks and opinions of investors regarding fundamental & technical analyses.

3.2.1 Hypotheses of the Study

This research work is based on the following hypotheses:

H_0: There is no significant impact of macroeconomic indicators on BSE Sensex.

H_0: There is no cause of Sensex volatility on Sensex returns.

H_0: There is no significant difference in the financial performance of the selected industries.

H_0: There is no significant impact of financial performance parameters on industrial stock returns.

H_0: There is no significant difference in the financial performance of the selected companies.

H_0: There is no significant impact of financial performance parameters on company stock returns.

H_0: There is no significant difference in the perceptions of investors for fundamental and technical analyses.

3.2.2 Period of the Study

Ten years of the study period i.e. 2004-05 to 2013-14 has been taken into consideration for measuring the relative performance of Indian economy, industry & company and to check the impact of indicators on stock returns.

3.2.3 Sample Design for the study of Fundamental & Technical analyses

The study is focused on the relationships of economic, industry and company indicators with stock returns in India. BSE Sensex is considered as a proxy of Indian stock market for checking the impact of macroeconomic indicators on stock market and examining the nature of volatility of Indian stock market. Five top industries are selected on the basis of their market capitalisation in BSE Sensex to investigate the impact of financial performance indicators on industrial stock returns. Sample for industry analysis includes; Automobile Industry (Automobile), Information Technology Industry (IT), Oil and Gas Industry (Oil & Gas), Healthcare Industry (Healthcare), Metal, Metal Products & Mining Industry (Metal). In the direction of fundamental analysis, financial status has been accomplished in the study for suggesting the rationale decision of investment in Sensex representative stocks. Two top companies from each selected industry of the study have been taken on the basis of their market capitalisation for company analysis; hence, total ten Sensex representative companies have been considered. The market trend of stocks is also measured for these companies under technical analysis and sample for this purpose includes; Mahindra & Mahindra Ltd. (M&M), Tata Motors Ltd. (Tata Motors), Infosys Ltd. (Infosys), Wipro Ltd. (Wipro), Gail (India) Ltd. (GAIL), Oil and Natural Gas Corporation Ltd. (ONGC), Dr. Reddy's Laboratories Ltd. (Dr. Reddy), Sun Pharmaceutical Industries Ltd. (SunPharma), Hindalco Industries Ltd. (Hindalco), Tata Steel Ltd. (Tata Steel).

3.2.4 Parameters for Fundamental & Technical analyses

The current research work examines the price behaviour of selected stocks with the help of economic, industry and company indicators. The essential indicators which unfold the growth of economy, earnings, market condition and value of industry & companies of India are selected for fundamental and technical analyses.

3.2.4.1 Parameters for causality of macroeconomic indicators on Indian Stock Market

An impact of macroeconomic indicators on stock market has been observed on the basis of monthly data. Sensex has been used as endogenous variable and selected macroeconomic indicators as exogenous variables with 120 observations. The relationship of Sensex has been checked with industrial production index (IIP), wholesale price index for inflation (WPI), money supply (MS), exchange rate (ER), gold price (GOLD) and foreign exchange reserve (FER). The selection of variables is based on availability of data and extensive literature review. Only those variables have been selected which proved as most influencing factors to affect the stock price in earlier studies. The brief description of selected macroeconomic indicators considered for analysis has been presented in table- 4.1 of chapter- 4.

3.2.4.2 Parameters for Industry Analysis

Financial Performance is defined as the collaboration of various performance measures such as fixed assets, sales, cash, debtors, capital etc. Financial performance plays an important role in effecting the behaviour of share price in the market. A significant role of financial performance on share price leads investors to study the financial performance of industry for better decision of investment. In this study, some performance measuring variables have been identified and considered for the purpose of industry analysis on the basis of literature and these are as follows:

Percentage of employee cost to total cost (ECTC) which measures the dependency of firm on labour, percentage of fixed assets to total sales (FATS) to measure capital intensity, export earning as percentage of sales (EES) which stands for the share of export sales in total sales and shows the foreign dependency of firm for sales revenue, debt equity ratio (D/E) for leverage, current ratio (CR) to indicate liquidity, return on net worth (RONW) to measure profitability. Industrial stock returns (RET) have been used as dependent variable to measure the impact of financial performance indicators on Industrial stock price.

3.2.4.3 Parameters for Company Analysis

Performance measuring fundamental valuation ratios such as price earning ratio (P/E), earnings per share (EPS), book value per share (BV), dividend yield (DY), price to book value ratio (P/B), market capitalisation (MC) and beta (BETA) have been taken on the basis of availability of data and review of literature for company analysis. Return of the stock price of each company has been also analysed to determine the performance of stocks and understand the affect of financial performance of companies on stock price.

3.2.5 Sample Design for the study of Investors' perspective

It is an important step to understand the perspectives of investors regarding fundamental and technical analyses while deciding to invest. It is pertinent to unfold various factors which influence investors' decisions to purchase a share and to recommend the best strategy to policymakers and market. Differentiation on the basis of the characteristics of the sample investors has been observed to better identify the respondents for discovering the challenges for the companies and policymakers. Usefulness of various appraisal techniques have also been analysed by obtaining the responses of the investors. A well structured questionnaire with close-ended questions was distributed for obtaining the responses of the respondents. Convenience sampling method was used for the selection of the respondents. The data were collected from the respondents of selected five cities of North India i.e. Delhi, Gurgaon, Faridabad, Noida & Ghaziabad. Only, those respondents were selected for the study who have the rich experience of stock market with a high percentage of disposable income. A pilot survey was conducted before administering the questionnaire at large level for checking the adequacy and accuracy of the questionnaire. The respondents were asked to indicate the degree of agreement/disagreement on a five point Likert scale. The survey included several issues related to the perspectives of investors towards appraisal techniques, influencing factors, suggestions and problems related to stock market. Ninety respondents from each of the city were finalized. Reliability of questionnaire was also tested by applying Chronbach's alpha to confirm the internal consistency of the questionnaire. Demographic profile of the investors considered gender, age-group, marital status, monthly income, educational background and occupation. Total 600 questionnaires were distributed to the investors and 450 filled questionnaires were received which were found to be completed in all respect for the analysis purpose. Hence, the survey is orgainsed over the sample size of 450 respondents.

3.2.6 Collection of Data

The study is based on secondary as well as primary data. Primary data has been collected from respondents (investors) by using the well structured questionnaires. Secondary data of macroeconomic indicators have been obtained from various issues of Handbook of Statistics on Indian Economy published by Reserve Bank of India and various reports of Economic Survey. Websites of Ministry of Commerce & Industry and Ministry of Statistics & Programme Implementation (MOSPI) have been also visited for authenticity of the data. Official website of Bombay Stock Exchange (BSE) has been used to collect the data for industry indices and closing stock prices of companies. The database of CMIE Prowess (Centre for Monitoring Indian Economy Pvt. Ltd.) has been accessed for getting the financial data pertaining to the industries and companies selected for the study. Official websites and annual reports of selected companies have been also referred to gather information related to companies. Other authentic government reports, magazines, journals and newspapers have also been referred as per the requirement of the study.

3.3 TOOLS/ TECHNIQUES USED

3.3.1 Tools/ Techniques for analysis

This study has employed various statistical techniques such as cross-tabulation, average, weighted average score, standard deviation, CAGR, annual growth rate, correlation, ANOVA, t- test, unit root tests, co-integration test, vector error correction model, GARCH-based models, panel data unit root tests, fixed effect model, oscillators (RSI, MACD), volume, exploratory factor analysis and cluster analysis as per the requirement of the objectives. Compound annual growth rate (CAGR) and annual growth rate have been calculated to measure the historical growth of various indicators. The time series analysis techniques have been employed to capture the relationships between macroeconomic variables and stock price. It is prerequisite that the data series must obey the pre-conditions of time series analysis to avoid spurious results. One of the properties of time series analysis is the stationarity of the data, hence ADF & PP tests have been performed in this study to test the stationary condition of the data series. Descriptive statistics are also computed to observe the nature of data series. Further, error correction model (ECM) followed by Johansen procedure i.e., Johansen (1991) and Johansen & Juselius (1990) has been applied to test the presence and the number of co-integrating relationships among the underlying macroeconomic variables. GARCH-type models are applied to check the volatility of Indian stock market.

CAGR and annual growth rate of financial parameters are calculated to find out the meaningful inference of industry and company performance. Thereafter, comparative performance has been analysed to observe the best performing industry and company. ANOVA test has been applied to compute the significant difference in the financial performance of all selected industries and companies. Fixed effect model has been constructed to evaluate the causality of financial performance on stock returns. EVeiws version 7 has been used to analyse the data. Oscillators i.e. MACD and RSI have been applied for technical analysis of the stocks. Other issues related to the perspectives of investors towards appraisal techniques, influencing factors, suggestions & problems related to stock market have been analysed using SPSS version 22. Part-A and part-B of the questionnaire consist various items/statements which have also been analysed with the help of statistical tools like mean, standard deviation, weighted average score, cross-tabulation, rank, t-test and ANOVA.

Exploratory factor analysis has been applied to extract the most important factors which influence investors' decision, while cluster analysis has been used in the later part of the analysis to differentiate the respondents on the basis of their characteristics.

3.3.2 Description of Tools/Techniques

3.3.2.1 Unit-Root Tests

Various time series techniques have been employed to determine the relationships between macroeconomic variables and stock price. There is always requirement to check stationarity of time series data for avoiding the spurious results because usually, times series are assumed to be of non-stationary nature. Stationary means constant mean & variance over the time and covariance depends only on the gap of the two time periods. There are two approaches for testing the stationarity of a variable in time series. One approach is based on the time plot of the variable and second preferable method is to perform a formal test of stationarity which is known as unit root tests. Unit root test is widely accepted over the period of time for testing the stationary condition (Gujarati, et al., 2012).

A unit root test shows an autoregressive statistical model for the time series which is a test for finding the presence or absence of stationarity in the data series, while non-stationary variable shows a positive/negative trend over the time period and hence, it is called to have unit root. The following is an expression of unit root test:

$$\mathbf{Y_t = \gamma\, Y_{t-1} + \varepsilon_t} \qquad \text{---------------------} \ (3.1)$$

If value of γ in equation (3.1) is less than one, then it is known as stationary which means Y_t will be maintained by coming back to its mean value. Graphically, the time path of Y_t will have no trend of upward /downward, and the fluctuations will be around the mean value and contained within the constant bounds. If γ =1, then in that case it will behave like a random walk model without drift. This is known as the process of non-stationary stochastic and it will represent an upward trend. As γ is the root of the process, so non-stationarity of the series depicts presence of unit root. If a variable is found to be non-stationary, variables can be made stationary with the help of differencing and first difference is taken for illuminating the trend of series. An expression at first difference is as follows:

$$\Delta Y_t = \delta Y_{t-1} + \varepsilon_t \qquad \text{---------------} (3.2)$$

Here, ε_t represents white noise error term and if $\delta = 0$, it is a case which is called as unit root case and it shows that series is non-stationary in nature. The first difference of the series will usually show the stationary series and the variables will be known as integrated of order 1, and will be written as I (1). In the current study, the stationary condition of the data series has been tested by most widely used test for stationary i.e. unit root test which comprises ADF test proposed by Augmented Dicky - Fuller (1981), and PP test proposed by Phillips-Perron (1988). The unit root tests under the study have been tested for both in level and first difference.

i) Augmented Dickey-Fuller (ADF) test

ADF test is most accepted tool of unit root in a time series sample which is basically developed by Dickey & Fuller (1981) and this test depends on the logic that every non-stationary process consists infinite memory and it does not express a decay in shock which takes place during the process. If it is assumed that the data series shows an AR (p) process, ADF test depicts a parametric correction and it also controls for the correlation of higher order by using the lagged difference terms to the right hand side in the regression equation. This test can be represented in the following manner:

$$\Delta y_t = \mu + \beta_t + \delta y_{t-1} + \sum \alpha_p \Delta y_{t-p} + \varepsilon_t \qquad \text{----------------------} (3.3)$$

Here, ε_t represents a pure error term of white noise, β is a coefficient on time trend, while μ represents a constant. Generally, the number of terms of lagged differenced is estimated empirically for getting the unbiased estimate of δ and coefficient of lagged $y_{t-p.}$ ADF tests is used to check the null hypothesis which is $\delta = 0$ and its failure to reject null hypothesis shows an evidence of the presence of unit root. ADF statistics which is used in this test is a negative number and if, it is highly negative, the chances for the rejection of hypothesis will increase. As this test is criticized because of low power and not distinguishing process of unit root & near unit root, hence this has been complemented with the help of PP test which expresses a non-parametric technique to control the higher order serial correlation in the data series. This test provides robustness for checking the stationary condition.

ii) Phillips-Perron (PP) test

ADF test helps to check the possible serial correlation in error terms by addition of the lagged difference terms. Phillips (1987) and Perron (1988) use non-parametric statistical tools to estimate the functional forms and serial correlation in the terms of error without considering lagged differenced terms. Distribution of PP test is somehow same as ADF. PP test determines the equation of non-augmented DF test and alters the ratio of the coefficient because of the illumination of the effect of serial correlation on the asymptotic distribution. The main benefit of this test is that it is free from any parametric error. In the current study, these unit root tests are carried out with intercept term and trend with intercept term as data series exhibits a trend for all variables. One lag has been added in the given equation to estimate the stationary nature of the data series. In both the tests of unit root, the null hypothesis is that the data set has unit root. Unit root tests also produce the order of integration in the variables of series.

3.3.2.2 Co-integration test

Long term and short term relationships between macroeconomic variables and stock market has been checked by applying vector error correction model by following the Johansen procedure [Johansen and Juselius (1990) and Johansen (1991)] which test the presence and the number of co-integrating relationships among the underlying variables as there is possibility of existence of more than one linear combinations in a multivariate practice. Necessary condition for the applicability of co-integration test is that the variables which are considered must be integrated in same order and stationary. Multivariate analysis, i.e. two-step estimation approach is applied to conduct the co-integration test. In the first step, variables are tested for ensuring the integration of the same order and then, it is recommended to run the co-integration test under the null hypothesis of no presence of co-integration between variables. If the variables considered are observed to be I(1), the variables are known to be co-integrated in a multivariate context (Enders, 2004). Engel and Granger (1987) suggested long run combination among the variables, if the variables are co-integrated because these variables would not go apart over the period of time. The co-integration based on Johansen methods can be stated by assuming N time series and each of which is I (1) as the following model:

$$\Delta X(t) = \mu + bt + \sum_{j=1}^{k-1} \Gamma_j \, \Delta X(t-j) + \pi \, X(t-k) + \varepsilon(t) \qquad \text{----------- (3.4)}$$

Here, X (t) is vector, π_i is matrices of unknown constants and Ɛ (t) is error vector.

Johansen and Juselius (1990) show that rank of r of π is equal to number of co-integrating vector in the system and suggested two test statistics i.e. trace statistics J_T and and Max statistics λ_{max}.

$$J_T = -T \sum_{i=r+1}^{N} \ln\left(1-\hat{\lambda}_i\right)$$
$$\lambda_{\max} = -T \ln\left(1-\hat{\lambda}_{r+1}\right)$$
------------ (3.5)

Here, T is the effective number of observations. The two test statistics work under different hypothesis and in case of trace statistics, the null hypothesis is; H_0: at most r co-integrating vectors, while alternate hypothesis is; H_1: more than r co-integrating vectors. Max statistics works under the null hypothesis of H_0: exactly r co-integrating vectors against alternate hypothesis of H_1: exactly (r+1) co-integrating vectors (Nachane, 2010). The application of a dynamic VECM is suggested with the presence of co-integrating vectors which depicts the feedback process for short run deviation towards the long run equilibrium and it shows the presence of short run dynamics.

3.3.2.3 Vector Error Correction mechanism

Second stage of Johansen's procedure consists ECM (error correction mechanism) which shows of reconciling short-run behaviour of variables with long-run behaviour. Engle and Granger (1987) expresses that if two time-series are co-integrated, the ECM can produce the dynamic changes in case of short-run and also consider variations in the mode of partial adjustment. For capturing the long-run behaviour, an error correction term (ECT) is added in short-run equation and logarithmic transformation of variables is performed to convert into unit less data series for establishing the relationship between selected variables by using linearizing the model. The ECM specification applied in the current study is displayed below:

Δ log SX = α_0 + α_1 Δ log WPI_t + α_2 Δ log ER_t + α_3 log IIP_t + α_4 Δ log MS_t + α_5 Δ log $GOLD_t$ + α_6 Δ log FER_t + ECM (-2) + μ_t --------------- (3.6)

3.3.2.4 GARCH-Type Models

If the residual values of security fall in a range with normal distribution, zero mean and constant variance, there is no existence of volatility in that case for forecasting the model. On the other hand, if residual terms are observed with unequal variances, falls in a range several times and show extraordinary jumps for a period of short-time, this can be known as volatility in the behaviour of assets. In such case, squared returns of assets are positively autocorrelated. Application of historical standard deviation is one of the approaches to examine the volatility. But, there are some other improved techniques for measuring volatility too. GARCH models are having widespread usage in financial studies and these models are the popular non-linear financial models which are used for modeling and forecasting the volatility for understanding the behaviour of the series.

The simplest and first model is an ARCH (Autoregressive Conditional Heteroscedasticity) model. The AR basically comes from the evidence that GARCH-models are autoregressive in squared returns. Conditional means that volatility of next period is conditional on the information of current period and heteroscedasticity stands for non-constant volatility. ARCH-model can be expressed to the general case where the error variance basically depends on q lags of the squared errors. The variance of dependent variable is computed as a function of past information of the dependent and independent variables in the model. Two specifications have to be considered while developing an ARCH model. One specification is conditional mean equation which may be structured regression equation, whereas second is conditional variance equation. Engle (1982) developed ARCH (1) model and simplest **mean equation** is as follows:

$$\mathbf{Y_t = aX_t + \varepsilon_t} \qquad \text{------------- (3.7)}$$

Where, Y_t is the mean return, X_t is the independent variable & ε_t is error term and an inclusion of ε_t in the equation depicts an effect of news for the volatility on the basis of the past period on current variance. Residuals are applied in the formation of variance equation which are derived from mean equation (3.7). **Variance equation** for ARCH (q) Model is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 \qquad \text{-------------- (3.8)}$$

Where, σ_t^2 is conditional variance at time-period t for q lags added in the model, a_{t-1}^2 is past square term, while α_0 and α_1, parameters to be checked. $\alpha_0 > 0$ & $\alpha_1 \geq 0$ to ensure the positive variance, while $\alpha_1 < 1$ for stationarity. If residual return is big in magnitude, prediction for conditional volatility of next period (σ_{t+1}) will be large under an ARCH (1) model. The returns are conditionally normal in this model. An ARCH is similar to an AR model based on squared residuals, a_t^2.

Initiating with pioneering research of Engle (1982), numerous betterments have been added in the variance models for estimating the better time varying volatility because of the number of difficulties like decision of number of lags selection and violation of non- negativity constraints. Number of models based on ARCH are proposed to overcome problems such as GARCH, EGARCH and GJR-GARCH models. These models are different due to their structural forms, and usually depict the difference in the equation of conditional variance, while they use same kind of data of the return or squared returns. Models based on GARCH are widely accepted and applied by various researchers to better explain the conditional heteroscedasticity and GARCH based models express the behaviour of speculative markets.

3.3.2.5 Symmetric GARCH Model

In an ARCH (1) model, variance of next period depends on the squared residual of the last period. An extension of the ARCH model is GARCH and it is also known as Generalized ARCH model which is developed by Bollerslev (1986) and it is same in the spirit to an ARMA model. GARCH model is the popular model which argues that volatility is not affected by squared zero mean of variables only but it is also affected by past estimated volatility. In other words, the condition variance affected by conditional variance and squared error term of previous time period. An expression for GARCH (p,q) model is as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \qquad \text{---------- (3.9)}$$

Where, α_0, α_1, β_1= parameters to be estimated, σ = conditional variance at period t, q= number of return innovation lags included in the model, p= number of past volatility lags included in the model, a = innovation in return at time t.

Where, $\alpha_1 + \beta_1 < 0$ and $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta_1 > 0$, which means that the prediction of variance of next period is a blend of the forecast of previous period and squared return of previous period. The conditional variance not only depends on the squared error term of the previous time period but it also depends on its conditional variance of previous time period. Hence, conditional variance at any time t is the weighted sum of the past squared residuals and weights decrease as researcher go back in time.

The current study has applied GARCH (1,1) model and $\alpha + \beta < 1$ is the stationary condition for GARCH (1,1). The completion of this condition signifies that conditional variance is finite. The estimated coefficient states that constant α0 is volatility of long term average, α1 and β1 represent, how the current news and past information has affected the volatility in the above equation. Asymmetric variants were finalized by adding the different adjustment in standard GARCH models.

3.3.2.6 Asymmetric Variations of GARCH Models

A huge number of extensions and modifications have been suggested as a consequence of perceived problems of violation of non-negativity condition and lack of leverage effects with standard GARCH model. GARCH model enforce a symmetric response of volatility on positive and negative shocks. However, one observation is that in many markets, impact of the negative price moves on the future volatility is basically different in comparison to positive price moves and this is true in equity markets too. Magnitude of a_t^2 does not affect future volatility alone, and the sign of a_t affects future volatility too. However, it is still not clear why volatility should increase more if level of stock prices goes down compared to stock price rise? EGARCH and TGARCH models are widely used asymmetric GARCH models for this purpose.

i) EGARCH Model

Exponential GARCH (EGARCH) is the most famous model for checking the asymmetry. It is a powerful asymmetric model of GARCH which is develoopd by Nelson (1991). Basically, EGARCH explains the asymmetric impact of returns on conditional variance and based on transformation of log of conditional variance. Equation for EGARCH (p, q) is as follows:

$$\ln(\sigma_t^2) = \alpha_0 + \frac{\alpha_1 a_{t-1} + \gamma_1 |a_{t-1}|}{\sigma_{t-1}} + \beta_1 \ln(\sigma_{t-1}^2) \quad \text{---- (3.10)}$$

Here, σ_t^2 = variance of residuals derived from mean equation which is known as current day's variance or it can also be said as volatility of Sensex return, while σ_{t-1}^2 = Residual variance of previous day or it can also be said as the previous volatility of Sensex return and known as GARCH term. a_{t-1} = Squared residuals of previous period derived from mean equation and it is information about Sensex return volatility of previous day. It is ARCH term , γ is leverage effect and α_0 = constant.

There is always an asymmetric effect between negative and positive returns and for avoiding the chance of negative variance, this model is an AR (1) on $\ln(\sigma_{t-1}^2)$ instead of σ_t^2 . Since $\ln(\sigma_t^2)$ is modeled, σ_t^2 will be positive even if the parameters are negative. This is the main advantage of EGARCH model and there is no need to impose non negativity constraints artificially on parameters of model and asymmetries are also allowed under this model. A negative value of γ is consistent with the effect of leverage and it explains whenever total value declines with fall in prices, the value of equity produces smaller value to its total value.

ii) TGARCH Model

Threshold GARCH (TGARCH) model is an another variant on GARCH to measure the asymmetry between up and down moves and it is also known as GJR-GARCH model which followed the study of Glosten, Jagannathan, and Runkle (1993):

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \gamma_1 S_{t-1} a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

where

$$S_{t-1} = \begin{cases} 1, & \text{if } a_{t-1} < 0; \\ 0, & \text{if } a_{t-1} \geq 0. \end{cases} \qquad \text{-------- (3.11)}$$

Here, there is an additional parameter, γ which estimate the leverage effect, if γ > 0. It can also be said that if γ coefficient is not negative, then there is a fact of asymmetric effects in time-series and the coefficient must be negative for accepting the null hypothesis of asymmetry effect in TGARCH model. There are various models in the literature which try to capture asymmetry of the moves on future volatility. On the basis of literature, number of other variations of asymmetric GARCH models can also be found.

3.3.2.7 GARCH-M Model

GARCH-M Model is another variation on the basis of GARCH model and it tests whether variance can affect the mean of future returns or not and this model is known as GARCH in the mean or GARCH-M model developed by Engle, Lilien & Robins (1987) as ARCH-M. The GARCH-M specifies that conditional mean return is the linear function of conditional variance and any of GARCH specification may be followed for conditional variance. GARCH-M is shown as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$
$$r_t = \mu + \sigma_t \epsilon_t + \lambda \sigma_t^2 \; . \qquad \text{-----------} \; (3.12)$$

Among all parameters λ is most important because it explains the nature of relationship between volatility and stock market returns. If λ is positive and significant, then increased risk, which is given by an increase in conditional variance leads to rise in the mean of returns. Therefore, λ can be explained as a risk premium and if $\lambda \neq 0$, the models show a serial correlation of returns due to the serially correlated variance and the returns depend on variance. Various researches have tried to examine, whether λ is significantly different from zero.

3.3.2.8 Panel Data Unit Root Tests

Panel data unit root tests have been applied to check the stationary condition of the data series firstly, as current study use panel time series data. Panel unit root tests have been emerged from the testing of time series unit root and become popular in the recent years. Individual and time effects are marked in panel data analysis. The prime difference to time series unit roots analysis is that the panel data unit root tests are statistically stronger in comparison to the time series unit root tests because they consider both the time-series dimension and the cross-sectional dimension. Individual unit root tests have limited power for rejecting the null hypothesis when it is false. Various procedures of unit root in a panel context have been formed for the analysis purpose and the most widely used tests are Levin-Lin- Chu (LLC) test which is developed by Levin, Lin and Chu in 2002 and Im-Pesaran-Shin (IPS) tests developed by Im-Pesaran-Shin in 2003. Both tests have been used in the current study. Im-Pesaran-Shin (IPS) test is not as restrictive as LLC test because LLC test is basically based on homogeneous model hypothesis, whereas IPS test is depends on heterogeneous model hypothesis. LLC test designed for independent cross-section units in the panel data to test the null hypothesis of presence of common unit root. It is based on H_0: $p_1 = p_2 = \ldots\ldots = p_n = p = 1$ and suggest the following hypotheses:

H_0: $\alpha_i = 1$ for all cross section units, so each time series contains a unit root.

H_1: $\alpha_i < 1$ for at least one cross section unit, so each time series is stationary.

IPS test depends on the average of individual Dickey-Fuller tests of unit root which are calculated for each unit of cross-section in the panel separately. It works on sufficiently large cross-section, time period and serially correlated error term across cross-sectional units (u_{it}) with different serial correlation patterns. The null hypothesis is test is the presence of a unit root process in each cross section unit. These tests represents as:

$$\Delta Y_{it} = \propto_i Y_{it-1} + \sum_{j=1}^{P_j} \beta_{ij} \Delta Y_{it-j} + X'_{it}\delta + \varepsilon_{it} \quad \text{--------} \ (3.13)$$

Where, α_i is the error correction term. If $\alpha_i < 1$, series is trend stationary and if $\alpha_i \geq 1$, it has unit root. Tests enable α_i to differentiate for cross section units. When probability value which is obtained from results of tests is smaller than 0.05, H_0 is rejected and depicts that the series are stationary.

3.3.2.9 Fixed Effect Model

The relationship of financial performance indicators and returns is investigated for the selected industry and companies by using the panel data estimation models as panel data extract the rich information that can be applied to change the model in case of time and cross-sectional dimensions. The basic advantage of using the panel data instead of applying single cross section/series of cross sections is that it helps to relax the basic assumptions which are implicit in cross-sectional analysis. Fixed effect model has been employed in the study to identify the important determinants of investment in India. The assumption of fixed effect model is the lack of correlation between the random effects & explanatory variables. A fixed group model tests the group differences in intercepts, while assuming the slopes and constant variance across subjects. Fixed effect model considers the firm specific effects and it is expressed as follows:

$$y_{it} = \alpha_i + \beta\, x_{it} + u_{it}$$

$$y = 1 \ldots.N;\ t = 1 \ldots T \qquad \text{--------------}\ (3.14)$$

Here, y_{it} is return of i^{th} subject in t^{th} period, β is the parameters to be estimated, while u_{it} is the error term, x_{it} is the vector of explanatory variables of i^{th} subject in t^{th} period, α_i is the constant over time. Fixed effect model expresses the differences across the considered subjects by assuming differences in the intercept term.

3.3.2.10 Oscillators

Oscillators have been employed to observe the market trend of stock prices on the basis of monthly closing price of selected stocks. An oscillator momentum expresses the price movement between two time periods. The momentum of oscillators includes oversold/overbought conditions, trend reversal and rise/decline in the assets' price. Usually, oscillators are analysed along with the chart of price and depict reversals of trend which have to be confirmed with the price movement to take buy/sell signals. Generally, Oscillators are formed with monthly, weekly and daily closing prices. The current study has employed two oscillators on the basis of monthly closing price of selected stocks from April 2004 to August 2015 and the description of these oscillators is as follows:

i) Moving Average Convergence and Divergence (MACD)

MACD measures the divergence/convergence with the difference of two exponential moving averages (EMA) of two time periods. These moving averages are calculated by using closing price of security whether daily or monthly. 12-day and 26-

day moving averages are taken in the current study which are most commonly used for MACD. MACD line is calculated as:

MACD line = 12-day EMA (short term) – 26-day EMA (Long term)

There is convergence, If both EMA moves in similar direction; whereas divergence takes place if both EMA moves away to each other. Usually, the short term EMA is more reactive to change in price of underlying assets. The decision of bullish and bearish trends depends on the movement of MACD line across signal line.

Signal line = 9-day EMA of MACD line.

MACD histogram = MACD line – Signal line.

When MACD line cross the signal line from below & moves above and MACD histogram reaches above the zero line, it gives a buy signal. There are positive values of MACD that indicates rising price trend and give the signal of bullish market in such conditions and it is advisable to buy the stocks. Likewise, when MACD line cross the signal line from above and moves down and MACD histogram intersects the zero line, it gives a sell signal. There are negative values of MACD that indicates declining price trend in such conditions and give the signal of bearish market and it is advisable to sell the stocks in this situation.

ii) Relative Strength Index (RSI)

It is an oscillator which is used to identify the inherent technical strength/weakness in a particular stock. As per the requirement of technical analyst, RSI can be estimated for any number of days. In the current study, 14 months average has been taken for RSI as it is widely used in literature to measure the trend of stock price. If analyst considers the longer period, chances of getting the wrong signal is minimized. If the stock price is falling and RSI is increased, a divergence is said to have occurred. If RSI is rising in the overbought zone, it shows a fall in prices and generates sell signal. When RSI is in the oversold region, it gives a buy signal. RSI is calculated by using the following formula:

$$RSI = 100 - \left(\frac{100}{1+R}\right)$$

$$\text{Where, } R = \frac{\text{Average Gain per day}}{\text{Average Loss per day}}$$

3.3.2.11 Exploratory Factor Analysis

There may be number of variables in a research and may be correlated which need to be reduced upto a manageable level and associations among the sets of various interrelated variables are tested and represented in few underlying factors. Although, in case of multiple regression, discriminant analysis and analysis of variance, researcher consider one variable as dependent variable and other as independent, whereas factor analysis is a technique of interdependence where interdependent relationship of variables is tested. There are various uses of factors analysis and it is also known as exploratory factor analysis. The basic application of factor analysis is to recognize underlying factors which express the correlations among a set of variables. In other words, this technique is useful to find out smaller set of variables which will be uncorrelated for replacing the basic set of correlated variables. This technique is very useful in various business analyses. Principal components analysis method of factor analysis is employed to extract the factors. This method is widely accepted and used because it considers total variance in the data. Whenever, the prime concern is to find out the minimum number of factors that will express maximum variance in the data for the use, it is recommended to use principal components analysis. Varimax rotation method is used for factor rotation. This is the method which minimizes the number of variables with high loadings on a factor; hence, increase the interpretability of the extracted factors (Malhotra & Dash, 2013).

3.3.2.12 Cluster Analysis

Cluster analysis is a technique to classify objects into relatively homogeneous groups which are called clusters. This technique is also known as classification analysis. There is no a priori information about the group/cluster membership for objects under cluster analysis. This technique is basically used for segmenting the market, understanding the behaviour of respondents and recognising new opportunities etc. This technique adopts various steps for conducting the cluster. Formulating the problem is the first step of this analysis. Further, an appropriate distance measure must be selected and this distance measure calculates similarity/dissimilarity of the objects. Then, an appropriate clustering procedure is opted to solve the clustering problem and number of clusters will be finalised. Last step of cluster analysis is to interpret the clusters on the basis of variables and to check the validity of clustering process. Hierarchical and non-hierarchical clustering methods are performed and then, results are compared. Initially, hierarchical clustering is applied to identify the number of clusters and non-hierarchical clustering is applied in the later stage to validate the results (Malhotra & Dash, 2013).