Share Price Volatility in Indian Stock Market A Study with Special Reference to Behavioral Aspects of Investors in Kerala

Thesis

Submitted to the University of Calicut

for the award of the degree of

Doctor of Philosophy in Commerce

Mohamed Nishad T

Under the Supervision of

Dr. K.P Muraleedharan

Professor (Rtd.)

Department of Commerce and Management Studies

School of Business Studies

University of Calicut

June 2018

Mohamed Nishad T
Research Scholar
Department of Commerce and Management Studies
University of Calicut
Kerala - 673 635.

Declaration

I hereby declare that the thesis entitled **Share Price Volatility in Indian Stock Market – A Study with Special Reference to Behavioral Aspects of Investors in Kerala** done under the guidance and supervision of Dr. K.P Muraleedharan, is a record of bonafide research work done by me and no part of the thesis has been presented for the award of any degree, diploma, associateship, fellowship, or other similar title or recognition of any University/Institution before.

Calicut University
5th June, 2018.

Mohamed Nishad T
Doctoral Candidate

Dr. K.P Muraleedharan
Professor (Rtd.)
Department of Commerce and Management Studies
University of Calicut
Kerala - 673 635.

CERTIFICATE

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No part of the thesis has been submitted for any degree, diploma, fellowship or other similar title of this or any other Institute or University. He is permitted to submit the thesis.

Calicut University — **Dr. K.P Muraleedharan**

5th June, 2018. — Doctoral Guide

Dr. K.P Muraleedharan
Professor (Rtd.)
Department of Commerce and Management Studies
University of Calicut
Kerala - 673 635.

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It is also certified that the reports of the adjudicators of the thesis have not been suggested any modifications / corrections on the work.

Calicut University
11th January, 2019

Dr. K.P Muraleedharan
Doctoral Guide

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Mohamed Nishad T

Contents

List of Abbreviations

AGFI	Adjusted GFI
ANOVA	Analysis of Variance
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive Moving Average
AVE	Average Variance Extracted
BFMA	Behavioural Finance Macro
BFMI	Behavioural Finance Micro
BSE	Bombay Stock Exchange
CDSL	Central Depository Services Limited
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CMIN/DF	Minimum Discrepancy / Degrees of Freedom
CRISIL	Credit Rating Information Services of India Limited
CRM	Customer Relationship Management
DJIA	Dow Jones Industrial Average
EFA	Exploratory Factor Analysis
EGARCH	Exponential GARCH
EIC	Economy, Industry and Company
EMH	Efficient Market Hypothesis
FIIs	Foreign Institutional Investors
FMCG	Fast Moving Consumer Goods
GARCH	Generalised Autoregressive Conditional Heteroskedasticity
GARCH-M	GARCH-in-Mean
GDP	Gross Domestic Product
GFI	Goodness of Fit Index
IFI	Incremental Fit Index
IQ	Intelligent Quotient
IT	Information Technology

KMO	Kaiser-Meyer-Olkin
MACD	Moving Average Convergence Divergence
MENA	Middle East and North Africa
M-GARCH	Multivariate GARCH
NDA	National Democratic Alliance
NFI	Normed Fit Index
NFO	New Fund Offer
NSDL	National Securities Depository Limited
NSE	National Stock Exchange
PCA	Principal Component Analysis
PGARCH	Power GARCH
RMR	Root Mean Square Residuals
RMSEA	Root Mean Square Error of Approximation
RSI	Relative Strength Index
S&P BSE Sensex	Standard & Poor's BSE Sensitive Index
S&P CNX Nifty	Standard & Poor's CRISIL and NSE Index Fifty
SD	Standard Deviation
SEBI	Securities Exchange Board of India
SEM	Structural Equation Modeling
SSIM	Sharpe's Single Index Model
TGARCH	Threshold GARCH
TLI	Tucker Leiws Index
Tukey HSD	Tukey Honestly Significant Difference
UAE	United Arab Emirates
US	United State
VAR	Vector Autoreggression

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Chapter 1
Introduction

1.1 Preamble

The income that a person receives may be exercised for purchasing goods and/or services that he currently requires or it may be saved for purchasing goods and/or services that he may require in future. Savings are generated when a person or an organization abstains from present consumption with a view to future application. Investment involves the commitment of resources which have been saved in the hope that some benefit will accrue in course of time. Fisher & Jordan (2006)[1] defined investment as “a commitment of funds made in the expectations of some positive rate of return.”

There are four dimensions of investment: return, risk, time and liquidity. Investments are made with the primary objective of deriving return. The return may be received in the form of yield plus capital appreciation. The return from an investment depends upon the nature of investment, the maturity period and number of other factors. There two type of return - Nominal and real. Nominal return is the return which is offered without the consideration of inflation while real return is the return after deducting inflation. We have to consider real return while we select investment opportunities. Risk is one of the hallmarks of every investment. It is the variability in expected return. Risk and return of an investment are positively correlated. Normally, the higher the risk, the higher is the return. Time, by doing long-term investment one can experience the “magic of compounding”. So, lengthening the duration accelerates aggregate return, reduces volatility and risk, and the burden of cost. Liquidity refers to the ability to convert the investment to cash without much loss. The higher is the liquidity, better the investment option.

The objective of investor is to minimize the risk involved in investment and maximize the return from it. Our savings as cash are not only a deadwood as they don’t earn anything, but also lose its value to the extent inflation.

The goal of investment may be to beat the inflation, to make the money grow, to meet the future requirement and to maintain or improve the standard of living after some times. Investors may expect regular income, capital appreciation, safety, liquidity & tax planning from their investment. One should plan their investment according to one's income, requirement, age, risk tolerance capacity, liquidity requirements and the expertise one is having of the different investment avenues

One may invest in physical assets or financial assets. A physical asset is an item of economic, commerce or exchange value that has tangible or material existence, for example; Real estate, Gold, Silver etc. Financial asset is an asset that derives value because of a contractual claim, for example; Govt. securities, Post office savings, Fixed deposits, Bonds, Mutual funds, Shares etc.,

Volatility

Volatility is one of the yardsticks to measure risk. It makes sense that an asset which has had huge price swings is more risky than an asset that is not volatile. Prices vary on account of the buyer-seller estimations in the value of stock. Basically, share prices change in relation to supply and demand. If more people want to buy a stock than sell it - the price moves up. Conversely, if more people want to sell a stock than buy it - the price tends to fall. Volatility in the stock price is an integral part of stock market with the alternate bull and bear phases. In the bullish market, the share prices soar high and in the bearish market share prices fall down; these ups and downs determine the return and volatility of the stock market.

Volatility is a statistical measurement of ups and downs of asset price fluctuations over time. If an asset has rapid dramatic price swings, volatility will be high. If prices are consistent and rarely change volatility is low. It is a symptom of a highly liquid stock market. Pricing of securities depends on volatility of each asset. An increase in stock market volatility brings a large stock price the change of advances or declines. It has an impact on business investment spending and economic growth through a number of channels.

Certain factors are held responsible for this phenomenon. In some studies micro variables like dividend per share, earnings per share, company size and book value per share have got prominence and in others macro variables like bank rate of interest, index of industrial growth, union budget, inflation rate and exchange rate of foreign currency have been highlighted. Changes in local or global economic and political environment also influence the share price movements. If these are the only reason for the change in share price, the share price doesn't change by minutes and even seconds as they do in the stock market. In practice, the behaviour of the investor affects largely the share price movements which are explained in behavioural finance.

Behavioural Finance

Behavioural Finance is an emerging field and new domain of financial research that recognizes a psychological element in financial decision making. Behavioural finance is the study of how human psychology affects the investment decisions- and how these decisions affect stock prices and broad market movements. Investors are basically human beings and human beings aren't flawlessly rational; they are irrational also. They are influenced by feelings and emotions. When they buy on emotion, they not only jeopardize their own investment plans, but also create opportunities for others in the market.

Some of the psychological variables that cause the investors to behave in irrational ways are overconfidence bias, availability bias, loss aversion bias, herd behaviour, mental accounting etc. To study these behavioural aspects, first of all, anomalies existing in the stock market, which show deviations from the standard financial theories, have to be considered. One such widely accepted standard financial theory is Efficient Market Hypothesis (EMH). As per EMH, investors being wealth maximisers behave rationally. EMH is associated with 'Random Walk' theory. The logic of the random walk idea is that if the flow of information is unimpeded and information is immediately reflected in stock prices, and then tomorrow's price change will reflect only tomorrow's news and will be independent of the price changes today. However, there are many instances where emotions and psychology influence investor's decision making, causing them to behave in unpredictable or irrational ways. Such irrational decisions can better be explained with the help of Behavioural Finance.

Behavioural Finance is a study of investor market behaviour that derives from psychological principles of decision making, to explain why people buy or sell the stocks as they do. The two building blocks of behavioural finance are cognitive psychology (**how people think**) and the limits to arbitrage (**when markets will be inefficient**). The growth of behavioural finance research has been fuelled by the inability of traditional frame work to explain many empirical patterns, including stock market bubbles in Japan, Taiwan and the US (Pompian, 2008)[2].

The two primary sub topics in behavioural finance are Behavioural Finance Micro and Behavioural Finance Macro.

1. **Behavioural Finance Micro (BFMI)** examines behaviours or biases of individual investors that distinguish them from the rational actors envisioned in classical economic theory.
2. **Behavioural Finance Macro (BFMA)** detects and describes anomalies in the efficient market hypothesis that behavioural models may explain.

The figure 1.1 shows the consequences of behavioural bias on the investor level and on the stock market level as a whole.

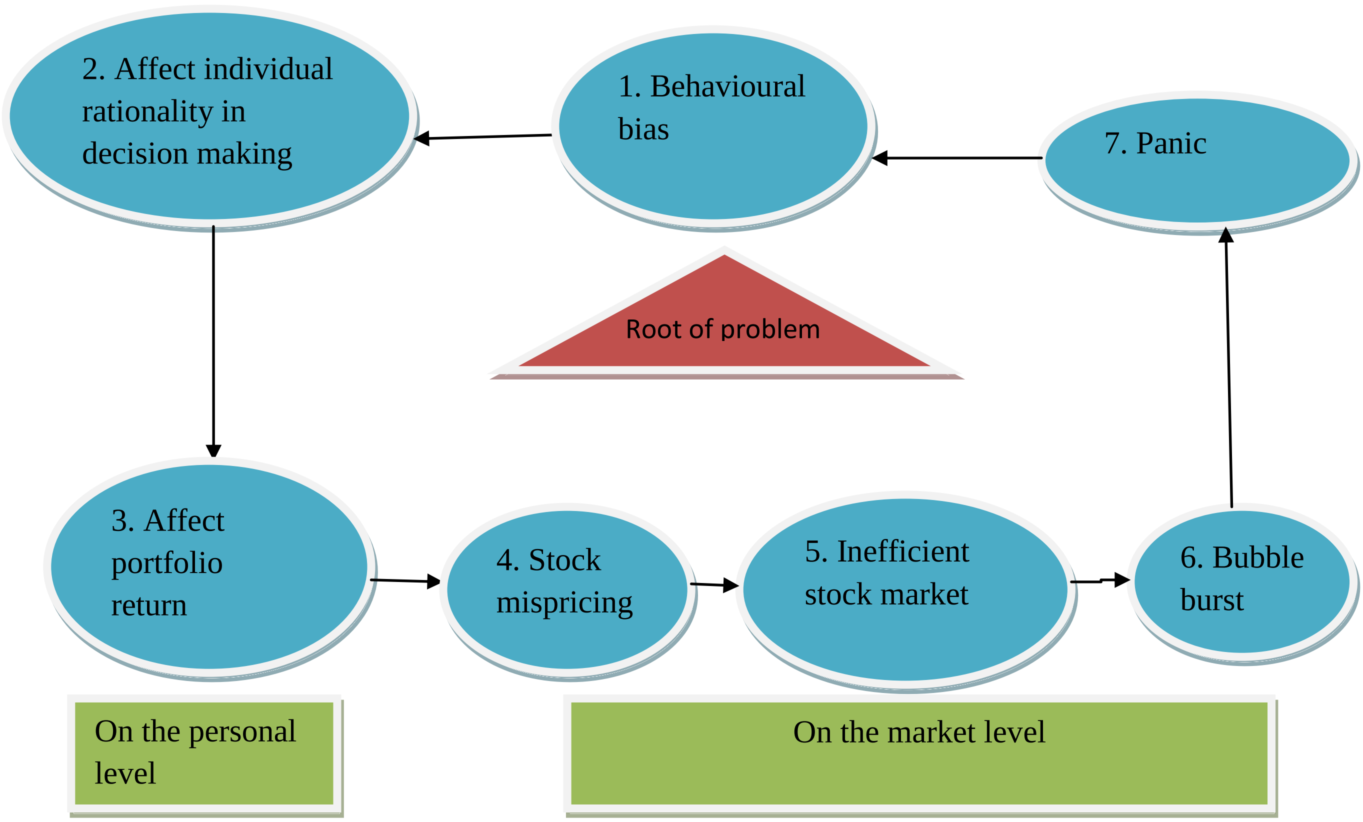

Figure 1.1 The Circle of Negative Consequences of Relying Heavily on Behavioural Bias

Adapted from

Alsedrah, I., & Ahamed, N. (2014)[3]. Behavioural Finance: The Missing Piece in Modern finance. *First Middle East Conference on Global Business, Economics, Finance and Banking*, Dubai.

The root of the problem is behavioural bias; it affects the individual rationality while taking investment decision. This irrationality adversely affects the portfolio return of the investor on individual level, but in the stock market irrationality makes the mispricing of the stock. On the market level irrationality makes the market inefficient. This creates bubble and consequently crash in the market. This situation makes panic among investors which again contributes behavioural bias.

1.2 Significance of the Study

‘As per latest data with Securities Exchange Board of India (SEBI), total number of investor accounts at National Securities Depository Limited (NSDL) stood at nearly 1.53 crore as on December 31, 2016 against 1.43 crore a year earlier. Central Depository Services Limited (CDSL) reported 1.18 crore investor accounts at the end of December 2016 — an addition of about 14 lakh accounts year-on-year. Together, the total number of demat accounts stood at 2.71 crore, at the end of December, last year — translating to an addition of 24 lakh accounts from the same period in 2015.’Standard (2016)[4]

The population in India in 2016 is 132.68Crore Worldometers (2017)[5]. That means only two percent of the population is having demat account in NSDL and CDSL. If we deduct those who have demat account in both, the percentage will again comes down. Moreover, ‘only 30-40 percent of accounts are active, which can be attributed to each client’s personal reasons (The reason that some traders lose money at the initial phase is only one of the many reasons)’ as opined by Kalyanaraman (2017)[6], senior vice-president of Sales at retail-focused brokerage Sharekhan, a unit of BNP Paribas. The Indian equity market is one of best among the world stock markets in terms of returns. But the equity culture is not spread among the individual investors as the number equity investors is just two percent of the total population. In the US when people seek to check up the ones without a stock market account, in India the question turns to the ones without a bank account. Stock market volatility is the major reason attributed to why individual investors stay away from the stock market.

1.3 Statement of the Problem

Individual investors presume equity investment as highly risky due to its volatility. An increase in stock market volatility brings a large stock price change of advances or declines. Investors interpret an ascent in stock market volatility as an increase in the risk of equity investment and consequently they shift their funds to less risky assets. Volatility of shares reduces the investment in equity shares. It has an impact on business investment and economic growth. The issues of return and volatility have become increasingly important in recent times to the Indian investors, regulators, brokers, policy makers, dealers and researchers.

To the Economy

To ensure a sustainable growth of our economy we should give more importance to inclusive growth. Inclusive growth means all the citizens of the country will benefit from its development. Attracting retailers to the stock market is the only way to have inclusive growth. But they are afraid of stock market volatility. Stock market volatility indicates the degree of price variation between the share prices during a particular period. A certain degree of market volatility is unavoidable, even desirable, as the stock price fluctuation indicates changing values across economic activities and it facilitates better resource allocation. But frequent and wide stock market variations cause uncertainty about the value of an asset and affect the confidence of the investor. The risk averse and the risk neutral investors may withdraw from a market at sharp price movements. Extreme volatility disrupts the smooth functioning of the stock market.

To the Financial Planner and Portfolio Managers

Private clients can greatly benefit from the application of behavioural finance to their unique situations. The understanding of how investor psychology impacts investment outcomes will generate insights that benefit the advisory relationship. The key result of behavioural finance-enhanced relationship will be a portfolio to which the advisor can comfortably adhere while fulfilling the client's long term goals.

To the Individual Investors

Individual investors can understand the different behavioural biases that exist in the stock market, once they know about it, even they can check themselves whether they are prone to such biases or not. In this study the researcher tries to give suggestions to control the same, so that they can adjust their behaviours to achieve better investment performance.

The proposed study would help to get an insight into some of the underlying reasons and biases that cause some people to behave irrationally while making financial decisions. The scope of study extends to explain the actions of the investors which cannot be explained by the conventional theories. The behavioural finance principles, if studied can be applied by the asset management organizations, mutual fund etc for constructing portfolios which would maximize the wealth of the investors.

The study of stock price volatility, Su (2010)[7], Kaur (2002)[8], Loomba (2012)[9], Market efficiency, Fama (1970)[10], MacKinlay (1997)[11], Jonsson & Radeschnig (2014)[12], Chakraborty (2011)[13] and Behavioural finance, Luong & Thu Ha (2011)[14], Bakar & Chui Yi (2016)[15]has been analysed separately by a lot of researchers from different angles. But no specific study has been done in India, to check the pattern and volatility in Indian market along with market efficiency and connecting the same with the behavioural aspects of investors. Hence there is a gap in research regarding volatility, market efficiency and the behavioural aspects of investors in Indian stock market. It is quite relevant to discover this fact and the study is designed to focus on these particular aspects. Hence the present study is proposed. It arise the following research questions:

- What is the extent and pattern of stock price volatility in Indian capital market?
- Is the Indian stock market efficient at weak form and semi-strong form of the Efficient Market Hypothesis?
- How do the security analysis, behaviour bias, emotional intelligence and investment performance change according to investor's gender, age, education, annual income and marital status?
- What is the role and impact of security analysis, behavioural bias and emotional intelligence on investment performance?

1.4 Scope of the Study

This study focuses on volatility, stock market efficiency and examining the role and influence of security analysis, behavioural bias and emotional intelligence on the investment performance of individual equity share investors in Kerala.

To study the volatility of Indian stock market, the data of indices (S&P BSE Sensex and S&P CNX Nifty) and selected stock prices are collected for the period of fifteen years from 2002 to 2016. To study the market efficiency of Indian stock market, two events (Bonus share and Stock split) are considered for the period of three years from 1st January, 2014 to 31st December, 2016. Moreover, it also studies the behavioural aspects of individual equity investors in Kerala

In case of secondary data, the scope of the study is limited to the performance of equity shares in terms of volatility and stock market efficiency in Indian stock market for the period of 2002 to 2016. In case of primary data, the present work is confined to behavioural aspects of individual equity share investors in Kerala.

1.5 Objectives of the Study

The main objectives of the present study are as follows:

1. To identify the extent and pattern of stock price volatility in Indian capital market.

2. To test the stock market efficiency at its weak form and semi-strong form with regard to Efficient Market Hypothesis in Indian Stock Market.

3. To assess the level of security analysis, behavioural bias and emotional intelligence of the individual investors in Kerala and their variability with regard to their gender, age, educational qualification, annual income and marital status.

4. To find out the role and impact of security analysis, behavioural bias and emotional intelligence on investment performance.

1.6 Hypotheses

The following hypotheses are formulated based on the objectives of the study.

- There is no stock price volatility in Indian stock Market
- Indian stock market follows weak form of Efficient Market hypothesis.
- Indian stock market is efficient in its semi-strong form of Efficient Market Hypothesis.
- There is no significant difference between security analysis with regard to their gender, age, educational level, annual income and marital status.
- There is no significant difference between behavioural biases with regard to their gender, age, educational level, annual income and marital status.
- There is no significant difference between emotional intelligence with regard to their gender, age, educational level, annual income and marital status.
- There is no significant difference between investment performance with regard to their gender, age, educational level, annual income and marital status, and
- There is no significant relation between security analysis, behavioural biases and emotional intelligence on the investment performance of individual investors.

1.7 Operational Definition

Investors

Investors are individuals who are having demat account, purchase shares directly for themselves to benefit from the growth of the stock market and increase their wealth.

Quantitative Analysis

The fundamental analysis which is capable of being measured or expressed in numerical terms is called as quantitative analysis. For example: dividend per share, earnings per share, price earnings ratio etc.

Qualitative Analysis

The fundamental analysis which is based on the quality or character of something and not capable of being measured in numerical terms is called as qualitative analysis. For example: quality of a company's management and key executives, its brand-name recognition, patents, proprietary technology etc.

Belief Perseverance Bias

It is the tendency to cling one's previously held or recently established beliefs irrationally or illogically. Examples are representativeness, conservatism, confirmation etc.

Information Processing Bias

Information processing bias results in information being processed and used illogically or irrationally. On the contrary to clinging irrationally to one's own beliefs, these have more to do with how information is processed. Examples are anchoring and adjustment, mental accounting, framing, availability, self-attribution etc.

Investment performance

Investment performance is the performance of the return (regular income plus capital appreciation) on the investment.

1.8 Research Methodology

Following are the methodologies used in the present study.

1.8.1 Research Design

The study is designed as a descriptive one and mainly based on secondary data and primary data. It attempts to describe the volatility and anomalies in the Indian stock market.

1.8.2 Source of Data

The data are collected from secondary sources as well as through structured interview schedule from the investors in Kerala.

1.8.2.1Secondary Data

The secondary data analysis necessary for the study are taken from the official websites of Bombay Stock Exchange (BSE), National Stock Exchange (NSE). The companies which have declared bonus share and stock split during the period from 01/01/2014 to 31/12/2016 are treated as population for the study of volatility and for testing stock market efficiency

Other secondary data are collected from the following periodicals, journals, books and study reports.

1. Worldometers
2. Business standard
3. SEBI website
4. RBI website
5. The website of money control
6. Research Dissertations and Theses
7. Journal of finance
8. Journal of behavioural finance
9. Other Research Journals
10. Periodicals
11. Study Reports
12. Research Publications
13. Books related to the study area and
14. Other websites

1.8.2.2 Primary Data

First-hand information required for the study has been collected from the individual investors of Kerala. The investors of Kerala are the target population for the present study. Since the population size is very large, census survey is not possible. Hence sample survey has been carried out.

1.8.3 Sampling Design

As stated earlier, the study is having two main purposes.

1. To check the extent and pattern of stock market volatility and market efficiency of Indian Stock Market.

2. To examine the impact of security analysis, behavioural bias and emotional intelligence on investment performance.

   For these purpose two sets of samples are required.

   1. Sample Companies
   2. Sample Investors.

1. Selection of Sample Companies

Companies have to be selected to check the pattern and the extent of volatility and to test weak and semi-strong form of market efficiency with regard to Efficient Market Hypothesis.

A. Population of the Companies to Analyse Volatility and to Test Efficient Market Hypothesis

The companies who have declared bonus share and stock split of the share during the period from 01/01/2014 to 31/12/2016 are treated as population for the present study. The following are the details of population.

Table 1.1

Summary of Population
Companies which have Declared Bonus Issue and Stock Split

Year	Bonus Issue	Stock Split	Stock Split & Bonus Issue	Total
2014	33	75	6	114
2015	60	88	2	150
2016	59	72	4	135
Total	152	235	12	399

Source: money control

From the above table, it can be seen that we select the companies from three categories, firstly the companies which had declared bonus share (152 companies), secondly which had declared stock split (235 companies) and thirdly which had declared bonus share as well as stock split simultaneously (12 companies). The total number of the above three categories are 399 companies.

B. Sample Size of Companies

The following statistical equation is used to calculate the sample size of the infinite population. The highest standard deviation among variables was taken.

$$n_0 = \left(\frac{zs}{e}\right)^2$$

n_0= number of sample size

z = standardized value corresponding to a confidence level (1.96 for 95% confidence level)

s = sample standard deviation or estimate (0.4875)

e = acceptable magnitude of error (assumed as 0.024)

$$n_0 = \left(\frac{1.96 \times 0.04875}{0.024}\right)^2 = 3.98125^2 = 15.85035$$

After applying finite population correction factor, the following the formulae may be considered, Berenson, Levine, & Szabat (2016).[16]

$$n = \frac{n_0 N}{n_o + (N - 1)}$$

Where N is population size

$$n = \frac{15.85 \times 399}{15.85 + (399 - 1)} = \frac{6324.15}{403.85} = 15.6597$$

The sample size of companies calculated for the study has been rounded to 20.

C. Sampling Method

Simple random sampling method is used to select the companies. Samples are selected through computer generated random numbers.

Table 1.2

Description of Secondary Data Sample

Year	Bonus Issue	Stock Split	Stock Split & Bonus Issue	Total
2014	2	2	0	4
2015	2	2	1	5
2016	5	4	2	11
Total	9	8	3	20

The data of indices (Nifty and Sensex) collected from their respective website and daily closing price for the selected shares are collected from the Bombay Stock Exchange website during the period 01/01/2002 to 31/12/2016. But some of the stocks were listed after 01/01/2002; in that case observations are collected from the date of the listing of the stock.

Table 1.3

Period of Study of Different Stocks

Stocks	Period	Observations
Bajaj Finance Limited	01/01/2002 – 31/12/2016	3731
Berger Paints India Limited	01/01/2002 – 31/12/2016	3712
Grasim Industries Limited	01/01/2002 – 31/12/2016	3738
Hindustan Petroleum Corporation Ltd.	01/01/2002 – 31/12/2016	3738
ITC Limited	01/01/2002 – 31/12/2016	3738
Mindtree Limited	07/03/2007 – 31/12/2016	2435
Oil & Natural Gas Corporation Limited	01/01/2002 – 31/12/2016	3738
V-Guard Industries Limited	13/03/2008 – 31/12/2016	2175
Welspun India Limited	01/01/2002 – 31/12/2016	3700
Kothari Products Limited	01/01/2002 – 31/12/2016	3691
Gulshan Polyols Limited	26/08/2002 – 31/12/2016	3354
Sunil Hightech Engineers Limited	02/03/2006 – 31/12/2016	2688
ChamanlalSetia Exports Limited	23/01/2002 – 31/12/2016	3401
JK Tyre Industries Limited	01/01/2002 – 31/12/2016	3650
Punjab National Bank	26/04/2002 – 31/12/2016	3656
Bata India Limited	01/01/2002 – 31/12/2016	3738
Tech Mahindra Limited	28/08/2006 – 31/12/2016	2564
Colgate-Palmolive (India) Limited	01/01/2002 – 31/12/2016	3725
Infosys Limited	01/01/2002 – 31/12/2016	3738
HCL Technologies Limited	01/01/2002 – 31/12/2016	3738

2. Selection of Sample Investors

Individual investors have to be selected to know the role and impact of security analysis, behavioural bias and emotional intelligence on the investment performance of the investors.

A. Population of Investors

The target population of the study comprises individual investors in Kerala who are buying and selling the shares in any of the stock exchanges in India. An official data of equity investors in Kerala and their geographical distribution are not available. Hence the assistance of share broking firms such as Karvy, Vertex Securities , Geojit PNB Paribas, JRG Securities and Motilal Oswal has been sought for identifying investors. They cover a vast geographical area of the sample districts. With their help a comprehensive list of investors has been prepared in the three selected districts and it is considered as population.

B. Determination of Sample Size Investors

The exact data regarding the number of equity investors in Kerala and their geographical distribution is not available. The following statistical equation is used to calculate the sample size of investors. The highest standard deviation among variables from the pilot study was taken.

$$n = \left(\frac{zs}{e}\right)^2$$

n= number of sample size

z = standardized value corresponding to a confidence level (1.96 for 95% confidence level)

S = sample standard deviation or estimate (1.2903)

E = acceptable magnitude of error (assumed as 0.129)

$$n = \left(\frac{1.96 \times 1.2903}{0.129}\right)^2 = 19.60456^2 = 384.3387$$

The sample size of investors calculated for the study has been rounded to 390.

C. Sampling Method

In the initial stage, three districts have been selected from the fourteen districts in Kerala by random sampling method using lottery method for the investigation. Accordingly Ernakulam, Kozhikode and Thiruvananthapuram are selected. In the second stage, one Corporation, one Municipality and one Gramapanchayath were selected from each sample district by adopting the random sampling method by employing computer generated random numbers. Accordingly, from Ernakulam District - Cochin corporation, Aluva Municipality out of 13 Municipalities and Edathala Gramapanchayath out of 82 Gramapanchayath from Thiruvanthapuram District- Thiruvanathapuram Corporation, Attingal Municipality out of 5 Municipalities, and Vellarada Gramapanchayath out of 78 Gramapanchayaths and from Kozhikode District- Kozhikode Corporation, Ramanattukara Municipality out of seven Municipalities and Kadalundi Gramapanchayath out of 70 Gramapanchayaths were chosen. The researcher selected the Corporations, Municipalities and Gramapanchayaths from each districts to get the representation of investors from urban, semi-urban and rural areas. The table of sample location is presented below.

Table 1.4

Selection of Sample Investors

Sl No.	District	Corporation	Municipality	Grama panchayath
1.	Ernakulam	Cochin	Aluva	Edathala
2.	Thiruvananthapuram	Thiruvananthapuram	Attingal	Vellarada
3.	Kozhikode	Kozhikode	Ramanattukara	Kadalundi

As mentioned earlier, assistance of share broking firms such as Karvy, Vertex Securities , Geojit PNB Paribas, JRG Securities and Motilal Oswal been sought for identifying investors. Not all brokers in all the selected locations were ready to give the full list of investors with them. From the list provided by these brokers, a population frame has been created. The total number of investors in the population frame is 11,326 consisting of 3174 investors from Trivandrum district 4,743 investors from Ernakulam district and 3409 investors from Kozhikode district.

Considering the fact that some of the schedules will have to be deleted due to incompletion of the response, non-response and other reasons the researcher administered 420 schedules. From each of the three districts 140 investors have been taken by using simple random sampling method where the random numbers are generated by computer.

1.8.4 Research Instrument

Pre-tested structured interview schedule is used as the instrument towards the purpose of collecting primary data for the study. A detailed interview schedule which consists of every aspect of the present study was prepared in consultation with experts in the field of finance and behavioural finance. The interview schedule starts with socio-economic details of investors followed by questions relating to security analysis, behavioural bias, emotional intelligence and investment performance.

1.8.4.1 Pre-testing of Interview Schedule

The pre-testing of first draft interview schedule has been done among 10 investors in Kozhikode district. The investors were motivated to comment on any of the questions which they considered unclear or difficult to answer. Modifications were made to the wordings and layout of the interview schedule and some additions and deletions of questions were made from the feedback received from the investors. The final version of the interview schedule is in Appendix I of this report.

1.8.5 Method of Contact

Undisguised personal interview method was followed for the purpose of the collection of primary data. The researcher has personally met the respondents and collected necessary information. The actual survey was conducted from March 2015 to October 2016.

1.8.6 Variables Used for the Study

The present study aims to study the influence of security analysis, emotional intelligence and behavioural bias towards investment performance. To fulfil these objectives the following variables are used.

Table 1.5

Variables Used for the Study

Sl. No.	Purpose	No. of Variables	Name of the Variables
1.	Security Analysis	5	1. Quantitative Analysis 2. Technical Analysis 3. Economic Analysis 4. Qualitative Analysis 5. Industry Analysis
2.	Behavioural Bias	3	1. Emotional Bias a) Overconfidence bias b) Loss aversion bias c) Regret aversion bias d) Herding bias 2. Information processing bias a) Anchoring bias b) Mental accounting bias c) Availability bias d) Self attribution Bias 3. Belief Perseverance bias a) Representativeness bias b) Cognitive dissonance bias c) Confirmation Bias d) Illusion of control bias
3.	Emotional Intelligence	5	1. Empathy 2. Motivating oneself 3. Social skills 4. Managing emotions 5. Self Awareness
4.	Investment Performance	1	1. Investment performance
5	Classification variables	5	1. Gender 2. Age 3. Education 4. Annual income 5. Marital status

1.8.7 Scaling Technique

Most of the information necessary for the study is qualitative in nature and its quantification is a problem. The researcher used scaling techniques for this purpose. Scaling is a method which changes attributes (a series of qualitative facts) into variables (a quantitative series). It is a procedure for the assignment of numbers or symbols to subjective abstract concepts.

The researcher developed a scale for measuring the security analysis in stock market investment context. It was designed by reviewing various studies related to security analysis and also by discussing with the supervisor and managers in this field. A total of 29 variables are identified. All the statements are positively worded, starting from 1 (Not at all used) to 5 (highly used).

In this study for fulfilling the objective of measuring the behavioural bias, the researcher developed an instrument which consists of 29 variables. All statements are worded positively, starting from 1 (highly disagree) to 5 (highly agree). The researcher developed a scale which consists of 15 variables after consultation with experts and psychologist to measure the emotional intelligence of investors in Kerala. The researcher made an attempt to measure the investment performance of the individual investor by using 3 statements.

1.8.8 Conceptual Model

Following is the model showing the influence of security analysis, behavioural biases and emotional intelligence on the investment performance.

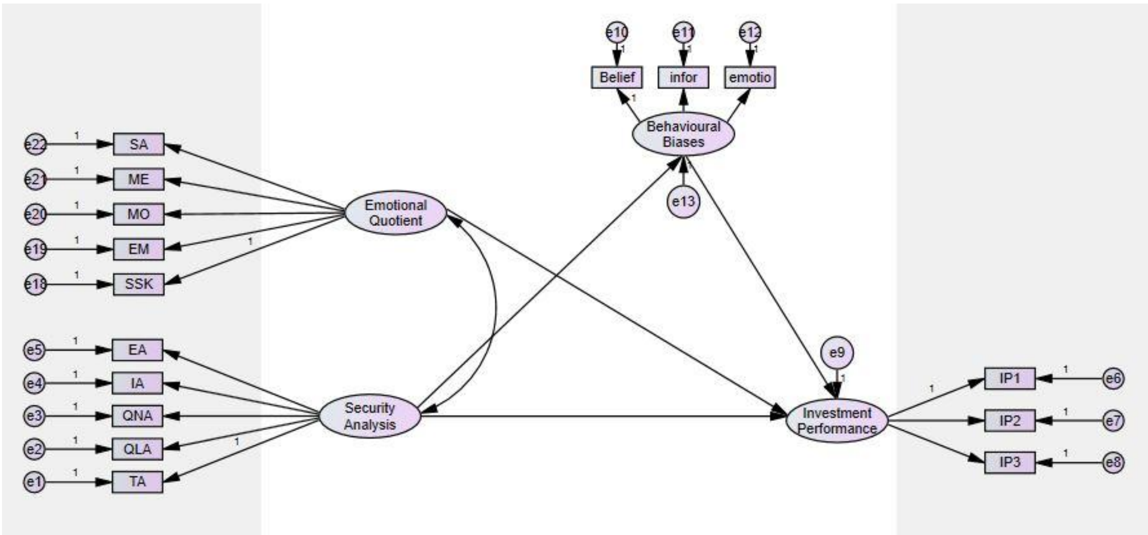

Figure 1.2 Conceptual Model

This model is based on four latent variable namely security analysis, emotional intelligence, behavioural bias and investment performance. The model seeks to identify the relationship between two independent variable (security analysis and emotional intelligence) and dependent variables (investment performance) and to check the behavioural bias is acting, mediating or moderating variable.

1.8.9 Pilot Study

For checking reliability and validity of the scale, the pilot study was done among fifty individual investors. After the pilot study, suitable modifications were incorporated into the interview schedule and thereafter the work of data collection started.

1.8.10 Reliability and Validity Testing

For the scale evaluation, reliability and validity testing are generally applied.

A Reliability Testing

Reliability testing is very essential for the validation of the scale. A measure is said to be reliable when it elicits the same response from the same person when the measuring instrument is administered to that person successively in similar or almost similar circumstances (Bajpai, 2011)[17]. In this study, the reliability of the measurement scales was tested by using Cronbach' Alpha Reliability Coefficient.

The measured variables and their respective alpha values are presented in a table 1.6 shown below:

Table 1.6

Reliability Statistics

Serial No:	Variables	Number of Items	Alpha Value
Security Analysis			
1	Economic Analysis	6	0.860
2	Industrial Analysis	3	0.823
3	Qualitative Analysis	5	0.875
4	Quantitative Analysis	8	0.900
5	Technical Analysis	7	0.906
	Total Items	**29**	
Behavioural Bias			
1	Belief Perseverance Bias	9	0.893
2	Information processing Bias	9	0.908
3	Emotional Bias	11	0.929
	Total Items	**29**	
Emotional Intelligence			
1	Self Awareness	3	0.814
2	Managing Emotions	3	0.816
3	Motivating Oneself	3	0.818
4	Empathy	3	0.859
5	Social Skills	3	0.801
	Total Items	**10**	
Investment Performance		**3**	0.834

The table 1.6 shows that all the values of Cronbach alpha is above the standard value 0.7 (Hair, Black, Babin, & Anderson, 2015)[18]. Hence, it is proved that the measurement scales have the internal consistency and scale is reliable.

B Validity Testing

The validity of a measurement scale means the ability of the measurement scale to measure what it is supposed to measure (Bajpai, 2011)[19]. In this study, two approaches of validity are tested. They are:

1. Content Validity

The researcher inquired about the expert's opinion regarding the validity of the instrument. Henceforth, the researcher showed the questionnaire to the supervisor teacher, senior academicians, statistician, financial analyst, managers of the share broking and other financial experts and the senior colleagues in the field of research and ensures that all the questions are relevant and suitable for fulfilling the research objectives. The researcher also made an attempt to confirm that the instrument contained all the important items.

2. Construct Validity

Construct validity occurs when the measurement of construct correlates with the theoretical measurement. To achieve construct validity, both convergent and discriminant validity must be there. Both of this validity is checked during data analysis through Confirmatory Factor Analysis.

Convergent validity is established when one measurement scale correlates with other measurement scale in the same construct. In the present study, there is convergent validity for all the measurement scales because the factor loadings associated with the loadings are greater than 0.7 and the p values associated with loadings are lower than 0.001(Hair, Black, Babin, & Anderson, 2015)[20].

Discriminant validity is ensured when the measurement scale is sufficiently different from other items of different constructs. It is said that there is discriminant validity for the measurement scale, when Average Variance Extracted (AVE) values for any two constructs is higher than the square of the correlation estimate between these two constructs. (Fornell & Larcker, 1981)[21]. In present research, all the constructs fulfil the condition, thus ensures discriminant validity.

1.8.11 Data Cleaning

Before starting the analysis, it is inevitable to check the quality of the data. Thus it enables the generalisation of results.

Data cleaning was done by removing the missing data and removing outliers. Outliers must be removed, otherwise it significantly change the shape of nonlinear as well as linear relationships. Among the total of 420 data collected, 22 filled questionnaires were deleted because of missing figures. Similarly, 8 filled questionnaires were forced to be removed as it represented outliers. Thus the balances of 390 data were used for the final analysis. The final sample respondents taken for the analysis is shown in the table 1.7.

Table 1.7

Final Sample Investors

Residential Location	Districts			Total
	Thiruvananthapuram	Ernakulam	Kozhikode	
Corporation	51	54	60	165
Muncipality	44	39	42	125
Panchayath	35	37	28	100
Total	130	130	130	390

1.8.12 Normality Testing

Skewness and kurtosis are the measures used by the statisticians to assess the normality. Skewness refers to the symmetry of a distribution. A distribution is said to be normal when the values of skewness is equal to zero. If the distribution is not symmetric, it may be negative skewed distribution or positive skewed distribution. Kurtosis refers to the degree of flatness or peakedness in the region about the mode of a frequency curve. If a curve is more peaked than a normal curve, it is leptokurtic (kurtosis> 3) when a curve is more flat topped than the normal curve, it is Platykurtic (kurtosis < 3). The normal curve is called as Mesokurtic (kurtosis = 3). The non-normality will be serious only when the value of skewness is more than three and the value of kurtosis is more than ten (Kline, 2011). Here none of the values are above this limit; hence normality assumed and proceed with parametric test.

The researcher should also consider the effects of sample size on normality. Sample size has the effect of increasing statistical power by reducing sampling error. The lager sample sizes reduce the detrimental effect of non-normality (Hair, Black, Babin, & Anderson, 2015)[23]. According to the central limit theorem:

1. If the sample data are approximately normal then the sampling distribution too will be normal

2. In large samples the sampling distribution tends to be normal, regardless of the shape of the data

3. Means of random samples from any distribution will themselves have normal distribution.

The central limit theorem means that there are variety of situations in which we can assume normality regardless of the shape of our sample data (Lumely, Diehr, Emerson, & Chen, 2002)[24]

1.8.13 Randomness Testing

The Run test is used to test the randomness of data. The result shows that for all the variables, the p values are above 0.05. Therefore the randomness of the data is assumed.

1.8.14 Data Independence

Data independence is assumed by most statistical procedures, including multiple regression, logistic regression and other general linear models. Durbin Watson coefficient can be used for testing the data independence. For achieving the data independence, the Durbin Watson statistic should be in between 1.5 and 2.5. In the present study, data fulfil the conditions; hence the data independence is assumed (Garson, 2012)[25].

1.8.15 Data Analysis

1.8.15.1 Secondary Data Analysis

The tools used for the analysis are briefly discussed below

1. **Mean, Standard Deviation and Percentage**

The mean or average is a measure for representing the entire data by one value. It is a measure of central tendency that attempts to describe a set of data by identifying the central position within that set of data. Standard deviation is used for measuring the deviation of values from the mean score. Percentages are used for comparing information of two different samples.

2. EGARH

Standard GARCH (Generalised Autoregressive Conditional Heteroskedasticity) models assume that positive and negative error terms have a symmetric effect on the volatility. In other words, good and bad news has the same effect on the volatility in this model. In practice this assumption is frequently violated, in particular by stock returns, in that the volatility increases more after bad news than after good news. This is called as *Leverage Effect.* So from an empirical point of view, the volatility reacts asymmetrically to the sign of the shocks, and the exponential GARCH (EGARCH) parameterized extensions of the standard GARCH model to consider this asymmetry in the model.

3. **Dickey-Fuller Unit Root, Phillip-Perron Unit Root and Auto Correlation Test**

These three tests have used to check weak form efficiency of Indian Stock Market.

4. **Event Study**

Event study is an important tool used to measure the effect of an economic event on the value of firms. An event study analyses the impact of definite event on the value of a firm. This study has used to test the semi-strong form efficiency of Indian Stock Market.

1.8.15.2 Primary Data Analysis

The tools used for the primary analysis apart from Mean, Standard Deviation and percentage are briefly discussed below.

1. **Independent Sample t Test**

The Independent Sample t test is a statistical test for comparing the means of two independent groups in order to determine whether there is any significant difference between these groups.

In independent sample t test, there is an assumption that each group (category) of one or more categorical independent variables has the same variance on an interval dependent. This assumption can be tested by using Levene's test. It tests the null hypothesis that the variance of the group is homogeneous. If the p value of the Levene's test is less than .05, then we can conclude that the variance is heterogeneous(Garson, 2012)[26]. In that case second set of analysis (equal variance not assumed) has to be considered. In all cases of ' t test' the researcher tested the homogeneity and chose the result accordingly.

2. **One Way ANOVA/ Welch F**

The One-way ANOVA stands for One-way Analysis of Variance (ANOVA). It is used to determine whether there is any significant difference among the means of three or more independent groups.

In ANOVA, there is an assumption that the variance of outcome is homogeneous. This assumption can be tested by using Levene's test. The null hypothesis of this test is that the variance of the group is homogeneous. If the p value of the Levene's test is less than .05, then we can conclude that the variance is heterogeneous. Then we should adjust the F test to correct this problem. The researcher use Welch's F to correct the heterogeneity. In all cases of 'ANOVA' the researcher tested the homogeneity and chose the ANOVA or Welch's F accordingly. Welch's F test is an alternative to ANOVA F test and is used when equality of group means cannot be assumed (Garson, 2012)[27].

3. Tukey HSD / Tamhane's T2 Post Hoc Test for Multiple Comparisons

Post hoc tests are designed for situations in which the researcher has already obtained a significant difference among three or more independent groups using ANOVA and to know the exact difference between these groups. Tukey HSD test is one of the most popular, conservative and flexible methods of post hoc test and it is used when equal variances are assumed. If the equal variances are not assumed Tamhane's T2 are used instead of Tukey HSD.

4. Multiple Regression

Multiple regression analysis is a 'statistical technique used to analyse the relationship between a single dependent variable and several independent variables' Hair, Black, Babin, & Anderson (2015)[28].

5. Exploratory Factor Analysis

Exploratory factor analysis attempts to identify the underlying variables, or factors, that explain the pattern of correlation within a set of observed variables. It is useful for placing variables into meaningful categories.

6. Confirmatory Factor Analysis

Confirmatory Factor Analysis is used to provide a confirmatory test of our measurement theory. A measurement theory specifies how the measured variables logically and systematically represent constructs involved in a theoretical model (Hair, Black, Babin, & Anderson, 2015)[29].

In order to assess the goodness of model fit, the experts recommended various indices. The details are presented in the following table.

Table 1.8

Model Values of Goodness of Fit

Sl. No	Indices of Common Fit	Value of Good Fit	Reference
1.	CMIN/DF (Minimum discrepancy / Degrees of Freedom)	<5	(Wheaton, Muthen, D.F, & Summers, 1977)[30]
2.	RMR (Root Mean Square Residuals)	<0.05	(Tabachnick & Fidell, 2007)[31]
3.	Goodness of Fit Index (GFI)	>0.90	(Byrne, 2010)[32]
4.	Adjusted GFI (AGFI)	>0.90	(Hooper, Coughlan, & Mullen, 2008)[33]
5.	Comparative Fit Index (CFI)	>0.90	(Byrne, 2010)[34]
6.	Incremental Fit Index (IFI)	>0.90	(Bollen, 1989)[35]
7.	Tucker Leiws Index (TLI)	>0.90	(Bentler & Bonnet, 1980)[36]
8.	Normed Fit Index (NFI)	>0.90	(Bentler & Bonnet, 1980)[37]
9.	Root Mean Square Error of Approximation (RMSEA)	<0.08	(MacCallum, Browne, & Sugawara, 1996)[38]

7. Structural Equation Modeling (SEM)

Structural Equation Modeling (SEM) is a statistical methodology that takes confirmatory (i.e., hypothesis testing) approach to the analysis of a structural theory bearing on some phenomenon. It conveys two important aspects of the procedure (Byrne, 2010)[39].

a. Casual processes under study are represented by a series of structural (i.e., regression) equations.

b. These structural relations can be modelled pictorially to enable a clearer conceptualisation of the theory under study.

Structural Equation Modeling refers to both structural and measurement model together.

The analysis of the quantitative data has been done with the help of statistical software called Eviews, Gretl, SPSS and the research model was prepared using the SPSS Amos software.

1.8.16 Period of Study

Secondary Data

- The data of indices (Nifty and Sensex) were collected from their respective website and daily closing prices for the selected shares were compiled from Bombay Stock Exchange website during the period 01/01/2002 to 31/12/2016. But some of the stocks are listed after 01/01/2002; in that case observations were collected from the date of listing of the stock.

Primary Data

- The work of primary data collection was started during March 2015 and got completed in October 2016.

1.9 Limitations of the Study:

The present study is subject to the following limitations.

- Only two events (stock split and bonus issue) were taken for the event study. Moreover, the event 'stock split' and 'bonus issue' which were announced within the period of 1st January 2014 to 31st December 2016 were chosen, the period of three years only was considered.

- The human behaviours are complex and difficult to be understood as they vary according to situations, so it is not possible to ensure 100% accuracy in the result. However efforts have been made to ensure as much as accurate as possible.
- Samples are not taken from the full fledged sample frame. It is collected from stock brokers; some of the brokers are hesitant to provide the details of

investors. It may affect sampling even though the researcher has taken all the efforts to make the sample frame comprehensive.

- The researcher finds it difficult to get data on investor’s real return and investment performance; so the researcher uses the subjective assessment. It is made by asking them to compare their current real return to expected return and rate of return of the market. Moreover, satisfaction level of investment decision also used as criteria to measure the investment performance.
- The study is limited to only the area of security analysis, behavioural bias and emotional intelligence.

1.10 Structure of the Thesis

The whole research report is mainly divided into nine chapters, which will further include some sub-chapters.

1. Introduction

This chapter covers a brief introduction to the topic under study, scope and significance of the study, research problem, objectives of study, research methodology, adopted variables and their operational definition and the limitations of the study.

2. Literature Review

This chapter is devoted for brief reviews of previous studies on the problem and significant writings on behavioural finance.

3. Theoretical Framework

This chapter summarizes the theoretical overview of share price volatility, its pattern, reasons and conceptual framework of Behavioural Finance & anomalies of Standard Finance.

4. Extent & Pattern of Indian Stock Market Volatility

This chapter empirically analyses the extent and pattern of Indian Stock market by using the daily closing price of two indices and twenty sample shares.

5. Market Efficiency of Indian Stock Market

The researcher tests the weak and semi-strong form efficiency of Indian stock Market by empirically analysing the data of sample shares.

6. Role of Security Analysis on Investment Decision.

This Chapter discusses different factors of security analysis and how it influences among the various socio-economic factors.

7. Impact of Behavioural Biases & Emotional Intelligence on Investment Decision

This Chapter discusses various behavioural bias and emotional intelligence and how it influences among the different socio-economic factors.

8. Factors Influencing Investment Performance – An Empirical Analysis

This chapter explains the relation of different independent variables like security analysis, behavioural bias and emotional intelligence and how they affect the investment performance

9. Summary, Findings and Recommendations

The chapter is a self-contained summary of the whole report, containing a summary of essential background information, findings and recommendations.

References:

1. Fisher, D. E., & Jordan, R. J. (2006). *Security Analysis and Portfolio Management.* Noida: Pearson Education.

2. Pompian, M. M. (2008). *Behavioral Finance and Wealth Management.* New Jersey: John Wiley & Sons.

3. Alsedrah, I., & Ahamed, N. (2014). Behavioural Finance: The Missing Piece in Modern finance. *First Middle East Conference on Global Business, Economics, Finance and Banking* (p. 1 to 13). Dubai: www.globalbiz research.org.

4. Standard, B. (2016, March 8). *Home: Business Standard*. Retrieved January 14, 2017, from Business Standard: http://www.business-standard.com/ article/pti-stories/investor-accounts-in-nsdl-cdsl-recorded-at-2-5-crore-116030800936_1.html

5. Worldometers. (2007, December 27). *population, worldometers*. Retrieved march 31, 2017, from Worldometers: www.worldometers.info/world-population/india-population/

6. Kalyanaraman, R. (2017, May 21). *E paper: Livemint*. Retrieved May 2017, 25, from Livemint: http://www.livemint.com/Money/1obv YAc2YiDh WSbBtaYG3J/24-million-new-demat-accounts-opened-last-year-highest-sin.html

7. Su, C. (2010). *Application of EGARCH Model to Estimate Financial Volatility of Daily Returns.* Sweden: University of Gothenburg.

8. Kaur, H. (2002). *Stock Market Volatility in India.* New Delhi: Deep & Deep Publications Pvt. Ltd.

9. Loomba, J. (2012). Do FIIS Imapct Volatility of Indian Stock Market? *International Journal of Marketing, Financial Services & Management Research, 1* (7), 80-93.

10. Fama, E. (1970). Efficient Capital Market: A Review of Theory and Empirical Work. *Journal of Finance, 25* (2), 382-417.

11. MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature, 35* (1), 13-39.

12. Jonsson, R., & Radeschnig, J. (2014). *From Market Efficiency to Event Study Methodology.* Sweden: Malardalen University.

13. Chakraborty, P. (2011). Semi- Strong of Pricing Efiiciency of Indian Stock Market - An Emiprical Test in the Context of Stock-Split Announcement. *EXCEL International Journal of Multidisciplinary Management Studies, 1* (2), 1-13.

14. Luong, L. P., & Thu Ha, D. T. (2011). *Behavioral Factors Influencing Individual Investors' Decision-making and Performance.* Vietnam: Umeå School of Business.

15. Bakar, s., & Chui Yi, A. N. (2016). The Impact of Psychological Factors on Investors' Decision Making in Malaysian Stock Market, A Case of Klang Valley and Pahang. *Procedia Economics and Finance* , 319-328.

16. Berenson, M. L., Levine, D. M., & Szabat, K. A. (2016). *Basic Business Statistics: Concepts and application.* New Jersey: Pearson.

17. Bajpai, N. (2011). *Business Research Methods.* Delhi: Pearson Education in South Asia.

18. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2015). *Multivariate Data Analysis.* Noida: Pearson India Education Service Pvt Ltd.

19. Op. Cit. 17

20. Op. Cit. 18

21. Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equations Models with Unobservable Variables and Mesurement Error. *Journal of Marketing Research* , 39-50.

22. Kline, R. B. (2011). *Principles and Practicce of Structural Equation Modeling* (3rd ed.). New York: The Guilford Press.

23. Op. Cit. 18

24. Lumely, T., Diehr, P., Emerson, S., & Chen, L. (2002). *The Importance of the Normality Assumption in Large Public Health Data Sets.* Washington: Annual Reviews.

25. Garson, D. (2012). *Testing Statistical Assumptions.* USA: G David Garson and Statistical Associate Publishing.

26. Ibid

27. Ibid

28. Op. Cit. 18

29. Op. Cit. 18

30. Wheaton, B., Muthen, B., D.F, A., & Summers, G. (1977). Assessing Reliability and Stability in Panel Models. *Sociological Methodology, 8* (1), 84-136.

31. Tabachnick, B. G., & Fidell, L. (2007). *Using Multivariate Statistics (5th ed.).* New York: Allyn and Bacon.

32. Byrne, B. M. (2010). *Structural Equation Modeling with AMOS.* New York: Routledge.

33. Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural Equation Modelling: Guidelines for determining model Fit. *The Electronic Journal of Business Research Methods, 6* (1), 53-60.

34. Op. Cit. 32

35. Bollen, K. (1989). *Structural Equations with Latent Variables.* New York: John Wiley & Sons, Inc.

36. Bentler, P., & Bonnet, D. (1980). Significance Test and Goodness of Fit in the analysis of Covariance Structures. *Psychological Bulletin, 88* (3), 588-606.

37. Ibid

38. MacCallum, R., Browne, M., & Sugawara, H. (1996). Power Analysis and Determination of Sample Size for Covariance Structure Modeling. *Psychological Methods*, *1* (2), 130-149.

39. Op. Cit. 32

Chapter 2

Review of Literature

2.1 Introduction

The present study explores the behavioural aspects of investors in Kerala in relation to share price volatility in Indian stock market. It aims to examine the role and impact of security analysis and emotional intelligence on investment performance of individual equity share investors in Kerala. The mediating role of behavioural bias between security analysis and emotional intelligence on investment performance is also covered by this study. The researcher has made an attempt to review the relevant related studies to the present research work conducted so far in order to identify the research gap. The related studies are classified in to six sections, namely, Studies relating to (1) Stock price volatility (2) Market efficiency (3) Security analysis (4) Behavioural finance (5) Emotional intelligence and (6) Investment performance.

2.2 Studies Relating to Stock Price Volatility

This study starts with volatility and enquires the reasons of volatility in the Indian stock market. Volatility is a statistical measurement of up and down asset price fluctuations over time. If an asset has rapid dramatic price swings, volatility will be high. If prices are consistent and rarely change, volatility is low. Pricing of securities depends on volatility of each asset. An increase in stock market volatility brings a large stock price change of advances or declines. Investors interpret a raise in stock market volatility as an increase in the risk of equity investment and consequently they shift their funds to less risky assets. Several studies are available in this area. Some of the most relevant studies are reviewed below.

Bhowmik (2013)[1] evaluated various dimensions of stock market volatility comprising measurement, factors and nature of impact of volatility. It considers the political factors of volatility and tried to connect economic growth. He finds the stock market volatility negatively correlates growth of the nation. i.e. high volatility inversely affect the growth rate.

Nalina and Karthik (2013)[2] estimated the conditional volatility models to find out characteristics of stock market volatility in India. They also analyse the leverage effect of Indian companies. The estimation of volatility is calculated at the macro level on two main market indices, namely NSE Nifty and BSE Sensex. These indices are used to ascertain the Heteroskedasticity behaviour of the stock market in India at macro level. They found that Indian stock market showed the conditional volatility and leverage effect.

Satish & Nayia (2012)[3] tested the impact of 2008 U.S crisis on Indian stock market volatility. They have used both conventional and modern approaches for this study. This shows that the volatility in Indian stock market is too high during the subprime mortgage crisis in the US. They used ARCH & augmented E-GARCH models in the Study.

Nawazish and Sara (2012)[4] examined the volatility pattern of Karachi Stock Exchange. They have considered a sample period which is most volatile in the history of Pakistan’s stock market. They estimate the model by using ARMA (1, 1) and found that Pakistan is an emerging market with high volatility. The study also found empirical evidence which indicates the presence of time varying volatility in Pakistan stock market.

Loomba (2012)[5] evaluated the role of FIIs in the volatility of Indian stock market. The study uses the daily data on BSE Sensex and FII activity over a period of 10 years from 01/01/2001 to 31/12/2010. He used Pearson correlation to analyse the data and concludes that FIIs have significant role in making volatility in Indian stock market.

Mukhopadhyaya (2011)[6] studied volatility of Indian stock market and analysed some factors like gold price, crude oil price, FII and US stock market movement to check how they impacted the Indian stock market. He has collected Nifty and DJIA closing price to compare Indian and US stock market. Tools like regression analysis, vector auto regressive test are used for the analysis. The study found the relation between dependent and independent variable and developed a regression model for the prediction of volatility.

Rahman & Moazzem (2011)[7] studied the causal relationship between the volatility of Dhaka Stock exchange and the regulatory controls imposed by the Securities Exchange Commission. They estimated the volatility & then used Vector Autoreggression (VAR) to determine the relationship when there was simultaneity among the variables. They found that the stock exchange became more volatile over time and the regulators were not able to control the volatility.

Ahamed S (2011)[8] investigated the international transmission of daily stock index volatility movements from America & Britain to selected MENA emerging markets: Egypt, Israel & Turkey. The M-GARCH modeling is used to model multivariate conditional volatility and test for the spill over among different market. He finds that both British and American market has no spill over effect on Turkish market and there is significant spill over effect from American market to Egypt and Israel.

Ahmed & Suliman (2011)[9] estimated the volatility of Khartoum Stock Exchange (KSE), Sudan. They used different varieties of GARCH (GARCH-M, EGARCH, TGARCH and PGARCH) including both symmetrical and asymmetrical model to test this phenomenon. It has shown that positive and negative shocks of the same magnitude have the same impact and it leads to the high volatility.

Mallikarjunappa and Afsal (2008)[10] analysed the implications of derivatives on Indian stock market by using GARCH model in NIFTY index. They find clustering and persistence of volatility before and after derivatives. They found that "the introduction of derivatives does not have any stabilizing or destabilizing effect in terms of decreasing and increasing volatility. As per this study derivative does not help to decline volatility.

Debjiban (2007)[11] analysed the trends, similarities and patterns of Indian stock market volatility in comparison with its international stock markets. The period of the study is from 1st Jan, 1955 to 31st Jul, 2006 which is divided into different sets of years to understand the effects in different time periods. He used the tools like correlation analysis, exponential trend analysis and the risk-return analysis to test the hypothesis. This study reasserts that the Indian stock market started to integrate with global counter parts, especially after 2002-03.

Raju & Ghosh (2004)[12] compares the Indian stock market volatility with its international counterparts. They checked inter-day and intra-day volatility by using skewness and kurtosis. Among the emerging markets except China and India, all other countries exhibited low returns – sometimes negative returns – with high volatility. They concluded that many of the developed markets and all emerging markets experienced high volatility during 1997 to 2002.

Kaur (2002)[13] evaluated the extent of volatility of the Indian stock market in different period and different stocks and also examined the effect of firm's size, presence of day of the week effect and FIIs investment on the stock returns and volatility. He has used ARCH (Auto Regressive Conditional Heteroskedasticity) and generalised ARCH (GARCH) to model the volatility. The study finds that the overall monthly volatility of Sensex and Nifty has been in the range of 7% to 16 % for the total period, where as the annualised volatility has been in the range of 24% to 56% approximately.

Mehra (1998)[14] studied the volatility at aggregate level rather than the individual firm level. He examined the issues of volatility using aggregate stock market value and aggregate after-tax net cash flows as a ratio to National income. The result discerns that while low frequency movements in the growth rate are important in deciding the volatility of stock prices, persistence in growth rates reduces the equity premium.

Bollerslev & Mikkelsen (1996)[15] explain pricing the long memory in the stock market volatility and model the same by using the GARCH (Generalised Auto Regressive Conditional Hetroskedasticity) and Exponential GARCH (EGARCH). It shows the clear long run dependence in U.S stock market volatility and it is explained by mean-reverting fractionally integrated process.

Day & Lewis (1992)[16] compared the information content of the implied volatility from stock index call option to Generalised Autoregressive Conditional Heteroskedasticity (GARCH) and exponential GARCH (EGARCH) models of conditional volatility. They administered maximum likelihood estimation using Berndt-Hall-Hall-Hausman algorithm to estimate the GARCH model and found that implied volatilities may contain incremental information relative to the conditional volatility estimate from GARCH and EGARCH model.

Baillie & DeGennaro (1990)[17] assess the empirical evidence for a relationship between the return on portfolio of stock and the standard deviation of those returns. It is found that simple mean variance model is inappropriate. They then used Generalised Autoregressive Conditional Heteroskedasticity to model the volatility. The estimated model does not show significant relationship between a stock portfolio's return and its own volatility.

Schwert (1990)[18] analysed the long term and short term volatility in the stock market. He has measured the volatility by the standard deviation of rates of return to a stock market index such as standard & poor's 500. Three return series such as 15 minute returns, daily returns, and monthly returns have been used to calculate different terms volatility. The study also indicates that future returns are more volatile than the stock returns.

French & Roll (1986)[19] tested the volatility of equity returns during exchange trading and non-trading hours. They find that the variance return from open to close of trading on an average day is more volatile than variance of close to open returns in a weekend. So the volatility is more in trading hours than in non-trading hours. The study concluded that the differences in the flow of information (more in trading hours, less in non-trading hours) affects the volatility positively.

Shiller (1981)[20] investigates the volatility in real stock prices and whether it can be explained by new information on subsequent real dividend. He used the simple efficient market model and he has witnessed high kurtosis in stock price change distributions. It is found that expected total returns are constant and that the capital gain component of returns is in accordance to the information on the future dividend.

2.3 Studies on Stock Market Efficiency

According to Efficient market hypothesis, security prices are expected to move randomly in an efficient market. It is a logical extension of the technical and fundamental analysis approaches to investment decision. So when the market is efficient, it is impossible to beat the market i.e. nobody can make abnormal return from the market. In efficient capital market security prices are almost equal to their intrinsic value at all times, and most securities are correctly priced. The efficient Market Hypothesis is divided into three forms, namely weak form, semi-strong form and strong form. Weak form holds the view that the current market price of shares reflects all the information regarding the past sequence of the price movements. So past sequence of the securities prices cannot be used to predict the future price of the same security. It is the direct refusal of technical analysis. The semi-strong form implies that the current share price reflects all publicly available information about the company (not only information about historical price but also other available information). Whenever the information becomes public, the share price absorbs it and imbibes the full information. Semi strong form refuses fundamental analysis as it says that fundamental analyst cannot make superior gains. Strong form argues that the current price of a share absorbs all information, both publicly available and insider information. This means that nobody can make abnormal return by using public as well as private information.

Sarmiento-Sabogal, Hatemi-J, & Cayón-Fallon (2016)[21] test the market efficiency of efficient market hypothesis in Colombian Stock Market with regard to exchange rates and yield to maturity. The data is collected during the period from 2001 to 2013 which does not have the normality. Here he used leveraged bootstrap test of causality. The result shows that Colombian stock market is efficient with regard to both the exchange rates and the yield to maturity

Kalsie & Kalra (2015)[22] conducted empirical study on the efficiency of Indian stock markets in relation to efficient market hypothesis during the period from 2001 to 2011. The weak form of efficient market is tested using NIFTY and major NSE sectoral indices like FMCG, IT, Bank, Pharma and Nifty Junior. They check the stationarity and auto correlation of the data and used Run test to analyse the same. The result shows the rejection of weak form of efficiency in Indian Stock market.

Titan (2015)[23] in his study "The Efficient Market Hypothesis: review of specialized literature and empirical research" argued that Efficient Market hypothesis was a major area in specialised literature. This theory is supported as well as discarded by various authors. He examines the growing body of empirical research on efficient market hypothesis. The finding of this study tells that testing of market efficiency is not easy and new theoretical model should be developed to explain the changes in the market and economy.

Degutis & Novickyte (2014)[24] analysed the stock market efficiency in relation to EMH (Efficient Market Hypothesis) theory with the emphasis on Baltic Stock Market. In his study he analyses the former studies of weak and semi-strong efficiency of Baltic Stock Market conducted over different years. Moreover he examines the different methods (unit root test & auto correlation test) used to test the weak form efficiency. He finds that most of the investors fail to earn excess profit, even when the stock market anomalies are observed and market prices often deviate from their intrinsic value.

Neeraj & Ashiwn (2014)[25] tested the weak form of efficient market hypothesis in Indian stock market. They used the Run test to analyse the same and conclude that the current stock prices are independent of past price. That means the market is weakly efficient.

Sewell (2012)[26] empirically studied the market efficiency in relation to efficient market hypothesis on daily, weekly, monthly and annual Dow Jones Industrial Average log returns in the US. It is shown that first-order auto correlation is small but positive for all time periods. Run test shows that the market is not efficient in case of daily return, whereas it is efficient in case of weekly, monthly and annual return.

Joshi (2012)[27] analyses the market efficiency of Indian stock market and random walk nature of the stock market. He has collected the data from Bombay stock exchange during the period 2000 to 2010 and used Run test to analyse the data. He has studied six major indices like Sensex, BSE100, 200, 500, BSE Small Cap & Mid Cap. The result shows that all indices of the BSE are not efficient in the weak form.

Chakraborty (2011)[28] empirically investigated the semi-strong form of efficiency in Indian stock market in the context of stock-split announcement by 17 stocks included in Nifty Index during the period from 2000 to 2010 by applying the event study methodology. He collected 41 days (including stock split announcement day called event day, 20 days pre-event and 20 days post event) closing price of sample stock for the analysis. They calculated the average abnormal return and cumulative average abnormal return and concluded that Indian stock market is not efficient in its semi strong form.

Khan & Ikram (2011)[29] investigate the strong form market efficiency of Indian stock market by assessing the performance of mutual fund during the period from 2000 to 2010, using monthly returns on the basis of NAV. Nifty is used as benchmark to compare the performance of mutual fund. They used various models like Sharpe model, Jenson model and Treynor model to analyse the performance of mutual fund and to compare it with Nifty. They found that mutual fund return outperformed the market return which hinted that the Indian stock market is not efficient in the strong form.

Khan, Ikram, & Mehtab (2011)[30] analysed the weak form of market efficiency in Indian stock market based on the indices of two major stock exchanges of India, namely Bombay Stock Exchange and National Stock Exchange. The efficiency was tested by using the daily closing values of Nifty & Sensex for one decade from 2000 to 2010. They used a non-parametric test namely Run test to analyse the data. The result showed that Indian capital Market was not efficient in the weak form.

Sharma & Seth (2011)[31] empirically analysed the Indian Stock Market in relation to recent financial crisis and market efficiency. The objectives of the study were to test whether Indian stock market followed random walk and to study the effect of recent financial crisis. They collected the data from both Bombay Stock Exchange and National Stock Exchange for the previous 10 years. These data were divided into two sub-periods, one before the crisis and the other during the crisis. Run test was used to analyse the data. The result showed that Indian stock market was not efficient in weak form and did not follow random walk in both periods and the recent crisis did not make much effect on the Indian stock market.

Tahir (2011)[32] made an attempt to test evidence on weak form of the efficient market hypothesis in Karachi stock market. He used the techniques like unit root test, runs test and Autoregressive Integrated Moving Average to know the predictability of stock prices using historical data. It was found that the Karachi stock market was not efficient in the weak form.

Raja & Sudhahar (2010)[33] empirically tested Indian stock market efficiency in respect of bonus announcement. All the information about IT companies listed in the Bombay stock exchange as on 30th Dec, 2007 was collected from "PROWESS" published by centre for monitoring Indian Economy. They analysed average security return variability, abnormal return and cumulative abnormal return and concluded that security prices reacted to the bonus issue announcement.

Khan & Ikram (2010)[34] attempted to test the efficiency of Indian capital market in relation to semi-strong form of efficient market hypothesis. This was tested in relation to the effect of FIIs (Foreign institutional investors) on the Indian capital market's major indices Nifty and Sensex. Monthly average of Nifty and Sensex and FII's net investment were collected from 1st April, 2000 to 30th April, 2010. They used the statistical test of Karl Pearson's correlation co-efficient and regression. The result showed that the FII's investment had significant effect on both the indices Nifty and Sensex. FII's investment made instant reaction in the capital market and it was impossible to earn abnormal return. So they found that Indian stock market is efficient in its semi-strong form.

Mehndiratta & Gupta (2010)[35] tested the effect of stock market prices in relationship to dividend announcement. The data for the analysis was collected from National stock exchange (NSE). Then, they used the event study methodology and calculated the abnormal return and the cumulative abnormal return by using Sharpe Model. They found that investors did not gain in the period preceding as well as dividend announcement day.

Mallikarjunappa & Manjunath (2009)[36] attempt to study stock price reactions to the dividend announcement to test the semi strong form of Efficient Market Hypothesis. The study was based on 149 companies which included BSE200-index that declared the dividend for the year 2002. They calculated the average abnormal return and cumulative average abnormal return to analyse the data and concluded that Indian market was not efficient in the semi strong form.

Jagadeesh & Titman (1993)[37] analysed the strategy of buying, winners and selling looser in the stock market and find out the implications for stock market efficiency. It analysed the efficiency of stock market by examining the profitability of a number of trading strategies based on their past return. The result showed that the trading strategies of buying winners and selling losers got significant return over the period of 1965 to 1989. The result also shows that investor expectations were systematically biased.

Christos (1992)[38] empirically investigates the efficiency of the Athens stock exchange in relation to efficient market hypothesis. He tests all the three forms namely, weak, semi-strong, strong of the efficient market hypothesis. He used regression techniques, event studies, econometric analysis etc., to analyse the data. As far as this study, it shows that Athens stock exchange did not support the efficient market hypothesis in all forms.

Shiller (1990)[39] explains the popular economic models which disagree with the rational expectations model that assumes that people know the true model that describe the economy. This study reports on such a data collection efforts on popular models by using questionnaires to know about speculative market. Stock market crash, real estate boom, and IPO under pricing are the three case studies of the research on popular model discussed in this study. The case studies are also suggestive of some ordinary tendencies among popular models.

Black (1986)[40] explores the concept of noise trading and its impact in financial market. Noise is that which makes our observations imperfect. Noise makes investing in financial market posing and allows us to watch prices for financial assets. Noises cause the market to be inefficient. Noise in the form of expectation that don't follow rational rules causes inflation. Generally, noise makes it very difficult to test either practical or academic theories about the way that financial market works.

2.4 Studies on Security Analysis

This is the first step of the portfolio management. In this step, investors analyse the risk-return characteristics of each securities. The law of the market is 'buy underpriced securities and sell the overpriced securities'. Security analysis is all about identifying the underpriced and the overpriced securities. Basically there are two approaches; fundamental analysis and technical analysis. The main motive of investing in share is to get the returns in the form of dividend and capital appreciation. This is primarily determined by the performance of the company, industry and economy. So the investor has to evaluate a lot of information on the past performance and the expected future performance of the same (company, industry & economy). This evaluation is called fundamental analysis or EIC analysis as it includes economy, industry and company analysis. Technical analysis helps us to take the decision when to buy and sell. Entry and Exit decision is very important as it decides the profits or losses of investment. It include stock charts, mathematical indicators and market indicators analysis.

De Souza, Ramos, Pena, Sobreiro, & Kimura (2018)[41] examine the efficiency and profitability of technical analysis while applying to the stock markets of Brazil, Russia, India, China and South Africa and also the complementarily of fundamental and technical analysis in these stock market. They used moving average strategies to analyse the same by using automated trading system that simulated transactions.

From the result it can be reasoned out that the nations in BRICS give heterogeneous result even though their share market shows similar characteristics.

Ramesh & Devendar (2017)[42] attempt to predict the future share price and to take the investment decision (Buy, Sell or Hold) through technical analysis. The data of thirteen companies which listed in National Stock Exchange is collected for the period from January 1, 2016 to June 30, 2017. The tools for the study are Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI). They find that nine shares have buy signal and two shares have sell signal and two shares have neutral signal.

Pathade (2017)[43] investigates the basic tool of fundamental analysis which can be used to apply to take investment decision and to interpret the results of ratios. They selected Tata Consultancy Services (TCS) and Infosys Technologies to analyse the same. The study is conducted for five years from 2011 to 2016. He used earning per share, current ratio return on capital employed, inventory turnover ratio, debtor turnover ratio and gross profit ratio to analyse the data. The result shows that TCS is better in the cases of earning per share and return on capital employed than Infosys whereas Infosys is better in the cases of current ratio, debtors turnover ratio and gross profit ratio.

Wafi, Hassan, & Mabrouk (2015)[44] analyse the better stock valuation model of fundamental analysis existing in financial markets. They examine the various models like Dividend Discount model, Models which depend upon multiples, Discounted Cash Flow models and Residual Income Valuation Model and found that Dividend Discount Model is more useful in developed financial market and when we compare Discounted Cash Flow models with Residual Income Valuation Model, Discounted Cash Flow models are more accurate. But we find it difficult to use Dividend Discount model and Discounted Cash Flow models in the emerging markets.

Roy (2015)[45] attempts to study the tools and techniques of fundamental and technical analysis while taking the investment decision. Fundamental analysis includes the Economic, Industry & Company analysis. Technical analysis analyses only the market behaviour without explaining the reason for the same.

Baradi & Mohapatra (2014)[46] investigates the importance given by the stock exchange brokers to fundamental and technical analysis while they take investment decisions. They collected the sample of 152 corporate stock brokers of Bombay Stock Exchange through the structured questionnaire. They used analysis of variance and cluster analysis to analyse the data and found the result that at shorter time period fundamental analysis doesn't perform, while in longer period technical analysis of doesn't work.

Boobalan (2014)[47] studied the importance of Technical analysis in investment decision in the scenario of Indian stock market by selecting some stocks. The tools used in the study are Candle Stick Chart, Exponential Moving Average, Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI). The result shows that, he got an idea of future trend of selected shares through technical analysis.

Nithya & Thamizhchelvan (2014)[48] investigate the effectiveness technical analysis to achieve financial goals. They selected fifteen stocks from banking sectors listed in National Stock Exchange. This study was done during the period 2013 to 2104. The technical indicators used in the study are MACD, Stochastic, Money Flow Index, Relative Strength Index and Bollinger bands. They find that technical analysis can be used to predict the change in stock price whereas, they warned that if the use of technical analysis is improper, it gives false signals.

Lubnau & Todorova (2014)[49] investigate the forecasting power of technical trading rules which can generate the abnormal return. The period used in this study is from January 1, 1990 to September 30, taking almost all the indices in important Asian countries. Independent sample 't' test is used to analyse the data. They find that technical analysis is more predictable in emerging markets whereas it is less significant in a country like Japan.

Gang & Zhu (2014)[50] analyse the effectiveness of technical indicators with volume to improve the investment performance. They test the method which considers volume namely volume-weighted moving average. They collected a sample of 2139 shares which were in China's A share during the period from 2003 to 2013 and concluded that the technical indicator which considered volume was more effective than technical indicator which did not consider the volume.

Rajan & Parimala (2013)[51] examine the price changes of equity shares of companies which deal Fast Moving Consumer Goods (FMCG). They collected the data from National Stock Exchange website. The period of study is from December 2011 to December 2012. Bollinger bands and moving average are the tools used for the analysis. Only three FMCG companies are selected for the study. They find that investor can predict the future price by using the tools and techniques of technical analysis.

Seng & Hancock (2012)[52] investigated how the changes in the fundamental statements made the changes on subsequent earnings. The data used for the study are obtained from Global vantage database of Standard and Poor during the year 1990 to 2000. They used regression analysis to analyse the data and found that the fundamental statement and current change in earnings could explain the changes of future earnings. They also found that fundamental analysis is useful and relevant to earn even abnormal return.

Chitra (2011)[53] analyses the stock price of selected companies by using the tools and techniques of technical analysis and interpret the same to recommend investment decision (buy, sell or hold). The data are collected from the National Stock Exchange for the period from April 1, 2007 to March 31, 2010. The tools for the analysis are beta of the security, Relative Strength Index and Moving Average. She finds that it is advisable to do the technical analysis for better return

Al-Qaisi (2011)[54] analyses the impact of financial ratios on the prediction of profit per share. The ten companies' data are collected from industrial sectors of Amman stock exchange for the period 2005-10. Linear regression has been used for analysing the data. He finds that economic ratios and commercial ratios are having an impact on profit of shares whereas, exchange ratio and working capital ratio are not having any impact on profit on shares.

Venketesh & Ganesh (2011)[55] analyse fundamental analysis as a method of share valuation in relation with technical analysis. They want to find out the commonly used trend forecasting methods and turning points in stock market. They used closed ended questionnaire to collect the data. Mean, standard deviation and one way ANOVA are the statistical tools used to analyse data. The results show that technical analysis is better than fundamental for the short-term investment, but the latter is better for long-term investment.

Metghalchi (2008)[56] examines the profitability of moving average trading technique in the Mexican stock market. The data used are the closing price of the IPC index, an index with the 35 stocks listed in the Mexican stock market from the period from April 1, 1988 to February 25, 2004. Overall result shows that moving average trading rules is effective to determine the entry price and exit price.

Kamath & Wang (2006)[57] investigate the relation between daily trading volume and rates of return on the stock market indices of six Asian financial markets. The period of study is during the period from 2002 to 2005. They used granger causality to analyse the data. The result shows that increase in the market index is dependent upon the rising volumes. The volume and return relationship is significantly positive. The Granger causality test reveals the absence of causality in four of the six markets.

Barber & Odean (2000)[58] examine the investment performance of shares owned by households. The tools used for the analysis are descriptive statistics, time series regression and Capital Asset Pricing Model. They find that the gross return earned by the retail investor is not bad whereas the net return is poor. This indicates that retail investors are doing excessive trading. At an average household changes 75% of their portfolio annually.

Abarbanell & Bushee (1997)[59] examine the relations between financial statements and future earnings of a company and how it affects stock price. They also examine the efficient use of financial statements by the analyst. They identified nine accounting related fundamental signals. The data are taken from the 1992 Compustat PST Active File. The return data is taken from 1992 CRSP monthly NYSE/AMEX file. They used regression analysis to analyse the data and found that fundamental signal has explanatory power for future earnings and it affects stock price.

Brock, Lakonishok, & Lebaron (1992)[60] analyse the two simple trading rules, trading range brake and moving average. They used the data of Dow Jones Index to analyse and the period is during 1897 to 1986. They used AR (1), GARCH-M and EGARCH to analyse the data. They found that technical analysis is having the prediction ability, but they give warning about transaction cost while the investor trades.

2.5 Studies Relating to Behavioural Bias

Biases are the systematic errors in the way investor processes information while taking the investment decision. The way investors think and feel affects the way they behave when making investment decisions. These influences can be identified as behavioural biases. Behavioural biases can be of two types namely cognitive and emotional. Cognitive bias deals with the way one thinks. Cognitive bias arises from basic statistical, information processing, or memory errors. It is the result of the faulty reasoning where upon the better information and advice can correct them. Emotional bias deals with the way one feels. It arises from the impulse or intuition rather than conscious calculations.

Manuel & Mathew (2017)[61] analyse the impact of cognitive biases in Investment decision of retail investors in Indian stock market. They collected the data from a sample of 62 respondents through a structured questionnaire. They used the statistical tools like percentage analysis, mean score and correlation analysis to analyse the data and found that emotional as well as cognitive bias is having high impact on investment decision.

Usman, Muturi, & Memba (2017)[62] analyse the role of anchoring on investment decision in property market in Plateau State, Nigeria. The sampling method used in this study is multistage sampling, and the data are collected through a standard questionnaire with open ended and closed ended questions. Correlation and regression analysis are used to examine the data. The result shows that there is a significant positive linear relationship between anchoring bias and invest decision by the investors in the property market in Nigeria.

Ghelichi, Nakhjavan, & Gharehdaghi (2016)[63] examine the influence of psychological factors on investment decision making of investors in Tehran stock exchange. The data are collected from the sample of 384 investors in the Teheran Stock Exchange though a structured questionnaire. The structural equation modelling is used to analyse the data. They found that variables comprise confidence and belief influences the investment decision positively whereas the sense of remorse and snake bites affects the investment decision negatively.

Irshad, Badshah, & Hakam (2016)[64] explore the effect of representativeness bias on investment decision. The study used convenient sampling method, and the data are collected from a sample of 120 investors of Islamabad Stock Exchange through a structured questionnaire. They used regression analysis to analyse the data. It is found that there is significant impact of representativeness bias on investment decision.

Kubilay & Bayrakdaroglu (2016)[65] examines the relation between personality traits, behavioural biases and risk tolerance of investors in Istanbul. The data are collected from the 539 individual investors through questionnaires. The statistical tools used for the analysis are chi-square and logistic regression. The study found that personality traits have a significant relation with behavioural biases and risk tolerance. Investors having the low risk tolerance are mostly prone to representativeness heuristic bias. Investors in 'neurotic' personality type is least affected by behavioural bias.

Shusha & Touny (2016)[66] examine the attitudinal determinants of herd behaviour of retail investors in Egyptian Stock Exchange and the effects of theses determinants variability according to investor's demographic variables like gender, age, experience, educational level, and income. The data are collected from a sample of

255 Egyptian investors through a structured questionnaire. They used Ordinary Least Squares to analyse the data and found that hasty decision, decision accuracy and investor mood as the main attitudinal determinants that explain why individual investors follow herd behaviour but the effects of these dimensions may differ according to investors' demographic variable.

Rostami & Dehaghani (2015)[67] analyse the impact of overconfidence, ambiguity aversion and loss aversion on investment decision of investors in Tehran stock exchange. The data are collected from a sample 302 respondents through structured questionnaire and the tools used for data analysis are one sample t test, binomial test, Friedman test, one way analysis of variance. They found that there is a significant impact of behavioural bias on investment decision of investors in Tehran stock exchange.

Khan M. Z. (2015)[68] investigates the impact of availability bias and loss aversion bias on investment decision. The data are collected from a sample 207 investors through structured questionnaire. He used correlation and regression analysis to analyse the data. The result shows that there is weak negative correlation between availability bias and investment decision. It also shows that risk perception strengthens the relation between loss aversion and investment decision.

Zalane (2015)[69] examine the presence of anchoring bias among retail investors of the Tunisian stock market. The data are collected from a sample of 125 investors through a structured questionnaire. They used the descriptive statistics to analyse the data. The result shows that the retail investors of the Tunisian stock exchange do not suffer from Anchoring bias.

Qadri & Mohsin (2014)[70] investigate the behavioural biases that influence the investment decision of retail investors in Islamabad Stock Exchange. They collected the data through the structured questionnaire. They choose the overconfidence and illusion of control biases to examine the same. The study uses regression analysis to analyse the data. The result shows that overconfidence and illusion of control biases are having high impact on investment decision and also found that male investors are more overconfident than female investors.

Hassan, Khalid, & Habib (2014)[71] examine the impact of gender and age on overconfidence and loss aversion. The data are collected from the sample of 391 investors through structured questionnaire. They used statistical tools like chi-square, ordinary least squares, correlation analysis to analyse the data and found that male and older investors are more overconfident than female investors who are more loss averse. The result also shows that risk lovers are more overconfident.

Jagongo & Mutswenje (2014)[72] study the factors influencing investment decision at the Nairobi Stock exchange through a sample survey. They collected the data through questionnaires which included five categories, namely; self image, accounting information, neutral information, advocate recommendation and personal financial needs. Simple random sampling method was used and the sample size is 50. They used frequencies, mean scores, standard deviations, percentages, Friedman's test and factor analysis to analyse the data and found that the behavioural biases that influence the investment decision.

Ranjbar, Abedini, & Jamali (2014)[73] analyse the relationship between effective behavioural factors on the investor's performance in Tehran Stock Exchange. They collected data from 148 investors through the questionnaire and used the structural equation modelling as the tools for this study to test the relationship. They found that availability bias and anchoring bias are the main effective factors which affect the investors' performance followed by the herding behaviour.

Chaudhary (2013)[74] examines the meaning and importance of behavioural bias and its application in investment decision. Understanding behavioural biases itself will help the investor to take the correct investment decision and through that they can have better investment performance. They should know what the behavioural biases they are prone to. They should focus specific investment strategy to overcome the behavioural bias to which they have an inclination. Behavioural finance identifies the behavioural pattern of investors and also empowers the investors to take correct investment decision.

Subash (2012)[75] investigate that the individual investors in Indian stock market shows rational behaviour. The influence of nine identified behavioural bias on investment decision of individual investors in Indian stock market has been tested in this study. The data are collected through a structured questionnaire among the individual investors who were categorised as young and experienced. The sample includes 92 individual investors selected through judgment sampling. The tools used for the analysis are weighted averages, percentages and econometric analysis like linear and logit regression models. The study reveals the degree of exposure to the biases among young and experienced investors. Anchoring, gambler's fallacy and hindsight biases were seen to significantly affect the young investors than the experienced investors.

Sahni (2012)[76] analyses the applicability on Indian investors with regard to behavioural finance. It studied the various theories and concepts related with the behavioural finance and try to prove the loss averse nature of investors. The sample size of the survey is 135 which are selected randomly. He has used the statistical tool chi-square to analyse the same. He find that risk seeking in losses causes them to hold loosing shares too long and risk aversion in gain causes selling the winning shares too early. He also finds that anchoring theory is relevant in case of Indian Investors.

Islam (2012)[77] identifies the factors responsible to mould the individual investors in Dhaka stock exchange to take the investment decision. For this purpose, demographic and socio-economic variables of investors were collected through questionnaires. He used multivariate statistical tool like factor analysis and found out that psychological factor is the most influential component on investment decision making followed by micro economic factor and social factor. The least influencing factor is technical consciousness followed by influence of index and macro economic factors. He suggested that investors have to collect more information about the stock market and respond in matured manner. He asserts that education and income have a significant impact on stock market investment.

Luong & Thu Ha (2011)[78] analyse the behavioural factors that influence individual investor's decision making and performance at the Ho Chi Minh Stock Exchange. They attempt to find out the relation between behavioural factors such as Herding, Market, Prospect and Heuristic to investment decision and performance. They collected the data through the questionnaire distributed to individual investors at the Ho Chi Minh Stock Exchange. Most of the factors have moderate impacts while market has high impact in investment decisions; whereas heuristic factors are found to be the highest influence on investment performance. They used factor analysis and structural equation modelling as the tools for this study.

Ahamed, Ahamed, & Khan (2011)[79] examine the decision making process of retail investors in Lahore Stock Exchange within the framework provided by behavioural finance as contradicted to traditional financial theories. The sample survey was done through questionnaire and the valid responses generated from 147 investors. Descriptive analysis is used to analyse the data. They found that the investors in Lahore Stock Exchange do not hold the principles of rationality; instead they confirm the explanation given by the behavioural finance while making the investment decisions. Moreover, the behavioural biases like regret aversion, disposition effect, heuristics and prospects theory play an important role in shaping the investment behaviour of the investors.

Barber & Odean (2001)[80] test the theoretical prediction that overconfident investors trade excessively. They test this by categorising on gender. Human beings are more confident of their abilities, skill and knowledge than they actually have. It is found that men are more overconfident than women in terrain of finance, investment and so on. Overconfidence leads to excessive trading and lower returns. So men will trade more and perform worse than the women. They find that both men and women reduce their net returns through excessive trading, men do so by 0.94 percentage points more a year than women.

Banarjee (1992)[81] investigates the social and economic situation which we are influenced by what other people do around us while taking a decision. The researcher aims to develop a sequential decision model (one investor chosen at random takes his decision first. The next investor, once again chosen at random takes his decision next but he is allowed to observe the choice made by the previous investor and can benefit from information contained it) in which one studies the rationale where each decision maker looks at the decision taken by the herd. The people tend to show the herd behaviour, i.e. people like to do what others do rather than analysing the information at hand.

Shefrin & Statman (1985)[82] analyse the decision making process to get profits and losses in a market setting. This study is concerned with two aspects of loss realisation. First, we place the behavioural pattern into theoretical framework of sell winners too early and hold looser too long. Second, the evidence that suggests that dis-position shows up in real world financial markets. They find that pattern of gain or loss realisation is consistent with combined effect of tax considerations also.

2.6 Studies Relating to Emotional Intelligence

The dictionary meaning of emotional intelligence is ‘the capacity to be aware of, control and express one’s emotions and to handle interpersonal relationships judiciously and empathetically’. Self awareness, managing emotions, motivating oneself, empathy and social skills are the five domains of emotional intelligence.

Dhiman & Rajeha (2018)[83] examines the impact of personality traits and emotional intelligence on risk tolerance. The sample of the study is 500 investors who invest through LSC Securities limited in Punjab. The data are collected through questionnaire by using purposive sampling. Multiple regression analysis is used to analyse the data. The result shows that there is relation between personality traits and emotional intelligence on risk tolerance, but of these two, emotional intelligence sustains more influence than personality traits.

Shashikala & Chitramani (2017)[84] identify the attributes necessary to understand the emotional intelligence of the investors through an extensive review stating the importance of emotional intelligence in investment behaviour. Investors are human beings; human beings are fully rational, so that they themselves take the wrong investment decision which, in turn, creates investment opportunities for other investors. Investors have to identify their irrational behaviour themselves, so that they can understand the consequences of their investment decision. This study asserts that investment behaviour of the investors is closely related to their level of emotional intelligence.

Hadi (2017)[85] analyses the role of emotional intelligence on investment decision making with a moderating impact of financial literacy. He collected the data from a sample of 160 investors through questionnaire by using convenience sampling. The tools used for the analysis is correlation and regression analysis. He finds the significant impact of emotional intelligence on investment decision making. He also establishes the impact of financial literacy on investment decision making and finds the moderated role of financial literacy among the relationship between emotional intelligence and investment decision making.

Raheja & Dhiman (2017)[86] examine the role of various dimensions of emotional intelligence on investment performance of retail investors. The data is collected from a sample of 300 investors through a well structured questionnaire. Purposive sampling technique is used for the study. Correlation analysis is used for analysing the data. The result shows that there is a significant relation between various dimensions of emotional intelligence like empathy, motivation, social skills and the investment performance of the investors

Tanvir, Sufyan, & Ahsan (2016)[87] analyse emotional intelligence of investors and the impact of emotional intelligence on investment decision. As stated by Goleman, emotional intelligence is determined from five domains namely self awareness, self management, motivating oneself, empathy and relationship management. They took the 225 sample investors from Karachi, Islamabad and Lahore stock exchanges. They used simple and multiple linear regressions to analyse the data and found that emotional intelligence has significant impact on investment decisions and has an important role in the selection of securities.

Danquah (2014)[88] examines the effect of emotional intelligence on organisational growth in terms of return on investment in Ghana banking sector. The study is conducted on a sample of 220 investors chosen from 20 participating banks by using structured questionnaire. The sampling method is stratified random sampling. He used regression analysis to analyse the data. The result shows a strong positive relation between emotional intelligence and customer relation which causes the growth of organisation.

Ezadinea, Fathi & Salami (2011)[89] analyse the effect of emotional intelligence and its components on portfolio performance of stakeholders. They have collected the data from a sample of 122 investors through structured questionnaire. Descriptive statistics, Analysis of Variance and Regression analysis are the statistical tools used to analyse the data. The result shows that there is a significant effect of emotional intelligence on the investment performance of individual investors.

Ameriks, Warnik, & Salovey (2009)[90] analyse the impact of emotional intelligence and personality traits on investment decision. They have collected the data from a sample of 2,595 investors at Vanguard. They used regression analysis to analyse the data and found that individual differences in perceptions of emotional intelligence are vital for the social relationship but with a minor role in financial decision making. They also find that each of the Big Five personality factors plays different role for making investment decision. The result shows strong effect of psychological variables on risk taking.

Al-Tamimi & Kalli (2009)[91] investigate the level of financial literacy of the individual investors who invest in the UAE financial markets. It also analyses the factors influencing the investment decision. Data are collected from a sample of 290 investors through structured questionnaire. They used one way ANOVA and regression analysis to analyse the data. The result shows that the UAE investors are having low level of financial literacy. They are even least knowledgeable about the financial market indices in UAE. It also shows that religious, reputation of the firm are the most influencing factors of investment decision.

Pirayesh (2004)[92] empirically investigates the effects of components of the emotional intelligence on individual investors' investment strategies. The study collected the data from a sample of 270 investors from Tehran Stock Exchange by using questionnaires. The study used Kolmogorov-Smirnov test and Spearman correlation ratio to analyse the data. The result shows that there is a positive relationship between emotional intelligence and investment decision. It also shows that when an investor is risk averse he is more likely to use his emotional intelligence.

2.7 Studies Relating to Investment Performance

Investment performance is the rate of return (dividend plus capital appreciation) received from the investment. Usually when the rate of return is high, high performance is attributed, otherwise vice versa. Investment performance is calculated over a specific period of time.

Kavitha (2015)[93] investigates the investor's perception and attitude towards Indian stock market and analyses how the level of awareness influences investor's intention to invest in the Indian stock market. The primary data are collected through a semi-structured questionnaire from 125 respondents. The study used correlation analysis for analysing the data. The result shows that investor's attitude is having the significant relation on stock market investment. The local investors invest more in the stock market if the strategies are introduced to enhance the positive attitude of investors.

Khan & Gedamkar (2015)[94] examines the performance of equity shares and mutual fund by considering the risk and return and estimating best fund or sector to invest. They also investigate importance of different statistical tools used by the portfolio managers and brokers for the performance evaluation of equity shares and mutual funds. The period of study is from 1st April, 2013 to 31st March 2014. They collected data through personal interview with brokers and portfolio managers. They used non-probability judgemental sampling in the study. The statistical techniques used in the study are standard deviation, beta, alpha, R squared and Sharpe ratio and found that if the investor wants to make more return he has to spent time to learn the tools and techniques of stock analysis and keep track of stock market.

Burlakanti & Chiruvoori (2013)[95] evaluate the equity fund in terms of risk and returns and find out the outperforming fund. The data is collected from the website of moneycontrol and amfiindia. The statistical tools used for the analysis are standard deviation, Average Growth Rate, Compounded Annual Growth Rate, Beta, Shape index and Treynor index model. The period of study is from Dec, 2007 to Dec, 2012. They find that it is better for small investors to invest in mutual fund as they can afford only small amount. They have to invest in better yielded fund rather than low yielded securities and NFO.

Obamuyi (2013)[96] explores the factors influencing investment decisions of individual investors in Nigerian capital market. He used the convenient sampling method and collected information from 297 respondent. Independent t test, Analysis of Variance and post hoc test are used to analyse the data. He identified past performance of the company's stock, expected stock split/capital increase/bonus, dividend policy and expected corporate earnings are the most influencing factors on investment decision and the least influencing factors are religion, rumours, loyalty to the company's product and services, opinion of members of the family and expected losses in other investment. The study discloses that the socio economic variables of investors are influenced in the investment decision.

Luong & Thu Ha (2011)[97] attempt to study the behavioural factors influencing individual investor's decision making and performance at the Ho Chi Minh Stock Exchange. They collected the data through questionnaire among the individual investors at the Ho Chi Minh Stock Exchange. It proves out the relation between behavioural factors and investment performance. Herding, prospect and heuristic are the main factors that influence the investment performance.

Ginblatt, Keloharju, & Linnainmaa (2011)[98] investigate the influence on IQ on trading, performance and transaction cost. They collected the data from Finnish Central Security Depository Registry, HEX stock data, Thomsom world scope, HEX microstructure data and FAF intelligence score data. Descriptive statistics and regression analysis are the tools to analyze the data. The result shows that High IQ investors outperform the low IQ investors in case of equity share investment and low IQ investors are herd in their investment decisions.

Ahamed & Samajpati (2010)[99] analyse the performance of various equity based mutual funds to examine the stock selection skills and market timing skills of fund managers. They use multifactor model to analyse the data. The data used for the study includes dividend adjusted Net Asset Values for 60 natural fund schemes during the period from 2005 to 2009. The test on selectivity is done on the basis of Jenson Model. The result shows that stock selectivity improves marginally when one uses daily return than monthly return. The fund managers in India do not have significant timing ability when they use monthly return.

Westerholm & Kuuskoski (2003)[100] compares the return of retail equity share investor who invests directly in shares with the return of mutual funds. The data is collected from Finnish stock market during the period from 1995 to 2000. They classified the investors according to their portfolio size as small, medium and large. The study uses correlation and regression analysis to probe the data. The result shows that the small investors' portfolio underperform mutual fund, medium type investors equals the mutual funds if we don't consider the transaction costs and tax but if we reckon the same, medium type investors also underperform the mutual fund. Large investor over performs the mutual fund even after the transaction cost and tax.

Edelen & Warner (2001)[101] examine the relation between market return and total flow into US equity funds. The study based on a sample of 424 equity funds for the period from February 1998 to June 1999. They used daily – high frequency- data and used correlation and regression analysis to analyse the data. The result shows that the total mutual fund flows have a significant effect on daily market return. It also shows the significant relation between aggregate flow and previous day's return.

Grinblatt & Keloharju (2000)[102] examines the behaviour and performance of various types of investors. The data are collected from the centre register of shareholdings for Finnish stock in the Finnish Central Securities Depository. The period for the study is from 1995-1997. They used binomial nonparametric test to analyse the data. The result shows that the foreign investors in Finland financial market do pursue momentum strategies – buying past winners and selling past losers - whereas domestic investors are contrarians – buying losers and selling winners.

2.8 Research Gap

From the forgoing survey of literature on related area, it is found that different studies have been carried out by several researchers and institutions in the area of stock market volatility, market efficiency and behavioural finance at national and international level. But no study has been conducted on volatility of stock market by relating behavioural aspects of investors, especially in India. Similarly there had been no studies on the mediating effect of behavioural bias on relation between the relationship of security analysis and emotional intelligence on investment performance. In this scenario, the researcher has made an endeavour to fill the gap.

References:

1. Bhowmik, D. (2013). Stock Market Volatility: An Evaluation. *International Journal of Scientific and Research Publications , 3* (10), 1-17.

2. Nalina, K., & Karthik, N. (2013). Volatility in Indian Stock Market- A Case Study of Selected Indices. *Advances in Management , 6* (7), 32-42.

3. Satish, D. V., & Nayia, M. (2012). Stock Return, Volatility and the Global Financial Meltdown:. *International Journal of Arts and Commerce , 1* (7), 166-178.

4. Nawazish, M., & Sara, S. M. (2012). Time Varying Stock Market Volatility: The Case of an Emerging Market. *Research Journal of Recent Sciences , 1* (11), 41-46.

5. Loomba, J. (2012). Do Fiis Impact Volatility of Indian Stock Market? *International Journal of Marketing, Financial Services & Management Research , 1* (7), 80-93.

6. Mukhopadhyaya, J. N. (2011). An Analytical Study of Indian Stock Market Volatility and Its Linkage. *International Journal of Business Management, Economics and Information Technology , 3* (1), 91-109.

7. Rahman, M. T., & Moazzem, K. G. (2011). Capital Market of Bangladesh: Volatility in the Dhaka Stock Exchange (DSE) and Role of Regulators. *International Journal of Business and Management , 6* (7), 86-93.

8. Ahamed S, A. Z. (2011). Volatility Spillover Effects in Emerging MENA Stock Market. *Review of Applied Economics , 7* (1-2), 107-127.

9. Ahmed, A. E., & Suliman, Z. S. (2011). Modeling Stock Market Volatility using GARCH models, Evidence from Sudan. *International Journal of Business and Social Science , 2* (23), 114-128.

10. Mallikarjunappa, T., & Afsal, E. M. (2008). The impact of derivatives on stock market volatility: Astudy of the NIFTY index. *Asian Academy of Management Journal of Accounting and Finance , 4* (2), 43-65.

11. Debjiban, M. (2007). Comparative Analysis of Indian Stock Market with International Markets. *Great Lakes Herald , 1* (1), 39-71.

12. Raju, M. T., & Ghosh, A. (2004). *Stock Market Volatility – An International Comparison.* Mumbai: Securities and Exchange Board of India Working Paper Series with number 8.

13. Kaur, H. (2002). *Stock Market Volatility in India.* New Delhi: Deep & Deep Publications.

14. Mehra, R. (1998). On the Volatility of Stock Prices: An Exercise in Quantitative theory. *International Journal of System Science , 29* (11), 1203-1211.

15. Bollerslev, T., & Mikkelsen, H. O. (1996). Modeling and pricing long memory in stock market volatility. *Journal of Econometrics , 73* (1), 151-184.

16. Day, T. E., & Lewis, C. M. (1992). Stock Market Volatility and the Information Content on Stock index Option. *Journal of Econometrics , 52*, 267-287.

17. Baillie, R. T., & DeGennaro, R. P. (1990). Stock Returns and Volatility. *Journal of Financial and Quantitative Analysis , 25* (2), 203-214.

18. Schwert, W. (1990). Stock Market Volatility. *Financial analyst journal* , 23-34.

19. French, K., & Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics , 17* (1), 5-26.

20. Shiller, R. J. (1981). Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *The American Review , 71* (3), 421-436.

21. Sarmiento-Sabogal, J., Hatemi-J, A., & Cayón-Fallon, E. (2016). A test of the efficient market hypothesis with regard to the exchange rates and the

yield to maturity in Colombia. *WSEAS Transactioons on Business and Economics , 13*, 321-329.

22. Kalsie, A., & Kalra, J. K. (2015). An Empirical Study on Efficient Market Hypothesis of Indian Capital Markets. *Journal of Management Research and Analysis , 2* (2), 108-114.

23. Titan, A. G. (2015). The Efficient Market Hypothesis: Review of Specialized Literature. *Procedia Economics and Finance* (32), 442-449.

24. Degutis, A., & Novickytė, L. (2014). The Efficient Market Hypotheis: A Critical Review of Literature and Methodology. *Ekonomica , 93* (2), 7-23.

25. Neeraj, G., & Ashiwn, G. (2014). Testing of Efficient Market Hypothesis: astudy on indan stock Market. *IOSR Journal Business and Mangement , 16* (8), 28-38.

26. Sewell, M. (2012). The Efficient Market Hypothesis: Empirical Evidence. *International Journal of Statistics and Probability , 1* (2), 164-178.

27. Joshi, D. J. (2012). Testing Market Efficiency of Indian Stock Market. *International Journal of Scientific and Research Publications , 2* (6), 1-4.

28. Chakraborty, P. (2011). Semi-Strong Form of Pricing Efficiency of Indian Stock Market- An Empirical Test in the Context of Stock split Announcements. *EXCEL International Journal of Multidisciplinary Management Studies , 1* (2), 1-13.

29. Khan, A., & Ikram, S. (2011). Testing Strong Form Market Efficiency of Indian Capital Market: Performance Appraisal of Mutual Funds. *International Journal of Business & Information Technology* , 15-161.

30. Khan, A. Q., Ikram, S., & Mehtab, M. (2011). Testing Weak Form Market Efficiency of Indian Capital Market: A Case of National Stock Exchange (NSE) and Bombay Stock Exchange (BSE). *A. Q. Khan1,2, Sana Ikram3 , 3* (6), 115-127.

31. Statman, M. (1999). Behavioral Finance: Past Battles and future engagements. *Financial Analyst Journal , 55* (6), 18-27.

32. Tahir, A. (2011). Capital Market Efficiency: Evidence from Pakistan. *Interdisciplinary Journal of Contemporary Research in Business , 3* (8), 947-953.

33. Raja, M., & Sudhahar, J. C. (2010). An Empirical Test of Indian Stock Market Efficiency in Respect of Bonus announcement. *Asia Pacific Journal of Finance and Banking Research , 4* (4), 1-14.

34. Khan, A., & Ikram, S. (2010). Testing Semi-Strong Form of Efficient Market Hypothesis in Relation to the Impact of Foreign Institutional Investors' (FII's) Investments onIndian Capital Market. *International Journal of Trade, Economics and Finance , 1* (4), 373-379.

35. Mehndiratta, N., & Gupta, S. (2010). Impact of Dividend Announcement on Stock Prices. *International Journal of Information Technology and Knowledge Management, 2* (2), 405-410.

36. Mallikarjunappa, T., & Manjunath, T. (2009). Stock Price Reactions to Dividend Announcements. *Journal of Management & Public Policy , 1* (1), 43-56.

37. Jagadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Loosers: Implication for Stock Market Efficiency. *Journal of Finance , 48* (1), 65-91.

38. Christos, A. (1992). *An Empirical Investigation of the Efficient Market Hypothesis: The Case of The Athens Stock Exchange.* York: Department of Economics and Related Studies, University of York.

39. Shiller, R. J. (1990). Speculative Prices and Popular Models. *Journal of Economic Perspectives , 4* (2), 55-65.

40. Black, F. (1986). Noise. *The Journal of Finance , XLI* (3), 529-543.

41. De Souza, M. J., Ramos, D. g., Pena, M. G., Sobreiro, V. A., & Kimura, H. (2018). Examination of the Probability of Technical Analysis based on moving average strategies in BRICS. *Financial Innovation , 4* (3), 2-18.

42. Ramesh, K., & Devendar, V. (2017). Technical Analysis: Price behavior of Select Indian Equities. *International Journal of Business and Management Invention , 6* (7), 35-42.

43. Pathade, V. K. (2017). Equity Research: Fundamental anlysis for long term investment. *International Journal of Applied Research , 3* (4), 678-682.

44. Wafi, A. S., Hassan, H., & Mabrouk, A. (2015). Fundemental Analysis Model in Financial Markets - Review Study. *Procedia Ecnomics and Finance , 30*, 939-947.

45. Roy, S. G. (2015). Equity Research: Fundamental and Technical Analysis. *International Journal of Science and Research , 4* (9), 272-275, Retrieved on 26/09/2016 from https://www.ijsr.net/archive/v4i9/SUB157950.pdf.

46. Baradi, N. K., & Mohapatra, S. (2014). The Use of Technical and Fundamental Analyses by Stock Exchange Brokers: Indian Evidence. *Journal of Empirical Evidence , 2* (4), 19o-203.

47. Boobalan, C. (2014). Technical Analysis in Select Stocks of Indian Companies. *International Journal of Business and Administration Research Review , 2* (4), 26-36.

48. Nithya, J., & Thamizhchelvan, G. (2014). Effectiveness of Technical Analysis in Banking Sector of Equity Market. *IOSR journal of Business and Management , 16* (7), 20-28.

49. Lubnau, T., & Todorova, N. (2014). Technical Trading Revisited: Evidence from the Asian Stock Markets. *Corporate Ownership and Control* , 511-532.

50. Gang, L., & Zhu, J. (2014). Research on Effectiveness of Technical Indicators with the Volume. *International Confereance on Education,*

Management and Computing Technology (pp. 436-439). Shanghai: Atlantis press.

51. Rajan, G. S., & Parimala, S. (2013). Stock Price Movement through Technical Analysis: Empirical Evidence from the Fast Moving Consumer Goods (FMCG Sector). *Indian Journal of research , 2* (2), 142-45.

52. Seng, D., & Hancock, J. R. (2012). Fundamental Analysis and the Prediction of Earnings. *International Journal of Business and Management , 7* (3), 32-46.

53. Chitra, R. (2011). Technical Analysis on Selected Stocks of Energy Sector. *Inetrnational Journal of Managment & Business Studies , 1* (1), 42-46.

54. Al-Qaisi, K. (2011). Predicting the Profit per Share Using Financial Ratios. *Asian Journal of Finance and Accounting , 3* (1), 162-173.

55. Venketesh, C., & Ganesh, L. (2011). Fundamental Analysis as a Method of Share Valuation in Comparison with Technical Analysis. *International Economics & Finance Journal , 6* (1), 27-37.

56. Metghalchi, M. (2008). Are Moving Average Trading Rules Profitable? Evidence from the Mexican Stock Market. *The Journal of Applied Business Research , 24* (1), 115-128.

57. Kamath, R., & Wang, Y. (2006). The Casuality Between Stock Index Returns and Volumes in the Asian Equity Market. *Journal of International Business Research , 5* (2), 63-74.

58. Barber, B. M., & Odean, T. (2000). Trading is Hazardous to Your Wealth: The common Stock Investment Performance of Individual Investors. *Journal of Finance , LV* (2), 773-806.

59. Abarbanell, J. S., & Bushee, B. J. (1997). Fundamental Analysis, Future Eanings and Stock Prices. *Journal of accounting research , 35* (1), 1-24.

60. Brock, W., Lakonishok, J., & Lebaron, B. (1992). Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *The Journal of Finance , 47* (5), 1731-1764.

61. Manuel, J., & Mathew, G. (2017). Impact of Cognitive Biases in Investment Decision of Individual Investors in Stock Market. *International Journal of Engineering Technology, Management and Applied Sciences , 5* (6), 531-538.

62. Usman, D. I., Muturi, W. M., & Memba, F. S. (2017). Influence on Anchoring Bias on Investors' Decision Making in Property Market in Plateau state, Nigeria. *International Journal of Management and Commerce Innovations , 5* (1), 49-59.

63. Ghelichi, M. A., Nakhjavan, B., & Gharehdaghi, M. (2016). Impact of Psychological Factors on Investment Decision Making in Stock Exchange Market. *Asian Journal of Management Sciences and Education , 5* (3), 36-44.

64. Irshad, S., Badshah, W., & Hakam, U. (2016). Effects of Representativeness Bias on Investment Decision Making. *Management and Administrative Sciences Review , 5* (1), 26-30.

65. Kubilay, B., & Bayrakdaroglu, A. (2016). An Empirical Research on Investor Biases in Financial Decision-Making, Financial Risk Tolerance and Financial Personality. *International Journal of financial research , 7* (2), 171-183.

66. Shusha, A. A., & Touny, M. A. (2016). The Attitudinal Determinants of Adopting the Herd Bahavior:An Applied Study on the Egyptian Exchange. *Journal of Finance and Investment Analysis , 5* (1), 55-69.

67. Rostami, M., & Dehaghani, Z. A. (2015). Impact of Behavioral Biases(Overconfidence, Ambiquity-Aversion and Loss Aversion) on Investment Making Decision in Tehran Stock Exchange. *Journal of Scientific Research and Development , 2* (4), 60-64.

68. Khan, M. Z. (2015). Impact of Avilability Bias and Loss Aversion Bias on Investment Decision Making, Moderating Role of Risk Perception. *Impact Journal of Research in Business Mangement , 1* (2), 1-12.

69. Zalane, S. (2015). Behavioral biases of Individual Investors: The Effects of Anchoring. *Eurasian Journal of Social Sciences , 3* (1), 13-19.

70. Qadri, S. U., & Mohsin, S. (2014). An Empirical Study of Overconfidence and Illusion of Control Biases, Impact on Investor's Decision Making: An Evidence from ISE. *European Journal of Business Management , 6* (14), 38-45.

71. Hassan, T. R., Khalid, W., & Habib, A. (2014). Overconfidence and Loss Aversion in Investment Decisions: A Study of the Impact of Gender and Age in Pakitani Perspective. *International SAMANM Journal of Finance and Accounting , 2* (3), 44-61.

72. Jagongo, A., & Mutswenje, V. S. (2014). A Survey of the Factors Influencing Investment Decisions: The Case of Individual Investors at the NSE. *International Journal of Humanities and Social Science , 4* (4), 92-102.

73. Ranjbar, H. M., Abedini, B., & Jamali, M. (2014). Analyzing the Effect of Behavioral Factors on the Investors Performance in Tehran Stock Exchange. *International Journal of Technical Research and Applications* , 80-86.

74. Chaudhary, A. K. (2013). Impact of Behavioural Finance in Investment Decisions and Strategies - A Fresh Approach. *International Journal of Mnangement Research and , 2* (2), 85-92.

75. Subash, R. (2012). *Role of Behavioral Finance in Portfolio Investment Decisions: Evidence from Indai.* Prague: Institute of Economic Studies, Chales University.

76. Sahni, D. (2012). Behavioral Finance: Testing Applicability on Indian Investors. *Shiv Shakti International Journal of Multidisciplinary and Academic Research , 1* (2), 1-12.

77. Islam, S. (2012). Behavioral Finance of an Inefficient Market. *Global Journal of Management and Business Research , 12* (14), 13-34.

78. Luong, L. P., & Thu Ha, D. T. (2011). *Behavioral Factors Influencing Individual Investors' Decision-making and Performance.* Vietnam: Umeå School of Business.

79. Ahamed, N., Ahamed, Z., & Khan, S. K. (2011). Behavioural finance: Shaping the Decisions of Small Investors of Lahore Stock Exchange. *Interdisciplinary Journal of Research in Business , 1* (2), 38-43.

80. Barber, B. M., & Odean, T. (2001). Boys will be Boys: Gender, Overconfidence and common stock investment. *The quarterky journal of economics , 16* (1), 261-292.

81. Banarjee, A. V. (1992). A Simple Model of Herd Behavior. *The Quarterly Journal of Economics , 107* (3), 797-817.

82. Shefrin, H. M., & Statman, M. (1985). The Disposition to Sell Winners too Early and Ride Losers too long. *The Journal of Finance , XL* (3), 777-790.

83. Dhiman, B., & Rajeha, S. (2018). Do Personality Traits and Emotional Intelligents of Investors determine thier Risk Tolerance. *Managemnt and Labour Studies , 43* (1&2), 88-99.

84. Shashikala, V., & Chitramani, P. (2017). A Review on Emotional Intelligence and Investment Behaviour. *International Journal of Management , 8* (3), 32-41.

85. Hadi, F. (2017). Effects of Emotional Intelligence on Investment Decision Making with a moderating role of Financial literacy. *China-USA Business Review , 16* (2), 53-62.

86. Raheja, S., & Dhiman, B. (2017). Role of Emotional Intelligence on Investment Decision of Individuals. *International Journal of Applied Business and Economic Research , 15* (22(2)), 1-9.

87. Tanvir, M., Sufyan, M., & Ahsan, A. (2016). Investor's Emotional Intelligence and Impact on Investment decision. *International Journal of Academic research in Economics and Management Sciences , 5* (3), 12-28.

88. Danquah, E. (2014). Analysis of the Impact of Emotional Intelligence on Organisational Performance: A Banking Perspective. *British Journal of Marketing Studies , 2* (3), 34-50.

89. Ezadinea, N., Fathi, S., & Salami, S. (2011). The Effect of Emotional Intelligence on Portfolio Performance of Stakeholders: Empirical Evidence from Iran. *Interdisciplinary Journal of Contemporary Research in Business , 3* (5), 679-685.

90. Ameriks, J., Warnik, T., & Salovey, P. (2009). Emotional Intelligence and Investor Behaviour. *The Research Foundation of CFA institute*.

91. Al-Tamimi, H. A., & Kalli, A. A. (2009). Financial Literacy and Investment Decisions of UAE investors. *The Journal of Risk Finance , 10* (5), 500-516.

92. Pirayesh, R. (2004). A Study on the Effects of Emotional Intelligence on Retail Investor's Behaviour. *Managemenr Science Letters* , 43-48.

93. Kavitha, C. (2015). Investors Attitude towards Stock market Investment. *International Journal of Scientific Research and Management , 3* (7), 3356-3368.

94. Khan, E., & Gedamkar, P. (2015). Performance Evaluation Equity Shares and Mutual funds with respect to their Risk and Return. *MIT-SOM PGRC KJIMRP1ST International Conference* (pp. 149-155). Maharashtra: MIT School of managment.

95. Burlakanti, K., & Chiruvoori, R. (2013). Performance Evaluation of Selected Equity Fund in India. *International Journal of Social Science & Interdisciplinary research , 2* (5), 69-78.

96. Obamuyi, T. M. (2013). Factors Influencing Investment Decisions in Capital Market: A Study of Individual Investors in Nigeria. *Organizations and Markets in Emerging Economies , 4* (1(7)), 141-161.

97. Luong, L. P., & Thu Ha, D. T. (2011). *Behavioural Factors Influencing Individual Investor's Decision-Making and Performance.* Sweden: Umea School of Business, Umea University.

98. Grinblatt, M., & Keloharju, M. (2000). The investment behaviourand performance of various investor types: A study of Finnland's unique data set . *Journal of Financial Economics* , 43-67.

99. Ahamed, M., & Samajpati, U. (2010). Evaluation of Stock Selection Skills and Market Timing Abilities of Indian Mutual Fund Managers. *Management Insight* , 71-82.

100. Westerholm, J., & Kuuskoski, M. (2003). Do Direct Stock Market Investments Outperform Mutual Funds? A Study of Finnish Retail investors and Mutual Funds. *LTA* , 197-212.

101. Edelen, R. M., & Warner, J. B. (2001). Aggregate price effects of institutional trading: A study on mutual fund flow and market return. *Journal of inancial economics* , 195-220.

102. Ginblatt, M., Keloharju, M., & Linnainmaa, J. T. (2011). IQ, Trading Behaviorand Performance. *Journal of Financial Economics* , 1-24.

Chapter 3

Theoretical Framework

3.1 Introduction

Theoretical framework is the foundation of any research. It is a conceptual model of how the researcher makes logical sense of the relationship among the various factors that have been identified as important to the problem being studied. This chapter explains the theoretical framework of the study and discusses the relationships among the variables that have been identified, explains the theories underlying these relations and also describes the nature and direction of the relationships. The framework has been developed from the extensive literature survey and from the interviews that were conducted with investors and experts in the field. The chapter also explains the choice of theories that compose the theoretical framework. The theories have been chosen with consideration to the research question and objectives.

Everyone wants to become rich and needs to have the financial freedom, but never achieves the same, although one has the potential to have the financial freedom. Financial freedom implies one's income will meet all his expenses which means finance won't be the constraints to fulfil one's needs and wishes. Investors invest their hard-earned money to make the maximum possible return. According to Lord Keynes, "unexpected will always happen and inevitable doesn't happen". So it is common that institution and/or person must save and invest a buffer for the future days. Consequently they abstain from current consumption to use it for future purpose. Warren Buffet, one of the richest in the world, who made fortune through investment says "investing is lying out money today to receive more money tomorrow". Fischer & Jordan (2006)[1] defines "investment as a commitment of funds made in the expectation of some positive return. If the investment is properly undertaken, the return will be commensurate with the risk the investor assumes". Two different dimensions of investment are Time and Risk. An investor sacrifices today's consumption and certainty of the money invested. The return comes later which is generally uncertain. We have variety of investment avenues or assets to invest. Assets can broadly be classified into Real assets and financial assets. Real assets is an item of economic, commerce or exchange value that has tangible material existence which usually include physical (tangible) assets like Plant and Machinery, Land and Building, Gold etc., whereas financial asset derives value because of contractual claim like Government Securities, Post Office Savings, Mutual Funds, Shares etc.

Investment in Equity

Our focus is investment in equity shares since it meets investor's all expectations like regular income, capital appreciation, safety, liquidity, affordability and tax exemption. Moreover nobody can deny the handsome average return given by equity shares. Returns from equity investment are dividend, in the form of regular income and terminal return in the form of capital appreciation. Out of these, capital appreciation from the market price of securities constitutes a major component. Apart from return, the investors are also concerned with risk associated with securities. They select the securities which have higher return with the same risk level; or they select the securities which have lesser risk with same return. Risk is the variability in expected return. It is the possibility that the actual return will be less than the expected return. There are two types of risks, systematic and unsystematic. Systematic risk is caused due to factors external to the company and affects the market price of all securities. It is uncontrollable and cannot be avoided whereas unsystematic risk is company specific risk which is controllable and avoidable. Investors can reduce and even make unsystematic risk zero through diversification. As the returns constitute two elements, dividends and price changes, risk includes the variability in expected dividends and variability in expected market price of the shares after a certain period. Variability in expected dividends may not be very crucial whereas variability in expected share price is considered as the major contributor to risk.

Risk and return have a positive proportional relationship. That is, the greater risk accepted, the greater must be the potential return as reward for committing one's fund to an uncertain outcome. Higher fluctuations in returns, greater will be the risk of the investment. Risk is the variability of the actual returns around the average expected return of the investors.

Risk-Return Trade-off

Every investment is characterised by risk and return. These are the bases to take investment decision. So one should estimate the expected risk and return to take the investment decision. The expected return of the investment is the probability weighted average of all possible return.

Symbolically,

$$\bar{X} = \sum_{i=1}^{n} X_i \; P_i \qquad 3.1$$

Where, $\bar{X}$ is the expected return, X_i is the possible return, P_i is the probability associated X_i

Expected returns are insufficient for investment decision making. The risk also should be considered. Risk is measured by dispersion of the probability distribution. The measure of risk is Variance and Standard Deviation. It measures total variability of returns, so we come to know the total risk.

$$\sigma = \sum_{i=1}^{n} [(X_i - \bar{X})^2 P_i] \qquad 3.2$$

Where σ is the standard deviation, $\bar{X}$ is the expected return, X_i is the possible return, P_i is the probability associated X_i

The present research work makes an attempt to test the volatility and market efficiency of the Indian stock market. Moreover it investigates the role of security analysis, behavioural bias, and emotional intelligence in the investment performance of investors in Kerala. This chapter aims to formulate a theoretical framework regarding volatility, stock market efficiency, security analysis, behavioural bias, emotional intelligence and investment performance.

Therefore, the discussion in this chapter is divided into six sections. They are volatility of stock market, stock market efficiency, security analysis, behavioural bias, emotional intelligence and investment performance.

3. 2 Concept of Volatility

Volatility is the statistical measure of risk. It is used to measure the market risk of a security or a portfolio of securities. The volatility of a share indicates the variability of its expected return. Volatility of the share price hampers individual investment, as a result it also affect economy as a whole. It creates more uncertainty in the market and adversely affects the flow of fund to productive investment.

The estimation of volatility is very important for several reasons to several people in the stock market. Pricing of security is assumed to be dependent on volatility of each asset. The statistical tool which is used to measure the volatility is the standard deviation of its return. The standard deviation measures the variability of its return from the mean return which they vary from period to period. It can be calculated for quarter-to-quarter return, month-to-month returns, day to day return, and minute to minute return. Volatility gives emphasis on the variability, not the direction of the trend.

Merton Miller (1991)[2] the winner of the 1990 Nobel Prize in economics - writes in his book Financial Innovation and Market Volatility …. "By volatility public seems to mean days when large market movements, particularly down moves, occur. These precipitous market wide price drops cannot always be traced to a specific news event. Nor should this lack of smoking gun be seen as in any way anomalous in market for assets like common stock whose value depends on subjective judgement about cash flow and resale prices in highly uncertain future. The public takes a more deterministic view of stock prices; if the market crashes, there must be a specific reason."

To some extent, volatility is the normal part of the process whereas excess volatility caused by the irrational behaviour of the investors is detrimental as it will affect the smooth functioning of financial system and economic performance.

Investors who consider high volatility as high risk, may move away from the market and find alternative investment opportunities. Consequently policy makers consider high volatility as a threat to the smooth functioning of financial institutions, markets and economy as a whole. Excessive speculation will lead to excessive volatility which results in bubbles and the busts making good number of investors insolvent.

3.2.1 Hyper Volatility

According to Kurt (1991)[3] 'Hyper volatility refers to price movements, which in their magnitude, speed and disorderliness are symptomatic of a pathological state where the circumstances necessary to arrive a rational purchase or sale decision do not exist.' Series of hyper volatility adversely affect the public confidence in the stock market. It seriously affects the role of stock exchanges as providers of liquidity and facilitator of price mechanism.

The estimation of volatility is important for several reasons and for different people in the market. Pricing of securities is supposed to be dependent on volatility of each asset. Mature/developed markets have lower volatility but they continue to provide high returns over the long period of time.

There are some factors which responsible for the excessive volatility. In some studies micro variables like dividend per share, earnings per share, company size and book value per share have got prominence and in others macro variables like bank rate of interest, index of industrial growth, union budget and inflation rate and exchange rate for foreign currency have been highlighted. Changes in local or global economic and political environment influence the share price movements and show the state of stock market to the general public. But in practice, the behaviour of the investor affects largely the share price movements which are explained in behavioural finance.

To study these behavioural aspects, first of all, the researcher has to identify the anomalies existing in the stock market, which show deviations from the standard financial theories. One such widely accepted standard financial theory is Efficient

Market Hypothesis (EMH). As per EMH investors being wealth maximisers behave rationally and EMH is associated with ‘Random Walk’ theory.

3.3 Random Walk Theory

Bachelier's (1900)[4] and Kendall (1953)[5] studies enforce the randomness of security price behaviour in the market. It has shown that each day’s market price is independent of last day’s price. It is impossible to predict the price of a security based on its past price behaviour. The random walk theory states that market prices evolve at random and do not follow a regular pattern. According to this theory a change appears in the price of a share only because of a certain change in the economy, industry or company. Changes in share price completely show independent behaviour and are dependent on the new pieces of information that are received, and then tomorrow’s price change will reflect only tomorrow’s news and will be independent of the price changes today. The information on changes in the economy, industry, and company performance is immediately and fully spread so that all investors have complete knowledge about information. This makes changes in share price immediately and the price moves to new equilibrium, depending on the type of information. Thus, the current price fully reflects all available information on the stock. The random walk theory assumes that stock markets are so efficient and competitive that there is an immediate price alteration. It is based on the premise that the stock markets are efficient.

3.4 The Efficient Market Hypothesis (EMH)

As per Efficient market hypothesis security prices are expected to move randomly in an efficient market. It is a logical extension of the technical & fundamental analysis approaches to investment decision. This concept has been one of the important themes in academy since 1960s. According to Elton & Gruber (1994)[6] “when someone refers to efficient capital markets, they mean that security prices fully reflect all available information”. Fama (1970)[7] argued that in an efficient market, prices fully reflect all available information. So when the market is efficient, it is impossible to beat the market i.e. nobody can make abnormal return from the market. In efficient capital market security prices are almost equal their intrinsic value at all times, and most securities are correctly priced. Market efficiency implies that every investor have same access to information without any cost and the investors will rationally process the information so that all known information is immediately discounted and reflected in share prices in the stock market. In short, in the efficient market, everybody has access to all information simultaneously without any cost, they interprets it similarly, and behave rationally.

'The basic theoretical case for the EMH rests on three arguments which rely on progressively weaker assumptions. First, investors are assumed to be rational and hence to value securities rationally. Second, to the extent that some investors are not rational, their trades are rational and therefore cancel each other without affecting prices. Third, to the extent that investors are irrational in similar ways, they are met in the market by rational arbitrageurs who eliminate their influence on prices (Shleifer, 2000)[8]

The efficient market model is concerned with how fast the information is incorporated into security prices. The technical analyst affirms that past price sequence contains information about future price changes because they believe that information is slowly incorporated into security prices. This gives investor a chance to earn excess returns by studying the patterns in price movements and investing accordingly.

Fundamental analyst thinks that it may take number of days or weeks before investors can fully understand the importance of new information. As a consequence, the price may be volatile for several days before it changes to new level. This provides a chance to the fundamental analyst to outperform others and earn excess returns.

The supporters of efficient market argued that in an efficient market, new information is processed and interpreted as it arrives and prices at the same time adjust to new levels. Consequently, an investor cannot always earn abnormal returns by doing fundamental analysis or technical analysis.

3.4.1 Forms of Market Efficiency

The efficient Market Hypothesis is divided into three forms.

1. **Weak Form**: It holds the view that the current market price of shares reflects all the information regarding the past sequence of the price movements. So past sequence of the securities prices cannot predict the future price of the same security. It is the direct refusal of technical analysis

2. **Semi-strong Form**: The semi-strong form implies that the current share price reflects all publicly available information about the company (not only information about historical price but also other available information). Whenever the information becomes public the share price changes and imbibes the full information. Examples are announcement of dividends, stock splits, corporate annual reports etc. As weak form repudiates technical analysis, semi strong form refuses fundamental analysis as it argues that fundamental analyst cannot make superior gains.

3. **Strong Form**: This implies that the current price of a share absorbs all information, both publicly available and insider information. This means that nobody can make abnormal return by using public as well as private information.

3.4.2 Empirical Tests of Efficiency

Test of Weak Form

The weak form of the EMH says that no investor can use any historical information to make abnormal profits. Current market prices of shares already fully reflect all the historical information. The new price movements are produced by new pieces of information and no way is it related to past price. So there is no need of analysing the past information since the future price cannot be determined by the same. The weak form denies the abnormal return to investor by using the sequence or trend of historical movement of share prices. It denotes that technical analysis, which is based on the charts and historical information of price movement is not effective to make abnormal gain from the market.

Tools to Test the Weak form of market efficiency

Serial Correlation Test

Since the weak form looks for independence between subsequent price changes, such randomness in share price movement can be tested by using the correlation between price changes in one period and changes in the same share in another period. Highly positive correlated co-efficient indicates direct relation, a negative correlation coefficient indicates inverse relation, and coefficient near to zero indicates no relationship. If correlation co-efficient is close to zero, price changes is serially independent and we can establish the efficiency of markets in the weak form.

Runs Test

Runs test ignores the absolute values, instead test the direction of movement of security prices. An increase in price is represented by +ve signs & the decrease by –ve sign. If there is no change it is represented by '0'. A consecutive sequence of the same sign is considered as a run. In this test, the actual number of runs observed in a series of stock price movements is compared with the number of runs in randomly generated number series. If no dominated run are found, then the security price changes are considered to be random in nature. This is the indicator of the efficiency of the stock market in its weak form.

Filter Tests

Filters are rules that help the investor to identify the profitable opportunities when the price breaks the two barriers around the fair price. The returns generated according to the filter rule are compared with the return earned by buy and hold strategy. If the former is significantly more than the latter, it indicates the existence of patterns in price movements and disapproves the weak form of EMH.

Unit Root Test

The weak form market efficiency has introduced a new methodology to test random walk nature of share price which is known as unit root test. A unit root test examines whether a time series is stationary or non-stationary. If it is non-stationary it means that it follows a random walk process. The term non-stationarity, random walk and unit root are used synonymously. In this study, researcher uses two unit root tests, namely Augmented Dickey-Fuller unit root test and Phillip-Perron unit root test

Tests of Semi-Strong Form Efficiency

As per the semi strong form of efficient market hypothesis, current prices of stocks not only reflect historical prices, but also reflect all publicly available information about the company under study. Examples of publicly available information are – corporate annual reports, company announcements, press releases, announcements of dividends, stock splits etc. The semi strong hypothesis maintains that as soon as the information becomes public, the stock prices instantaneously adjust to the information received.

According to semi-strong hypothesis, the fundamental analyst cannot make abnormal gains by undertaking fundamental analysis because stock prices adjust to new pieces of information instantaneously as they are received. There is no time gap in which the fundamental analyst can trade for superior gains. Thus the semi- strong hypothesis disapproves fundamental analysis.

Semi-strong form tests deal with whether or not security prices fully reflect all publicly available information. Much of these methodologies have been introduced by Fama, Fisher, Jensen and Roll. The general methodology followed in these studies has been to take an economic event and measure its impact on the share price. The impact is measured by taking the difference between the actual return and the expected return on the security. The expected return on a security is generally estimated by Single Index Model suggested by William Sharpe.

$$R_i = \alpha_i + \beta_i R_m + u_i \tag{3.3}$$

where R_i is return on security, R_m is the market return, α_i, β_i are constants, u_i is the error term.

This analysis is known as residual analysis. Expected return can also be calculated using Capital Asset pricing Model (CAPM)

$$R_i = R_f + \beta_i(R_m - R_f) \tag{3.4}$$

where R_i is return on security, R_f is the risk free rate of return, R_m is the market return, β_i is the relative change of the security with market index.

The positive difference between the actual return and the expected return represents the excess return earned on a security. If the excess return is close to zero, it implies that the price reaction following the public announcement of information is immediate and the price adjusts to a new level almost immediately. Thus the lack of excess returns would validate the semi-strong form EMH.

Other items of information whose impact on share prices have been tested include announcements of purchase and sale of large blocks of shares of a company, takeovers , annual earnings of companies , quarterly earnings, accounting procedure changes , and earnings estimates made by company officials.

Test of Strong Form Efficiency

According to strong form, current security prices adjust to all information both public as well as private information or inside information. This indicates that no information whether public or private, can be used to earn abnormal return. Persons occupying key post in the corporate have access to much information that is not available to the public. This is called as insider information. Mutual funds and other professional analyst with large research facilities may gather private information regarding the different stocks which is not available to the public. The strong form of efficiency can be tested by comparing the market return and the return generated by mutual fund.

3.4.3 Challenges to the EMH

Hyper Volatility

In a perfectly efficient market, stock market hyper volatility (large increase and decreases over time) should be no higher than the underlying volatility in the fundamental value. In fact, indicators of fundamental value, such as dividend, change very slowly but stock prices change very quickly. This has led critics of the Efficient Market Hypothesis to contend that the stock prices are too volatile given the low level of observed volatility in dividends.

Bubbles & Crashes

Market bubbles (a significant overvaluation of economic fundamentals in the stock market) and subsequent crashes are good examples of market inefficiency. Market bubbles are identified after a tremendous inflation in prices is followed by a dramatic decline.

Investment Fraud

A microcap stock is a company with a low or “micro” market capitalization, usually between $50 million and $250 million. Most microcap companies are legitimate businesses with real products or services. However, the lack of reliable available information about some microcap stocks opens the door to fraud. It is far easier for stock promoters to manipulate a stock when there is little or no reliable public information about the company. Microcap fraud depends on spreading wrong information.

Anomalies of Stock Market

Anomalies or abnormal behaviour are the occurrence of market events, which cannot be explained by standard finance. Following are the different types of anomalies

Fundamental Anomalies

These are irregularities that emerge when a stock’s performance is considered in light of the fundamental assessment of the stock’s value as price to book value ratio

(P/B ratio), price earnings ratio, earning per share etc., There is a large body of evidence documenting that investors consistently overestimate the value of popular companies and underestimate the value of out-of-favour companies.

Technical Anomalies

Technical analysis encompasses a number of techniques that attempt to forecast the securities prices by studying past prices. Sometimes, technical analysis reveals inconsistencies with respect to the EMH; these are technical anomalies. In general, the majority of research focused technical analysis trading methods finds that prices adjust rapidly in response to new stock market information and that technical analysis techniques are not likely to provide any advantage to the investors who use them.

Calendar Anomalies

It occurs due to special reference given to some specific months, weeks, or days in investment activities. One calendar anomaly is known as “the January Effect”. Historically stocks in general and small stocks in particular have delivered abnormally high returns during the month of January. The January Effect is particularly illuminating because it hasn’t disappeared, despite being well known for 25 years (according to arbitrage theory, anomalies should disappear as traders attempt to exploit them in advance).

Emotions & Psychology

There are many instances where emotions and psychology influence investor’s decision making, causing them to behave in unpredictable or irrational ways. Such irrational decisions can better be explained with the help of Behavioural Finance.

According to traditional financial theory, all the participants in financial markets are rational "wealth maximisers". On the other hand; there are many occasions where emotion and psychology influence our decisions, inducing us to behave in unpredictable or irrational ways. Statman (1999)[9] said “Standard finance is the body of knowledge built on the pillars of the arbitrage principle of Miller and

Modigliani, the portfolio principles of Markowitz, capital asset pricing theory of Sharpe, Linter, and Black, and option –pricing theory of Black, Scholes, and Merton."

Traditional financial theory held that investors were rational, or if they were not, that sophisticated investors would trade aggressively and force stocks to be accurately priced. Eugene Fama made this argument persuasively in the 1960s and, by the late 1970s, it had become an academic orthodoxy. The early 1980s marked a turning point. Anomalies in stock prices give birth of Behavioural Finance theory, built on the psychology of Daniel Kahneman and Amos Tversky, whose collaborative work earned the 2002 Nobel Prize.

There are number of studies conducted to find out why investing shares is uncomfortable. This shows two broad areas. One is prospect theory which explains how investors evaluate gains and losses and the other is heuristics which is cognitive shortcuts that simplify decisions.

Behaviourists explain that, rather than the anomalies, irrational behaviour is common place. Behavioural finance is a relatively new field that seeks to combine behavioural and cognitive psychological theories with conventional economics and finance to furnish explanations for the irrational financial decisions of people. Behavioural finance explains that people are not nearly as rational as traditional finance theory makes out.

Certainly, investors as a whole are far from irrational, for large and persistent disparities between fair values and market values are difficult to be found. Nevertheless the behavioural observations of cognitive psychologists are likely to provide a better understanding of how investors make decisions and help to explain certain apparent market inefficiencies. Indeed, it has opened up a whole new field known as behavioural finance.

3.5 Behavioural Finance

Behavioural finance is an emerging field that combines the understanding of behavioural and cognitive psychology with financial decision-making processes'

Parikh (2010)[10]. Linter (1998)[11] defines it as 'the study of how human beings interpret and act on information to make informed investment decisions. Fromlet (2011)[12] defines Behavioural finace as that which 'closely combines individual behaviour and market phenomena and uses knowledge taken from both the psychological field and financial theory'. 'Behaviour is an observable response or activity by an organism and is extremely compex in nature. Behaviour is also referred to as the internal psychic condition and the actions reflected to the outside world' Sulphey (2014)[13]. Behavioural finance is to replace the efficient markets hypothesis as the most widely accepted paradigm, it is not sufficient to simply find flaws with the EMH, it finds out the reasons of stock market anomalies by justifying them with explanation of various investor biases while taking investment decisions. It is an open-minded finance. Kahneman and Tversky have shown empirically that people are irrational in a consistent and correlated manner. They have started this revolution at the beginning of 1970s.

Behavioural finance is commonly defined as the application of psychology to finance. It has become an important topic with the burst of tech-stock bubble in March of 2000. Behavioural finance explains how and why market might be inefficient. The two building blocks of behavioural finance are cognitive psychology (how people think) and the limits to arbitrage (when markets will be inefficient). The growth of behavioural finance research has been fuelled by the inability of traditional frame work to explain many empirical patterns, including stock market bubbles in Japan, Taiwan and the US.

The two primary sub topics in behavioural finance are: Behavioural Finance Micro and Behavioural Finance Macro.

1. Behavioural Finance Micro (BFMI) explains behaviours or biases of individual investors. In this, we compare the 'normal investors' to the rational investors as observed in classical economic theory.

2. Behavioural Finance Macro (BFMA) deals with anomalies in the efficient market hypothesis that behavioural models may explain." Pompian (2006)[14]

Need

Standard financial theories such as, Modern Portfolio Theory, Capital Asset Pricing Model (CAPM), Efficient Market Hypothesis (EMH), and Arbitrage Pricing Theory assume that people behave rationally and markets are efficient. For a while, theoretical and empirical evidence suggested that CAPM, EMH and other rational financial theories did a respectable job of predicting and explaining certain events. However, as time went on, academics in both finance and economics started to find anomalies and behaviours that couldn't be explained by theories available at the time. While conventional theories could explain certain "idealized" events, the real world proved to be a very messy place in which market participants often behaved very unpredictably.

Rational Economic Man

One of the most important assumptions in conventional economics and finance is that people are rational "wealth maximizers" who seek to increase their own well-being. According to conventional economics, emotions and other extraneous factors do not influence people when it comes in making economic choices. In most cases, however, this assumption doesn't reflect how people behave in the real world. The fact is that people frequently behave irrationally. Consider the outlook of people in purchasing lottery tickets in the hope of hitting the big jackpot. From a purely logical standpoint, it does not make sense to buy a lottery ticket when the odds of winning are overwhelming against the ticket holder. Despite this, millions of people spend countless money on this activity. These anomalies prompted academics to look to cognitive psychology to account for the irrational and illogical behaviours that traditional finance had failed to explain.

Scope

The scope of behavioural finance is extended to its role in the investment decision of individuals as well as corporate. It is not restricted to any economy, industry or company but can be found around the world. There exist a variety of market anomalies in stock market even though the standard finance predicts the market at certain extent. Through the behavioural finance we provide explanation for these anomalies and even find out the remedial actions for the same. The study of behavioural finance also helps to understand the different kinds of investor personality. This understanding of how investor psychology impacts investment outcomes which generate insights that benefit the advisory relationship. The key result of behavioural finance-enhanced relationship will be a portfolio to which the advisor can comfortably adhere while fulfilling the client's long term goals. This also provides explanation to various corporate activities

Behavioural Finance as a Science or an Art

Behavioural finance has taken inputs from standard finance which is systematic and well designed based on various theories. To a certain extent the latter explains the price movements and trend of stocks, direction of markets, construction, evaluation and revision of investor portfolio. Behavioural finance helps the investor to identify themselves better by providing various models of human personality. Once the investor understands his / her strength and limitations and also the remedies of one's mental condition, one can plan one's investment better.

Important Contributors

The field of behavioural finance has many thoughtful psychologist, economists and academicians who have provided major theoretical and empirical contributions. A few are the following:

- Professor Robert Shiller, Yale University, known for his work 'Irrational Exuberance'

- Alan Greenspan, the US Federal Reserve Chairman, known by his remark about 'irrational exuberance' at the annual Dinner and Francis Boyer Lecture on the American Enterprise Institute for Public Policy Research in Washington, D.C., on December 5, 1996.

- Professor Richard Thaler, University of Chicago Graduate School of Business with Owen Lamont has written a classic book ‘Can the Market Add and Subtract? Mispricing in Tech Stock Carve-Outs’.

- Professor Hersh Shefrin, university in Santa Clara, California has written a successful book entitled ‘Beyond Greed & Fear: Understanding Behavioural finance and psychology of investing’.

- Anndrei Shelfier, Harvard University, published an excellent book entitled ‘Inefficient Markets: An introduction of behavioural finance’.

- Meir Statman, Leavey School of Business, Santa Clara University, published a paper entitled ‘Behavioral finance: Past Battles and Future Engagements’.

- Cognitive psychologists Daniel Kahneman and Amos Tversky are considered the fathers of behavioural economics/finance. . In 2002, Kahneman received the Nobel Memorial Prize in Economic Sciences for his contributions to the study of rationality in economics. Kahneman and Tversky have focused much of their research on the cognitive biases and heuristics (i.e. approaches to problem solving) that cause people to engage in unanticipated irrational behaviour. Their most popular and notable works include writings about prospect theory and loss aversion. Economist Richard Thaler also joined Kahneman and Tversky, blending economics and finance with psychology to present concepts, such as mental accounting, the endowment effect and other biases.

- Vernon Smith established laboratory experiment as a tool in empirical economic analysis.

History of Behavioural Finance

Economics had a close connection with psychology during the classical period. For example, Adam Smith wrote “The Theory of Moral Sentiments”, an important text describing the mental and emotional principles of individual behaviour; and Jeremy

Bentham wrote considerably on the psychological foundations of utility. Economists began to distance themselves from psychology and reshape economics as a quantitative science during the development of neo-classical economics, with explanations of economic behaviour deduced from assumptions about the nature of economic agents. The concept of homo economicus was developed, and the psychology of this entity was fundamentally rational. Rational Economic man tries to maximise his wealth. Nevertheless, psychological explanations continued to inform the analysis of many important figures in the development of neo-classical economics such as Francis Edgeworth, Vilfredo Pareto, Irving Fisher and John Maynard Keynes.

Psychology had largely disappeared from economic discussions by the mid 20th century. A number of factors contributed to the resurgence of its use and the development of behavioural economics. Expected utility and discounted utility models began to gain wide acceptance, generating testable hypotheses about decision making under uncertainty and inter temporal consumption respectively. Soon a number of observed and repeatable anomalies challenged those hypotheses. Furthermore, during the 1960s cognitive psychology began to describe the brain as an information processing device (in contrast to behaviourist models). Psychologists in this field such as Ward Edwards, Amos Tversky and Daniel Kahneman began to compare their cognitive models of decision making under risk and uncertainty to economic models of rational behaviour.

An important paper in the development of the behavioural finance and economics fields was written by Kahneman and Tversky in 1979. This paper, 'Prospect theory: Decision Making under Risk', used cognitive psychological techniques to explain a number of documented divergences of economic decision making from neo-classical theory. Over time many other psychological effects have been incorporated into behavioural finance, such as overconfidence and the effects of limited attention. Another milestones in the development of the field include a well attended and diverse conference at the University of Chicago, special 1997 edition of the Quarterly Journal of Economics ('In Memory of Amos Tversky') devoted to the topic of behavioural economics and the award of the Nobel prize to Daniel Kahneman in 2002 "for having integrated insights from psychological research into economic science, especially concerning human judgment and decision-making under uncertainty". Prospect theory is an example of generalized expected utility theory. Although not commonly included in discussions of the field of behavioural economics, generalized expected utility theory is similarly motivated by concerns about the descriptive inaccuracy of expected utility theory.

Serious questioning of modern finance as a paradigm started when ‘Prospect Theory’ of (Kahneman & Tversky, 1979)[15], was imported into studies of asset pricing. Prospect Theory, founded on the outcome of numerous experimental psychological studies, is just one alternative to the expected utility maxim of Von Neuman and Morgenstern (1967) upon which modern finance has been based.

In short, due to irrational behaviour and multiplied effect of different personalities of investors, market will not be efficient. This inefficiency causes the share price to deviate from the predictions of traditional market models.

Standard Finance versus Behavioural Finance

People in standard finance are rational. People in behavioural finance are normal – Meir Statman, Santa Clara University. Standard finance is based on four principles:

(1) Investors are rational,

(2) Markets are efficient,

(3) Investors design their portfolios based on mean-variance portfolio theory and

(4) Expected return is the function of risk alone.

According to behavioural finance, ‘investors are normal not rational’. Behavioural finance is built on the framework of standard finance but supplies a replacement for standard finance as a descriptive theory. Behavioural finance reflects a different model of human behaviour and is constructed of different components- prospect theory, cognitive errors etc. These components help make sense of the world of finance including investor preferences, the design of modern financial products and financial regulators by making sense of normal investor behaviour.

The two basic concepts in standard finance that behavioural finance disputes: 'perfect markets' and 'rational economic man'. It also covers the basis on which behavioural finance proponents challenge each tenet and discusses some evidence that has emerged in favour of the behavioural approach.

During the 1970s, the standard finance theory of market efficiency became the model of market behaviour accepted by majority of academics and a good number of professionals. The Efficient Market Hypothesis (EMH) had matured in the previous decade, stemming from the doctoral dissertation of Eugene Fama. Fama persuasively demonstrated that in securities market populated by many well-informed investors, investments will be appropriately priced and will reflect all available information. When someone invests in the stock market, it is done with the goal of making a return on the capital invested. Many investors try not only to make a profitable return, but also to make abnormal return. So, according to the EMH, nobody has an upper hand in forecasting a return on a share price because no one has access to news not already available to everyone else.

The Effect of Efficiency: Non-Predictability

In efficient markets, as prices respond only to information available in the market, and, because all market participants access to the same information, no one can beat the market. According to EMH, prices become not predictable but random, so no investment pattern can be anticipated. So, a planned approach to investment cannot be successful. This "random walk" of prices, results in the failure of any investment strategy that leads to make abnormal return.

Anomalies: The Challenge to Efficiency

Anomalies are termed as abnormal behaviour shown by financial markets. These anomalies are the occurrence of market events, whose explanation is not within the reach of standard finance (Singh & Bahl, 2015)[16]. There are obvious arguments against the EMH. There are investors who have beaten the market - Warren Buffett, who made billions through his investment strategy of focussing undervalued stocks. There are portfolio managers who are making the better wealth to their clients than others, and there are mutual funds with more renowned research analysis than others. So how can stock market be random when investors are clearly profiting from and beating the stock market?

Counter arguments to the EMH state that consistent patterns are present. For example: the January effect which shows more returns like to be obtained in the first month of the year; "blue Monday on Wall Street" tend to discourage the investor from buying on Friday afternoon and Monday morning because of the weekend effect and the inclination for prices to be higher on the day before and after the weekend than during the rest of the week.

If a market is efficient, then no amount of information or rigorous analysis can be expected to result in performance of a selected benchmark. An efficient market can basically be defined as a market wherein large numbers of rational investors act to maximize profits in the direction of individual securities. A key assumption is that relevant information is freely available to all participants. This competition among market participants results in a market wherein, at any given time, prices of individual investments reflects the total effects of all information, including information about the events that have already happened and events that the market expects to consider in the future. In short, at any time in an efficient market, the price of a security will match that security's intrinsic value. If markets are truly efficient and current prices fully reflect all pertinent information, then trading securities in an attempt to surpass a benchmark, is a game of luck, not skill.

Market efficiency debate has inspired literally thousands of studies attempting to discover whether specific markets are in fact “efficient”. Many studies do indeed point to evidence that supports the EMH. Researchers have documented numerous persistent anomalies, however that contradict the EMH. There are three main types of market anomalies: fundamental anomalies, technical anomalies, and calendar anomalies which we discussed earlier (Page no. 76)

Rational Economic Man versus Behaviourally Biased Man

Stemming from neoclassical economics, Homo Economicus is a simple model of human economic behaviour, which assumes that principles of perfect self-interest, perfect rationality, and perfect information govern economic decisions by individuals. Like EMH, Homo Economicus is a tenet that economists uphold with varying degrees of stringency i.e. a) semi strong form in which rational economic behaviour is not perfectly predominant but assumes an abnormally high occurrence of rational economic traits b) weak form in which the corresponding traits exists but are not strong. All of these versions share the core assumption that humans are "rational maximisers" who are purely self-interested and make perfectly rational economic decisions. Economists lie to use the concepts of rational economic man for two reasons: (1) Homo Economicus makes economic analysis relatively simple (2) homo Economicus allows economists to quantify their findings, making their work more elegant and easier to digest

To conclude, people are neither perfectly rational nor perfectly irrational; they possess diverse combinations of rational and irrational characteristics, and benefit from different degrees of enlightenment with respect to different issues.

Behavioural Finance: Key Concepts

If irrational traders cause deviations from fundamental value, rational traders will often be powerless to do anything about it. In order to say more about the structure of these deviations, behavioural models often assume a specific form of irrationality. For guidance on this, economists turn to the extensive experimental evidence compiled by cognitive psychologists on the systematic biases that arise when people form beliefs, and on people's preferences. A crucial component of any model of financial markets is a specification of how agents form expectations. These psychological biases give rise to excessive trading and retention of losing positions well after the evidence indicates that the basis for the original investment has changed. The concept of behavioural finance has to do with taking into consideration a range of psychological variables and how the resulting emotional reactions of these variables can impact both personal and general economic conditions. Closely associated with behavioural economics, the concept seeks to explain what occurs when emotional responses are involved in decisions that impact the stock market and the prices of individual stocks, market prices in selected markets, and the allocation of financial resources in both savings and spending habits.

3.6 Investment Decisions

Decision making is a process of choosing best alternatives among a number of alternatives. This decision has come out after a proper evaluation of all the alternatives. Decision making is the most complex and challenging activity of investors. Every investor differs from the other in all aspects due to diverse factors like demographic factor, socioeconomic background, educational level, sex, age and race. An optimum investment decision plays an active role and is a significant consideration.

Investor is a rational being who will always act to maximize his financial gain. Yet we are not rational beings; we are human beings; an integral part of this humanness is the emotion within us. Indeed, we make most of our life decisions on purely emotional considerations.

Investment performance depends mainly on the quality of investment decision they take. Most of the investors may take the investment decision through the security analysis. But, even without the knowledge of themselves, their decision may affect their behavioural bias and level of emotional intelligence.

3.6.1 Security Analysis

Security analysis is the first step of the portfolio analysis. In this step, investors analyse the risk-return characteristics of each securities. The law of the market is ‘buy underpriced securities and sell the overpriced securities’. Security analysis is all about identifying underpriced and overpriced securities. Basically there are two approaches; fundamental analysis and technical analysis.

Fundamental Analysis

The principal motive of investing in share is to get the returns in the form of dividend and capital appreciation. This is primarily determined by the performance of the company, industry and economy. So the investor has to evaluate a lot of information on the past performance and the expected future performance of the same (Economy, Industry and Company). This evaluation is called fundamental analysis or EIC analysis.

Economic Analysis

'Economic analysis aims at determining whether the economic climate is conducive and is capable of encouraging the growth of the business sector. When the economy expands, most industry groups and companies are expected to benefit and grow. When the economy declines, it adversely affects industries and companies' (Ranganatham & Madhumathi, 2012)[17]. Gross Domestic Product, Inflation rate, Interest rate, Exchange rate, Infrastructure, Economic & political stability etc., are the tools for economic analysis. It is generally believed that approximately 30 percent of the price variations in stocks are due to economic factors.

Industry Analysis

An industry is a homogeneous group of companies. 'For the invertors industry analysis demands insight into (1) the key sectors or subdivisions of overall economic activity that influence particular industries, and (2) the relative strength or weakness of particular industry or other groupings under specific set of assumptions about economic activity' (Fischer & Jordan, 1995)[18]. Industry growth relative to the GDP, Permanence (need for particular industry), Cost structure (fixed cost to variable cost) etc., are the tool for industry analysis. It is generally believed that approximately 25 percent of the price variation of stocks is explained by the industry related factors.

Company Analysis

It is the final stage of fundamental analysis. 'Company analysis deals with the estimation of return and risk of individual stock. Many pieces of information influence investment decisions. Information regarding companies can be broadly classified into two broad groups: internal as well as external. Internal information consists of data and events made public by companies concerning their operations. The internal information sources include annual reports to shareholders, public and private statements of officers of the company, the company's financial statement etc. External source of information is that generated independently outside the company. These are prepared by investment services and financial press' (Kevin, 2011)[19]. Business plan of the company, Quality of the management, Debt equity ratio, Competitive Edge, Promoters holding in shares, Company's market share, Analysis of financial statement, Earnings per share, Price Earning ratio, Price to book ratio, Divident payout ratio, Return on equity etc., are the tools of Company analysis. It is generally believed that company specific factors contributes another 30 percent of the stock price variations

Technical Analysis

'Investment timing is cruicial as the market is continuosly jolted by waves of buying and selling and prices are moving in trends and cycles and never stable. Technical analysis help us take the decision of when to buy and sell. Entry and Exit decision is very important as it decides the profits or losses of investment' (Avadhani, 2011)[20].

Stock Charts

Stock charts gained popularity in the late 19th century from the writings of Charles H. Dow in the Wall Street Journal. A stock chart is simple XY graph (two axis) where the X axis represents the trading days and the Y axis denotes the prices. 'The purpose of "chart analysis" is to determine the probable strength of demand versus pressure of supply at various price levels, and thus to predict the probable direction in which a stock will move, and where it probably will stop. The clues are provided by the history of a stock's price movements, as recoded on the chart' (Bhalla, 2011)[21].

Mathematical Indicators

Apart from price charts, the analyst also uses mathematical indicator to know the underlying trend of a stock. Mathematical indicators are used to project future finacial or economical trend. It helps to identify momentum, trends, volatility etc. Mathematical indicators like moving averages smoothen out the apparent erratic movements of share prices and highlight the underlying trend.

Market Indicators

Stock charts and mathematical indicators assist the investor in analysing the data of one individual share whereas market indicatos help him gauge the changes in all shares within a specified market. Indicators used by technical analyst to study the trend of the market as a whole is known as market indicators.

3.6.2 Behavioural Biases

'Any decision making process requires an appropriate use of mental and financial resources to acquire and process information. In an attempt to make quick and easy decisions, individuals tend to deviate from rationality, or what is required for a standard decision making process when she or he is rational. These decisions are termed biases' (Sulphey, 2014)[22]. Biases are systematic errors in the way investor processes information while taking investment decision. The way investors think and feel affects the way they behave when making investment decisions. These influences can be identified as behavioural biases.

There are three financial decisions taken by individuals in stock trading: buy, sell, and hold. Many authors have identified the following pattern of individual behavioural biases while taking their investment decisions. 'Decision making is fraught with irrationality; most of behavioural finance is concerned with the study of this irrationality.' (Azzopardi, 2012)[23]

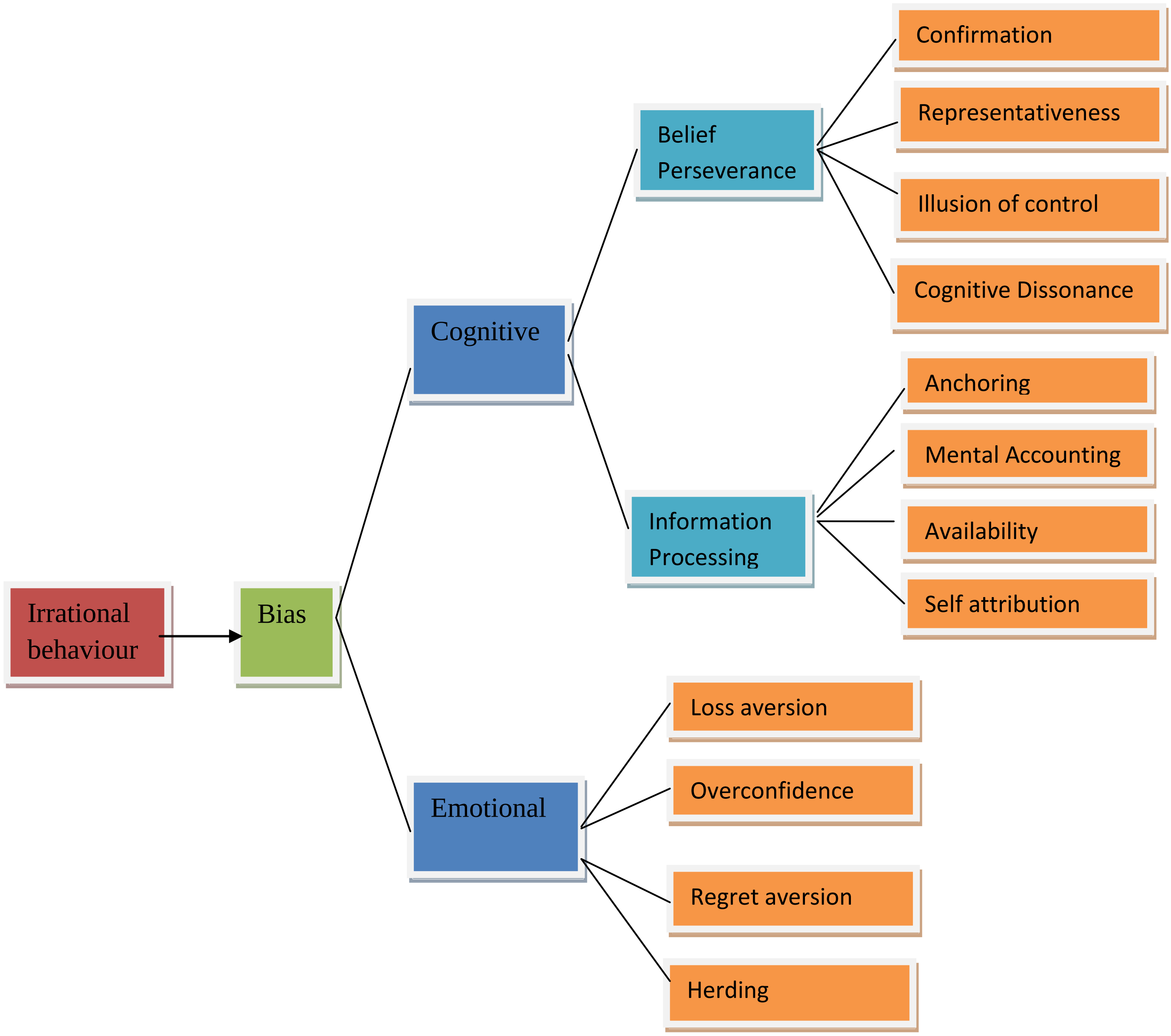

Figure 3.1 Classifications of Behavioural Bias

Biases

'A bias is a systematic error in the way we process information of the world around us' (Azzopardi, 2012)[24]. Biases are irrational financial decisions on account of faulty cognitive reasoning or reasoning caused by emotions. Behaviouaral bias causes to make irrational decision as against the rational decisions of tradtional finance. Bahvioural biases fall into two broad categories, cognitive and emotional (Pompian, 2006)[25].

Cognitive Biases

Cognitive bias deals with the way one thinks. Cognitive bias arises from basic statistical, information processing, or memory errors. It is the result of the faulty reasoning so that the better information and advice can correct them. Cognitive biases are again classified into two categories, Belief Perseverance and Information Processing.

Belief Perseverance Biases

It is the tendency to cling to once previously hold or recently established belief irrationally or illogically. Investors continue to hold and justify the belief because of their bias toward belief in themselves or their own ideals or abilities (Pompian, 2006)[26]. The examples are confirmation, representativeness, illusion of control and cognitive dissonance.

Confirmation Bias

It is difficult to encounter something or someone without having a preconceived opinion. This first impression can be hard to shake because people also tend to selectively filter and pay more attention to information that supports their opinions, while ignoring or rationalizing the rest. This type of selective thinking is often referred to as the confirmation bias.

In investing, the confirmation bias suggests that an investor would be more likely to look for information that supports his or her original idea about an investment rather than information that contradicts it. As a result, this bias can often result in faulty decision making because one-sided information tends to skew an investor's frame of reference, leaving him with an incomplete picture of the situation.

Implications for Investors

1. Confirmation bias induces investors to seek out only the information that confirms their beliefs about an investment that they have made and not to seek out information that contradict it.

2. Confirmation bias can cause investors to continue to hold under-diversified portfolios. In this case, the investors do not want to hear anything negative about favoured investments but rather seek, single-mindedly, confirmation that the position will pay-off.

Representativeness Bias

Representativeness is a heuristic driven bias. ‘When psychologists use the term “heuristic” they mean rule of thumb.’ (Shefrin, 2008)[27]. ‘Representativeness refers to judgments based on stereotypes’ (Shefrin, 2002)[28].

Representativeness refers to the tendency to form judgment based on stereotype. For example, you may form an opinion about how a student would perform academically in college on the basis of how he has performed academically in school. While representativeness may be a good rule of thumb, it can also lead people astray.

Implications for Investors

1. Investors may be too quick to detect patterns in data that are in fact random.

2. Investors may believe that a healthy growth of earnings in the past may be representative of high growth rate in future. They may not realize that there is a lot of randomness in earnings growth rates.

3. Investors may be drawn to mutual funds with a good track record because such funds are believed to be representative of well performing funds. They may forget that even unskilled managers can earn high returns by chance.

4. Investors may become overly optimistic about past winners and overly pessimistic about past losers.

5. Investors generally assume that good companies are good stocks, although the opposite holds true most of the time.

Illusion of Control Bias

In illusion control bias investors induce to think that they can control outcomes when, in fact, they cannot (Pompian, 2006)[29]. According to Langer (1975)[30] illusion of the control bias is the 'expectancy of a personal success probability inappropriately higher than the objective probability would warrant.'

Implications for Investors

1. Illusion of control bias induce the investors to trade more than is prudent
2. Illusion of control bias induces investors to maintain under diversified portfolio.

Cognitive Dissonance Bias

In 1956 the US psychologist Leon Festinger introduced a new concept in social psychology: the theory of cognitive dissonance. Cognitive dissonance is the mental struggle that people sense when they are presented with evidence that their beliefs are wrong. The theory is that dissonance, being unpleasant, motivates a person to change his cognition, attitude, or behaviour. If a person holds two cognitions that are psychologically inconsistent, he experiences Dissonance: a negative drive state (not unlike hunger or thirst). Because the experience of dissonance is unpleasant, the person will strive to reduce it—usually by struggling to find a way to change one or both cognitions to make them more consonant with one another.

Implications for Investors

Cognitive dissonance can induce investors to keep losing stocks that they otherwise would sell because they want to avoid mental struggle collaborated with accepting that they made a bad decision.

1. Cognitive dissonance induces investors to keep on to invest in a stock that they already own after it has gone down to justify an earlier decision to invest in that stock without analysing the new investment in stock with neutrality and rationality.

2. Cognitive dissonance can induce investors to be in herds of behaviour; that is investors evade news that contradicts an earlier decision until so much counter news is released that investors heard together.

Information Processing Biases

It arises when information is being processed and used illogically and irrationally in financial decision making (Pompian, 2006)[31]. It includes Anchoring, Mental Accounting, Availability and Self Attribution

Anchoring Bias

Similar to how a house should be built upon a good, solid foundation, our ideas and opinions should also be based on pertinent and appropriate facts in order to be considered valid. However, this is not always so. The concept of anchoring draws on the tendency to attach or "anchor" our thoughts to a reference point - even though it may have no logical relevance to the decision at hand.

Although it may seem an unlikely phenomenon, anchoring is fairly prevalent in situations where people are dealing with concepts that are new and novel.

Investment Anchoring

Anchoring can be a source of dissatisfaction in the financial world, as investors base their decisions on irrelevant figures and statistics. For example, some investors invest in the stocks of companies that have fallen considerably in a very short period of time. In this case, the investor is anchoring on a recent "high" that the stock has achieved and consequently believes that the drop in price provides an opportunity to buy the stock at a discount.

While, it is true that the fickleness of the overall market can cause some stocks to drop substantially in value, allowing investors to take advantage of this short- term volatility. However, stocks quite often also decline in value due to changes in their underlying fundamentals.

Implications for Investors

1. Investors tempt to make stock market forecasts that are too close to current levels.
2. Investors justify their original estimates when new information is learned about a company.
3. Investors tempt to predict a particular asset class might rise or fall based on the current level of returns.
4. Investors can become anchored on the economic states of the countries or companies.

Mental Accounting Bias

Mental accounting refers to the tendency for people to separate their money into separate accounts based on a variety of subjective criteria, like the source of the money and intent for each account. According to the theory, individuals assign different functions to each asset group, which has an often irrational and detrimental effect on their consumption decisions and other behaviours.

Although many people use mental accounting, they may not realize how illogical this line of thinking really is. For example, people often have a special "money jar" or fund set aside for a vacation or a new home, while still carrying substantial credit card debt. In this example, money in the special fund is being treated differently from the money that the same person is using to pay down his or her debt, despite the fact that diverting funds from debt repayment increases interest payments and reduces the person's net worth. Simply put, it's illogical (and detrimental) to have savings in a jar earning little to no interest while carrying credit-card debt accruing at 20% annually. In this case, rather than saving for a holiday, the most logical course of action would be to use the funds in the jar (and any other available prospect) to pay off the excessive debt.

Different Source, Different Purpose

Another aspect of mental accounting is that people also treat money differently depending on its source. For example, people tend to spend a lot more "found" money, such as tax returns and work bonuses and gifts, compared to a similar amount of money that is normally expected, such as from their pay checks. This represents another instance of how mental accounting can cause illogical use of money.

Mental Accounting Investing

The mental accounting bias also enters into investing. For example, some investors divide their investments between a safe investment portfolio and a speculative portfolio in order to prevent the negative returns that speculative investments may have from affecting the entire portfolio. The problem with such a practice is that despite all the work and money that the investor spends to separate the portfolio, his net wealth will be no different than if he had held one larger portfolio.

Implications for Investors

1. Mental accounting bias induces investors to perceive that their investment occupy separate accounts. Envisioning different accounts to correspond with financial goals, induce the investors to neglect positions that offset or correlate across accounts. This can lead to below average aggregate portfolio performance.

2. Mental accounting induces investors to irrationally distinguish between the return earned from income and those from capital appreciation. Many people tend to protect principal sums and tend to spend dividend. Consequently, some investors invest in risky investment to get more return, but eventually it leads to erosion principal amount.

Availability Bias

Availability is a cognitive heuristic in which a decision maker relies upon knowledge that is readily available rather than examine other alternatives or procedures. There are situations in which people assess the frequency of a class or the probability of an event by the ease with which instances or occurrences can be brought to mind. For example, one may assess the risk of heart attack among middle-aged people by recalling such occurrences among one's acquaintances. Similarly, one may evaluate the probability that a given business venture will fail by imagining various difficulties it could encounter. This judgmental heuristic is called availability. Availability is a useful clue for assessing frequency or probability, because instances of large classes are usually reached better and faster than instances of less frequent classes.

According to the availability bias, people tend to heavily weigh their decisions toward more recent information, making any new opinion biased toward that latest news.

This happens in real life all the time. Another example, suppose you see a car accident along a stretch of road that you regularly drive to work. Chances are you'll begin driving extra cautiously for the next week or so. Although the road might be no more dangerous than it has ever been, seeing the accident causes you to overreact, but you'll be back to your old driving habits by the following week.

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Implications for Investors

1. Investors choose securities based on only the information they have and will not engage in any analysis to verify that the security selected is a good one.

2. Investors choose securities that fit their narrow range of life experiences, like the industry they work in, the people they associate with etc.

Self Attribution Bias

Self attribution bias refers to the tendency of investors to attribute their successes to their talent or foresight, while charging failures on bad luck. For example, Students fairing well on an examination, for example might credit their own intelligence or work ethic, while those failing might cite unfair grading.

Self-attribution is a cognitive phenomenon by which people attribute failures to situational factors and successes to dispositional factors. Self-attribution bias can be classified into two constituent tendencies i.e. self-enhancing bias and self-protecting bias.

Self enhancing bias represents people's propensity to claim an irrational degree of credit for their successes. Self-protecting bias represents the corollary effect- the irrational denial of responsibility for failure

Implications for Investors

1. Investors think that their gain from their investment is due to their skill rather than to factors out of their control. This attitude can lead to taking on too much risk, as the investors become over confident in their attitude.

2. As investors believe are over confident they begin to trade too much, which has been shown to be "dangerous to their wealth"

3. This bias leads investors to "hear what they want to hear".

Emotional Biases

Emotional bias deals with the way one feels. It arises from the impulse or intuition rather than conscious calculations. It is rather difficult to correct the emotional bias, because emotion is a mental state that acts spontaneously than through conscious effort. Actually, investors need to control their emotions, but often they fail to control. It includes loss aversion, overconfidence, regret aversion and herding.

Loss Aversion Bias

This bias is coined by Daniel Kahman and Amos Tversky in 1979 while they were working on developing prospects theory. 'Prospects theory begins with the contention that standard expected theory cannot fully account for observed decision-making under risk. This contention is based on the empirical evidence that people often behave contrary to expected utility theory' Ackert & Deaves (2011)[32]. Academics tend to use "utility" to describe enjoyment and contend that we prefer instances that maximize our utility. However, research has found that people do not actually process information in such a rational way. If a person is given two equal choices, one expressed in terms of possible gains and the other in possible losses, he will choose the former - even when they achieve the same economic end result. According to prospect theory, losses have more emotional impact than an equivalent amount of gains. For example, in a traditional way of thinking, the amount of utility gained from receiving $50 should be equal to a situation in which you gained $100 and then lost $50. In both situations, the end result is a net gain of $50. However, despite the fact that you still end up with a $50 gain in either case, most people view a single gain of $50 more favourably than gaining $100 and then losing $50.

Following are the line of thinking that created the asymmetric value function:

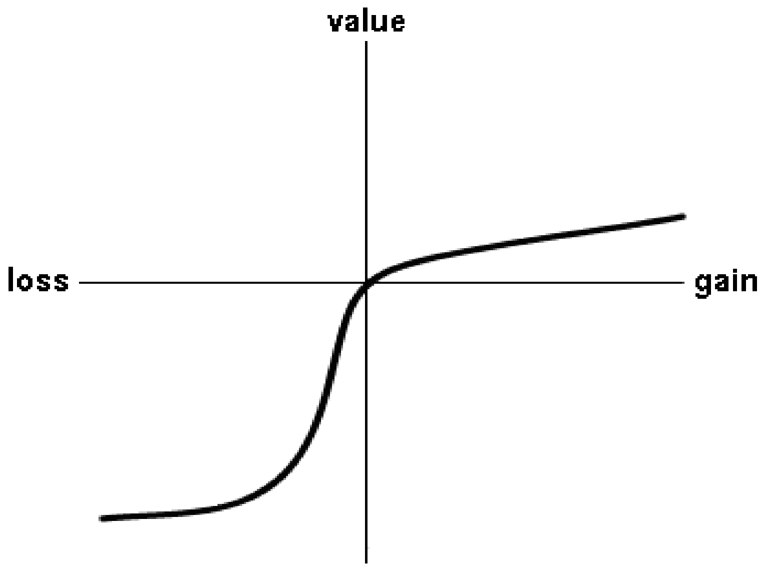


Figure 3.2 The Value Function

Thaler & Johnson (1990)[33] state 'people are even more averse to the prospect of future losses when they have experienced loss in the recent past.' This function is a representation of the difference in utility (amount of pain or joy) that is achieved as a result of a certain amount of gain or loss. It is important to note that not everyone would have a value function that looks exactly like this; this is the general trend. The most evident feature is how a loss creates a greater feeling of pain compared to the joy created by an equivalent gain.

Financial Relevance

The prospect theory can be used to explain quite a few illogical financial behaviours. For example, there are people who do not wish to put their money in the bank to earn interest or who refuse to work overtime because they don't want to pay more taxes. Although these people would benefit financially from the additional after-tax income, prospect theory suggests that the benefit (or utility gained) from the extra money is not enough to overcome the feelings of loss incurred by paying taxes.

Prospect theory also explains the occurrence of the disposition effect, which is the tendency for investors to hold on to losing stocks for too long and sell winning stocks too soon. The most logical course of action would be to hold on to winning stocks in order to further gains and to sell losing stocks in order to prevent escalating losses

Implications for Investors

a. In loss aversion investors tend to hold losing investments too long. This behaviour has serious negative consequences as it depresses portfolio returns.

b. In loss aversion investors tend to sell winners too early, in the fear that their profit will disappear unless they sell. This attitude restricts upside potential of a portfolio.

Overconfidence Bias

Confidence implies realistically trusting in one's abilities, while overconfidence usually implies an overly optimistic assessment of one's knowledge or control over a situation.

'Overconfidence means the dispersion of my beliefs about future asset value is not set wide enough to be consistent with actual outcomes' (Forbes, 2009)[34]. Researcher Terrence Odean found that overconfident investors generally conduct more trades than their less-confident counterparts. Odean found that overconfident investors/traders tend to believe they are better than others at choosing the best stocks and best times to enter/exit a position. Unfortunately, Odean also found that traders that conducted the most trades tended, on average, to receive significantly lower yields than the market.

Implications for Investors

Investors with overconfidence overestimate their competence to assess a company as a potential investment. So they become blind to any negative news that might normally imply a warning that either a share should be purchased or sold.

1. Investors with overconfidence tend to trade excessively as a result of believing that they possess special knowledge that others don't have.
2. Investors with overconfidence tend to under estimate their downside risks which leads to poor performance of portfolio.

Regret Aversion

It is the general tendency to avoid actions that have been potential to create discomfort over poor or faulty investment decisions. Generally, human beings feel fear of failure or fear of making mistake when they take decisions. So investors are often hesitant to sell the losing shares. They think when they sell the shares, the price of the share may increase which could lead to stress and mental pain. This bias can happen even when we are holding the winning stocks. They sell the winning stock too early thinking that the price may come down in the near future.

Implications for Investors

1. It will make investors too conservative in their investment opportunities. They think low risk investment is better even though they give low return. It leads them to underperformance in their investment decision.
2. This type of investors hold loosing shares too long and sells the winning shares too early. Sometimes, they hold the winning shares too long to the extent that they lose the opportunity to make good profit.

3. This type of investors shows 'herding behaviour' so that they can reduce the pain of regret. They feel safer in popular investments.

4. They underestimate their expertise and resort to recommendations of others.

Herd Behaviour Bias

Herd behaviour is the tendency for individuals to mimic the actions (rational or irrational) of a larger group. Individually, however, most people would not necessarily make the same choice. Herd behaviour is the mutual imitation leading to convergene in action space. It is also said to be the patterns of behaviour that are clustered or correlated across individuals by interaction, where incentive to adopt a behaviour increases with the number of previous adopters (Welch, 2000)[35]. There are a couple of reasons why herd behaviour happens. The first is the social pressure of conformity i.e. most people are very sociable and have a natural desire to be accepted by a group, rather than be branded as an outcast. Therefore, following the group is an ideal way of becoming a member. .

The second reason is the common rationale that it's unlikely that such a large group could be wrong. After all, even if you are convinced that a particular idea or course of action is irrational or incorrect, you might still follow the herd, believing they know something that you don't. This is especially prevalent in situations in which an individual has very little experience. When a market is volatile, investors fear that others know more or have more information. As a result, investors will have the tendency to do what others are doing.

A strong herd mentality can even affect financial professionals. The ultimate goal of a money manager is to follow an investment strategy to maximize a client's invested wealth. The problem lies in the amount of scrutiny that money managers receive from their clients whenever a new investment fad pops up. In many cases, it's tempting for a money manager to follow the herd of investment professionals. After all, if the aforementioned gimmick pans out, his clients will be happy. If it doesn't, that money manager can justify his poor decision by pointing out just how many others were led astray.

Implication for Investors

By the time a herd investor knows about the newest trend, most other investors might have already taken advantage of this news, and the strategy's wealth-maximizing potential has probably already been peaked. This means that many herd-following investors will probably be entering into the game too late and are likely to lose money as those at the front of the pack move on to other strategies.

3.6.3 Emotional Intelligence

Emotional intelligence is a term created by two researchers – John Mayer, University of Hampshire and Yale's Peter Salavoy – and popularised by Daniel Goleman in his book 'Emotional Intelligence'. The dictionary meaning of emotional intelligence is 'the capacity to be aware of, control and express one's emotions, and to handle interpersonal relationships judiciously and empathetically'. John Mayer and Peter Salavoy define emotional intelligence as 'the ability to recognise, understand and manage our own emotions and recognise, understand and influence the emotions of others. It is a person's ability to recognise and interpret emotions and to use and integrate them productively for optimal reasoning and problem solving.' (Goleman, 2005)[36] define emotional intelligence as 'the capacity for recognising our own feelings and those of others, for motivating ourselves, and for managing emotions well in ourselves and in our relationships.' He explained the definition of emotional intelligence, expanding the same into five main domains:

1. **Self Awareness**

   The dictionary meaning of self awareness is 'conscious knowledge of one's own character and feeling'. It is being aware of our mood and our thoughts about that mood. Recognising a feeling as it happens is the keystone of emotional intelligence. People with greater certainty about their feeling are better pilot of their lives.

2. **Managing Emotions**

   Managing emotions is the basic skill of Psychological resilience. To be resilient, one should recognise negative emotions, handle it and take necessary steps to make it positive. People who are poor in this ability are constantly battling feeling of distress, while those who excel in it can bounce back far more quickly from life's setbacks and upsets.

3. **Motivating Oneself**

   The dictionary meaning of motivating oneself is 'the ability to do what needs to be done without influence from other people or situations. People with self motivation can find a reason and strength to complete a task, even when challenging, without giving up or needing another to encourage them'. People who have this skill tend to be more highly productive and effective in whatever they undertake.

4. **Empathy**

   Empathy means the ability to understand and share the feelings of another. 'Put our legs in other's shoes' means feel another person is experiencing from within their frame of reference. People who are empathetic are more attuned to the subtle social signals that indicate what others need.

5. **Social Skill**

   These are the skills we used to communicate and interact with each other. It means the ability to communicate, persuade and interact with other members of the society, without undue conflict and disharmony. These are the abilities that pave the foundation for popularity, leadership, and interpersonal effectiveness.

According to (Goleman, 2005),[37] emotional intelligence helps investor to have better decision making.

3.7 Investment Performance

Investment performance is the rate of return (dividend plus capital appreciation) received from the investment. Usually when the rate of return is high, high performance is attributed, otherwise, vice versa. Investment performance is calculated over a specific period of time. One of the ways to measure the performance of your investment is to have realistic expectation and compare the actual return with the same. The other way is compare the actual return with the market return. The satisfaction level of investment decision can also be taken as a criterion to measure investment performance.

3.8 Conclusion

Decades of testing the EMH indicate that the theory has some cracks. Many market anomalies have been found. Some anomalies have persisted through time, while others have not. Also stock prices seem to under-react to news at sometimes and over-react at other times. Behavioural finance offers some possible explanations for all these.

References:

1. Fischer, D. E., & Jordan, R. J. (1995). *Security Analysis and Portfolio Management.* Noida: Pearson Education in South Asia.

2. Miller, M. H. (1991). *Financial Innovation & Market Volatility.* New York: Blackwell.

3. Kurt, S. (1991). Hyper Volatility of Securities Market. *The Bombay Stock Exchange Review* , 1-9.

4. Bachelier's, L. (1900). *The Theory of Speculation.* PhD Thesis, Parris: Gauthier-Villaras.

5. Kendall, M. (1953). The analysis of economic time series. *Journal of the Royal Statistical Society, Series A , 96*, 11-25.

6. Elton, E. J., & Gruber, M. J. (1994). *Modern Portfolio Theory and Investment Analysis* (4th ed.). New York: John Wiley & Sons.

7. Fama, E. F. (1970). Efficient Capital Market: A Review of Theory and Empirical Work. *Journal of Finace , 25* (2), 383-417.

8. Shleifer, A. (2000). *Inefficinet Markets - An introduction to Behavioural Finance.* New York: Oxford University Press.

9. Statman, M. (1999). Behavioral Finance: Past Battles and future engagements. *Financial Analyst Journal , 55* (6), 18-27.

10. Parikh, P. (2010). *Value Investing and Behavioral Finance.* New Delhi: Tata McGraw Hill Education Pvt. Ltd.

11. Linter, G. (1998). Behavioural Finance: Why Investors make bad decisions. *The Planner , 13* (1), 7-8.

12. Fromlet, H. (2011). Behavioral Finance- Theory and Practical Application. *Business Economics , 36* (3), 18-28.

13. Sulphey, M. (2014). *Behavioral Finance.* Delhi: PHI Learning Private Limited.

14. Pompian, M. M. (2006). *Behavioral Finance and Wealth Management.* New Jersey: John Wiley & Sons, Inc.

15. Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica , 47* (2), 263-291.

16. Singh, S., & Bahl, S. (2015). *Behavioural Finance.* New Delhi: Vikas Publishing House Pvt Ltd.

17. Ranganatham, M., & Madhumathi, R. (2012). *Security Analysis and Portfolio Management* (2nd Edition ed.). Noida: Pearson Education in South Asia.

18. Fischer, D. E., & Jordan, R. J. (2006). *Security analysis and Portfolio Management.* Neelhi: Pearson Education in South Asia.

19. Kevin, S. (2011). *Security Analysis and Portfolio Management.* New Delhi: PHI Learning Private Limited.

20. Avadhani, V. A. (2011). *Security Analysis and Portfolio Management* (10th Revised Edition ed.). Mumbai: Himalaya Publishing House Pvt. Ltd.

21. Bhalla, V. (2011). *Investment Management* (17th edition ed.). New Delhi: S. Chand & Company Ltd.

22. Op. Cit. 14

23. Azzopardi, P. V. (2012). *Behavioural Technical Analysis.* Delhi: Vision Books Pvt. Ltd.

24. Ibid

25. Op. Cit. 15

26. Op. Cit. 15

27. Shefrin, H. (2008). *A behavioural approch to Asset pricing.* New York: Elsevier.

28. Shefrin, H. (2002). *Beyond Greed and Fear- Understanding Behavioural Finance and Psychology of Investing.* New York: Oxford University Press.

29. Op. Cit. 15

30. Langer, E. (1975). The Illusion of Control. *Journal of Personality and Social Psychology* , 311-328.

31. Op. Cit. 15

32. Ackert, L. F., & Deaves, R. (2011). *Understanding Behavioural Finance.* Delhi: Cengage Learning India Private Limited.

33. Thaler, R., & Johnson, E. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science , 36*, 643-660.

34. Forbes, W. (2009). *Behavioural finace.* New Delhi: John Wiley & Sons.

35. Welch, I. (2000). Herding among security analysts. *Journal of Financial Economics , 58*, 369-396.

36. Goleman, D. (2005). *Emotional Intelligence, Why It Can Matter More Than IQ.* New York: Bantam Books.

37. Ibid

Chapter 4

Extent and Pattern of Indian Stock Market Volatility

4.1 Introduction

Volatility is the statistical measure of risk, i.e. the ups and downs of asset price fluctuations over time. It is used to measure the market risk of a security or a portfolio of securities. The volatility of a share indicates the variability of its expected return. Volatility of the share price hampers individual investment; as a result it also affects economy as a whole. It creates more uncertainty in the market and adversely affects the flow of fund to productive investment. The main goal of this chapter is to examine the pattern and extent of the volatility of Indian Stock Market.

Traditional econometrics models estimate a constant one period forecast variance. Volatility as calculated by standard deviation or variance of returns is often used as a crude measure of the total risk of financial assets. Recent developments in financial econometrics have guided to the use of models and techniques that can describe the attitude of investors not only towards expected returns but also towards risk or uncertainty, over a period of time. These require models that are capable of dealing with volatility (variance) of the series. The main objective of this study is to determine the extent and pattern of Indian stock market volatility. The sample includes BSE Sensex, S&P CNX Nifty and 20 individual stocks listed in Bombay Stock Exchange which are selected randomly for event analysis.

We usually come across hetroskedasticity, or unequal variance, in cross sectional data because of the heterogeneity among individual cross-section units that comprise cross sectional observations, such as families, firms regions and countries. We also usually observe auto correlation in time series data. But in time series data involving asset returns such as returns on stock or foreign exchange rate we observe autocorrelated hetroskedasticity. In the literature such a phenomenon is called

Autoregressive Conditional Hetroskedasticity (ARCH) i.e. time varying variances – hetroskedasticity – that depends on (conditional) lagged effects (auto correlation).

Financial time series such as stock prices, interest rates, foreign exchange rates and inflation rates often exhibit the phenomenon of volatility clustering. That is the periods of turbulence in which their prices show wide swings and period of tranquillity in which there is relative calm. ('wild' and 'calm' periods as some financial analysts like to call them). As Franses (1988)[1] notes "since such financial time series reflect the results of trading among buyers and sellers at, for example, stock markets, various sources of news and other economic events may have an impact on the time series pattern on asset prices. Given that news can lead to various interpretations, and also given that specific economic events like oil crisis can last for some time, we often observe the large positive and large negative observations in financial time series to appear in clusters." Volatility clustering is a series with some periods of high volatility and some periods of low volatility.

The non-stationary nature of the variables implied that they have means that change overtime. A time series is said to be stationary if its means and variance are constant over time and the value of covariance between two time periods depends only on the distance or gap between two periods and not the actual time at which covariance is computed (Gujarati, 2011)[2]. Here one is concerned with stationary series, but with conditional variances that change over time. Such models are called ARCH models. (Asset prices are generally non-stationary but asset returns are usually stationary).

A simple measure of asset return volatility is its variance over time. But it doesn't catch volatility clustering because it is a measure of unconditional variance. It doesn't take into account time-varying volatility (past history) in asset returns. A measure that takes into account the past history is known as ARCH (Autoregressive conditional heteroskedasticity).

4.2 ARCH Model

The first ARCH model was presented by Engle (1982)[3], original work was concerned with the volatility of inflation in United Kingdom. The model suggests that the variance of the residuals at time ‘t’ depends on the squared error terms from past periods. Engel suggested that’ it is better to simultaneously model the mean and the vaiance of a series when we suspect that the conditional variance is not constant. His idea start from the fact that he allows the variance of residuals to depend on past history, or to have hetroskedasticity because the variance will chage over time. One way of allowing for this is to have variance depend on one lagged period of the square error terms as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 \qquad 4.1$$

As per the suggestion of Engle (1982)[4] ARCH (1) model will simultaneously model the mean and variance of the model with the following specification.

$$Y_t = \alpha + \beta X_t + u_t \qquad 4.2$$

$$u_t / \emptyset_t = N\,(0, h_t)$$

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 \qquad 4.3$$

where $\emptyset_t$ is the information set. Equation 4.2 is called the mean equation and equation 4.3 is called variance equation. Note that we have changed the notation of variance σ_t^2 to h_t.

4.2.1 ARCH (q) Model

The conditional variance can depend not only on one lagged realization but more than one, for each case producing a different ARCH process. It is given by

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \cdots \ldots \ldots + \alpha_q u_{t-q}^2 \qquad 4.4$$

Since h_t is a conditional variance, its value must always be strictly positive, a negative variance at any point in time would be meaningless.

4.3 The GARCH Model – Generalized ARCH

One of the shortcomings of an ARCH(q) model is that there are q+1 parameters to estimate. If q is a large number we may lose accuracy in estimation. According to

Engle & Bollerslev, (1986)[5], one of the limitations of ARCH specification is that it is more similar to moving average specification than an auto regression.

Bollerslev (1986)[6] introduced the generalised autoregressive conditional heteroscedastic models. This model is the base of other dynamic time varying volatility model. The merit of the model is that it is easy to estimate in addition to allow us to do diagnostic test. There are numerous non-normal conditional densities introduced in the GARCH frame work.

Many authors - Christie (1982)[7] and Nelson (1991)[8] – pointed out 'the evidence of assymmetric responses, suggesting the leverage effect (the tendency for volatilliry to rise up following a large price fall than following a price of same magnitude) and differential risk depending on the direction of price change movements'. Nelson (1991)[9] introduced exponential GARCH models with a conditional variance formulation that successfully captured assymetric response in the conditional variance.

4.4 Methodology Framework

The standard GARCH model allows the conditional variance to be dependent upon previous own lags. The basic structure of the symmetric normal GARCH model is GARCH (1, 1) is given by Brooks (2008)[10]

$$h_t = \delta + \alpha_1 u_{t-1}^2 + \beta_1 h_{t-1} \tag{4.5}$$

where h_t denotes that the conditional variance.

Since the development of GARCH model, a large number of extensions and variants have been proposed. Many of the extensions to the GARCH model have been suggested as a consequence of obsevered problems with standard GARCH (p,q) models. Firstly, the non-negativity conditions may be disrupted by the estimated model, secondly, GARCH model cannot explain the leverage effects even if they can account for volatility clustering and leptokurtosis in a series.

As shown above, it is vivid that there are some limitations in GARCH (1, 1) model. The non-negativity conditions may be violated by the estimated method, since the coefficients of the model are probably negative. GARCH model also cannot account for leverage effects.

Two popular models of asymmetry are the Threshold GARCH (TGARCH) model introduced by Glosten, Jaganathan, & Runkle (1993)[11] and Exponential GARCH (EGARCH) model introduced by Nelson (1991)[12].

Though TGARCH model treats positive and negative shocks asymmetrically unlike ARCH and GARCH and GARCH-M models, this model is also based on the restriction that the parameters will be greater than or equal to zero. EGARCH model has no such restrictions. The model not only treats positive and negative shocks asymmetrically, but also ensures that the estimated coefficients are positive.

In this study, the researcher selected EGARCH model introduced by Nelson (1991)[13] to measure the volatility of indices and return of the selected stocks.

The variance specification for EGARCH model is:

$$\log(ht) = \lambda + \sum_{j=1}^{q} \alpha j \left|\frac{Ut-j}{\sqrt{ht-j}}\right| + \sum_{j=1}^{q} \gamma j \frac{Ut-j}{\sqrt{ht-j}} + \sum_{i=1}^{p} \delta i \, log(ht-j) \qquad 4.6$$

Where h_t is called as the conditional variance, the variable $Ut-j \sqrt{ht-j}$ captures the relative size of the shocks and $|Ut-j \sqrt{ht-j}|$ captures the relative magnitude of the shocks. The α parameter represents a magnitude effect or the symmetric effect of the model, the "GARCH" effect. $\lambda, \alpha, \gamma, \delta$ are parameters to be estimated. Since the $\log(ht)$ is modeled, then the important merit of EGARCH models is that even if the parameters are negative h_t will be positive.

'The α parameter measures the magnitude effect or the symmetric effect of the model, the "GARCH" effect. The δ measures the persistence in conditional volatility irrespective of anything happening in the market. When δ is relatively large, then volatility takes a long time to die out following a shock in the market' (Alexander, 2008)[14].

The γ parameter measures the asymmetry or leverage effect. If γ is zero, then the model is symmetric. If γ is less than zero, then positive shocks (good news) generate less volatility than negative shocks (bad news). If γ is greater than zero, positive shocks cause more in volatility than negative shocks.

The normal EGARCH models do not tend to fit financial returns in which market shocks have non normal conditional distributions. Market returns typically have leptokurtic conditional distributions. Thus we use EGARCH-GED (generalized error) model than simple EGARCH model (Nishad & Thomachan, 2005)[15].

4.5 Long Term Volatility

According to Alexander (2009)[16], without the market disturbances the EGARCH variance will eventually settle down to a certain state value. This is the value σ^{-2} such that $\sigma_t^2 = \sigma^{-2}$ for all t. This σ^{-2} is the unconditional variance of the EGARCH model. The unconditional variance is assumed to be constant over the entire period. It corresponds to a long term average value of the conditional variance. The theoretical value of the unconditional variance in an EGARCH model deviates depending on the GARCH model. The long term or unconditional variance is formatted by substituting $\sigma_t^2 = \sigma_{t-1}^2 = \sigma^{-2}$ into the EGARCH conditional variance equation. Following is the unconditional volatility of the EGARCH (1, 1)

$$\sigma = \sqrt{exp\left(\frac{\lambda}{1-\delta}\right)} \qquad 4.7$$

If unconditional volatility is high, then long term volatility of the indices or shares also is high.

4.6 Data and Preliminary Results

The analysis in this part was based on BSE Sensex , S&P CNX Nifty and 20 selected stocks listed in Bombay Stock Exchange for the entire sample period from 01/01/2002 to 31/12/2016 (except the share listed after 01/01/2002, in that case from the day of listing onwards which is shown in Table 1.1).

The daily indices are collected from their respective websites – NIFTY from the website www.nse.com and Sensex from the website www.bse.com and the closing price of selected stocks are also collected from the website of Bombay Stock Exchange.

In the present study, mode of calculation of rate of return is the logarithmic difference of prices of two successive periods. Symbolically, it may be stated as follows:

$$r_t = log_e\left(\frac{p_t}{p_{t-1}}\right) = log_e(p_{t)} - log_e(p_{t-1}) \qquad 4.8$$

4.6.1 Descriptive Statistics

A summary of descriptive statistics for all share returns series of 20 stocks listed in Bombay Stock Exchange for the entire selected period from 01/01/2002 to 31/12/2016 (except the share listed after 01/01/2002, in that case from the day of listing onwards which is shown in Table 1.1) are presented in Table 5.1. Bajaj finance limited has the highest mean return of 0.001492, whereas Sunil High-tech Engineers limited has the lowest mean return with relatively high standard deviation. Likewise, Gulshan ployols limited has the highest standard deviation (highly volatile) while Colgate-Palmolive has the lowest standard deviation followed by ITC limited (less volatile).

Skewness, Kurtosis and Jarque-Bera statistics and its p value reports the normality of the each share returns series. In general, skewness value zero and value of kurtosis three indicate that observed distribution is normally distributed. Jarque-Bera statistic and its corresponding 'p' value also used to test the null hypothesis that the daily return of stock market returns is normally distributed.

Table 4.1

Descriptive Statistics for the Daily Returns of Sensex, Nifty and Selected Stocks

Stocks	Mean	Standard deviation	Skewness	Kurtosis	Jarque-bera
BSE Sensex	0.000563	0.014516	-0.090230	11.99756	12607.24***
S&P CNX Nifty	0.00055	0.01447	-0.2615	13.0763	15847.68***
Bajaj Finance	0.001492	0.028054	0.646654	11.04314	10311.42***
Berger Paints	0.001229	0.024701	0.739779	10.54466	91460.33***
Grasim Industries	0.000738	0.020068	-0.211827	11.69297	11790.84***
HPCL	0.000603	0.025834	-0.169875	11.73080	11887.13***
ITC	0.000740	0.017990	0.115082	5.982324	1392.786***
Mindtree	0.000498	0.024726	1.185255	17.59695	22178.84***
ONGC	0.000679	0.022465	0.220137	9.383850	6374.143***
V-Guard	0.001424	0.022367	0.022367	9.060778	3660.908***
Welspun	0.000667	0.036701	0.199886	8.218229	4221.443***
Kothari Products	0.000462	0.028743	0.797429	14.58379	21021.88***
Gulshan Polyols	0.001353	0.048750	0.320550	6.827062	2103.646***
Sunil Hightech	0.000189	0.037450	0.354831	7.800396	2636.330***
Chaman lal Setia	0.001066	0.037600	0.273227	6.795107	2082.706***
JK Tyres	0.000955	0.032443	0.596696	8.590210	4967.905***
PNB	0.000749	0.027314	-0.048348	7.223951	2718.576***
Bata	0.000865	0.028857	0.206054	9.680826	6974.376***
Tech Mahindra	0.000493	0.026467	0.478530	10.73974	6495.016***
Colgate-Palmolive	0.000641	0.016727	0.784646	10.77961	9773.181***
Infosys	0.000558	0.021263	-1.238485	23.72615	67843.50***
HCL Technologies	0.000665	0.026180	-0.268023	8.511019	4772.533***

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

As shown in the table, skewness and kurtosis value denote that returns of all stocks are not normally distributed. This result is substantiated by Jarque-bera statistics at 1% significant level since all its p values are less than 0.01. Returns of five stocks are negatively skewed, indicating the probability of large decrease in return than increase in return. Apart from these, all other fifteen stocks are positively skewed. The kurtosis, peakedness, in stock returns also large ranging from 5.98 to 23.72 which means all the selected stock return distributions are leptokurtic. The standard deviations of the two are very less when compared to the stocks. The skewness and kurtosis are significant which shows the stock market returns are not symmetrically distributed.

4.7 Methodology

4.7.1 Testing for Unit Roots

An analysis of the properties of time series precedes any statistical investigation using time series variables. An important aspect of the time series that has received much attention in the time series literature is the phenomenon of nonstationarity. If the time series variables are nonstationary, regressing one time series on another using ordinary least squares will give rise to the problem of spurious regression; that is, absence of any meaningful statistical relationship between variables. Thus, it is necessary to examine the stationarity of the time series variables before using them in regression analysis. A number of testing procedures known as unit root tests are available in the literature to determine stationarity of time series variables. The present study utilizes Dickey Fuller & Phillip-Perron test of stationarity. The test is available in different forms depending on whether the variable under consideration has no intercept, with intercept and with intercept and trend. Moreover, the Dickey Fuller test is often used in augmented form to get rid of the problem of autocorrelation between residuals. The most general form of the test statistic in the augmented form is given as:

$$\Delta P_t = \mu + \beta t + \delta P_{t-1} + \sum_{i=1}^{n} \rho_i \, \Delta P_{t-i} + \varepsilon_t \qquad 4.9$$

where ΔP_t indicates first differences in P_t, and P_t is log of the price, μ is the constant, δ and ρ are co-efficient to be estimated, n is the number of lagged term, t is a trend, β is the coefficient of trend, ε_t is the error term which is assumed to be white noise. The null hypothesis is

H_0: ρ = 0 (Non-stationary or unit root)

H_0: ρ < 0 (Stationary or no unit root)

To check the significance of the estimated δ co-efficients, the Augmented DF test value is computed the $\hat{\tau}$ (tau) statistic for each co-efficient.

Both Augmented Dickey Fuller and Phillips-Perron test on all series in the level and first difference has been applied to check stationarity. The results of the unit root test for the series are shown in the Table (4.2). The P values corresponding to the ADF and PP test statistics for the two series in levels are larger than 0.05. It indicates that both series are non-stationary in their levels. However, they are stationary in the first differences (the P values of both series being less than .05 for both PP test and DF test)

Table. 4.2

Dickey Fuller / Phillips-Perron Unit Root Test

Indices & stocks		Dickey Fuller Test	Phillips-Perron Test
BSE Sensex	Level	-2.9916	-2.812761
	First Difference	-56.54***	-56.38***
S&P CNX Nifty	Level	-1.9452	-1.8732
	First Difference	-57.17***	-57.13***
Bajaj Finance	Level	-0.5236	0.0682
	First Difference	-7.96***	-61.50***
Berger Paints India	Level	-0.6807	-0.8598
	First Difference	-22.25***	-53.71***
Grasim Industries	Level	-2.5711	-2.9432
	First Difference	-50.02***	-59.37***
Hindustan Petroleum Corp	Level	0.4054	0.5425
	First Difference	-60.25***	-60.27***
ITC	Level	-3.0428	-2.7934

	First Difference	-61.25***	-61.87***
Mindtree	Level	-2.0141	-1.7761
	First Difference	-42.10***	-41.63***
Oil & Natural Gas Corp.	Level	-2.9810	-2.8402
	First Difference	-59.34***	-59.44***
V-Guard Industries	Level	-1.3666	-1.4645
	First Difference	-34.45***	-41.16***
Welspun India	Level	-1.7047	-1.5827
	First Difference	-36.45***	-52.43***
Kothari Products	Level	-3.4905*	-3.3737
	First Difference	-50.75***	-50.00***
Gulshan Polyols	Level	-2.5605	-2.3724
	First Difference	-25.78***	-47.54***
Sunil Hightech Engineers	Level	-2.5723	-2.5249
	First Difference	-31.25***	-46.60***
Chaman lal Setia Exports	Level	-2.6142	2.5728
	First Difference	-13.73***	-47.71***
JK Tyre Industries	Level	-2.0882	-1.7218
	First Difference	-44.22 ***	-57.31***
Punjab National Bank	Level	-1.8820	-1.8612
	First Difference	-57.16***	-57.16***
Bata India	Level	-2.1994	-2.0919
	First Difference	-57.94***	-57.85***
Tech Mahindra	Level	-1.6174	-1.5607
	First Difference	-46.17***	-46.09***
Colgate-Palmolive (India)	Level	-2.9830	-2.7148
	First Difference	-57.07***	-57.40***
Infosys Ltd	Level	-2.2020	-2.1796
	First Difference	-46.64***	-59.88***
HCL Technologies	Level	-1.7142	-1.5324
	First Difference	-60.34***	-61.41***

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

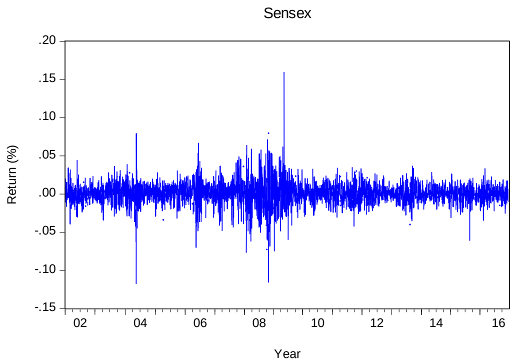
4.8 Empirical Results

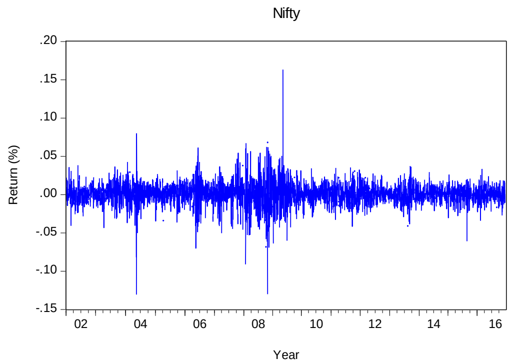
We present below the result of the empirical analysis carried out on S&P CNX Nifty, BSE Sensex and twenty individual stocks beginning with a plot of the share price (Appendix.2), return series and GARCH Variance. These plots clearly show the presence of ARCH effects.

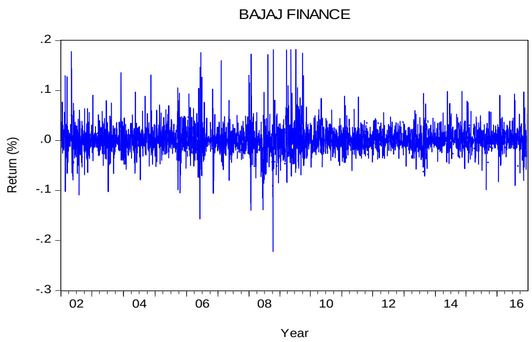
4.8.1 Volatility Clustering

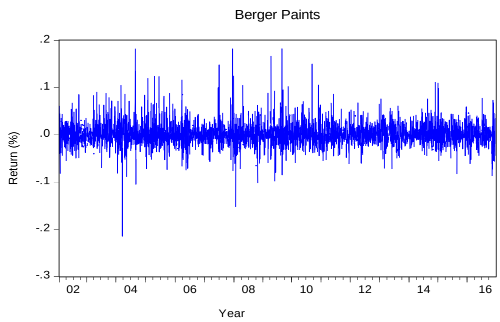
Figure 4.1 displays the return series of the selected twenty stocks, Nifty and Sensex during the period from 2002 to 2016 (except the share listed after 01/01/2002, in that case from the day of listing onwards which shows in Table 1.1). From the graph, it is clear that there are dimension of time where volatility is relatively high and relatively low. It shows an apparent volatility clustering in some periods.

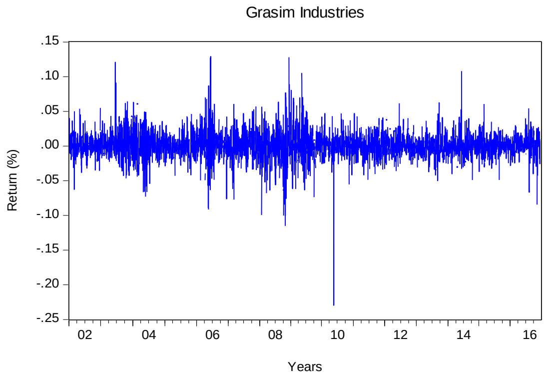
The following are the figures which show volatility clustering of daily return of Nifty, Sensex and different stocks selected from Indian Stock Market.

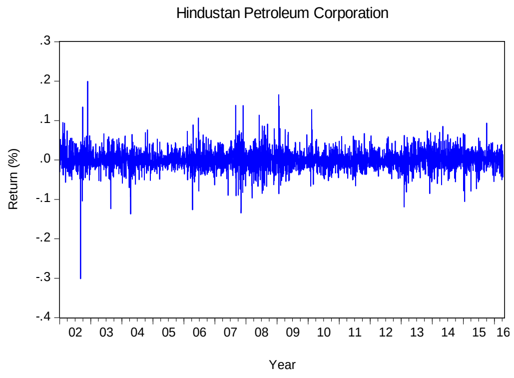


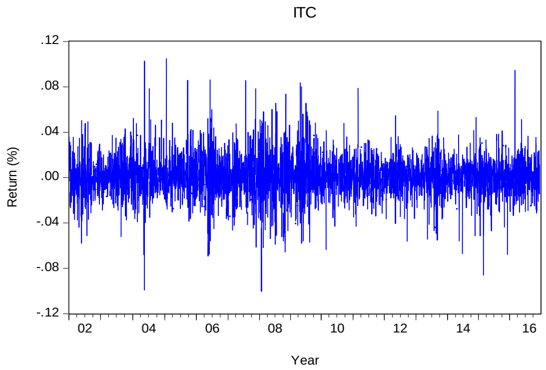


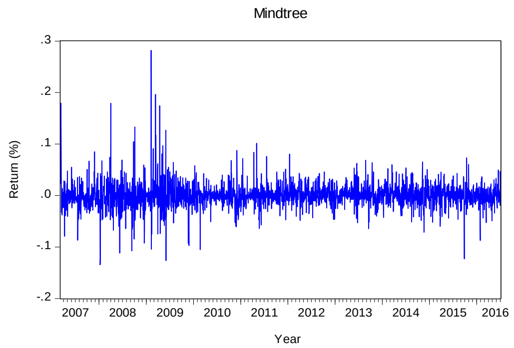


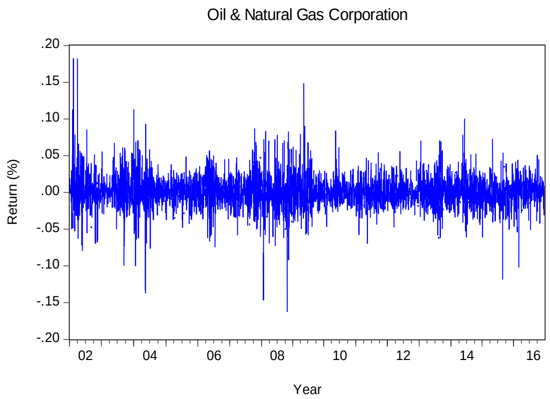


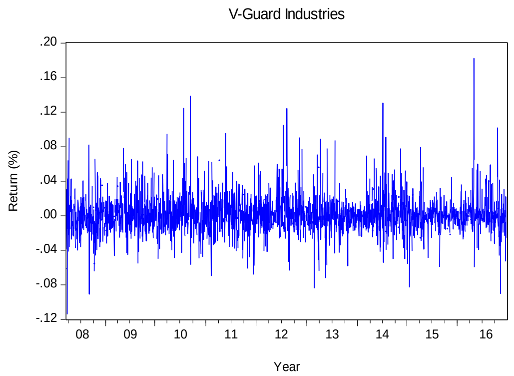

Grasim Industries
Return (%)
Years
.15
.10
.05
.00
-.05
-.10
-.15
-.20
-.25
02 04 06 08 10 12 14 16

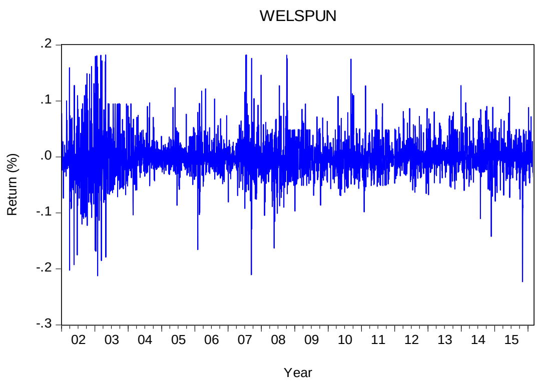

Hindustan Petroleum Corporation
Return (%)
Year
.3
.2
.1
.0
-.1
-.2
-.3
-.4
02 03 04 05 06 07 08 09 10 11 12 13 14 15 16

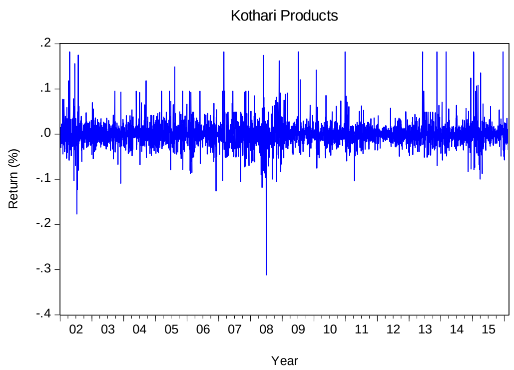

ITC
Return (%)
Year
.12
.08
.04
.00
-.04
-.08
-.12
02 04 06 08 10 12 14 16

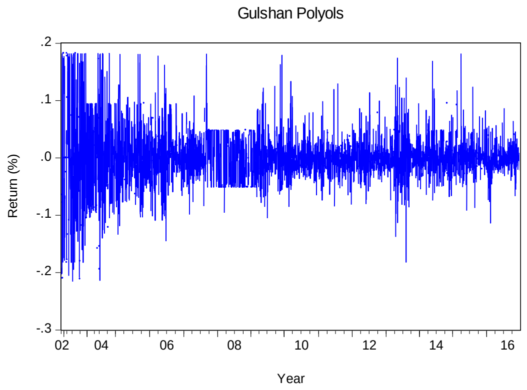

Mindtree
Return (%)
Year
.3
.2
.1
.0
-.1
-.2
2007 2008 2009 2010 2011 2012 2013 2014 2015 2016

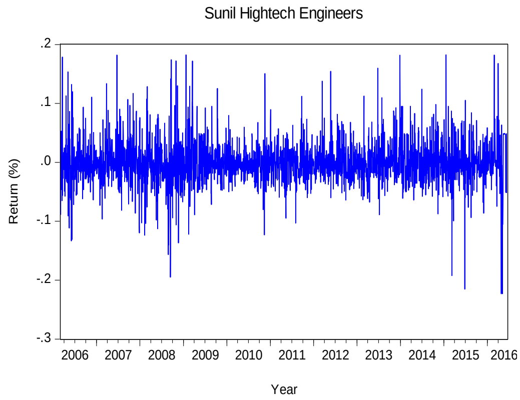

Oil & Natural Gas Corporation
Return (%)
Year
.20
.15
.10
.05
.00
-.05
-.10
-.15
-.20
02 04 06 08 10 12 14 16

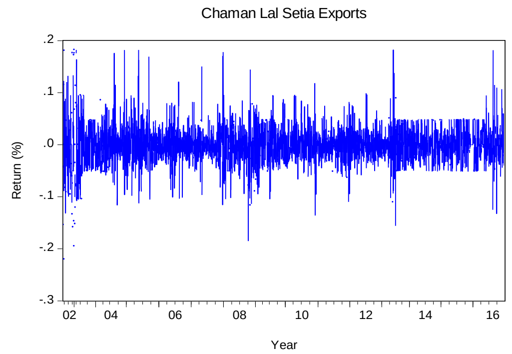

V-Guard Industries
Return (%)
Year
.20
.16
.12
.08
.04
.00
-.04
-.08
-.12
08 09 10 11 12 13 14 15 16

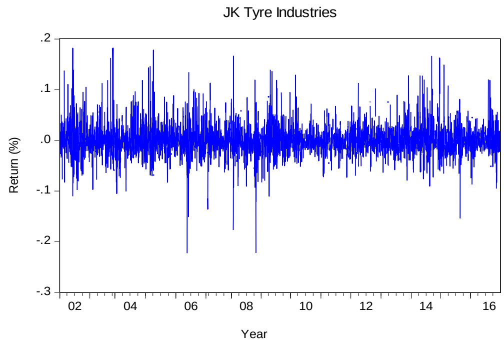

WELSPUN
Return (%)
Year
.2
.1
.0
-.1
-.2
-.3
02 03 04 05 06 07 08 09 10 11 12 13 14 15

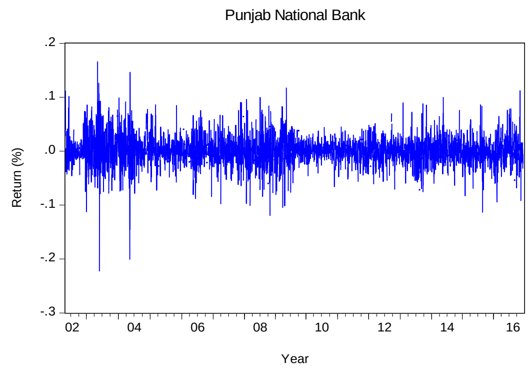

Kothari Products
Return (%)
Year
.2
.1
.0
-.1
-.2
-.3
-.4
02 03 04 05 06 07 08 09 10 11 12 13 14 15

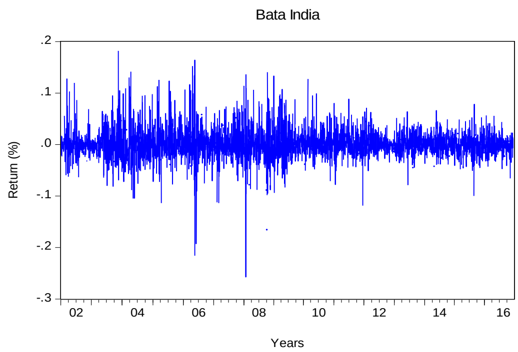

Gulshan Polyols
Return (%)
.2
.1
.0
-.1
-.2
-.3
02 04 06 08 10 12 14 16
Year

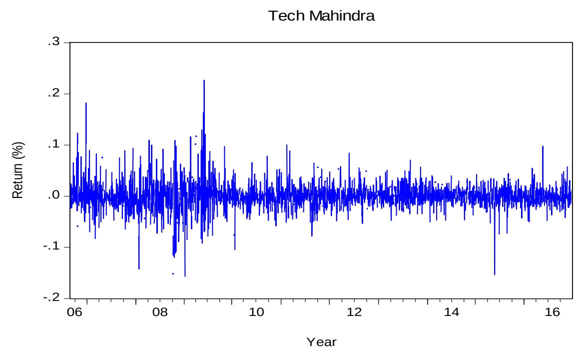

Sunil Hightech Engineers
Return (%)
.2
.1
.0
-.1
-.2
-.3
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
Year

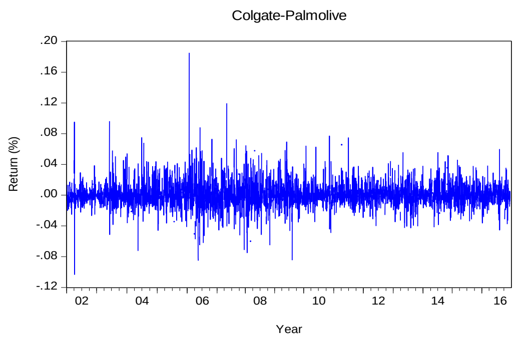

Chaman Lal Setia Exports
Return (%)
.2
.1
.0
-.1
-.2
-.3
02 04 06 08 10 12 14 16
Year


JK Tyre Industries
Return (%)
.2
.1
.0
-.1
-.2
-.3
02 04 06 08 10 12 14 16
Year


Punjab National Bank
Return (%)
.2
.1
.0
-.1
-.2
-.3
02 04 06 08 10 12 14 16
Year


Bata India
Return (%)
.2
.1
.0
-.1
-.2
-.3
02 04 06 08 10 12 14 16
Years


Tech Mahindra
Return (%)
.3
.2
.1
.0
-.1
-.2
06 08 10 12 14 16
Year


Colgate-Palmolive
Return (%)
.20
.16
.12
.08
.04
.00
-.04
-.08
-.12
02 04 06 08 10 12 14 16
Year

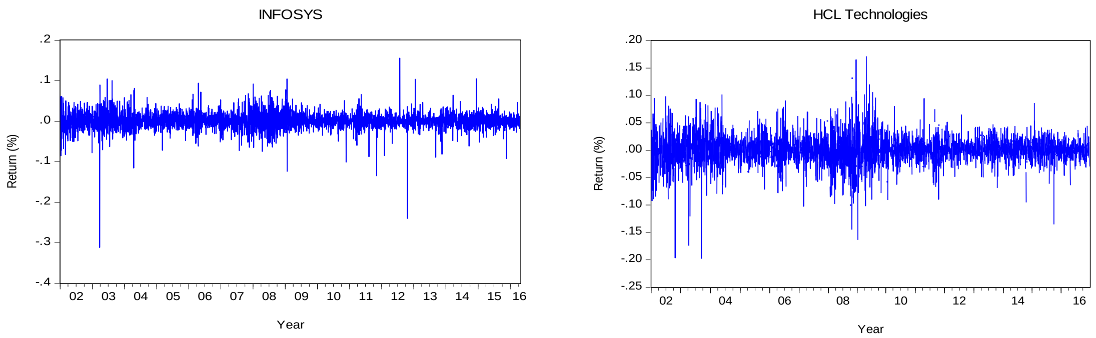
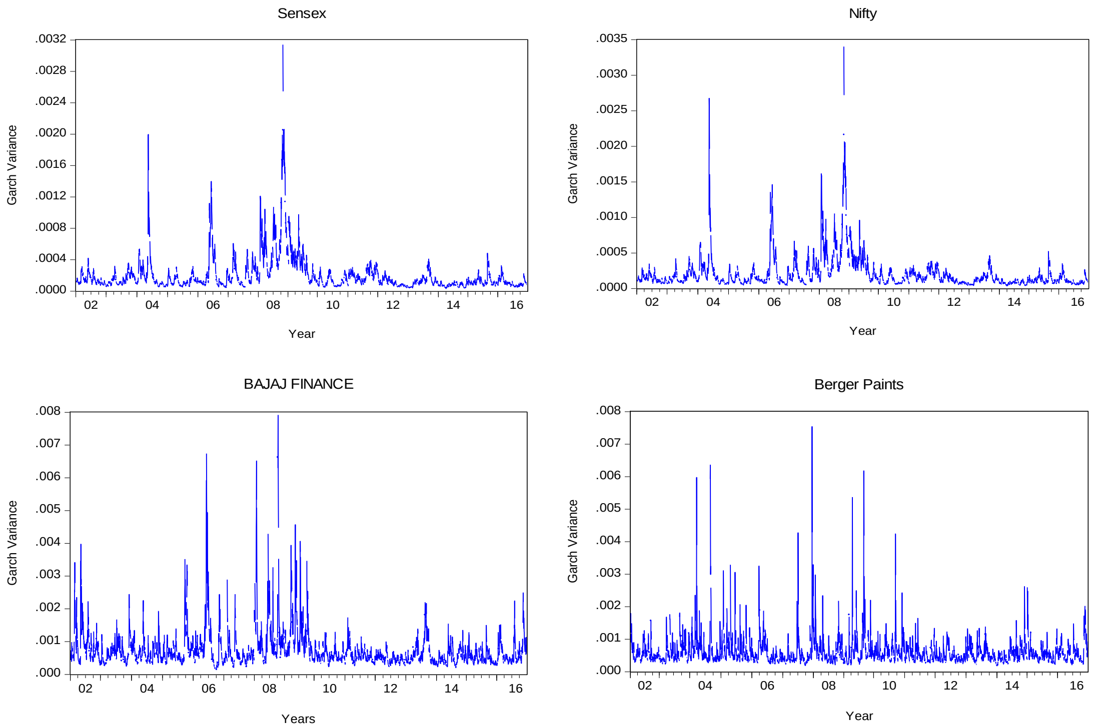
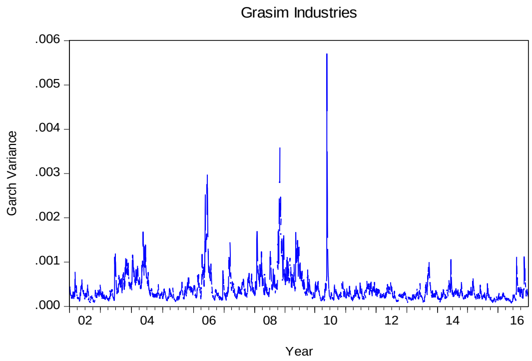


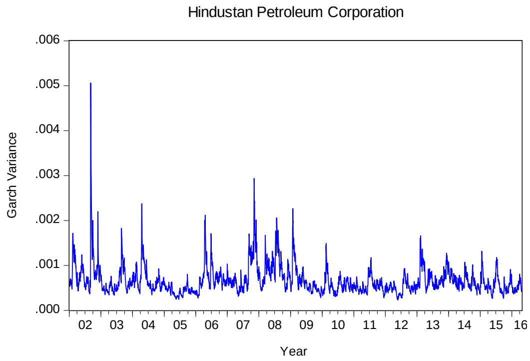
Figure 4.1: Volatility Clustering of Daily Return of Nifty, Sensex and Different Stocks Selected in Indian Stock Market

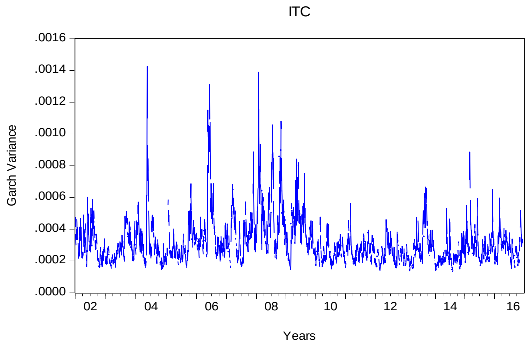
4.8.2 GARCH Variance

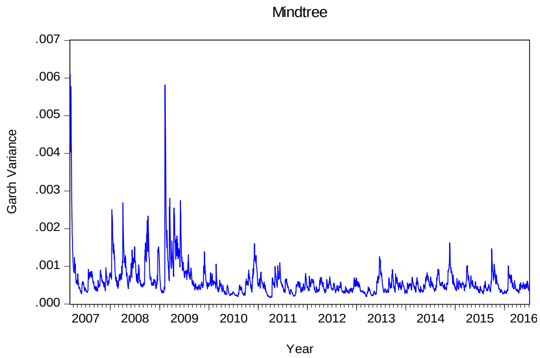
Conditional volatility of the daily return of both indices and 20 selected stocks are plotted in figure 4.2.

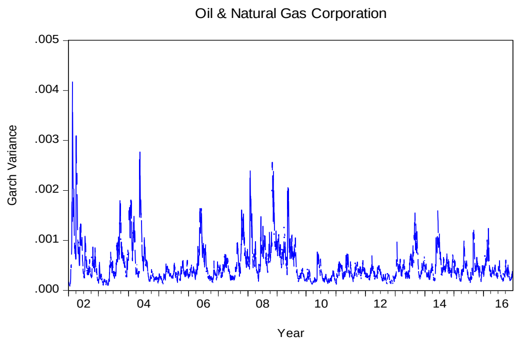


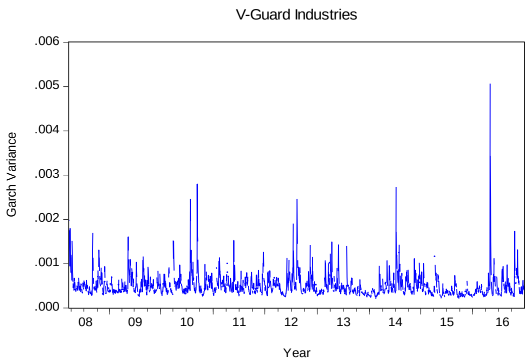

Grasim Industries
Garch Variance
.006
.005
.004
.003
.002
.001
.000
02 04 06 08 10 12 14 16
Year

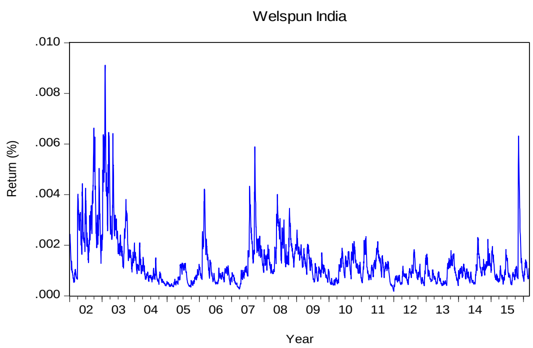

Hindustan Petroleum Corporation
Garch Variance
.006
.005
.004
.003
.002
.001
.000
02 03 04 05 06 07 08 09 10 11 12 13 14 15 16
Year

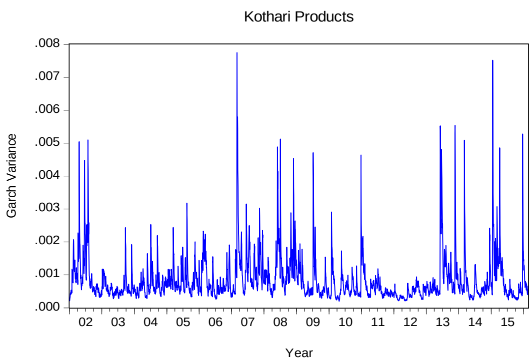

ITC
Garch Variance
.0016
.0014
.0012
.0010
.0008
.0006
.0004
.0002
.0000
02 04 06 08 10 12 14 16
Years

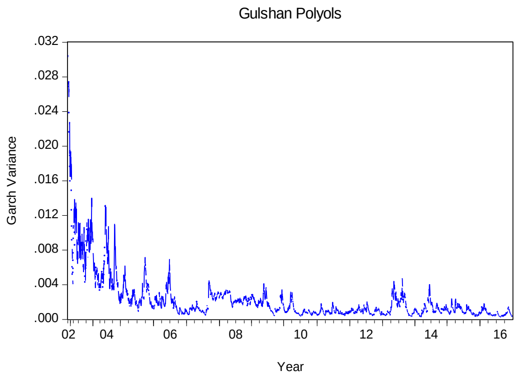

Mindtree
Garch Variance
.007
.006
.005
.004
.003
.002
.001
.000
2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
Year

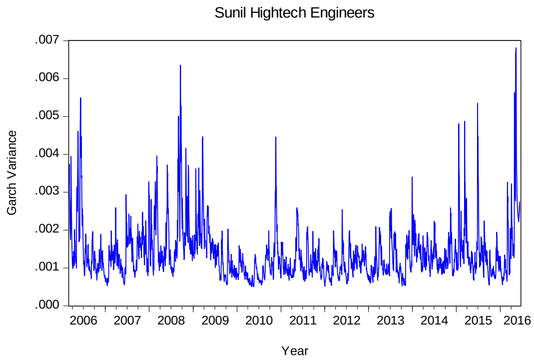

Oil & Natural Gas Corporation
Garch Variance
.005
.004
.003
.002
.001
.000
02 04 06 08 10 12 14 16
Year

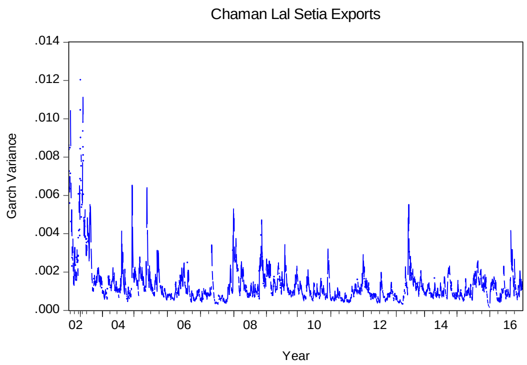

V-Guard Industries
Garch Variance
.006
.005
.004
.003
.002
.001
.000
08 09 10 11 12 13 14 15 16
Year

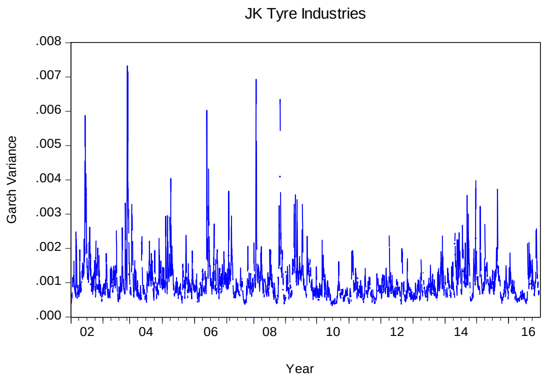

Welspun India
Return (%)
.010
.008
.006
.004
.002
.000
02 03 04 05 06 07 08 09 10 11 12 13 14 15
Year

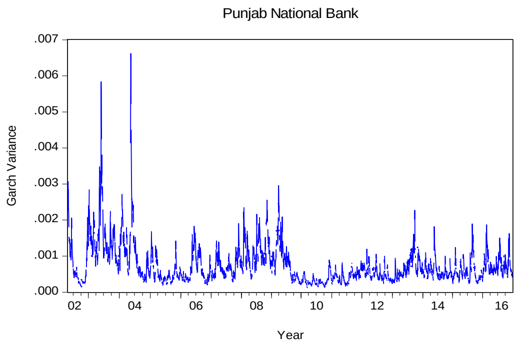

Kothari Products
Garch Variance
.008
.007
.006
.005
.004
.003
.002
.001
.000
02 03 04 05 06 07 08 09 10 11 12 13 14 15
Year

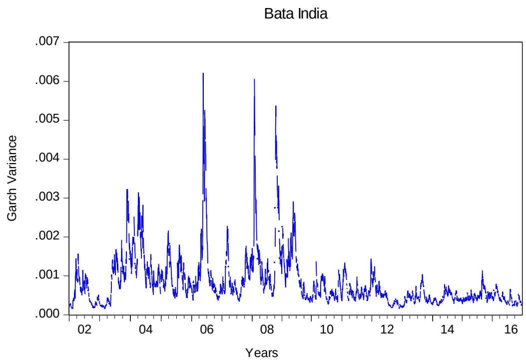

Gulshan Polyols
Garch Variance
.032
.028
.024
.020
.016
.012
.008
.004
.000
02
04
06
08
10
12
14
16
Year

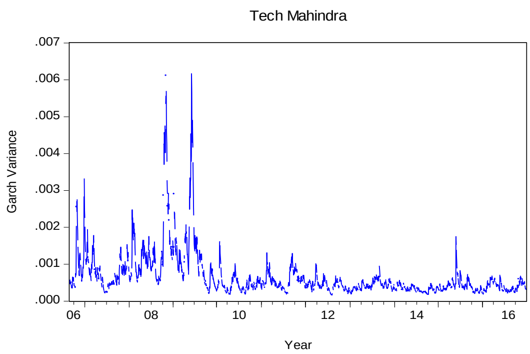

Sunil Hightech Engineers
Garch Variance
.007
.006
.005
.004
.003
.002
.001
.000
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
Year

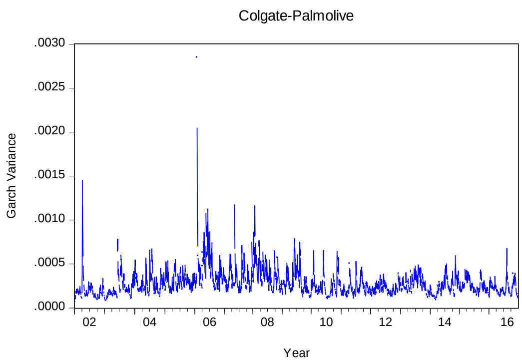

Chaman Lal Setia Exports
Garch Variance
.014
.012
.010
.008
.006
.004
.002
.000
02
04
06
08
10
12
14
16
Year


JK Tyre Industries
Garch Variance
.008
.007
.006
.005
.004
.003
.002
.001
.000
02
04
06
08
10
12
14
16
Year


Punjab National Bank
Garch Variance
.007
.006
.005
.004
.003
.002
.001
.000
02
04
06
08
10
12
14
16
Year


Bata India
Garch Variance
.007
.006
.005
.004
.003
.002
.001
.000
02
04
06
08
10
12
14
16
Years


Tech Mahindra
Garch Variance
.007
.006
.005
.004
.003
.002
.001
.000
06
08
10
12
14
16
Year


Colgate-Palmolive
Garch Variance
.0030
.0025
.0020
.0015
.0010
.0005
.0000
02
04
06
08
10
12
14
16
Year

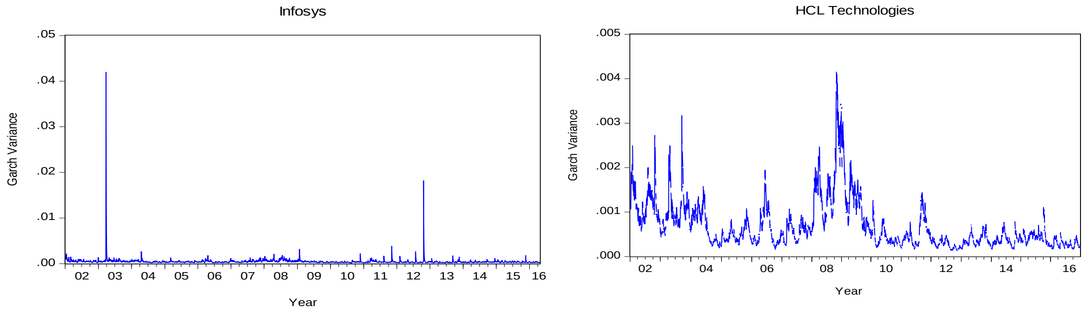


Figure 4.2: Conditional Volatility of the Return of Nifty, Sensex and Different Stocks Selected in Indian Stock Market

In Figure 4.1 & 4.2, the most of the plot exposes that there are large swings in returns. It can be seen that individually selected stocks are more volatile than indices because the indices are bundle of stocks where the volatility of one stock can be set off by others due to the negative correlation between shares. We could clearly understand the pattern of Indian stock markets from these charts. The period from 2008 to 2009 shows high fluctuation compared to other years. It is due to the subprime crisis in the US which developed into an international banking crisis. The crisis was followed by global economic downturn, the Great recession.. The reason for the volatility in 2006 is attributed to rise of interest rate in the United States due to inflationary expectations. The reason for the volatility in 2006 is attributed to the rise of interest rate in the United States because of inflationary expectations. The volatility in 2004 is due to the defeat of National Democratic Alliance (NDA) in Indian parliamentary election. Investors worried that communist parties would influence the policy of the incoming coalition government led by the Congress Party.

It can be found that volatility clustering is very less in the case of Infosys. It is very high in case of Berger paints, Kothari products, Sunil high-tech engineers, JK tyres etc.

Here the volatility clustering is affirmed. Now our aim is to GARCH model applicable to the return series.

4.8.3 Model Comparison

Modelling and forecasting volatility is perhaps the most significant area of research in the whole of finance literature during the last two decades. Volatility, as measured by the standard deviation or variance of returns is often used as a primitive measure of the total risk of financial assets. It involves calculating the variance or standard deviation of returns in the usual way over some past period and this becomes the volatility forecast for all future time periods. This volatility, however, will not take into account time varying volatility in asset returns. Thus we want a measure of volatility that changes overtime. Such a measure of time varying volatility known as Autoregressive Conditional Hetroskedasticity (ARCH) was first suggested by (Engle, 1982)[17]. The original model was later extended in many directions. (Bollerslev, 1986)[18] Bollerslev suggested a generalization of ARCH known as Generalized Autoregressive Conditional Heteroskedasticity (GARCH).

GARCH specification is well accepted because it fits many data series well. Another popular specification is the GARCH in mean or GARCH – M model introduced by Engle, Lilien, & Robins (1987)[19]. This model specifies return itself as a function of variance. The basic idea is that return to risky assets will be higher than return to safe assets to compensate the investor for taking more risk. In this specification conditional variance enters into the conditional expectation as an additional factor determining mean returns.

One basic problem with GARCH models is that they treat symmetric response of volatility to both positive and negative shocks. It is argued that there is an asymmetry in the response of volatility of financial time series to positive and negative shocks. A negative shock is likely to cause volatility to rise by more than positive shock of same magnitude. (This asymmetry in financial literature is known as ‘leverage effects’) Two popular models of asymmetry are the Threshold GARCH (TGARCH) model introduced by Glosten, Jagannathan and Runkle (1993)[20] and Exponential GARCH (EGARCH) model introduced by Nelson (1991)[21].

Though TGARCH model treats positive and negative shocks asymmetrically unlike ARCH, and GARCH and GARCH-M models, this model is also based on the restriction that the parameters will be greater than or equal to zero. EGARCH model has no such restrictions. The model not only treats positive and negative shocks asymmetrically, but also ensures that the estimated coefficients are positive. In the present study, the researcher uses EGARCH model to find out the extent and pattern volatility in Indian Stock Market.

4.8.4 Analysis of EGARCH Model

In this study, the researcher used three different time periods to model the volatility. One for the period of 15 years – near long term - (2002 to 2016), second for the period of 5 years - near middle term- (2012 to 2015) and third for the period 1 year- near short term - (2016) to study the effect of long term, medium term and short term volatility. The results for the EGARCH (1, 1) model are presented in Table 4.3 (2002 to 2016), in Table 4.4 (2012 to 2016) and in Table 4.5 (2016).

Table 4.3

EGARCH Parameters Estimates of Indian Indices and Share Returns for the Period 2002 to 2016- Long term- (15 years)

Indices & Stocks	λ	α	γ	δ
BSE Sensex	-0.376609***	0.200106***	-0.071818***	0.974611***
S&P CNX Nifty	-0.405263***	0.208296***	-0.077156***	0.971924***
Bajaj Finance	-0.797357***	0.283347***	-0.013618*	0.918599***
Berger Paints India	-1.337294***	0.336403***	0.041321***	0.853914***
Grasim Industries	-0.49862***	0.241426***	-0.023451***	0.960077***
Hindustan Petroleum Corp.	-0.48083***	0.166008***	-0.014245**	0.951234***
ITC	-0.644152***	0.170926***	-0.037774***	0.936311***
Mindtree	-0.568127***	0.203077***	-0.002105	0.94325***
Oil & Natural Gas Corp.	-0.437544***	0.223319***	0.003957	0.964905***
V-Guard Industries	-1.725582***	0.292433***	0.029218**	0.801524***
Welspun India	-0.291451***	0.160604***	-0.017283***	0.974162***
Kothari Products	-0.64912***	0.242015***	0.05744***	0.933168***
Gulshan Polyols	-0.246494***	0.162866***	0.012065	0.980972***
Sunil Hightech Engineers	-0.803863***	0.237968***	-0.024063**	0.904828***
Chaman lal Setia Exports	-0.518216***	0.222017***	0.024854***	0.94839***
JK Tyre Industries	-0.995637***	0.282796***	-0.001151	0.886093***
Punjab National Bank	-0.412636***	0.221143***	-0.002072	0.966624***
Bata India	-0.229572***	0.157221***	-0.00251	0.984152***
Tech Mahindra	-0.353272***	0.190924***	-0.012753*	0.971314***
Colgate-Palmolive (India)	-0.816412***	0.214416***	0.009843	0.919658***
Infosys Ltd	-1.292094***	0.310555***	-0.054984***	0.863014***
HCL Technologies	-0.208804***	0.142438***	-0.029321***	0.986438***

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

Table 4.4

EGARCH Parameters Estimates of Indian Indices and Share Returns for the Period 2012 to 2016- Medium Term- (5 years)

Indices & Stocks	λ	α	γ	δ
BSE Sensex	-0.333939***	0.067211***	-0.081811***	0.969789***
S&P CNX Nifty	-0.31938***	0.068286***	-0.081492***	0.971334***
Bajaj Finance	-0.822304***	0.179245***	-0.024063*	0.91081***
Berger Paints India	-1.480223***	0.325469***	0.036525*	0.841684***
Grasim Industries	-0.584518***	0.172818***	-0.00081	0.946079***
Hindustan Petroleum Corp.	-0.636408***	0.098584***	-0.004388	0.925582***
ITC	-0.458875***	0.073586***	-0.006545	0.951548***
Mindtree	-6.032367***	0.384274***	-0.023148	0.276404**
Oil & Natural Gas Corp.	-0.535407***	0.146794***	-0.00018	0.946628***
V-Guard Industries	-3.548598***	0.456193***	0.10419***	0.583559***
Welspun India	-2.382468***	0.280076***	0.004201	0.693419***
Kothari Products	-0.127855***	0.066927***	0.087912***	0.989024***
Gulshan Polyols	-0.513913***	0.20618***	0.007124	0.947639***
Sunil Hightech Engineers	-1.371239***	0.229118***	0.00756	0.818854***
Chaman lal Setia Exports	-1.300624***	0.311942***	0.007657	0.849014***
JK Tyre Industries	-1.058673***	0.231111***	0.001105	0.874089***
Punjab National Bank	-1.587053***	0.256666***	0.000536	0.813108***
Bata India	-0.264535***	0.077331***	-0.017455	0.974376***
Tech Mahindra	-3.297803	0.101362**	-0.021528	0.599602**
Colgate-Palmolive (India)	-1.995818***	0.240291***	-0.04664*	0.789139***
Infosys Ltd	-6.537184***	0.335377***	0.157503***	0.220408**
HCL Technologies	-2.79685***	0.279652***	-0.00636	0.681828***

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

Table 4.5

EGARCH Parameters Estimates of Indian Indices and Share Returns for the Period 2016 – Short term (1 year)

Indices & Stocks	λ	α	γ	δ
Sensex	-0.170494***	-0.086306	-0.068946***	0.975051***
Nifty	-0.222036***	-0.061224	-0.080472***	0.971428***
Bajaj Finance	-1.997771**	0.34619**	-0.099103*	0.765285***
Berger Paints India	-1.689576***	0.612053***	-0.015552	0.842513***
Grasim Industries	-9.721875***	0.12487	-0.423562***	-0.143308
Hindustan Petroleum Corp.	-1.063747	0.08834	-0.050843	0.870531***
ITC	-7.312641***	0.071017	0.229615**	0.127692
Mindtree	-6.640365***	0.353855***	-0.291159***	0.193063
Oil & Natural Gas Corp.	-10.2471***	0.520316***	-0.584223***	0.275327***
V-Guard Industries	-6.666365***	1.10815***	0.096277	0.246606***
Welspun India	-2.78892	0.234325***	-0.149471**	0.619317**
Kothari Products	-0.387417*	0.112794**	0.031542	0.958407***
Gulshan Polyols	-0.758957**	0.190219**	-0.123128**	0.91915***
Sunil Hightech Engineers	-5.302867***	1.010282***	-0.116989*	0.288274***
Chaman lal Setia Exports	-9.506992***	0.545532***	-0.021869	0.344441***
JK Tyre Industries	-0.591207***	0.345454***	0.004638	0.955469***
Punjab National Bank	-6.408211	-0.076834	-0.084919	0.096674
Bata India	-5.17152**	0.378113**	0.043358	0.405117
Tech Mahindra	-13.24186***	0.139622	0.146744**	0.625313***
Colgate-Palmolive (India)	-11.0231***	0.377974***	0.204851***	-0.224604
Infosys Ltd	-7.837888***	0.600458***	-0.342074***	0.132901
HCL Technologies	-6.424581***	0.276804**	-0.194017**	0.268018

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

From the above tables, it can be seen that the leverage effects γ are negative in almost all cases including Sensex and Nifty which are significant at 5% significant level which means that good news causes less volatility than bad news in Indian stock Market. It is interesting to note that the negative coefficients of γ during the period 2012 to 2016 are not at all significant at 5% significant level for the selected individual stocks. That means, in this period bad and good news makes the same extent of volatility. But, during the period 2016, again the γ shows negative co-efficient which is significant at 5% significant level. It can be concluded from the result that shareholders of Indian stock market like to hear good news than bad news. With this result, it is reliable to say that Indian stock market is more sensitive to bad news.

To all stocks and indices during 2016, the symmetric effect α which is different than it is in the previous period in EGARCH model in which all are significant at even 1% significant level. In most of the cases when the period comes shorter, the volatility increases, but in some cases, it is vice versa, depending on the nature of the stocks. With the present study, we can conclude that the volatility exists in individual shares in almost all the periods (long-term, medium term and short term) in Indian stock market.

The parameter δ shows the persistence in conditional volatility in the market. In almost all the stocks and indices (except some in the period 2016), parameter δ are all positive and large, then volatility have long memory following an event in the Indian stock market.

4.8.4 Volatility of the Return of Sensex, Nifty and Selected Stocks

In order to calculate the long term volatility, the researcher has to measure the long term variance initially, in the Exponential GARCH model. It is imperative to test several situations of volatility in Indian stock market. In this section, the researcher estimated the long term volatility for the period 2002 – 2016 (15 years), medium term volatility for the period 2012 – 2016 (5 years) and short term volatility for the year 2016 (one year) separately. Table 4.6 shows long term volatility calculated result based on EGARCH (1, 1) models.

Table 4.6

Volatility of the Return of Sensex, Nifty and Selected Stocks

Indices & Stocks	2002 – 2016 (Long-term)	2012 -2016 (Medium-term)	2016 (Short-term)
BSE Sensex	2.23%	6.29%	51.88%
S&P CNX Nifty	1.16%	6.02%	32.47%
Bajaj Finance	11.80%	15.74%	22.42%
Berger Paints India	16.26%	14.75%	7.40%
Grasim Industries	3.07%	7.00%	22.52%
Hindustan Petroleum Corp.	11.43%	21.98%	25.99%
ITC	10.06%	13.88%	23.91%
Mindtree	10.59%	24.47%	25.83%
Oil & Natural Gas Corp.	3.10%	10.48%	28.45%
V-Guard Industries	20.47%	22.32%	18.95%
Welspun India	5.62%	32.47%	40.56%
Kothari Products	12.30%	4.67%	15.00%
Gulshan Polyols	2.43%	11.69%	14.47%
Sunil Hightech Engineers	23.17%	35.91%	38.11%
Chaman lal Setia Exports	10.44%	21.30%	46.07%
JK Tyre Industries	20.00%	23.61%	2.07%
Punjab National Bank	3.27%	22.64%	45.55%
Bata India	1.13%	9.06%	20.48%
Tech Mahindra	3.35%	25.73%	26.90%
Colgate-Palmolive (India)	9.83%	13.92%	17.55%
Infosys Ltd	14.15%	23.88%	17.22%
HCL Technologies	0.72%	19.51%	19.64%
Mean volatility of above 20 stocks	9.66%	18.75%	23.95%

From the above table, it can be detected that the extent of volatility of most of the stocks, Nifty and Sensex are higher in the case of one year (2016) lesser in the case of five year (2012 – 2016) and least in the case of fifteen years (2012 – 2016). Sunil high-tech Engineers shows the highest volatility in long term and medium term. HCL technologies shows the lowest volatility in long-term whereas Kothari products shows lowest volatility in the medium term. BSE Sensex itself shows highest volatility in short term while JK Tyres shows the lowest volatility in short term. Even the mean volatility of the twenty stocks also shows the same result, 23.95% volatility in short term, 18.75% volatility in the medium term and 9.66% in the short term. When we analyse the individual stocks, only Kothari products gives the different result. In short-term (one year - 2016) the volatility of all the stocks except three stocks is increasing at an alarming rate. With this we can conclude that volatility will be very high in shorter period and the same can minimize if one can think of investing in long term.

4.9 Conclusion

The objective of this chapter is to find out the extent and pattern of Indian stock market volatility. For this, the researcher has collected the data of two important indices (BSE Sensex and S&P CNX Nifty) and twenty individual stocks which are used for the event study. The researcher considers the modelling of the daily stock returns volatility in Indian stock market during the period 2002 to 2016, 2012 to 2016 and 2016. In the model comparison, the results imply that it is relevant to determine the Exponential GARCH model which is competently adjustable to accommodate these data. Empirical evidences show that the Exponential GARCH model gives a better results and more prudent tool than the traditional GARCH model. The finding is that like any other emerging market, the volatility exists in the whole period in Indian stock market, leverage effect is negative in almost all stocks and indices and markets have long memory so that it will take long time to die out the volatility effect after an event. This is the pattern of Indian stock market. The extent of volatility and the time period is having the inverse relation, if the time period is low, volatility is high and vice versa.

References:

1. Franses, P. H. (1988). *Time series Model for business and Economic Forecasting.* New York: Camebridge University Press.

2. Gujarati, D. (2011). *Econometrics by Example.* New York: Palgrave Macmillan.

3. Engle, R. F. (1982). Autoregressive conditional hetroskedasticity withthe Estimates of the Variance of United Kingdom Inflation. *Econometrica , 50* (4), 987-1008.

4. Ibid.

5. Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of Conditional Variance. *Econometric Reviews , 5* (1), 1-50.

6. Bollerslev, T. (1986). Generalized Autoregressive Conditional hetroskedasticity model. *Journal of Econometrics* , 307-327.

7. Christie, A. A. (1982). The Stochastic Behavior of Common Stock Variances: Value, leverage and interest rate effects. *Journal of Financial Economics , 10* (4), 407-432.

8. Nelson, D. B. (1991). Conditional Hetroskedasticity in Asset Returns: A new Approach. *Econometrica* , 347-370.

9. Ibid.

10. Brooks, C. (2008). *Introductory Economics for Finance.* New York: Camebridge University Press.

11. Glosten, L. R., Jaganathan, R., & Runkle, D. E. (1993). On the Relation Between the Expected Value and the Volatility of the Nominal excess return of the stock. *The Journal of Finance , 48* (5), 1779-1801.
12. Op. Cit. 8
13. Op. Cit. 8

14. Alexander, C. (2008). *Practical Financial Econometrics.* New York: John Wiley & Sons.

15. Nishad, T. M., & Thomachan, K. (2015). How volatile Indian Stock Market ? A Study Based on Selected Sectoral Indices. *International Journal of Research - Granthalaya , 3* (12), 142-149.

16. Op. Cit. 14

17. Op. Cit. 3

18. Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating Time Varying Risk Premia in the Term Structure: The Arch-M Model. *Econometrica , 55* (2), 391-407.

19. Op. Cit. 11

20. Op. Cit. 8

Chapter 5
Market Efficiency of Indian Stock Market

5.1 Introduction

There are several schools of thought in the security price movements in the stock markets across the world. Bachelier (1900)[1], a French doctoral student reported that security price movements are random. Kendall (1953)[2], a British Statistician, reported in his controversial paper that 'he had expected to find regular price cycles, but could identify no predictable return in stock and commodity prices, each series appears to be a wandering one'. 'The efficient market hypothesis roots lie in the random walk hypothesis, which indicates that the share price changes are more random, rather than correlated' (Kishore, 2015)[3]. Fama (1970)[4] stated that 'in efficient market security prices always fully reflect all the available information'. 'Why prices in competitive markets must follow a random walk. If a past price change could be used to predict future price changes, investors could make easy profits. But in competitive market easy profit doesn't last. As investors try to take advantage of the information in past prices, price adjusts immediately until the superior profits from studying past price movements disappear' Brealey, Myres, Allen, & Mohanty (2014)[5] 'Efficient market is a market in which prices seem close to intrinsic values and stocks seem to be an equilibrium'. 'If the market is efficient, then there is a very important implication for market participants: All investments in that market are zero NPV investments. The reason is simple. If prices are neither too low nor too high, then the difference between the market value of an investment and its cost is zero; hence, NPV is zero. As a result, in an efficient market, investors get exactly what they pay for, and firms receive exactly what their stocks and bonds are worth' (Ross, Westerfield, & Jordan, 2008)[6]. Until the mid-1980s the EMH turned into an enormous theoretical and empirical success. Academics from the most prestigious universities and business schools developed powerful theoretical reasons why the efficient paradigm should hold. This was accompanied by a vast array of early empirical research – nearly all of them supporting the EMH. It strongly influenced the investment community (increased popularity of index funds and the buy-and-hold strategy).

From the beginning of the 1900s, new empirical studies of security prices have reversed some of the earlier evidence favouring the EMH. The traditional finance school named these observations anomalies, because they could not be explained in the neoclassical framework. In response to a growing number of puzzles, a new approach to financial markets has emerged – behavioural finance. It focuses on investors' behaviour and the decision making process. In contrary to the classical paradigm, behavioural finance assumes that agents may be irrational in their reactions to new information and make wrong investment decisions. As a result, the markets will not always be efficient and asset pricing may deviate from the predictions of traditional market models.

This study initially examines the main contentions of the Efficient Market Hypothesis. The different forms of Efficient Market Hypothesis are reviewed. Empirical tests are then performed to determine whether the Indian capital market is efficient in Weak form or Semi-Strong form. Unit root test, Auto-Correlation test and Run test are used for testing the weak form efficiency of the market. Event analysis has been used to test the efficiency of the market in semi-strong form. Event study is an important research tool used to measure the consequences of an event on the value of stocks. By analysing security prices before and after an event for abnormal returns, the efficiency of a market in the semi-strong form can be determined. The study has been concentrated around the impact of specific events across a number of companies. The market efficiency is also an indication of the presence of investor biases. If the market is not efficient, that indicates the existence of investor biases.

Investing in securities such as shares, debentures and bonds is profitable as well as risky; it is a popular form of investment these days. This involves a great deal of risk and calls for scientific knowledge as well as artistic skill. Stock prices are determined by a number of factors such as fundamental factors, technical factors and psychological factors. As the market is volatile, it is tough to make an investment decision. Fama (1970)[7] explained the efficiency of market into three forms: weak form, semi-strong form and strong form. In weak form all past prices and data are fully reflected in securities' prices. Hence, no investor can make consistently superior returns by studying the information on historical prices. 'This version of the market efficiency implies that the trend analysis is useless – one cannot predict tomorrow's price on the basis of previous prices. Hence it is based on the premise that stock prices have no memory' (Tripathi, 2015)[8]. In semi-strong form all publicly available information is fully reflected in securities prices. No investor can make consistently superior returns by analysing publicly available information on companies. Hence 'the implication of semi-strong hypothesis is that fundamental analyst cannot make superior gains by undertaking fundamental analysis because stock price adjusts to new pieces of information as soon as they are received' (Kevin, 2011)[9]. In the strong form, all information is fully reflected in securities prices. No investor can make consistently superior returns by having access to the insider information. This study will help to know the efficiency of the stock market by testing whether the market is strong, weak or semi-strong. An efficient capital market is a market that is efficient in processing the information. Thus an efficient capital market is one in which security prices equal their intrinsic values at all times.

5.2 Efficient Market Hypothesis

Efficient Market Hypothesis theoretical foundation rests on the following assumptions:

1. Rational investors: One of the most rudimentary assumptions that conventional economics and finance makes is that people are rational "wealth maximiser's" who seek to increase their own well-being. According to conventional economics, emotions and other extraneous factors do not influence people when it comes to making economic choices. Investors who avoid emotions on investment, wishes to maximize his profit. They have the access to all market information and analyses the same rationally.
2. Arbitrage: Even if all the investors are not rational, the rational investors use this opportunity to arbitrage and then remove pricing errors.

3. Collective rationality: The random errors made by the non-rational investors will set off in the market without affecting the prices.

Empirical studies have been attempted to find out whether specific markets are efficient and to what degree. This study will help to know the efficiency of the stock market by testing whether the market is weak or semi-strong. This research has been aimed at testing whether successive or lagged price changes are independent. And for this study we review some of the statistical techniques. Run test and auto-correlation are used for testing the efficiency in the weak form. Event study is an important research tool used to measure the effect of an economic event on the value of firms. By analysing security prices before and after an event for abnormal returns, the efficiency of a market in the semi-strong form can be determined. The study has been concentrated around the impact of specific events across a number of companies. Further the study also deals with testing the investor biases in order to examine whether behavioural finance disproves the efficient market hypothesis in the context of Indian Capital Market.

The efficient market model is actually concerned with the speed with which information is incorporated into security prices. This gives the technicians an opportunity to earn excess returns by studying the patterns in the price movements and trading accordingly. In an efficient market, new information is processed and evaluated as it arrives and price instantaneously adjusts to new and correct levels. This study shows the efficiency of stock markets at different forms of market efficiency and for this many empirical tests are conducted. The different forms of efficient markets and their tests are given below in figure 5.1.

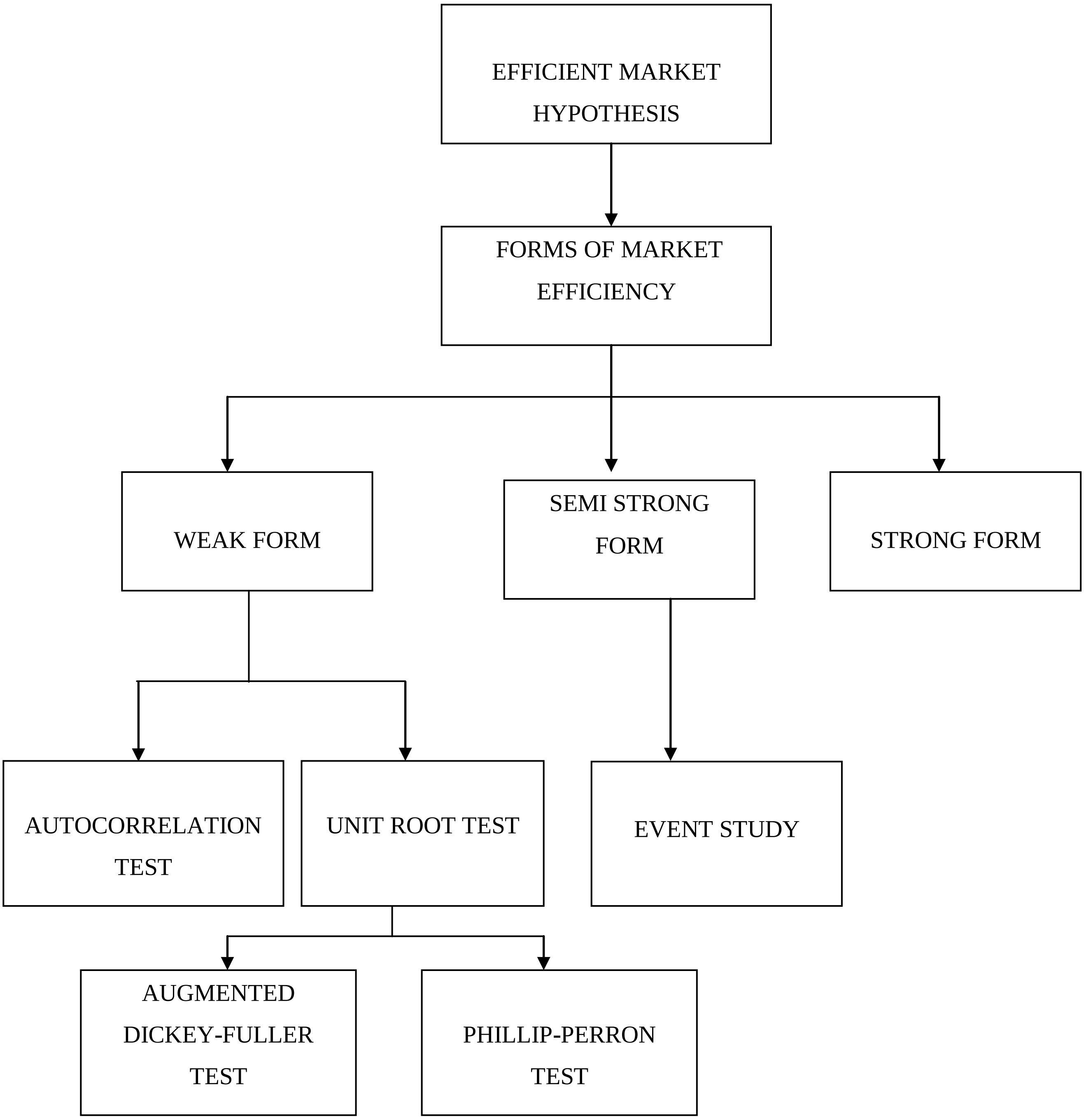


Fig.5.1 Forms of Efficient Market Hypothesis and its Tests

5.3 Empirical Tests of Efficient Market Hypothesis

The present study uses daily returns 20 stocks for 15 year period from 01/01/2002 to 31/12/2016. All stock returns are calculated using log returns or continuously compounded returns.

$$r_t = \ln\left(\frac{p_t}{p_{t-1}}\right) \qquad 5.1$$

Where r_t denotes continuously compounded return at time *t*, p_t and p_{t-1}denotes the stock price at time *t* and *t*-1, ln denotes the natural logarithm. Brooks (2008)[12].

H_0: Indian stock market is efficient in its weak form

$H_{1:}$ Indian stock market is not efficient in its weak form

5.3.1 Tests of Weak Form Efficient Market Hypothesis

According to the weak form of EMH, investors cannot reap abnormal profits by observing the historical data of stock prices as they follow a random path, i.e. the stock price on a particular day is not related to the stock price on any other day. 'The weak form market efficiency reveals that historical price cannot be used to predict future prices of a stock, therefore the movements of stock prices are independently and identically distributed' (Fama, 1970)[10].

$$P_t = P_{t-1} + \mu + \varepsilon_{t,} \qquad \varepsilon_t \sim IID\ N(0, \sigma^2) \qquad 5.2$$

where P_t, P_{t-1} are price of the stock at time *t* and *t*-1, μ is the expected price change and IID $(0, \sigma^2)$ implies that ε_t is independently and identically distributed with mean 0 and variance σ^2.

'The weak form hypothesis holds that if past data ever conveyed reliable signals about future performance, all investors already would have learned to exploit the signals' (Bodie, Kane, Marcus, & Mohanty, 2015)[11]. It assumes that the current share prices fully reflect all the historical stock market information.

Statistical Test for Market Efficiency

In the present study, the researcher uses three statistical methods, namely Augmented Dickey-Fuller unit root test, Phillip-Perron unit root test and Autocorrelation test.

5.3.1.1 Unit Root Test

The weak form market efficiency has introduced a new methodology to analyse random walk nature of share price, which is called as unit root test. It examines the stationarity of a time series. If it is non-stationary it means that it follows a random walk process. The term non-stationarity, random walk and unit root are used synonymously. In this study, researcher uses two unit root test, namely Augmented Dickey-Fuller unit root test and Phillip-Perron unit root test.

5.3.1.1.1 Augmented Dickey-Fuller Unit Root Test

This methodology is introduced by Dickey and Fuller (1979)[12] to determine the stationarity of the time series. This test is the most commonly used test to examine the unit root in a series. A series having unit root is non-stationary which means random walk. So this test gives indication on whether the share returns in Indian stock market pursue a random walk. So, it also tests whether the stock market is efficient or not in its weak-form of Efficient Market Hypothesis. The standard form of this test is suitable for series developed by an autoregressive process of order one, AR (1)

$$Y_t = \rho Y_{t-1} + u_t \qquad -1 \leq \rho \leq 1 \qquad 5.3$$

If $\rho = 1$, it is the case of unit root becomes a random walk model. Here the non-rejection of null hypothesis implies the series is non-stationary. If the series pursues AR (p) process where p > 1, the error term in the standard Dickey-Fuller test will be auto correlated. Autocorrelation will revoke the Dickey-Fuller distribution where the presumption that the error term is random. The Augmented Dickey Fuller test uses an augmented form to get rid of the problem of autocorrelation between residuals by including additional lagged difference terms.

The Dickey Fuller test is available in different forms depending on whether the variable under consideration has no intercept, intercept and intercept and trend.

$$\Delta P_t = \delta P_{t-1} + \sum_{i=1}^{n} \rho_i \, \Delta P_{t-i} + \varepsilon_t \qquad 5.4a$$

$$\Delta P_t = \mu + \delta P_{t-1} + \sum_{i=1}^{n} \rho_i \, \Delta P_{t-i} + \varepsilon_t \qquad 5.4b$$

$$\Delta P_t = \mu + \beta t + \delta P_{t-1} + \sum_{i=1}^{n} \rho_i \, \Delta P_{t-i} + \varepsilon_t \qquad 5.4c$$

where ΔP_t indicates first differences in P_t, and P_t is log of the price, μ is the constant, δ and ρ are co-efficient to be measured, n is the number of lagged term, t is a trend, β is the coefficient of trend, ε_t is the error term that is presumed to be white noise. The null hypothesis is

H_0: $\rho = 0$ (There is unit root)

H_0: $\rho < 0$ (There is no unit root)

To check the significance of the calculated δ co-efficients, the Augmented DF test estimates the $\hat{\tau}$ (tau) statistic for each co-efficient.

5.3.1.1.2 Phillips-Perron Unit Root Test

‘This test uses non parametric statistical methods to take care of autocorrelation in the error term without adding lagged difference terms’ (Gujarati, Porter, & Gunasekar, 2012)[13]. It does the heteroskedasticity and auto correlation consistency correction to dickey-Fuller test statistic. ‘This approach gives a simple test for a unit root in a univariate time series against stationary and trend alternatives. One needs only to estimate the first-order regression with a constant and possibly a time trend and to calculate the appropriate transformed Z statistic. The distribution theory underlying this procedure is asymptotic and critical values already provided by Dickey & Fuller may be used’ (Phillips & Perron, 1988)[14].

5.3.1.2 Autocorrelation Test

Autocorrelation test is the most commonly used parametric tests to check the randomness. The term autocorrelation is defined as 'the correlation between members of series of observation ordered in time or space' (Kalsie & Karla, 2015)[15]. Autocorrelation measures the correlation co-efficient between return series of a stock and its own lagged return series. The autocorrelation function at lag k is given as:

$$\rho_k = \frac{\gamma_k}{\gamma_0} = \frac{Cov(r_t, r_{t-k})}{Var\,(r_t)} \qquad 5.5$$

ρ_k is the autocorrelation co-efficient of time series r_t, r_{t-k} is the return on security at time *t*, k is the lag of the period, $Cov(r_t, r_{t-k})$ indicates the covariance between the return of a stock over a period of time *t*, and its lagged return of the time period (*t*-*k*), $Var(r_t)$ variance of return on security at time t.

Autocorrelation tests show whether the autocorrelation coefficients are significantly different from zero. In an efficient market, when the null hypothesis is zero autocorrelation will prevail. In this study, the researcher has considered time lags of 15 days.

The Q-statistic by Box and Pierce (1970) also used to check whether all the lags autocorrelation is simultaneously significantly different from zero. They model the Q-statistic as follows:

$$Q_n = T \sum_{k=1}^{n} \rho^2(k) \qquad 5.6$$

Under null hypothesis Q_n is asymptotically distributed as χ^2 with 'n' degrees of freedom and 'T' is the sample size, $\rho(k)$ indicates correlation co-efficient and k denotes given lag. If the estimated value of Q-statistic exceeds the chi-square table value, we can reject the null hypothesis of no auto correlation. Under the same hypothesis, Ljung & Box (1978)[18] report the finite sample correction that yields better fit to the chi-square for small samples.

$$Q_{ns} = T(T+2) \sum_{k=1}^{n} \frac{\rho^2 k}{T-K} \qquad 5.7$$

where $\rho(k)$ is calculated correlation co-efficient, k indicates given lag, k takes the value of 1 to 12 in this study and T is the sample size, n is degrees of freedom.
A plot of correlation co-efficient against it lag is known as correlogram.

If time series has unit root, then the autocorrelation function slowly decreases starting from the value of one and the partial auto correlation function has only first value which differs from zero. If one time series has two unit roots, autocorrelation function acts the same way as for the one unit root series, but the partial autocorrelation function has only first two nonzero values.

5.3.2 Tests of Semi-Strong Form of EMH

The second degree of market efficiency tests whether the information known to the public is incorporated into stock prices or not. Fama (1970)[16] 'defined this level as semi-strong, however after reviewing the literature from twenty years of research in this field, he changes the suggested name into event studies'. Event studies are more descriptive term since this level includes studying the impact of the announcement of a company.

5.3.2.1 Event Study

Event study is an important tool used to measure the effect of an economic event on the value of firms. An event study analyses the impact of definite event on the value of a firm. 'An event is an informational announcement of any kind which occurrence is assumed to be unexpected by the market, that is, the announcement doesn't necessarily have to involve an immediate change in the information' (Johnson & Radeschnig, 2014)[17]. The event studies can be different firm specific and economy wide events like a stock split, bonus shares, mergers and acquisitions, issue of new debt and equity, and announcement of macroeconomic variable like growth rate, inflation and trade deficit. 'A major concern in these event studies has been to assess the extent to which security price performance around the time of the event has been abnormal – that is, the extent to which security returns were different from those which would have been appropriate, given the model determining equilibrium expected returns' (Brown & Warner, 1980)[18]. It examines the market reaction, the possibility of excess returns about specific information events. Non-zero excess return that persists after a specific type of event is not consistent with the efficient market that security prices adjust immediately to fully reflect the new information.

Event studies are not a recent phenomenon. It tracks back the long way to Dolley (1933)[19], cited in MacKinlay (1997)[20] opined as probably the first published study. MacKinlay (1997)[21] reported that 'Dolley (1933)[22] examined the price effect of stock splits, studying nominal price changes at the time of the split. Using a sample of 95 splits from 1921 to 1931, he finds that the price increased in 57 of the cases and price declined in only 26 instances. In short, Event Study methodology may be interpreted as analysing the market's reaction to 'events' or as an empirical investigation of the relationship between security prices and economic events such as mergers, acquisitions, dividend announcements, bonus shares, stock splits, issuing new stocks etc.

Event study will help the investors to decide how to react to surprises earning announcement, one can:

1. Potentially use this announcement flow to develop active investment strategies taking advantage of this information, or 'buy and hold' investment technique that are at least on par with the market.

2. If such opportunities are not happening one can assume that either the stock market absorbs announcement quicker than investors accomplish return or some investors have an informational advantage before it's released to the public.

5.3.2.1.1 The Methodology of Event Studies

1. **Determine an Interested Event**

The first step in the event study is determining the type of event to be studied. According to this, one has to decide whether a certain share should be accommodated in the sample of investigation or not. The event may be the announcement of the merger, bonus share, stock split, etc. Since positive and negative events would affect price differently, this group is further separated into two groups, one for the positive and other for the negative earnings surprised.

2. Identify the Event Day and the Event Window

The second step is to identify the real day of the event. One may think that it is very simple as we can decide announcement day as the event day, but the reality is different. Following are the reasons for the same:

a) Opening and closing hours of the stock exchanges are not synchronized. So if the announcement is made after the stock exchange timing, the effect of the announcement is not measurable in the same day.

b) 'Some securities may be registered in multiple stock exchanges, causing the impact of the announcement made when domestic exchange closed was potentially being captured in an international exchange if open' Jonsson & Radeschnig (2014)[23].

Dyckman, Philbrick, & Stephen (1984)[24] argue that 'the improvement of specifying an exact date of the event and the likelihood of observing an abnormal performance are positively correlated.'

After this step, one has to specify the event window. MacKinlay (1997)[25] describes 'the customary event window, in the case of daily data, to involve at least the day of the announcement as well as next coming day, in order to capture those effects that occur after the closure of the stock market at the event day. Whereas Brown & Warner (1985)[26] describe that there exists the possibility that information is absorbed in the market prior to the event which causes the period ahead of the announcement to be of interest, as well as the succeeding the event may be of interest in interpreting how fast market stabilizes from the announcement.

$$\text{Event Window} = \{T_1 < t < T_2\}$$

Where T_1 implies the start of the window, and T_2 implies the end of it, where $t = 0$ is the of the informational announcement. Window's length is given by

$$L_E = T_2 - T_1$$

To analyse the effects of prior information one should consider the window prior to the event window which is called as estimation window. When the event window is set to be too long, then there is a possibility of clustering.

3. Calculate Abnormal Return

Analyse the impact of event by calculating the abnormal return is the next step. Abnormal return is the actual return of the security over the event window minus the expected (normal) return over the time period. Normal return is the expected return without conditioning on the event takes place. For the firm 'i' and the event date 't' the abnormal return is

$$AR_{it} = R_{it} - E(R_{it} \backslash X_t) \qquad 5.10$$

Where AR_{it} is the abnormal return, R_{it} is normal return, and $E(R_{it} \backslash X_t)$ is the normal return for time period 't'. X_t is the conditioning information for the normal return model. For selecting the normal performance model, the estimation window needs to be defined. Usually, the period prior to event window is used as estimation window. Normally, the event period itself is not combined with the estimation period to keep away the event from influencing the normal performance model parameter estimates.

There are several techniques in order to carry out the task of modelling. MacKinlay (1997)[27] suggests different statistical models for measuring normal performance in the form of constant mean return model (this model is assuming that the mean return of the stock is constant over time and that deviation are due to an error term alone). Factor model (it seeks to reduce the variance of the normal return through adding more explanations behind the variance of the normal return), market model (it is actually a special case of a factor model when only one factor is included, i.e., market return), Capital Asset pricing method, Arbitrage Pricing Theory (it is a multi factor regression model where the stock price is assumed to be linearly influenced by some set of factors with different sensitivity). In short, two models that

MacKinlay (1997)[28] suggest as 'common choices' are the constant Mean return model and the Market Model.

The Market Model

This is the very popular and widely used model for calculating the normal return.

It originates from **Sharpe's Single Index Model (SSIM)** which presents a linear relationship between the returns from a given security and some market portfolio. The return R_{it} on security 'i' at time 't', is given by

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \qquad 5.11$$

Where R_{it} is the period 't' return on security 'i', R_{mt} is the period 't' return on the market portfolio, α_i is the expected return on security when the value of β_i is zero. ε_{it} is a random error that causes the model to be probabilistic rather than deterministic. The error term is assumed to be normally distributed with zero mean and variance constant $\sigma^2_{\varepsilon it}$ and also unrelated with R_{mt}, that is

$$Cov[\varepsilon_{it}, R_{mt}] = 0$$

'With these properties of the error term, one can estimate the constants in the equation (5.11) through historical average of return' Jonsson & Radeschnig (2014) using

$$\bar{R}_i = \frac{1}{T}\sum_{t=1}^{T} R_{it} \qquad 5.12$$

Using ordinary least squares for estimation Shalit & Shlomo (2002) gives the constant β_i in equation (5.11) to be estimated by

$$\hat{\beta}_i = \frac{\hat{\sigma}_{im}}{\hat{\sigma}^2_m} \qquad 5.13$$

Numerator in equation

$$\hat{\sigma}_{im} = \sum_{t=1}^{T}[(R_{it} - \bar{R}_i)(R_{mt} - \bar{R}_m)$$

5.13a

Denominator in equation

$$\hat{\sigma}_m^2 = \sum_{t=1}^{T} (R_{mt} - \bar{R}_m)^2 \qquad 5.13b$$

Using the estimated beta, one can calculate the estimated alpha in equation (4.11) by

$$\hat{\alpha}_i = \bar{R}_i - \hat{\beta}_i \bar{R}_m \qquad 5.14$$

'To perform the ordinary least squares regression and find the estimates one has to define estimation window. The estimation window can be described by the following interval.

Estimation Window = $\{T_0 < t < T_1\}$

Where T_1 implies the start of the window, and T_2 implies the end of it, where t = 0 is the of the informational announcement. Window's length is given by

$$L_E = T_2 - T_1$$

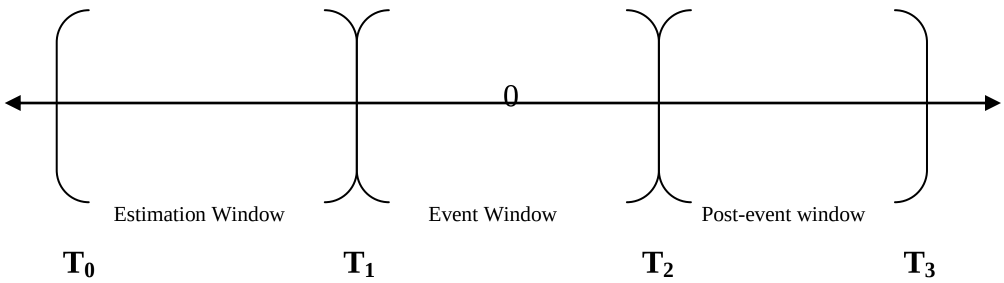


Figure 5.2 Study Period of an Event

Once the estimation window is set, historical data on returns must be collected in order to use as input for the market model return. The criterion for hypothesis testing is that the sample should be normally distributed. But, most of the times, the daily returns of the stock market do not show the normality. Brown & Warner (1985)[29] argued that since the return and event date selected randomly, non-normality of returns or abnormal returns don't have a large effect on event studies due to the mean abnormal return of the cross sectional regression, as assumed under the Central Limit Theorem does asymptotically converge to normality.

Then one can find out the abnormal return by the following equation:

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt} \qquad 5.15$$

If the estimation window is set moderately large, the variance of the abnormal return will converge to the variance of the error term in the market model, therefore, variance of error term will not have the serial correlation.

4. Aggregation of Abnormal Return

We normally look at the average effect of the announcements rather than examine each stock separately, in order to find a single measurement of abnormal return across stocks, over the entire event window. Thus we made the aggregation of abnormal return of different individual stocks. So average abnormal return (AAR_t) of each day of the event window is calculated as:

$$AAR_t = \frac{\sum_{i=1}^{N} AR_{it}}{N} \quad 5.16$$

Where N= Number stocks in the sample (20 in this study)

'In order to draw overall inference about the reaction of stock prices to the announcement of the event, the cumulative average abnormal return (CAAR) is calculated over a time interval (k1, k2) as follows' Chakraborty (2011)[30].

$$CAAR_{(k1,k2)} = \sum_{t=k1}^{k2} AAR_t \quad 5.17$$

5. Test of the Abnormal Return

Numerous varieties of tests are available to test the hypothesis, obviously all providing advantages and disadvantages in the form of correctness. Choosing one among them is dependent upon the nature of the study and the sample data.

The t-statistics for AAR_t as given below is used for testing null hypothesis (Asquith, 1983)[31].

$$t = \frac{AAR_t}{S.E} \quad 5.18$$

$$where\ S.E = \sqrt{\frac{\sum(AR_{it} - AAR_t)}{N-1}}$$

The t-statistics for finding out statistical significance of cumulative average abnormal return is given below. (Campbell, Lo, & MacKinlay, 2007)[32]

$$t = \frac{CAAR_{(k1,k2)}}{S.E} \qquad 5.19$$

where $$S.E = \sqrt{\frac{\sum_{i=1}^{N} \sigma_{i(k1,k2)}^{2}}{N^{2}}}$$

If the calculated value t-statistic of AAR_t ($CAAR_{(k1,k2)}$) is more than the critical value of 't' at 5% significance level and for (N-1) i.e., 19 degree of freedom, the null hypothesis is rejected denoting statistically significant average abnormal return (cumulative abnormal return) being generated by the stocks on or around the event day and hence pricing inefficiency is of the market in its semi-strong form. Chakraborty (2011)[33].

5.3.3 Tests of Strong Form Efficient Market Hypothesis

The strong form of hypothesis represents the extreme case of market efficiency. The strong form of efficient market hypothesis maintains that the current security prices reflect all information both publicly available information as well as private or inside information. This implies that no information, whether public or private, can be used to earn superior returns consistently. 'The first declared term for this level of efficiency was strong form' (Fama, 1970)[34], however, after reviewing the literature from twenty years of research in this area Empirical test of strong, 'he changed the suggested name to 'test for private information' in order to be more descriptive' (Fama, 1990)[35]. Strong form focuses on two problems - one, insider information results in excess profit and two, professional analyst and investors have profitable information. The directors of companies and other persons occupying senior management positions within companies have access to much information that is not available to the general public. This is known as insider information. Mutual funds and other professional analysts who have large research facilities may gather much private information regarding different stocks their own. These pieces of private information are not available to the investing public at large.

According to this hypothesis all the information, public as well as private, is known to the investors and hence a particular investor cannot reap abnormal profits using the information. Since there are people who are privy to certain types of information, to examine the validity of this hypothesis, we can divide this into two groups: (i) the super strong form consisting of corporate insiders and the specialists at the stock exchanges and (ii) the near form consisting of mutual fund managers. Many studies have been carried out regarding the performance of American Mutual Funds using fairly sophisticated evaluation models. All the major studies have found that mutual funds did no better than randomly constructed portfolios of similar risk. In conclusion, it may be stated that the strong form hypothesis is invalid as regards inside information, but valid as it regards private information other than inside information.

5.4 Empirical Results of EMH with Selected Stocks

As already stated in the methodology, the analysis has done and following are the results of weak form and semi-strong form efficiency tests of Indian stock market.

5.4.1 Descriptive Statistics

The descriptive statistics for all share returns series of 20 shares listed on Bombay Stock Exchange for the entire sample period from 01/01/2002 to 31/12/2016 (except the share listed after 01/01/2002, in that case from the day of listing onwards which is shown in Table 1.1) is presented in Table 5.1. Bajaj Finance Limited has the highest mean return of 0.001492, whereas Sunil Hightech Engineers Limited has the lowest mean return with relatively high standard deviation. Likewise, Gulshan Ployols Limited has the highest standard deviation (highly volatile) while Colgate-Palmolive Limited has the lowest standard deviation followed by ITC limited (less volatile).

Skewness, Kurtosis and Jarque-Bera statistics and its p value reports the normality of the each share return series. In general, the skewness value zero and the value of the kurtosis three indicate that the observed distribution is normally distributed. Jarque-Bera statistic and its corresponding ‘p’ value are also used to test the null hypothesis that the daily return of stock returns is normally distributed.

Table 5.1

Descriptive Statistics for the Daily Stock Log Returns

Stocks	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Berra
Bajaj Finance	0.001492	0.028054	0.646654	11.04314	10311.42***
Berger Paints	0.001229	0.024701	0.739779	10.54466	91460.33***
Grasim Industries	0.000738	0.020068	-0.211827	11.69297	11790.84***
HPCL	0.000603	0.025834	-0.169875	11.73080	11887.13***
ITC	0.000740	0.017990	0.115082	5.982324	1392.786***
Mindtree	0.000498	0.024726	1.185255	17.59695	22178.84***
ONGC	0.000679	0.022465	0.220137	9.383850	6374.143***
V-Guard	0.001424	0.022367	0.022367	9.060778	3660.908***
Welspun	0.000667	0.036701	0.199886	8.218229	4221.443***
Kothari Products	0.000462	0.028743	0.797429	14.58379	21021.88***
Gulshan Polyols	0.001353	0.048750	0.320550	6.827062	2103.646***
Sunil Hightech	0.000189	0.037450	0.354831	7.800396	2636.330***
Chaman lal Setia	0.001066	0.037600	0.273227	6.795107	2082.706***
JK Tyres	0.000955	0.032443	0.596696	8.590210	4967.905***
PNB	0.000749	0.027314	-0.048348	7.223951	2718.576***
Bata	0.000865	0.028857	0.206054	9.680826	6974.376***
Tech Mahindra	0.000493	0.026467	0.478530	10.73974	6495.016***
Colgate-Palmolive	0.000641	0.016727	0.784646	10.77961	9773.181***
Infosys	0.000558	0.021263	-1.238485	23.72615	67843.50***
HCL Technologies	0.000665	0.026180	-0.268023	8.511019	4772.533***

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

As shown in the table, skewness and kurtosis value denote that return of all stocks are not normally distributed. This result is substantiated by Jarque-bera statistics at the 1% significant level since all its p value is less than 0.01. Returns of five stocks are negatively skewed, ‘indicating the probability of large decreases in return than rises’ Chung (2006)[36]. Apart from these, all other fifteen stocks are positively skewed. The kurtosis, peakedness in stock returns also large ranging from 5.98 to 23.72 which means all the selected stock return distributions are leptokurtic.

5.4.2 Unit Root Test

A unit root test examines whether a time series is stationary or not. If it is non-stationary it means that the time series follows a random walk process, means the weak form is efficient. Otherwise, if the null hypothesis is rejected, it means that Indian stock market is not efficient in the weak form. In this study, the researcher uses two unit root tests, namely Augmented Dickey-Fuller unit root test and Phillip-Perron unit root test.

5.4.2.1 Augmented Dickey-Fuller Unit Root Test

This methodology was introduced by Dickey and Fuller in 1981 to determine the stationarity of the time series. The null hypothesis of this test is that the series has a unit root. The table 5.2 reports the result of the Augmented Dickey-Fuller test for selected twenty stocks in Indian stock market listed in Bombay Stock Exchange for the period of 2002 to 2016 (except the share listed after 01/01/2002, in that case from the day of listing onwards which shows in Table 1.1). The optimal lag length for the Augmented Dickey-Fuller unit root test is selected with Schwartz Information Criterion and Maximum lag length is 28. Here the researcher calculates t-statistic and corresponding level of significance at 1%, 5% and 10% for without constant and trend (equation 5.4a), with constant, but without time trend (equation 5.4b), and with constant and time trend (equation 5.4c) which are tested in both log levels and log first differences.

Table 5.2

Results of the Augmented Dickey-Fuller Test for Stock Prices & Return

Stocks	Level			First difference		
	None	Intercept	Trend & Intercept	None	Intercept	Trend & Intercept
Bajaj Finance	1.6484	0.9835	-0.5239	-7.63***	-7.76***	-7.96***
Berger Paints	2.5864	1.4385	-0.6807	-21.99***	-22.13***	-22.25***
Grasim Industries	0.7876	-1.1637	-2.5711	-59.00***	-50.02***	-50.02***
HPCL	2.2748	1.3596	0.4054	-60.16***	-60.21***	-60.25***
ITC	1.1424	-0.3948	-3.0428	-61.22***	-61.26***	-61.25***
Mindtree	0.2166	-0.7141	-2.0141	-42.10***	-42.10***	-42.10***
ONGC	-0.0945	-2.3928	-2.9810	-59.34***	-59.34***	-59.34***
V-Guard	2.2656	0.9863	-1.3666	-34.29***	-34.29***	-34.45***
Welspun	-0.2258	-0.8293	-1.7047	-36.43***	-36.43***	-36.45***
Kothari Products	0.6330	-2.2399	-2.7306	-55.50***	-55.50***	-55.50***
Gulshan Polyols	-0.6675	-1.6688	-2.5605	-25.77***	-25.78***	-25.78***
Sunil Hightech	-0.9552	-2.5279	-2.5723	-31.25***	-31.25***	-31.25***
Chaman lal Setia	4.6051	4.0065	2.6142	-13.12***	-13.33***	-13.73***
JK Tyres	0.0829	-0.8806	-2.0882	-15.12***	-15.15***	-44.22***
PNB	-0.4477	-2.1017	-1.8820	-57.16***	-57.15***	-57.16***
Bata	0.2352	-0.8632	-2.1994	-57.93***	-57.94***	-57.94***
Tech Mahindra	0.2014	-1.2180	-1.6174	-46.17***	-46.18***	-46.17***
Colgate-Palmolive	1.2664	-0.1932	-2.9830	-57.07***	-57.11***	-57.11***
Infosys	1.4950	-1.3212	-2.2020	-46.60***	-46.65***	-46.64***
HCL Technologies	1.2542	0.1037	-1.7142	-60.34***	-60.67***	-60.68***

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

Result from the table 5.2 shows that all the selected stock prices are non stationary at 5% level of significance, but become stationary in first differences. The augmented Dickey-Fuller test accepts the null hypothesis for all log stock prices, thereby indicating that all stock prices are non stationary. Whereas, after taking the log first difference in the price of the stocks, (i.e. the return of the stock), one can witness the rejection of null hypothesis that shows the unit root. It means that Indian stock markets are not efficient in its weak form.

5.4.2.2 Phillip-Perron Unit Root Test

'This test uses non parametric statistical methods to take care of autocorrelation in the error term without adding lagged difference terms' (Gujarati, Porter, & Gunasekar, 2012)[37]. The null hypothesis of this test is that the series has a unit root. The following table 5.3 reports the result of a PP test for selected twenty stocks listed in Bombay Stock Exchange for the period of 2002 to 2016 (except the share listed after 01/01/2002, in that case from the day of listing onwards which shows in Table 1.1). The spectral estimation for this test is Bartlett kernel and Band width is automatically selected by using Newey-West Bandwidth. Here the researcher reports adjusted t-statistic and corresponding level of significance at 1%, 5% & 10% for without constant & trend, with constant, but without time trend, and with constant and time trend which are tested on both levels and first differences.

Table 5.3

Results of the Phillip-Perron Test for Stock Prices & Return

Stocks	Level			First difference		
	None	Intercept	Trend & Intercept	None	Intercept	Trend & Intercept
Bajaj Finance	2.6604	1.8236	0.0682	-61.34***	-61.41***	-61.50***
Berger Paints	2.2701	1.1889	-0.8598	-53.49***	-53.60***	-53.71***
Grasim Industries	0.5708	-1.3263	-2.9432	-59.41***	-59.38***	-59.37***
HPCL	2.4065	1.4691	0.5425	-60.17***	-60.22***	60.27***
ITC	1.4537	-0.2235	-2.7934	-61.69***	-61.87***	-61.87***
Mindtree	0.5045	-0.5062	-1.7761	-41.61***	-41.63***	-41.63***
ONGC	-0.0203	-2.3352	-2.8402	-59.42***	-59.44***	-59.44***
V-Guard	2.1242	0.8764	-1.4645	-41.10***	-41.14***	-41.16***
Welspun	-0.9265	-0.7094	-1.5827	-52.52***	-52.44***	-52.43***
Kothari Products	0.6622	-2.1971	-2.680	-55.35***	-55.34***	-55.33***
Gulshan Polyols	-0.5079	-1.4952	-2.3724	-47.58***	-47.56***	-47.54***
Sunil Hightech	-0.9496	-2.4766	-2.5249	-46.61***	-46.61***	-46.60***
Chaman lal Setia	4.6713	4.4308	2.5728	-47.78***	-47.75***	-47.71***

JK Tyres	0.4580	-0.5245	-1.7218	-57.29***	-57.30***	57.31***
PNB	-0.4387	-2.0943	-1.8612	-57.15***	-57.15***	-57.16***
Bata	0.2838	-0.8319	-2.0919	-57.85***	-57.86***	-57.85***
Tech Mahindra	0.2378	-1.1642	-1.5607	-46.09***	-46.10***	-46.07***
Colgate-Palmolive	1.6572	0.0285	-2.7148	-57.17***	-57.36***	-57.40***
Infosys	1.5868	-1.3989	-2.1796	-59.82***	-59.88***	-59.88***
HCL Technologies	1.6284	0.3649	-1.5324	-61.19***	-61.34***	-61.41***

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

Result from the Table 5.3 shows that all the selected stocks prices are non stationary in log levels at 5% significance, but become stationary in log first differences. The Phillip-Perron test accepts the null hypothesis for all stock prices, thereby indicating that all stock prices are non stationary. Whereas, after taking the log first difference on the price of the stocks, (i.e. the return of the stock), the null hypothesis of unit root is rejected at the 1% significance level. The test statistics are more negative than the critical value in all cases. It suggests that the stock returns in Indian stock markets are not a weak form efficient. The result given by Augmented Dickey-Fuller test and Phillip-Perron are same in this case.

5.4.3 Autocorrelation

The result of fifteen sample auto correlation coefficients and Q-statistics for the first four, sixth, tenth & fifteenth order autocorrelation for each of the stock return series of selected twenty stocks for the full sample period 2002-2016 (except the share listed after 01/01/2002, in that case from the day of listing onwards which is shown in Table 1.1) are given in Table 5.4A, 5.4B and 5.4C.

Table 5.4A

Results of the Sample Autocorrelation co-efficient and Q-statistics

	Bajaj	**Berger**	**Grasim**	**HPCL**	**ITC**	**Mindtree**	**ONGC**
ρ_1	0.044***	0.067***	0.033**	0.031*	-0.026	0.057***	0.068***
ρ_2	0.008	-0.029*	-0.007	0.015	-0.042**	0.031	-0.05***
ρ_3	-0.006	0.00	0.037**	-0.001	-0.024	-0.03	-0.031*
ρ_4	0.013	-0.024	0.03*	-0.033**	-0.005	-0.022	0.018
ρ_5	-0.025	-0.072***	0.054***	-0.001	-0.011	-0.01	-0.027*
ρ_6	0.026	-0.003	0.021	-0.018	0.009	0.004	-0.032*
ρ_7	-0.011	-0.011	0.021	0.026	-0.001	0.005	0.004
ρ_8	-0.008	-0.003	0.01	-0.009	-0.009	-0.026	0.024
ρ_9	0.004	-0.012	-0.021	0.006	-0.003	0.015	0.007
ρ_{10}	0.025	-0.028*	-0.003	0.015	-0.006	-0.035*	0.00
ρ_{11}	0.029*	-0.034**	0.013	-0.002	-0.035**	0.038*	0.00
ρ_{12}	-0.034**	0.00	0.01	-0.005	0.018	0.038*	0.006
ρ_{13}	0.018	-0.003	0.047***	0.001	-0.007	-0.011	0.005
ρ_{14}	0.011	0.029*	0.014	0.046***	0.023	-0.006	0.013
ρ_{15}	0.018	-0.018	0.003	-0.016	-0.01	0.053***	0.005
Q(1)	7.2948***	16.86***	3.9893	3.6922*	2.4321	8.0098***	17.04***
Q(2)	7.5232**	19.949***	4.171	4.5048	8.9734**	10.389***	26.356***
Q(3)	7.6686*	19.95***	9.2318**	4.5108	11.167**	12.58***	29.996***
Q(4)	8.2948*	22.068***	12.574**	8.6938*	11.278**	13.791***	31.194***
Q(6)	13.183**	41.63***	25.137***	9.9451	12.027*	14.093**	37.807***
Q(10)	16.275*	45.669***	28.9***	13.633	12.477	19.334**	40.198***
Q(15)	26.443**	54.548***	38.994***	22.806*	20.804	33.865***	41.225***

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

Table 5.4B

Results of the Sample Autocorrelation co-efficient and Q-statistics

	V-guard	**Welspun**	**Kothari**	**Gulshan**	**Sunil**	**Chamanlal Setia**	**JK Tyres**
ρ_1	0.032	0.027	0.09***	0.009	0.107***	-0.009	0.041**
ρ_2	-0.016	0.043***	0.031*	0.072	0.067***	0.022	-0.004
ρ_3	0.015	-0.041**	0.018	0.00	0.027	0.033*	0.004
ρ_4	-0.002	0.031*	0.003	0.019	-0.014	-0.021	0.004
ρ_5	0.057***	0.01	-0.038**	-0.047	-0.011	0.007	0.005
ρ_6	0.002	0.028*	-0.015	-0.022	-0.006	-0.027	-0.008
ρ_7	0.019	-0.017	-0.035**	0.005	0.009	-0.047***	0.045***
ρ_8	-0.013	-0.01	-0.018	-0.025	-0.017	0.013	0.01
ρ_9	0.002	0.016	0.018	-0.013	-0.005	-0.033*	-0.003
ρ_{10}	0.004	0.016	-0.021	0.018	0.013	-0.01	0.028*
ρ_{11}	0.018	-0.013	-0.006	0.002	0.006	-0.012	0.009
ρ_{12}	0.003	-0.013	0.016	-0.006	-0.006	-0.016	0.02
ρ_{13}	-0.048**	0.033**	0.006	0.039	-0.016	0.006	0.02
ρ_{14}	-0.003	0.008	-0.019	0.032	0.041**	0.027	0.025
ρ_{15}	0.029	0.02	-0.006	-0.033	-0.04**	0.00	0.015
Q(1)	2.2934	2.7051	29.657***	0.2791	30.999***	0.2477	6.1026**
Q(2)	2.8688	9.4678***	33.164***	17.598***	42.948***	1.8497	6.1707**
Q(3)	3.3914	15.803***	34.356***	17.598***	44.88***	5.4779	6.2223
Q(4)	3.3987	19.41***	34.397***	18.783***	45.406***	6.9607	6.2729
Q(6)	10.571	22.695***	40.649***	28.018***	45.806***	9.5842	6.3838
Q(10)	11.74	26.02***	49.14***	31.892***	47.39***	21.629**	17.229*
Q(15)	19.303	33.09***	51.845***	44.189***	57.3***	25.528**	23.551*

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

Table 5.4C

Results of the Sample Autocorrelation co-efficient and Q-statistics

	PNB	**Bata**	**Tech Mahindra**	**Colgate**	**Infosys**	**HCL**
ρ_1	0.041**	0.024	0.106***	0.022	0.024	0.005
ρ_2	0.018	-0.017	-0.02	-0.052	-0.087***	-0.039**
ρ_3	-0.02	-0.026	-0.014	0.004	-0.038**	-0.042***
ρ_4	0.006	0.034*	0.023	0.009	0.00	-0.02
ρ_5	-0.034**	-0.022	0.065***	-0.01	-0.015	-0.038**
ρ_6	0.004	-0.01	-0.016	-0.025	-0.026	-0.038**
ρ_7	0.013	0.022	0.009	-0.016	0.013	-0.001
ρ_8	0.019	0.01	0.01	-0.02	0.025	0.037**
ρ_9	0.029*	0.003	0.016	0.023	0.006	0.002
ρ_{10}	0.04**	0.026	0.017	0.001	-0.002	-0.017
ρ_{11}	-0.015	-0.021	0.031	-0.012	0.001	0.003
ρ_{12}	-0.006	-0.016	0.043**	-0.001	0.00	-0.015
ρ_{13}	-0.029*	0.041*	0.049**	0.017	-0.016	-0.001
ρ_{14}	-0.004	0.025	0.039*	0.00	0.00	0.011
ρ_{15}	-0.03*	0.008	-0.003	-0.046	-0.019	-0.023
Q(1)	6.236**	2.1445	29.018***	1.7812	2.173**	0.0847
Q(2)	7.4095**	3.1971	30.094***	11.931**	30.47***	5.6671*
Q(3)	8.9054**	5.7341**	30.606***	12.005***	35.95***	12.415***
Q(4)	9.0232*	10.166**	31.927***	12.286**	35.951***	13.903***
Q(6)	13.395**	12.415*	43.469***	14.949**	39.314***	24.657***
Q(10)	24.005***	17.085*	45.328***	19.287**	42.45***	30.993***
Q(15)	31.37***	28.487**	62.498***	28.917**	44.855***	34.318***

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

Form the above table, 5.4, it is found that autocorrelation at lag one is the highest for Sunil Hitech Engineers (0.107) followed by Tech Mahindra (0.106) and the lowest for HCL Technologies (0.005). Out of the selected twenty stocks only two stocks - ITC Limited (-0.26), Chamanlal Setia (-0.009) – show negative autocorrelation at lag one, but they are not significant. Positive auto correlation denotes predictability of returns in the short run, which is the general evidence against weak form efficiency. There are lots of significant positive and negative autocorrelation for different stocks at different lags. Overall, almost all the stock returns except for very few lags, the auto correlation co-efficient are non-zero at 1%, 5%, 10 % significance levels.

Q statistics also gives the evidence for possible dependence in the first and higher order of the share return distributions. It can be concluded from the result that the null hypothesis of auto correlation is rejected for almost all returns on all selected stocks at lag one through fifteen at 5% level of significance. The non-zero autocorrelation of the series collaborated with Q statistics, which are jointly significant at 1%, significant level at one and fifteen degrees of freedom, indicates that all return series do not follow a random walk model. It can be understood from the results that the Indian stock market is not efficient in its weak form.

The result of these studies is consistent with the previous finding in Indian stock market, Gupta (2014)[38], Kalsie & Karla (2015)[39], Guptha & Basu (2007)[40] and Sachin & sanningammanavara (2014)[41]. They find significant presence of autocorrelation in Indian Stock Market, which indicates that the market is not efficient in a weak form of the Efficient Market Hypothesis.

5.4.4 Event Study

To conduct the event study, a sample of twenty companies which announced the stock split and/or the bonus share during the period 01/01/2014 to 31\12\2016 were selected. The daily closing price of the selected stocks has been collected for two periods : (I) for the event window (i.e. a period of 61 days, comprising 30 pre-event days, stock split or bonus share announcement day called the event day and 30 post event days) and (II) the period of three years prior to the event window (estimation window). All the data have been gathered from the website of BSE (www.bseindia.com). The information relating to bonus issue and stock splits and their announcement dates has been collected from the website of the moneycontrol (www.moneycontrol.com). The details have been shown in table 1.5.

Hypothesis Testing

On the basis of the data furnished, the following hypothesis have been set and tested empirically.

H_0: No abnormal return is generated by the stock on the bonus share / stock split announcement day (event day / day 0) and in the pre event period (day -30 to day -1) and post event period (day +1 to +30)

H_1: Abnormal return is generated by the stock on the bonus share / stock split announcement day (event day / day 0) and in the pre event period (day -30 to day -1) and post event period (day +1 to +30)

Acceptance of the null hypothesis denotes the pricing efficiency of Indian stock market at its semi strong level.

Empirical Results

Daily close price of all companies, 30 days before and 30 days after the event date are collected and converted into stock return on daily basis. All the stock returns are calculated after converting them into the adjusted price. Adjusted price is the price which converts the close price before the event into the new price that considers the impact of the event, so that one can compare the price with the price after the event. The parameters of the market model have been estimated from the estimation window three year period just before the event window pertaining to each the selected company under study. Then the parameters have been used in the regression model with respect to the return of market Index to get the expected market return. This market return is compared against the actual return of the sample companies to determine the abnormal return of each selected stock for the window period. The parameters alpha & Beta of the each selected stock is shown in the table 5.5.

Table 5.5

Estimated Market Parameters for Selected Shares

Name of the Company	Alpha	Beta
Bajaj Finance Limited	0.001875	0.835685
Berger Paints India Limited	0.001072	0.616563
Grasim Industries Limited	0.000287	0.838352
Hindustan Petroleum Corporation Ltd.	0.001187	1.194562
ITC Limited	0.000186	0.807389
Mindtree Limited	0.001838	0.390371
Oil & Natural Gas Corporation Limited	-0.000757	1.224746
V-Guard Industries Limited	0.001220	0.541701
Welspun India Limited	0.003305	0.880842
Kothari Products Limited	0.000357	0.466941
Gulshan Polyols Limited	0.001934	1.054632
Sunil Hightech Engineers Limited	0.001301	1.406902
Chaman lal Setia Exports Limited	0.002403	0.499294
JK Tyre Industries Limited	0.001534	0.912191
Punjab National Bank	-0.000824	1.374053
Bata India Limited	-0.000105	0.787138
Tech Mahindra Limited	0.001696	0.448622
Colgate-Palmolive (India) Limited	0.000442	0.428564
Infosys Limited	0.000154	0.712848
HCL Technologies Limited	0.001531	0.489070

Table 5.6 exhibits the average abnormal return for each day of the event window for the overall sample and the corresponding computed values of t-statistic. It is observed that the average abnormal returns of almost all days of the event window are very close to zero. In the pre-event period the average abnormal return ranges from the lowest value of -0.01140 on day -26 and highest value 0.00839 on day -19. In the event (announcement '0' day itself the value is -0.00483. In the post event period the abnormal average return ranges from the lowest value of -0.01165 in day 30 to the highest value of 0.01111 on day 10. The computed t-values for all average abnormal returns are lower than 2.539 the critical value of t-statistic at 1% level of significance and for 19 degrees of freedom also lower than 1.729, the critical t-value at 5% level of significance and for the same degree of freedom. This denotes that average abnormal return generated by the sample stock in the event window is

insignificant and hence accepts the null hypothesis (H_0: No abnormal return is generated by the stock on the event window). In short, the information content of the stock is quickly absorbed in the daily prices of the stocks in the event window, leaving no scope for abnormal returns from the shares. Even on the announcement day, no evidence of significant price reaction can be identified. All this results confirm that Indian stock market is efficient in the semi-strong form.

Table 5.6

Average Abnormal Returns of Event Window and Calculated t-values

Day	AAR_t	t-value	Day	AAR_t	t-value
-30	-0.00537	-0.0207	1	0.0001	7.32E-05
-29	-0.00091	-0.0035	2	0.0097	0.009698
-28	-0.00027	-0.0011	3	0.0194	0.019421
-27	-0.00241	-0.0093	4	-0.0057	-0.00566
-26	-0.01140	-0.0440	5	-0.0008	-0.00078
-25	-0.00152	-0.0059	6	0.0112	0.011222
-24	-0.00140	-0.0054	7	0.0042	0.004173
-23	-0.00350	-0.0135	8	0.0329	0.032901
-22	-0.00062	-0.0024	9	0.0174	0.017385
-21	0.00421	0.0163	10	0.0429	0.042892
-20	0.00323	0.0125	11	0.0206	0.020619
-19	0.00839	0.0324	12	-0.0206	-0.02056
-18	-0.00392	-0.0151	13	-0.0132	-0.01324
-17	-0.00021	-0.0008	14	0.0273	0.027282
-16	-0.00032	-0.0012	15	0.0175	0.017474
-15	-0.00114	-0.0044	16	-0.0058	-0.00576
-14	-0.00466	-0.0180	17	0.0058	0.005767
-13	-0.00036	-0.0014	18	0.0162	0.01616
-12	0.00831	0.0321	19	0.0153	0.015326
-11	0.00475	0.0183	20	0.0174	0.017383
-10	-0.00014	-0.0005	21	-0.0108	-0.01078
-9	0.00276	0.0107	22	0.0055	0.00553
-8	-0.00191	-0.0074	23	0.0262	0.026174
-7	-0.00256	-0.0099	24	-0.0007	-0.00068
-6	-0.00797	-0.0308	25	0.0220	0.021962
-5	-0.00545	-0.0210	26	0.0254	0.025398
-4	-0.01011	-0.0390	27	-0.0009	-0.00091
-3	-0.00125	-0.0048	28	0.0191	0.019126
-2	0.00221	0.0085	29	0.0070	0.006994
-1	0.00023	0.0009	30	-0.0450	-0.04497
0	-0.00483	-0.0187			

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

The graphical presentation of the above average abnormal return (Figure 5.3) also depicts that the abnormal returns are not significantly different from zero in almost all days of the event window (day -30 to day +30)

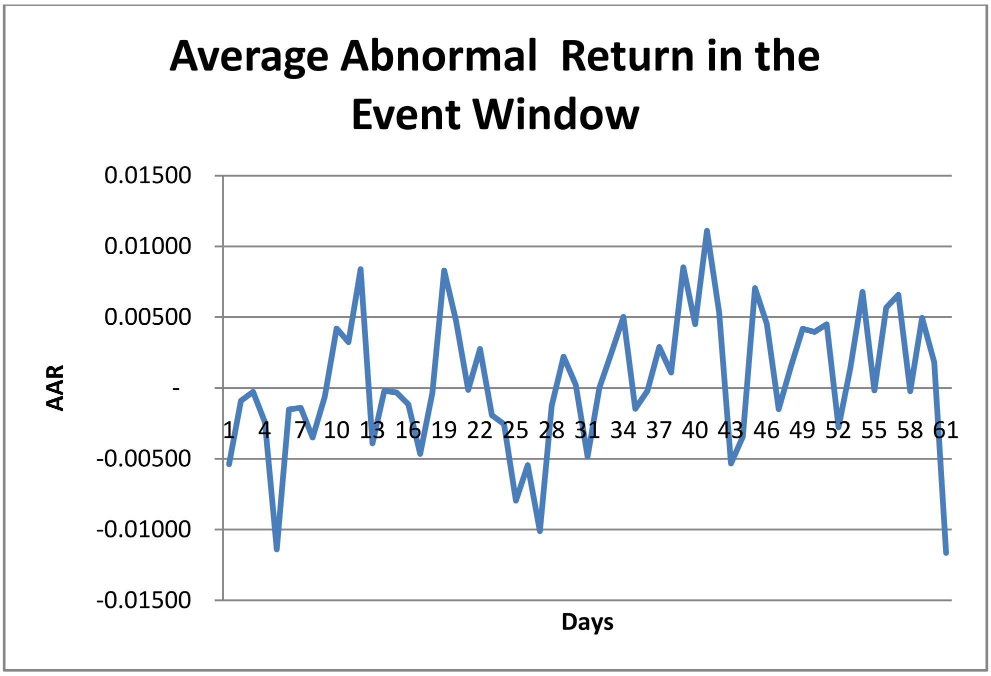


Figure 5.3 Average Abnormal Return

Sometimes the reaction of the share prices to the announcement of an event is not prominently seen in the behaviour of average abnormal return of a specific day. The real impact of any event is understood by the investors through accumulated abnormal returns of a time interval before, after and around the event day.

Table 5.7
Cumulative Average Abnormal Returns at Specific Time Intervals and its Computed t-values

Time Interval	CAAR	t-value
Day - 30 to day – 1 (-30, -1)	-0.03332	0.005447
Day -25 to day -1 (-25, -1)	-0.01296	0.005453
Day -20 to day -1 (-20, -1)	-0.01013	0.005631
Day -15 to day -1 (-15, -1)	-0.01732	0.00551
Day -10 to day -1 (-10, -1)	-0.02421	0.005134
Day -5 to day -1 (-5, -1)	-0.01437	0.004056
Day 1 to day 5 (1, 5)	0.00589	0.005732
Day 1 to day 10 (1, 10)	0.03402	0.005522
Day 1 to day 15 (1, 15)	0.04220	0.005607
Day 1 to day 20 (1, 20)	0.05486	0.005247
Day 1 to day 25 (1, 25)	0.06580	0.005121
Day 1 to day 30 (1, 30)	0.06726	0.005007
Day -5 to day 5 (-5, 5)	-0.01331	0.005827
Day -10 to day 10 (-10, 10)	0.00499	0.005779
Day -15 to day 15 (-15, 15)	0.02006	0.005826
Day -20 to day 20 (-20, 20)	0.03990	0.005698
Day -25 to day 25 (-25, 25)	0.04801	0.0055
Day -30 to day 30 (-30, 30)	0.02911	0.005421

*, **, *** statistically significant at the 10%, 5%, and 1% significant level

As per the result shown in the above table, the highest cumulative average abnormal return (0.06726) is the period day 1 to day 30, and the lowest return (-0.03332) is on the period of the day-30 today -1, but none of them are statistically significant. In all the different specific periods in the pre-window period and post-window period the null hypothesis is accepted. It can be concluded from the result that Indian stock market is efficient in its semi-strong form.

5.4.5 Strong-Form Test

'It is not surprising if insiders were able to make abnormal profits trading in their firm's stock. We do not expect the market to be strong-from efficient; we regulate and limit trades based on inside information' (Bodie, Kane, Marcus, & Mohanty, 2016)[42]. The ability of insiders to trade profitably in their own stock has been documented in studies by Jaffe (1974)[43], Seyhun (1986)[44] and Givoly & Palmon (1985)[45]. The researcher does not attempt to test strong form efficiency of Indian stock market in the present study.

5.5 Conclusion

Weak Form Efficiency

The augmented Dickey-Fuller test fails to reject the null hypothesis for all log stock prices, thereby implying that all stock prices are non stationary. Whereas, after taking the log first difference in the price of the stocks, (i.e. the return of the stock), the null hypothesis of unit root is rejected at the 1% significance level. The test statistics are more negative than the critical value in all cases. That means Indian stock markets are not a weak form of efficiency.

The Phillip-Perron test fails to reject the null hypothesis for all stock prices, thereby implying that all stock prices are non stationary. Whereas, after taking the log first difference on the price of the stocks, (i.e. the return of the stock), the null hypothesis of unit root is rejected at the 1% significance level. The test statistics are more negative than the critical value in all cases. That means that the stock returns in Indian stock markets are not a weak form efficient. The result given by Augmented Dickey-Fuller test and Phillip-Perron are same in this case.

Q statistics gives the evidence for possible dependence in the first and higher order of the return distributions. It shows that the null hypothesis of auto correlation is rejected for almost all returns on all selected stocks at lag one through fifteen at 1% , 5%, 10% level of significance. The non-zero autocorrelation of the series associated with Q statistics, which are jointly significant at 1%, 5%, 10% significant level at one and fifteen degrees of freedom, clearly suggest that all return series do not follow a random walk model. The results exhibit that the Indian stock market is not efficient in its weak form.

All the three test shows that Indian stock market is not efficient in its weak form.

Semi-Strong Form Efficiency

This part of the report attempts to examine the semi-strong form of pricing efficiency of the Indian Stock Market in relation to the impact of the Bonus issue and stock split announcements on the price behaviour of the related stock using a sample of 20 stocks listed in the Bombay Stock Exchange that witnessed the bonus issue and stock split announcement at different times in the period from 01/01/2003 to 31/12/2006. The market model of event study methodology is applied to calculate the return of the sample stocks in the window of 61 days. The analysis based on the average abnormal return and cumulative average abnormal return of the stocks clearly reveals that no abnormal return which is statistically significant is created on and around the event day. This result clearly shows the existence of semi-strong efficiency in Indian stock market.

According to the proponents of efficient market hypothesis, stock prices reflect all available information about companies and investors and cannot beat the market indexes by stock picking. They argue that investors trying to find a secret formula are wasting their time because stock price follow a random walk. Interestingly, this theory also implies that a monkey selecting stocks by throwing darts at newspaper's financial pages should perform as well as any star hedge fund manager who may or may not use inside information.

Even though the Indian stock market is efficient in semi-strong form in this period, since the market is not efficient in weak form and we have witnessed the bubbles and crashes in Indian stock market, behaviour biases may be present in the market especially among individual investors. Investors, including institutional investors should identify these behaviour biases present in the market in order to make strategic investment decisions.

The later part of the study tries to explain the anomalies in the individual investors' behaviour by the means of a survey.

References:

1. Bachelier's, L. (1900). *The Theory of Speculation.* PhD Thesis, Parris: Gauthier-Villaras.

2. Kendall, M. (1953). The analysis of economic time series. *Journal of the Royal Statistical Society, Series A , 96*, 11-25.

3. Kishore, R. M. (2015). *Financial Management.* New Delhi: Taxmann's.

4. Fama, E. (1970). Efficient Capital Market: A Review of Theory and Empirical Work. *Journal of Finance , 25* (2), 382-417.

5. Brealey, R. A., Myres, C. S., Allen, F., & Mohanty, P. (2014). *Principles of Corporate Finance.* Chennai: Mc Graw Hill Education.

6. Ross, S. A., Westerfield, R. W., & Jordan, B. D. (2008). *Fundamentals of Corporate Finance.* New Delhi: Tata McGraw Hill.

7. Op. Cit. 4

8. Tripathi, V. (2015). *Security Analysis and Portfolio Management.* New Delhi: Taxmann Publicatons.

9. Kevin, S. (2011). *Security Analysis and Portfolio Managemnt.* New elhi: PHI Learning Private Limited.

10. Op. Cit. 4

11. Bodie, Z., Kane, A., Marcus, A. J., & Mohanty, P. (2016). *Investments.* New Delhi: McGraw Hill Education.

12. Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Eestimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistics Association , 74* (366), 427-431.

13. Gujarati, D. N., Porter, D. C., & Gunasekar, S. (2012). *Basic Econometrics.* New Delhi: McGraw Hill Education.

14. Phillips, P. C., & Perron, P. (1988). Testing for Unit Root in Time Series Regression. *Biometrika, 75* (2), 335-346.

15. Kalsie, A., & Karla, J. K. (2015). An empirical study on Efficient Market Hypothesis of Indian Capital Market. *Journal of Management Research and Analysis , 2* (2), 108-114.

16. Op. Cit. 4

17. Jonsson, R., & Radeschnig, J. (2014). *From Market Efficiency to Event Study Methodology*. Sweden: Malardalen University.

18. Brown, S. J., & Warner, J. B. (1980). Measuring Security Price Performance. *Journal of Financial Economics , 8* (3), 205-258.

19. Dolley, J. C. (1933). Characteristics and Procedure of Common Stock Split-Ups. *Harvard Business Review , 37* (5), 316-326.

20. MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature , 35* (1), 13-39.

21. Ibid
22. Op. Cit. 19
23. Op. Cit. 17

24. Dyckman, T., Philbrick, D., & Stephen, J. (1984). A Comparison of Event Study Methodologies Using Daily Stock Returns: A Simulation Approach. *Journal of Accounting Research , 22,* 1-33.

25. Op. Cit. 20

26. Brown, S. J., & Warner, J. B. (1985). Using Daily Stock Returns: The case of Event Studies. *Journal of Financial economics , 14* (1), 3-31.

27. Op. Cit. 20
28. Op. Cit. 20
29. Op. Cit. 18

30. Chakraborty, P. (2011). Semi- Strong of Pricing Efiiciency of Indian Stock Market - An Emiprical Test in the Context of Stock-Split Announcement. *EXCEL International Journal of Multidisciplinary Management Studies , 1* (2), 1-13.

31. Asquith, P. (1983). Merger Bids, Uncertainty and Stockholder Returns. *Journal of Financial Economics* , 51-83.

32. Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (2007). *The Econometrics of Financial Markets.* New Delhi: New Age International .

33. Op. Cit. 30

34. Op. Cit. 4

35. Op. Cit. 4

36. Chung, H. Y. (2006). *Testing Weak Form Efficiency of the Chinese Stock Market.* Karhula: Lappeenranta University of Technology.

37. Op. Cit. 13

38. Gupta, R. K. (2014). Weak Form Efficiency of Indian Stock Market with Reference to BSE. *International Journal of Research in Business Management , 2* (9), 15-20.

39. Op. Cit. 15

40. Guptha, R., & Basu, P. K. (2007). Weak Form Efficiency in Indian Stock Markets. *International Business and Economics Research Journal , 6* (3), 57-64.

41. Sachin, K., & sanningammanavara, K. (2014). The Efficiency Testing of Weak Form of Indian Stock Market. *International journal of Engineering and Management Research , 4* (4), 44-53.

42. Op. Cit. 11

43. Jaffe, J. F. (1974). Special Information and Insider Trading. *Journal of Business* , 47-59.

44. Seyhun, H. N. (1986). Insiders' Profits, Costs of Trading and Market Efficiency'. *Journal of Financial Economics* , 16-29.

45. Givoly, D., & Palmon, D. (1985). Insider Trading and Exploitation of Insider Information: Some Empirical Evidence. *Journal of Business* , 58-71.

Chapter 6

Role of Security Analysis in Investment Decision

6.1 Introduction

As discussed in the previous chapters, Volatility exists in the Indian stock market and it is very high in short-term period when compared to medium term and long term periods and Indian stock market is not efficient in its weak form, but efficient in its semi-strong form. At the outset, the researcher investigates the reasons for anomalies and the role and relation of security analysis, behavioural bias and emotional intelligence and their impact on investment performance. In the previous chapter the theoretical frame work of the concepts of security analysis, behavioural bias, emotional intelligence and investment performance of individual investors have been presented. This and the next chapters are devoted to the analysis of the primary data regarding security analysis, behavioural bias, emotional intelligence and investment performance collected from 390 individual investors in Kerala. The researcher used the exploratory factor analysis to find out the underlying factors of the key variable and also the confirmatory factor analysis to confirm the factors under study.

The researcher selected five socio-economic variable namely gender, age, educational qualification, annual income and marital status to categorise response on above variables, (security analysis, behavioural bias, emotional intelligence and investment performance) and check the differences in response among the different categories of investors. As gender and marital status is having only two levels Independent sample ‘t’ test is used to evaluate the difference. Other categorical variable like age, educational qualification and annual income variables are having more than two levels hence, ANOVA has been used to test the difference among different level of variables.

The chapter is divided into two sections, namely section A and section B. Section A deals with the profile of the sample customers so as to get an idea of socio-economic character of investors and section B is dealt with the detailed analysis of the primary data.

Section A

6.1 Profile of Sample Investors

It is very relevant to appraise the profile of sample investors before entering into the primary data analysis. It is presented below:

6.1.1 Gender-wise Classification of Sample Investors

Kerala is one of the states known to have more female than male population. It gives a fair deal to women in all sectors like health care, education, employment and social participation. The gender-wise distribution of the data is presented in table 6.1

Table 6.1

Gender-wise Classification of Sample Investors

Gender	Frequency	Percent
Male	349	89.5
Female	41	10.5
Total	**390**	**100.0**

Source: Field Survey

It can be observed from the table that 349 (89.5%) of the sample investors are male and the remaining 41 (10.5%) are female. Even though the female population in Kerala outnumbers male population, they are very less in the field of corporate security investment.

6.1.2 Place of Domicile-wise Classification of the Sample Investors

Rural urban division is very thin in the state of Kerala when compared to the other states in India. It is very difficult to find any true rural places in Kerala. Hence, the researcher classified the place of domicile of informants as Municipal Corporation, Municipality and Grama Panchayath. Now, the Kerala state is having 6 Municipal Corporation, 87 Municipalities and 941 Grama Panchayaths. The classification of informants according to their place of domicile is presented in table 6.2

Table 6.2

Place of Domicile-wise Classification of Sample Investors

Place of Domicile	Frequency	Percent
Corporation	165	42.3
Municipality	125	32.1
Panchayath	100	25.6
Total	**390**	**100.0**

Source: Field Survey

Table shows that 165 (42.3%) of the sample investors reside in Corporation area, 125 (32.1%) in Municipality area and 100 (25.6%) Panchayath area. From the above distribution it can be inferred that majority of the investors in the sample belongs to urban areas of Kerala.

6.1.3 Religion-wise Classification of Sample Investors

Three main religious groups in Kerala are Hindus, Christians and Muslims. Others like Sikhs, Jains and Jews are very few in numbers.   Of these three major religions, Hindus contain half of the state population and are spread all over the state, other half consist of Christians and Muslims with more or less equal strength. Muslim are concentrated in the northern part of Kerala while Christians in the central part. Table 6.3 shows the religion-wise classification of sample investors.

Table 6.3

Religion-wise Classification of Sample Investors

Religion	Frequency	Percent
Hindu	178	45.6
Christian	112	28.7
Muslim	100	25.6
Total	**390**	**100.0**

Source: Field Survey

It can be understood from the table 6.3 that 45.6 % of the sample investors are Hindus, 28.7% are Christians and 25.6% are Muslims. This is a fare representation of the state's population.

6.1.4 Age-wise Classification of Sample Investors

The proportion of child population to the total population in Kerala is decreasing year by year whereas middle aged and elderly population are showing an increasing trend. Following is the age-wise distribution of sample respondent.

Table 6.4

Age-wise Classification of Sample Investors

Age (in years)	Frequency	Percent
18 – 30	68	17.4
31 – 40	128	32.8
41 – 50	118	30.3
Above 50	76	19.5
Total	**390**	**100.0**

Source: Field Survey

It can be noticed in the table that out of 390 investors 68 (17.4%) are in the age category 18-30 years, 128 (32.8%) from 31-40 years, 118 (30.3%) from 41-50 years and 76 (19.5%) from the above 50 years age category. The mean age of the sample investors is approximately 42 years which indicates that the youth are more involved in the corporate investment.

6.1.5 Education-wise Classification of Sample Investors

Kerala is one of the most educated states in India. The state gives more importance to female education. Child literacy is almost cent percent in Kerala. Number of college students is also high when compared to the other states in India. The following table shows the education-wise classification of sample investors.

Table 6.5

Education-wise Classification of Sample Investors

Educational Qualification	**Frequency**	**Percent**
Under Graduate	25	6.4
Graduate	232	59.5
Post Graduate	117	30.0
Professional	16	4.1
Total	**390**	**100.0**

Source: Field Survey

It can be noticed from the table that out of 390 sample investors 25 (6.4%) are under graduates, 232 (59.5%) are graduates, 117 (30%) are post graduates and 16 (4.1%) are having professional qualification. Hence it can be concluded that the informants selected for the study are reasonably educated and are able to understand the technical side of the study.

6.1.6 Occupation-wise Classification of Sample Investors

The table 6.6 shows the classification of sample investors on the basis of occupation. It can be observed from the table that out of 390 respondents 267 (68.5%) are employed in the private or government sector, 16 (4.1%) are in profession, 48 (12.3%) are in business and 59 (15.1%) are retired hands.

Table 6.6

Occupation-wise Classification of Sample Investors

Occupation	Frequency	Percent
Employed	267	68.5
Professional	16	4.1
Business	48	12.3
Retired	59	15.1
Total	**390**	**100**

Source: Field Survey

6.1.7 Marital Status-wise Classification of Sample Investors

It can be assumed that the married people are more serious and careful in investment than a single. To test this assumption, the investors are categorised into married and single investors.

Table 6.7

Marital Status-wise Classification of Sample Investors

Marital Status	Frequency	Percent
Married	343	87.9
Single	47	12.1
Total	**390**	**100.0**

Source: Field Survey

From the above table, it can be seen that 87.9% (343) of the sample investors are married and the rest are Single.

6.1.8 Annual income-wise Classification of Sample Investors

There are contradictory opinion about the relationship between annual income and investment decision. Some people argue that the one who is having less income will be more careful in investing, but others argue just opposite to that. To check this argument the investors are categorised according to their annual income and the relevant data is presented in the table 6.8.

Table 6.8

Annual income-wise Classification of Sample Investors

Annual Income (in rupees)	Frequency	Percent
Less than 5,00,000	129	33.1
5,00,000 – 10,00,000	143	36.7
10,00,000 – 15,00,000	90	23.1
More than 15,00,000	28	7.2
Total	**390**	**100.0**

Source: Field Survey

It can be seen from the table that out 390 of the sample investors, 129 (33.1%) belong to the annual income category 'less than Rs.5,00,000', 143 (36.7%) belongs to 'Rs.5,00,000 – 10,00,000', 90 (23.1%) belongs to Rs.10,00,000 to 15,00,000 and 28 (7.2%) belongs to 'More than Rs.15,00,000' income category. The mean annual income of sample investors is Rs.7,71,794.

6.1.9 Generation-wise Classification of Sample Investors

Here the researcher classified the investors as first generation investor and second generation investor. The first generation investor is the investor who starts the investment in equity for the first time in his / her family. The second generation investor is not the first to invest in equity, his parents or other elder members in the family started the equity investment. Normally, we assume that second generation investors outperform the first generation investors because they may learn all about the investment from their predecessors in the family

Table 6.9

Generation-wise Classification of Sample Investors

Generation of Investor	Frequency	Percent
First Generation Investor	342	87.7
Second Generation Investor	48	12.3
Total	**390**	**100.0**

Source: Field Survey

It can be noticed from the table 6.9 that most (87.7%) of the sample investors are first generation investors, only 12.3% of investors are second generation investors. Hence it can be concluded that family investment culture in corporate securities is less in Kerala.

6.1.10 Experience-wise Classification of Sample Investors

It may be assumed that the more experienced investors outperform the less experienced ones. To test this phenomenon, the investors are categorised according to their experience in years in the stock market. The following table shows the result.

Table 6.10

Experience-wise Classification of Sample Investors

Experience in Equity Investment (in years)	Frequency	Percent
Below 5 Years	130	33.3
5 – 10 Years	127	32.6
11 – 15 Years	41	10.5
Above 15 Years	92	23.6
Total	**390**	**100.0**

Source: Field Survey

The table shows the classification of sample investors according to the year of experience in the equity investment. It can be observed that one third (33.3%) of the investors is having the experience of less than 5 years, 32.6% is having the experience of 5-10 years, 10.5% is having the experience of 11 - 15 years and 23.6% having ‘more than 15 years’ experience. The mean experience in equity investment of the sample investors is 9.81 years.

6.1.11 Holding Period-wise Classification of Sample Investors

It may be assumed that the investor who is holding the shares for more periods outperform the investors holding shares for fewer periods. To test the assumption, the investors are categorised according to the average period they hold the shares.

Table 6.11

Holding Period-wise Classification of Sample Investors

Average Holding Period (in years)	Frequency	Percent
Below 1 year	191	49.0
1 – 3 years	168	43.1
Above 4 years	31	7.9
Total	**390**	**100.0**

Source: Field Survey

The above table classified the sample investors according to the year of average holding period of investment in equity shares. It can be noticed that almost half (49%) of the investors are holding the equity shares below one year, 43.1% of investors holding 1 to 3 year, only 7.9% of investors are holding more than 4 years. The mean average holding period of the sample investor is 1.09 years. Hence it can be concluded that majority of the sample investors are short term or medium term investors. Long term and very long term investors are less in number.

Section B

6.2 Security Analysis

Analysis is the careful study of the available facts with an attempt to draw conclusions based on the established principles and sound logic. It is a part of scientific method. But while applying analysis in the field of securities investment one encounters a serious obstacle that investment by nature is not an exact science rather an individual skill (art) and chances are important factors here in determining success or failure (Graham & Dodd, 2008)[1].

The golden rule of securities investment is to 'buy low and sell high'. If an investor wants to make fortune out of investment, he has to buy the undervalued stock of the good (fundamentally strong) companies. If the company is good and is already overvalued, it is not advisable to invest in the shares it. Similarly, if some stocks are undervalued and their fundamentals are weak, it is also not advisable to invest. Securities analysis is all about identifying the mispriced securities, i.e. underpriced and overpriced securities so that one can buy security at lower price, sell at a higher price and maximise the wealth. There are lots of approaches to security analysis. All these approaches fall into two broad classifications, namely fundamental analysis and technical analysis. Some people use the mix of these two approaches called techno-fundamental analysis.

Fundamental Analysis

This is based on the belief that the market price of the security will be almost equal to its intrinsic value in the long run. Then the fundamental analysis is nothing, but to determine the intrinsic value of a security. To calculate the intrinsic value of an equity share, the analyst must forecast the all expected future earnings (in the form of dividend, capital appreciation etc.,) from the equity share and the volatility of return indicated by risk of the equity share. This earnings potential and risk depends upon variety of economy wide, industry wide and company specific (which include quantitative and qualitative) factors.

Once the intrinsic value is calculated, the same should be compared with the market price. The market price is a function of market demand and supply of the shares. If the market price is less than the intrinsic value then the share is underpriced and hence should be bought. On the other hand, if market price is more than the intrinsic value then the share is overpriced and hence should be sold. Finally, if the intrinsic value and the market price are same, the investor has to hold the security and wait for the next movement.

Technical Analysis

This is the study of trends and price patterns of security in the market so as to take the investment decision. Technical analysis is purely based on the past data of stock prices and the philosophy of, “History repeats itself”, as stock prices are predicted based on precedence (Pandya, 2013)[2]. It is simply when demand is high without corresponding increase in supply; the price will go up and vice versa. The demand and supply is the function of the collective wisdom buyers, sellers and market intermediaries. By closely observing the price pattern one can predict the future price with a reasonable degree of accuracy. Technical analyst uses stock charts, mathematical indicators and market indicators to predict the future price of a share.

Techno-fundamental analysis assimilates the strength of both fundamental analysis and technical analysis. Fundamental analysis can be used to identify the stocks to buy or sell, whereas technical analysis can be used to determine when to buy.

To find out the extent of the use of security analysis by investors, a five point Likert scale is developed and the respondents were asked to rate the following items ranging from highly used (5) to not at all used (1).

The statements FI1 to FI22 are asked to know about extent of the use of fundamental analysis while statements FI 23 to FI 29 are about technical analysis. The statements FI 1 to FI 6 are related to Economic analysis, statements FI 7 to FI 9 are related to Industry analysis and FI 10 to FI 22 are related to Company analysis which include the statements of quantitative and qualitative analysis. The statements FI 23 to FI 29 include statements related to stock charts, mathematical indicators and market indicators. The mean values for these statements are given below with their respective standard deviations.

Table 6.12
Indicators of Security Analysis

Variable Name	Indicators	Mean	Standard deviation
FI1	Growth rate of the economy	4.0538	1.12904
FI2	Inflation rate	3.8051	1.13508
FI3	Interest rate	3.7564	1.18023
FI4	Exchange rate	3.7974	1.11889
FI5	Infrastructure	3.6641	1.16614
FI6	Economic & political stability	3.8590	1.10531
FI7	Industry growth relative to the GDP	3.2179	1.16336
FI8	Permanence – need for a particular industry	3.3179	1.13891
FI9	Cost structure – fixed cost to variable cost	3.3308	1.19158
FI10	Business plan of the company	3.6982	1.19681
FI11	Quality of the management	3.7308	1.16375

Variable Name	Indicators	Mean	Standard deviation
FI12	Debt Equity ratio	3.9128	1.06479
FI13	Competitive edge	3.7667	1.12892
FI14	Promoter's holdings in shares	3.7923	1.08765
FI15	Company's market share	3.7513	1.10952
FI16	Past performance of the company's share	3.9103	1.01386
FI17	Analysis of financial statement	3.9000	.99755
FI18	Earnings Per Share	3.9051	1.03349
FI19	Price Earnings ratio	3.8256	1.11330
FI20	Price to Book ratio	3.7128	1.07296
FI21	Dividend payout ratio	3.7205	1.08571
FI22	Return on equity	3.7641	1.06147
FI23	Volume of trade	3.6795	1.09795
FI24	52 weeks high and low	3.6154	1.10422
FI25	stock Charts	3.7256	1.09878
FI26	Moving Averages	3.6641	1.05015
FI27	Breadth of the market = advances - declines	3.6821	1.00969
FI28	Market indices	3.7154	.97449
FI29	Relative strength index	3.6744	1.02619

Source: Field Survey

It can be observed from the above table that 'growth of the economy' is having highest mean score of 4.0538(SD 1.12904) followed by 'debt equity ratio' 3.9128(SD 1.06479) and 'past performance of company's share' 3.9103 (SD 1.01386). The 'industry growth relative to GDP' is having least mean score of 3.2179 (1.16336).

6.2.1 Factors of Security Analysis

Factor analysis is used for grouping the abovementioned 29 variables to underlying factors in security analysis. It analyses the structure of correlation among large number of variables by defining group of variable that are highly correlated, called as factors. To evaluate the attitude of investors towards security analysis, a five point Likert scale is developed and the respondents were asked to rate the extent of the use of specific variables while taking investment decision in equity shares, ranging from highly used (5) to not at all used (1). The number of statements included in the measurement instrument was 35; further the statements were reduced to 29 based on the communalities in the extraction. Six statements were excluded from the analysis frame because of the low extraction values. It is seen that the communalities after deleting seven statements show significantly large values suggesting that the statements are useful to analyse the attitude of investors towards security analysis. In order to verify the adequacy or appropriateness of data for factor analysis, Kaiser- Meyer- Oklin Measure of sampling adequacy (KMO) and Bartlett's test of Sphericity are applied. The Kaiser-Meyer- Oklin measure of sampling adequacy is an index used for comparing the magnitudes of the observed correlation coefficients to the magnitudes of the partial correlation coefficients. KMO statistics vary between 0 and 1. A value of 0 indicates that the sum of partial correlation is large relative to the sum of correlation. Hence factor analysis is likely to be inappropriate. A value close to 1 indicates that patterns of correlation are relatively compact and hence the factor analysis should yield distinct and reliable factors. The Bartlett's Test of Sphericity reveals the validity and suitability of the responses collected to the problem being addressed through the study. It is recommended that the Bartlett's Test of Sphericity must be less than 0.05 to be suitable in factor analysis. The following table shows the KMO and BTS results:

Table 6.13

KMO and Bartlett's Test - Security Analysis

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.910
Bartlett's Test of Sphericity	Approx. Chi-Square	5844.740
	Df	406
	Sig.	.000

Source: Field Survey

The correlation matrix showed sufficient items to justify the factorability of data. The KMO and Bartlett's test of sphericity produces the Kaiser- Meyer- Olkin measure of sampling adequacy and Bartlett's test. KMO for overall matrix was found to be excellent (0.910) which is greater than 0.5 (Kaiser, 1974) and Barlett's test of sphericity (BTS) value is found significant ($p<0.000$) which meant that data is appropriate for Exploratory Factor Analysis (EFA). The details of factor analysis are given below:

Table 6.14

Total Variance Explained by Variables of Security Analysis

Factor	**Components**	**Initial Eigen values**			**Extraction Sums of Squared Loadings**		
		Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	Quantitative Analysis	8.615	29.706	29.706	8.615	29.706	29.706
2	Technical Analysis	3.254	11.221	40.926	3.254	11.221	40.926
3	Economic Analysis	2.631	9.074	50.000	2.631	9.074	50.000
4	Qualitative Analysis	2.168	7.476	57.476	2.168	7.476	57.476
5	Industry Analysis	1.728	5.958	63.434	1.728	5.958	63.434

Extraction Method: Principal Component Analysis.

Source: Field Survey

Table given above shows the percentage of variances and the Eigen values of the five factors namely quantitative analysis, technical analysis, economic analysis, qualitative analysis and industry analysis which explained the 63.43 percentage of total variances. With the principal component analysis, five components are extracted towards security analysis in the present context. The result shows that 63.434 % of the total variance is explained by these five factors. The first factor namely quantitative analysis explains 29.71 per cent of variance with the eigen value of 8.615. The second factor, technical analysis explains 11.22 per cent variance (eigen value of 3.254) followed by third factor, economic analysis 9.07 per cent variance (eigen value 2.631), fourth factor, qualitative analysis 7.48 per cent variance (eigen value 2.168) and the last factor, industry analysis 5.99 per cent variance (eigen value 1.728).

It is also clear from the following scree plot.

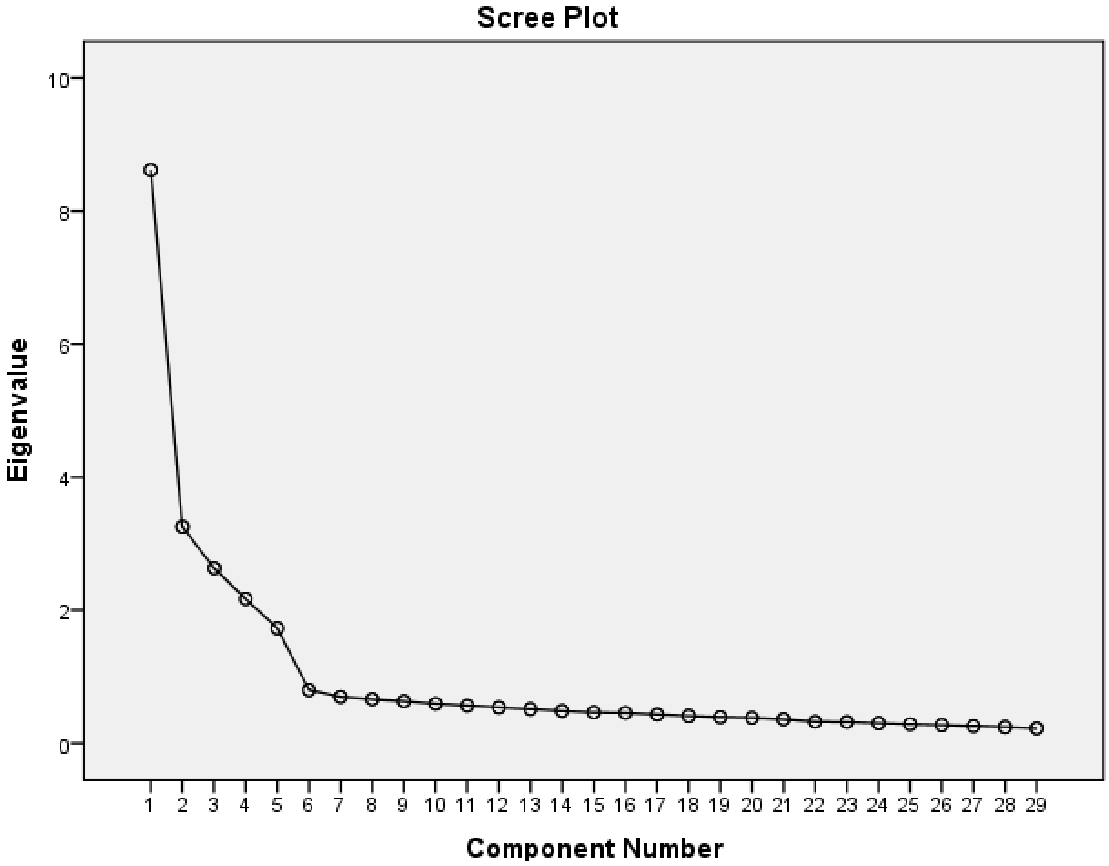


Figure 6.1 Scree Plot – Security Analysis

The diagram 6.1 makes it clear that all the 29 statements are combined and split into five components (having eigen value more than one).

The table presented below explains the rotated component factor loadings of security analysis.

Table 6.15

Rotated Component Matrix of Security Analysis

Variable Name	Items	Component				
		1	2	3	4	5
FI20	Price to Book Ratio	.787				
FI17	Analysis of Financial Statement	.759				
FI16	Past Performance of Company Share	.738				
FI21	Dividend Payout Ratio	.734				
FI22	Return on equity	.733				
FI19	Price Earnings Ratio	.720				
FI18	Earnings per Share	.706				
FI12	Debt Equity ratio	.695				
FI28	Market Indices		.820			
FI23	Volume of Trade		.798			
FI29	Relative Strength Index		.780			
FI26	Moving Averages		.754			
FI24	52 weeks high and low		.753			
FI27	Breadth of the market		.750			
FI25	Stock Charts		.734			
FI5	Infrastructure			.756		
FI2	Inflation Rate			.745		
FI3	Interest Rate			.736		
FI1	Growth Rate of the Economy			.700		
FI4	Exchange Rate			.675		
FI6	Economic and Political Stability			.674		
FI14	Promoter’s Holdings in Shares				.810	
FI15	Company’s Market Share				.787	
FI10	Business Plan of the Company				.784	
FI13	Competitive Edge				.779	
FI11	Quality of the Management				.778	
FI8	Permanence – need of industry					.840
FI9	Cost structure					.834
FI7	Industry growth					.829

Source: Field Survey

The table depicts the result of Principle Component Analysis construct after rotated factor matrix. Variables with factor loadings near to 0.70 were only chosen for the study. After performing Varimax Rotation Method in Kaiser Normalization, factors of security analysis are grouped into five factors as per the following:

- The first group is extracted 29.71 per cent. It consists of eight items. They are ‘Price to book ratio’ with highest loading (0.787), followed by ‘Analysis of financial statement’ (loading 0.759), ‘past performance of the company’s share’ (loading 0.738), ’Dividend Payout Ratio’ (loading 0.734), ‘Return on Equity’ (loading 0.733), ‘Price Earnings Ratio’ (loading 0.720), ‘Earning per share’ (loading 0.706), ‘Debt Equity Ratio’ (loading 0.695). These variables together constitute a common factor, whose characteristics are related to the fundamental analysis, but it does not include qualitative attributes of fundamental analysis. Hence, it is entitled as **‘Quantitative Analysis’.**

- Second group which is extracted 11.22 per cent of total variances included seven items. They are ‘Market Indices’ with highest loading (0.820), followed by ‘Volume of Trade’ (loading 0.798), ‘Relative Strength Index’ (loading 0.780), ’Moving Average’ (loading 0.754), ’52 weeks high and low’ (loading 0.753), ‘Breadth of the Market’ (loading 0.750), ‘Stock charts’ (loading 0.734). These variables together constitute a common factor, whose characteristics are related to the technical analysis. Hence, it is called as **‘Technical Analysis’.**

- Third group is extracted 9.07 per cent of total variances included six items. They are ‘Infrastructure’ with highest loading (0.754), followed by ‘Inflation Rate’ (loading 0.745), ‘Interest Rate’ (loading 0.736), ’Growth Rate’ (loading 0.700), ’Exchange Rate’ (loading 0.675), ‘Economic and Political Stability’ (loading 0.674). These variables together constitute a common factor, whose characteristics are related to the economy. Hence, it is named as **‘Economic Analysis’.**

- Fourth group which is extracted 7.48 per cent of total variances included five items. They are ‘Promoter’s Holdings in shares’ with highest loading (0.810), followed by ‘Company’s Market Share’ (loading 0.787), ‘Business Plan of the Company’ (loading 0.784), ’Competitive Edge’ (loading 0.779), ’Quality of the Management’ (loading 0.778). These variables together constitute a common factor, whose characteristics are related to the fundamental analysis which is qualitative in nature. Hence, it is termed as **‘Qualitative Analysis’.**

- Fifth and last group is extracted 5.99 per cent of total variances included three items. They are ‘Permanence’ with the highest loading (0.840), followed by ‘Cost Structure’ (loading 0.829. These variables together constitute a common factor, whose characteristics are related to the Industry. Hence, it is named as **‘Industrial Analysis’.**

Thus, through exploratory factor analysis, 29 variables are split into five components, i.e, Qualitative analysis, Technical analysis, Economic Analysis, Qualitative analysis and Industry Analysis. They are identified as the dimensions of Security analysis in the present study.

6.2.2 Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is used to validate the scale of security analysis and test how well measured variable represents a smaller number of constructs. It is a measurement model of Structural Equation Modeling (SEM), which deals with the relationship between observed measures or indicator. This statistical technique tells us the suitability of theoretical specification of factors to the reality. It is used to confirm the factor structure of a set of observed variables. Structural Equation Modeling software is typically used for performing confirmatory factor analysis. The researcher used CFA as a first step to assess the proposed Measurement model in a structural equation model. The following figure shows the measurement model:

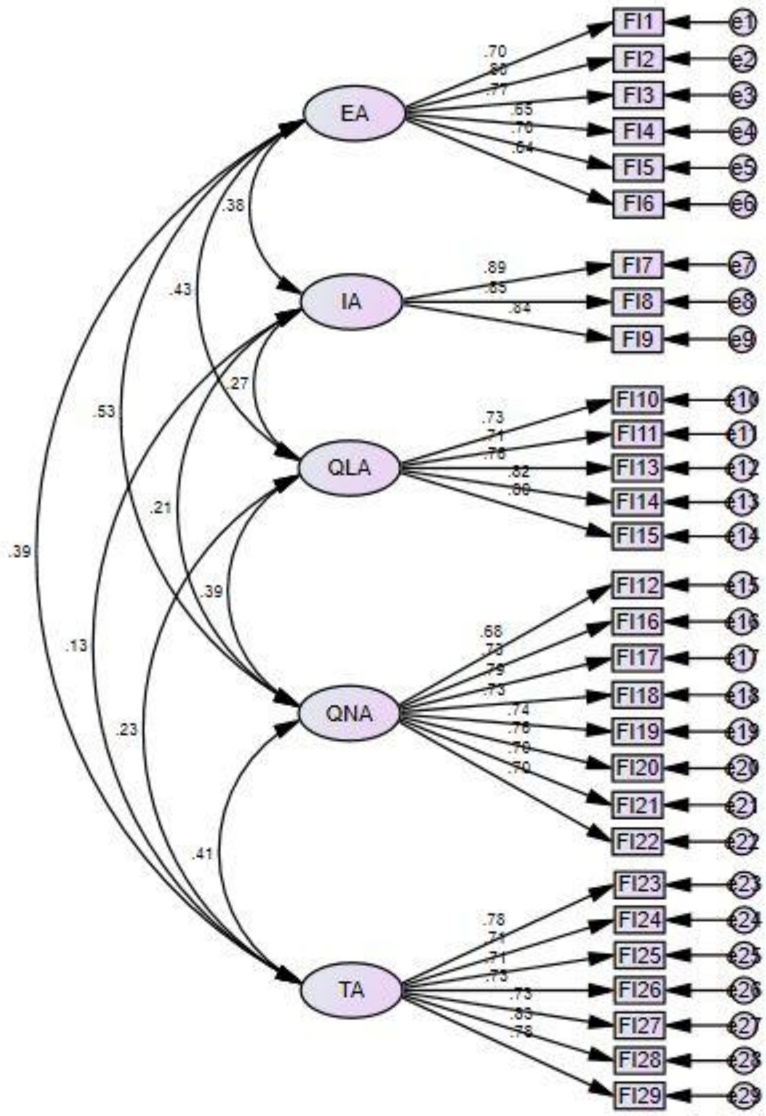


Figure 6.2. Confirmatory Factor Analysis – Security Analysis

Measurement model of security analysis is tested by a Confirmatory Factor Analysis by using Amos 21. This measurement model is developed to test the attitude of investors towards different factors of security analysis with regard to different socio-economic variables. Reliability of the scale developed for the study was tested by using Cronbanch's alpha value method and which is found to be significant. The structural equation model using Amos produces several indices of fit like measure of absolute fit, comparative fit and parsimonious fit etc. The following are the most commonly used fit indices:

Table 6.16

Model Fit Indices – Security Analysis

Sl. No	Indices of Common Fit	Value	Value of Good Fit
1.	CMIN/DF	1.636	<5
2.	RMR	0.048	<0.05
3.	Goodness of Fit Index (GFI)	0.954	>0.90
4.	Comparative Fit Index (CFI)	0.960	>0.90
5.	Adjusted GFI (AGFI)	0.905	>0.90
6.	Incremental Fit Index (IFI)	0.961	>0.90
7.	Tucker Leiws Index (TLI)	0.965	>0.90
8.	Normed Fit Index (NFI)	0.905	>0.90
9.	Root Mean Square Error of Approximation (RMSEA)	0.040	<0.08

Source: Field Survey

Table 6.16 shows the different model fit indices of confirmatory factor analysis. The confirmatory factor analysis is good with Goodness of Fit Index (GFI) 0.954; Tucker Lewis Index (TLI) 0.965; Comparative Fit Index (CFI) 0.960; Root Mean Square Error of Approximation (RMSEA) 0.040; CMIN/df 1.636 and p-value 0.000. The present scale developed for the study was supported by the result of the Confirmatory Factor Analysis. Hence all the fit indices are satisfactory and appropriate for the scale, the Confirmatory Factor Analysis Confirms the structure of measurement scale.

To know the extent of the use of different dimensions of security analysis while taking the investment decision, the researcher has calculated the mean score and the standard deviation of latent variables. It is shown in the table 6.17

Table 6.17

Descriptive of the Different Factors of Security Analysis

Variables	Mean	Standard deviation
Quantitative analysis	3.8314	.81050
Technical analysis	3.6795	.83318
Economic analysis	3.8226	.87351
Qualitative analysis	3.7738	.92929
Industry analysis	3.2889	1.00087

Source: Field Survey

The table 6.17 shows that quantitative analysis is having the highest mean score 3.8314 (SD 0.81050) followed by economic analysis having the mean score of 3.8226 (SD 0.87351) which are more than the mean score of overall security analysis 3.7269 (SD 0.58914). This hints that investors use quantitative and economic analysis mostly while they take the investment decision. The least mean score is for industry analysis 3.2889 (SD 1.00087).

6.2.3 Relation between Socio-Economic Variables with Security Analysis

The socio economic variable like gender, age, educational qualification, annual income and marital status are used for analyzing the extent of use of security analysis and its factors while taking the investment decision. The descriptive and inferential statistics of the socio economic variables in respect of security analysis and its factors are presented below.

6.2.4 Gender-wise Comparison of Security Analysis and its Factors

The male and female may have different extent of use of security analysis in their investment decision. In this section, the researcher tries to find out the proportional difference among gender. To know the difference, the researcher has calculated the mean score of security analysis. To find out the statistical significance of the difference in mean score ‘t’ is applied. The result is shown in table 6.18.

Table 6.18

Gender-wise Comparison of Security Analysis

Gender	N	Mean	Max Score	SD	t value	p value	Remarks
Male	349	107.92	145	17.70	-.236	.813	Equal variance assumed
Female	41	109.43		10.60			
Total	**390**	**108.08**		**17.09**			

Source: Survey Data

From the table 6.18, it can be observed that on an average the percentage use of security analysis by investors is 74.5% while taking investment decision. Mean score in this respect is 108.08 (SD 17.09) out of the maximum score of 145. The mean score security analysis of male is 107.92 (17.70) differing from female 109.43 (10.60). The Independent sample t test is used to check whether the difference is significant or not, among male and female with regard to security analysis. Since the p value of the t test is more than .05, it is concluded that there is no significant difference between male and female in their use of security analysis for investment decision.

Even though, there is no significant difference between male and female with regard to security analysis, the researcher tests the difference among gender with regard to the different dimensions of security analysis. The results have been shown in the table 6.19

Table 6.19

Gender-wise Comparison of Dimensions of Security Analysis

Dimensions	Gender	N	Mean	SD	Max Score	t value	p value	Remarks
Quantitative	Male	349	30.62	5.91	40	-.047	.963	Equal variance assumed
	Female	41	30.88	3.99				
	Total	**390**	**30.65**	**6.48**				
Technical	Male	349	25.99	5.79	35	2.364*	.019	Equal variance assumed
	Female	41	23.73	5.85				
	Total	**390**	**25.76**	**5.83**				

Dimensions	Gender	N	Mean	SD	Max Score	t value	p value	Remarks
Economic	Male	349	22.79	5.41	30	-2.263*	.027	Equal variance not assumed
	Female	41	24.10	3.17				
	Total	**390**	**22.94**	**5.24**				
Qualitative	Male	349	18.75	4.76	25	-1.934	.058	Equal variance not assumed
	Female	41	19.87	3.36				
	Total	**390**	**18.87**	**4.64**				
Industry	Male	349	9.75	3.06	15	-2.841**	.006	Equal variance not assumed
	Female	41	10.85	2.25				
	Total	**390**	**9.87**	**3.00**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.19 makes clear that in investors' extent of use among the dimensions of security analysis, the factors like quantitative fundamental analysis and qualitative fundamental analysis have no significant difference between male and female investor since the p value is more than 0.05.

In the case of technical factor of security analysis, there is significant difference between male and female investor, as the p value (0.019) is less than 0.05. The mean score of the technical analysis of male investor is 25.99 (74.25%) and the mean score of the female investor is 23.73 (67.8%) out of the total score of 35. From this result, it is clear that male investors must be very much concerned in technical analysis as they are having more trading mentality than female investors.

Similarly, when the dimension of economic analysis is concerned, the mean score of male and female investors are significantly different. Unlike the technical analysis, here the mean score of female investor 24.10 (80.33%) is more than that of male investor 22.79(75.96%). It is evidently clear from the result that females are more careful in analysing economic fundamentals than their counterpart while they make the investment decision.

In industry analysis, the mean score difference of male and female investors are significant even at 1% significant level (p value = 0.006). In this case also female mean score 10.85 (72.33%) is more than that of male 9.75 (65%) which means female gives more importance than male investors in industry analysis.

Hence it can be concluded that though there is no significant difference in mean score of male and female in overall security analysis, they are different in most of the elements of security analysis. The interesting finding is that male is having more average score only in technical analysis because of their trading mentality, in all others, the score of female is better than the male which shows that female folk are more careful in investment decision than their counterparts.

6.2.5 Age Category-wise Comparison of Security Analysis and its Factors.

Investors in different age category may have different perception about the importance of security analysis. Descriptive analysis has been done to check the same. It is found that the mean score is different for investors in different age categories. Then one way Analysis of Variance is applied to test the significance of difference among mean of different age category.
The result is shown in the Table 6.20.

Table 6.20

Age Category-wise Comparison of Security Analysis

Age Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
18 - 30 Years	68	112.69	13.37	145	4.790^{**}	.003	Welch
31 - 40 Years	128	108.98	14.48				
41 - 50 Years	118	102.96	20.88				
Above 50 Years	76	110.39	13.15				
Total	390	108.08	17.09				

Source: Survey Data
*, ** statistically significant at the 5%, and 1% significant level

From the above table it can be understood that the highest mean score is 112.69 (13.37) which is in the age category of '18 – 30 years' and the lowest mean is 102.96 (20.88) in age category '41-50 years'. The p value is 0.003 which means there is significant difference among the mean score of investors in different age categories. To know exact difference between different age groups one has to use the multiple comparisons. In this case, researcher uses the Tamhane's T2 test to identify the pair wise differences since the equal variances are not assumed. The result is shown in table 6.21.

Table 6.21

Age Category-wise Post Hoc Test - Security Analysis

Age Category (I)	Age Category (J)	Mean Difference (I-J)	Std. Error	p value
18 – 30 Years	31 - 40 Years	3.23943	2.01758	.505
	41 - 50 Years	9.17124*	2.47529	.002
	Above 50 Years	2.00464	2.16985	.929
31 – 40 Years	18 - 30 Years	-3.23943	2.01758	.505
	41 - 50 Years	5.93181	2.30903	.064
	Above 50 Years	-1.23479	1.97810	.990
41 – 50 Years	18 - 30 Years	-9.17124*	2.47529	.002
	31 - 40 Years	-5.93181	2.30903	.064
	Above 50 Years	-7.16659*	2.44321	.022
Above 50 Years	18 - 30 Years	-2.00464	2.16985	.929
	31 - 40 Years	1.23479	1.97810	.990
	41 - 50 Years	7.16659*	2.44321	.022

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The result of Tamhane's T2 test shows that there is significant difference in the pairs of age category '41 – 50 years' with '18-30' and 'above 50 years' (p=.002, .022). Since mean difference of age category '41-50' is negative, this category gives less importance to the security analysis than investors in other age categories.

To be more specific, the researcher has done the descriptive analysis of the different factors of security analysis with regard to age category. To test the statistical significance F test also is applied. To test the homogeneity of variance Levene test has applied. The results are shown below. The result of the Levene's test of homogeneity is presented in table 6.22.

Table 6.22

Age Category-wise Test of Homogeneity of Variances

Dimensions	Levene's Statistic	P Value
Quantitative Analysis	4.434**	.004
Technical Analysis	2.204	.087
Economic Analysis	10.606**	.000
Qualitative Analysis	4.721**	.003
Industry Analysis	3.544*	.015

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

It can be seen from the table 6.22 that all the dimensions except technical analysis show the heterogeneity.

Table 6.23
Age Category-wise Comparison of Factors of Security Analysis

Dimensions	Age Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Quantitative Analysis	18 - 30 Years	68	32.04	6.88	40	2.717	.068	Welch
	31 - 40 Years	128	30.73	5.25				
	41 - 50 Years	118	29.23	7.91				
	Above 50 Years	76	31.47	5.10				
	Total	390	30.65	6.48				
Technical Analysis	18 - 30 Years	68	28.13	5.14	35	5.843**	.001	ANOVA
	31 - 40 Years	128	25.63	5.62				
	41 - 50 Years	118	24.49	6.54				
	Above 50 Years	76	25.80	4.99				
	Total	390	25.76	5.83				
Economic Analysis	18 - 30 Years	68	23.51	4.48	30	2.006	.115	Welch
	31 - 40 Years	128	23.61	4.02				
	41 - 50 Years	118	22.05	6.61				
	Above 50 Years	76	22.66	5.17				
	Total	390	22.94	5.24				
Qualitative Analysis	18 - 30 Years	68	18.62	5.06	25	4.034**	.008	Welch
	31 - 40 Years	128	19.06	4.32				
	41 - 50 Years	118	18.02	.28				
	Above 50 Years	76	20.09	3.37				
	Total	390	18.87	4.65				
Industry Analysis	18 - 30 Years	68	10.38	3.29	15	3.397*	.019	Welch
	31 - 40 Years	128	9.94	2.80				
	41 - 50 Years	118	9.17	3.08				
	Above 50 Years	76	10.37	2.79				
	Total	390	9.87	3.00				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.23 shows the differences of various dimensions of security analysis among different age categories of investors. The result of F shows that in case of quantitative and economic analysis the null hypothesis is failed to reject at 5% level of significance. The p values of quantitative and economic analysis are 0.68 and 0.115 respectively.

In case of technical analysis (p value 0.001), qualitative analysis (p value 0.008) and industry analysis (p value 0.019), the null hypothesis is rejected. Hence, it is concluded that there is significant difference among the investors in age categories with regard to dimensions of technical analysis, qualitative fundamental analysis and industry analysis of investors. In order to find out the exact difference among the groups, post hoc test is done.

Age Category-wise Multiple Comparisons – Factors of Security Analysis

The one way ANOVA result and Welch F tests show that there is a significant difference among the investors in different age categories with regard to quantitative fundamental analysis, technical analysis, qualitative fundamental analysis, industry analysis and security analysis. In order to explore the exact differences, Tukey HSD (for equal variance assumed) and Tamhane's T2 (for equal variance not assumed) multiple comparison tests are done. The result is shown below.

1. **Technical Analysis**

Regarding the Technical Analysis factor, the age categories of investor show significant difference since the p value (.001) is less than .05. The table 6.24 shows the pair wise comparison, which was done through the Tukey's HSD post hoc test to find out the exact difference.

Table 6.24

Age Category-wise Post Hoc Test - Technical Analysis

Age Category (I)	Age Category (J)	Mean Difference (I-J)	Std. Error	p value
18 – 30 Years	31 - 40 Years	2.49954*	.85929	.020
	41 - 50 Years	3.64083**	.87183	.000
	Above 50 Years	2.32972	.95586	.072
31 – 40 Years	18 - 30 Years	-2.49954*	.85929	.020
	41 - 50 Years	1.14129	.73079	.402
	Above 50 Years	-.16982	.82923	.997
41 – 50 Years	18 - 30 Years	-3.64083**	.87183	.000
	31 - 40 Years	-1.14129	.73079	.402
	Above 50 Years	-1.31111	.84222	.405
Above 50 Years	18 - 30 Years	-2.32972	.95586	.072
	31 - 40 Years	.16982	.82923	.997
	41 - 50 Years	1.31111	.84222	.405

Source: Survey Data
*, ** statistically significant at the 5%, and 1% significant level

The table 6.24 demonstrates the result of Tukey HSD test of multiple comparisons. In this case, there is a significant difference in investors in the age category '18-30 years' with all other age categories. When we analyse the mean difference of investors in the age category, 18 -30 gives more importance to technical analysis showing that most of the youngsters act as short-term traders and not as long term investors.

2. Qualitative Analysis

The perceptions of four categories of age differ with regard to the qualitative analysis. Since the variance is not homogeneous in this case, the researcher used the Tamhane's T2 test which shows the pair wise comparison as shown in table 6.25.

Table 6.25

Age Category-wise Post Hoc Test - Qualitative Analysis

Age Category (I)	Age Category (J)	Mean Difference (I-J)	Std. Error	p value
18 – 30 Years	31 - 40 Years	-.44485	.72226	.990
	41 - 50 Years	.60070	.78206	.970
	Above 50 Years	-1.47446	.72455	.237
31 – 40 Years	18 - 30 Years	.44485	.72226	.990
	41 - 50 Years	1.04555	.61784	.439
	Above 50 Years	-1.02961	.54320	.308
41 – 50 Years	18 - 30 Years	-.60070	.78206	.970
	31 - 40 Years	-1.04555	.61784	.439
	Above 50 Years	-2.07516*	.62050	.006
Above 50 Years	18 - 30 Years	1.47446	.72455	.237
	31 - 40 Years	1.02961	.54320	.308
	41 - 50 Years	2.07516*	.62050	.006

Source: Survey Data
* Significant at 5% level

There is a significant difference in the mean score of investors between age categories ‘41-50 years’ and ‘above 50 years’, as the p value is 0.006. Since the mean score (20.09) of the age category ‘above 50 years’ is more, this age category gives more importance on qualitative analysis.

3. Industry Analysis

Regarding the Industry Analysis factor, the age categories of investor show significant difference since the p value (.014) is less than .05. The table 6.26 shows the pair wise comparison, which was done through the Tamhane’s T2 post hoc test to find out the exact difference.

Table 6.26

Age Category-wise Post Hoc Test - Industry Analysis

Age Category (I)	Age Category (J)	Mean Difference (I-J)	Std. Error	p value
18 – 30 Years	31 - 40 Years	.44485	.46968	.921
	41 - 50 Years	1.21286	.48941	.084
	Above 50 Years	.01393	.51163	1.000
31 – 40 Years	18 - 30 Years	-.44485	.46968	.921
	41 - 50 Years	.76801	.37602	.228
	Above 50 Years	-.43092	.40452	.870
41 – 50 Years	18 - 30 Years	-1.21286	.48941	.084
	31 - 40 Years	-.76801	.37602	.228
	Above 50 Years	-1.19893*	.42726	.033
Above 50 Years	18 - 30 Years	-.01393	.51163	1.000
	31 - 40 Years	.43092	.40452	.870
	41 - 50 Years	1.19893*	.42726	.033

Source: Survey Data
* Significant at 5% level

The result of Tamhane's T2 test shows that there is significant difference among the age categories of 'above 50 years' and '41-50 years' (p value =.033) .Since the mean difference is positive in the age category 'above 50 years', this category gives more importance to industry analysis than '41-50' age category.

6.2.6 Educational Qualification-wise Comparison of Security Analysis and its Factors

Investors in different education category may have different perception about the importance of security analysis in investment decision. This aspect has been studied by the researcher to know the difference in mean scores of investors with different education category. To test the statistical significance of these difference F test is applied. Homogeneity of variance is checked by using Levene's test. The p value of the Levene's test is 0.017 which is less than .05. Since the homogeneity of variance is not assumed, Welch F test has been applied instead of ANOVA. The result of descriptive analysis and F test is exhibited in Table 6.27.

Table 6.27

Educational Qualification-wise Comparison of Security Analysis

Qualification Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Under Graduate	25	102.68	11.30	145	14.635^{**}	.000	Welch
Graduate	232	103.00	18.65				
Post Graduate	117	108.75	12.18				
Professional	16	93.50	8.21				
Total	**390**	**108.08**	**17.09**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The post graduate is having the highest mean score (108.75) of security analysis and the lowest score (93.50) is among professional. Since the p value (0.000) is less than 0.05, at least one of the mean score is significantly different from others. To find out the exact difference among the groups multiple comparisons have been done through post hoc analysis.

Tamhane's T2 test has been applied to identify the pair wise differences since the equal variances are not assumed. The result is shown in table 6.28.

Table 6.28

Educational Qualification-wise Post Hoc Test - Security Analysis

Educational Qualification (I)	Educational Qualification (J)	Mean Difference (I-J)	Std. Error	p value
Under Graduate	Graduate	-.32000	2.56997	1.000
	Post Graduate	-6.07214	2.52481	.121
	Professional	9.18000*	3.05190	.027
Graduate	Under Graduate	.32000	2.56997	1.000
	Post Graduate	-5.75214*	1.66372	.004
	Professional	9.50000*	2.38901	.003
Post Graduate	Under Graduate	6.07214	2.52481	.121
	Graduate	5.75214*	1.66372	.004
	Professional	15.25214*	2.34035	.000
Professional	Under Graduate	-9.18000*	3.05190	.027
	Graduate	-9.50000*	2.38901	.003
	Post graduate	-15.25214*	2.34035	.000

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.28 shows that in case of security analysis, there is a significant difference in the educational qualification category between professional with all other category of investors. Since the mean score of the post graduate investors is higher than other educational categories, it gives more importance to security analysis, and investors in professional category give least importance to security analysis when compared to other educational categories.

To get clear idea about how the education classification shows the difference among the factors of security analysis, factor wise analysis has been done. First of all, Levene's test has been done to find out the homogeneity of variance. The results are as follows:

Table 6.29

Educational Qualification-wise Test of Homogeneity of Variances

Dimensions	Levene's Statistic	P Value
Quantitative Analysis	2.666*	.048
Technical Analysis	2.732*	.044
Economic Analysis	3.157*	.025
Qualitative Analysis	3.179*	.024
Industry Analysis	1.181	.317

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.29 shows that all the dimensions except industrial analysis show the heterogeneity. Therefore, the researcher uses one way ANOVA only for industrial analysis factor and Welch's F for all other factors since the variances are heterogeneous.

Table 6.30

Educational Qualification-wise Comparison of Factors of Security Analysis

Dimensions	Qualification Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Quantitative Analysis	Under Graduate	25	27.04	5.54	40	4.133*	.010	Welch
	Graduate	232	26.49	6.27				
	Post Graduate	117	27.92	4.71				
	Professional	16	24.88	3.26				
	Total	**390**	**30.65**	**6.48**				
Technical Analysis	Under Graduate	25	27.12	4.69	35	1.122	.348	Welch
	Graduate	232	25.49	6.28				
	Post Graduate	117	26.07	5.38				
	Professional	16	25.19	3.10				
	Total	**390**	**25.76**	**5.83**				

Dimensions	Qualification Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Economic Analysis	Under Graduate	25	20.92	3.01	30	26.520**	.000	Welch
	Graduate	232	22.79	5.35				
	Post Graduate	117	24.52	4.77				
	Professional	16	16.56	3.27				
	Total	**390**	**22.94**	**5.24**				
Qualitative Analysis	Under Graduate	25	19.04	3.27	25	4.649**	.006	Welch
	Graduate	232	18.56	4.90				
	Post Graduate	117	19.75	4.42				
	Professional	16	16.69	2.96				
	Total	**390**	**18.87**	**4.65**				
Industry Analysis	Under Graduate	25	8.56	3.38	15	3.704*	.012	ANOVA
	Graduate	232	9.67	3.04				
	Post Graduate	117	10.49	2.82				
	Professional	16	10.19	2.37				
	Total	**390**	**9.87**	**3.00**				

*, ** statistically significant at the 5%, and 1% significant level

The table 6.30 shows the differences of various dimensions of security analysis among different educational qualification categories of investors. The result of Welch F test shows that in case of technical analysis the null hypothesis is failed to reject at 5% level of significance. The p value is 0.348 which is more than .05. Whereas, in case of quantitative analysis (p value 0.010), economic analysis (p value 0.000), qualitative analysis (p value 0.006) and industry analysis (p value 0.012), the null hypothesis is rejected. Hence, it is concluded that there is a significant difference among the educational qualification with regard to dimensions of quantitative, economic, qualitative and industry analysis. To get the significant difference among the exact educational category, post hoc analysis has been done.

Educational Qualification-wise Multiple Comparisons – Factors of Security Analysis

The one way ANOVA (if equal variance assumed) and Welch F (if equal variance not assumed) test result shows that there is significant difference among the different educational qualification categories with regard to quantitative, economic, qualitative and industry analysis. Hence, in order to explore the exact difference, Tukey HSD (if equal variance assumed) and Tamhane's T2 (if equal variance not assumed) test are used. The result is shown below.

1. **Quantitative Analysis**

With regard to the quantitative analysis, the educational qualification categories of investors are differing, as the p value (.010) shows a value which is less than 0.05. The result of post hoc for making the pair wise comparison is shown in the table 6.31.

Table 6.31

Educational Qualification-wise Post Hoc Test - Quantitative Analysis

Educational Qualification (I)	Educational Qualification (J)	Mean Difference (I-J)	Std. Error	p value
Under Graduate	Graduate	.55293	1.18232	.998
	Post Graduate	-.88308	1.19065	.976
	Professional	2.16500	1.37619	.547
Graduate	Under Graduate	-.55293	1.18232	.998
	Post Graduate	-1.43601	.59916	.099
	Professional	1.61207	.91391	.435
Post Graduate	Under Graduate	.88308	1.19065	.976
	Graduate	1.43601	.59916	.099
	Professional	3.04808*	.92467	.018
Professional	Under Graduate	-2.16500	1.37619	.547
	Graduate	-1.61207	.91391	.435
	Post graduate	-3.04808*	.92467	.018

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.31 shows that in case of quantitative analysis, there is a significant difference in the educational category between professional and post graduate. Since the mean score of investors in educational category 'professional' is less than the educational category 'post graduate', the educational category professional gives least importance to quantitative analysis than education category 'post graduate'.

2. **Economic Analysis**

The educational qualification categories of investors are differing in the case of economic analysis, since the p value (.000) shows a value less than 0.05. The result of post hoc for making the pair wise comparison is shown in the table 6.32.

Table 6.32

Educational Qualification-wise Post Hoc Test - Economic analysis

Educational Qualification (I)	Educational Qualification (J)	Mean Difference (I-J)	Std. Error	p value
Under Graduate	Graduate	-1.87310	.69756	.060
	Post Graduate	-3.60137*	.74658	.000
	Professional	4.35750*	1.01463	.001
Graduate	Under Graduate	1.87310	.69756	.060
	Post Graduate	-1.72826*	.56377	.014
	Professional	6.23060*	.88878	.000
Post Graduate	Under Graduate	3.60137*	.74658	.000
	Graduate	1.72826*	.56377	.014
	Professional	7.95887*	.92775	.000
Professional	Under Graduate	-4.35750*	1.01463	.001
	Graduate	-6.23060*	.88878	.000
	Post graduate	-7.95887*	.92775	.000

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.32 shows that in the case of economic analysis, there is a significant difference in the educational qualification category between all the category of investors except undergraduates and graduates. When we analyse the mean difference we understand that Post graduate investors are gives more importance to economic analysis. Professional investors give least importance economic analysis when we compared other investors.

3. Qualitative Analysis

As regards to the use of Qualitative Analysis, the educational qualification categories of investors are differing, as the p value (0.006) shows a value which is less than 0.05. The result of post hoc for making the pair wise comparison is shown in the table 6.33.

Table 6.33

Educational Qualification-wise Post Hoc Test - Qualitative analysis

Educational Qualification (I)	Educational Qualification (J)	Mean Difference (I-J)	Std. Error	p value
Under Graduate	Graduate	.48397	.72933	.986
	Post Graduate	-.71214	.77141	.932
	Professional	2.35250	.98789	.130
Graduate	Under Graduate	-.48397	.72933	.986
	Post Graduate	-1.19610	.52006	.126
	Professional	1.86853	.80704	.171
Post Graduate	Under Graduate	.71214	.77141	.932
	Graduate	1.19610	.52006	.126
	Professional	3.06464*	.84526	.008
Professional	Under Graduate	-2.35250	.98789	.130
	Graduate	-1.86853	.80704	.171
	Post graduate	-3.06464*	.84526	.008

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.33 shows that in the case of qualitative analysis, there is a significant difference in the between the professional and the post graduate investors (p value is

0.008). Here also the professional investors are giving least importance on qualitative analysis. With the other groups, no significant difference has been found.

4. **Industry Analysis**

The educational qualification categories of investors are differing in the use of economic analysis, as the p value (.012) shows a value less than 0.05. Since equal variance assumed in this case, Tukey HSD has considered for post hoc analysis. The result of post hoc for making the pair wise comparison is shown in the table 6.34.

Table 6.34
Educational Qualification-wise Post Hoc Test - Industry Analysis

Educational Qualification (I)	Educational Qualification (J)	Mean Difference (I-J)	Std. Error	p value
Under Graduate	Graduate	-1.11241	.62556	.285
	Post Graduate	-1.92718*	.65478	.018
	Professional	-1.62750	.95143	.320
Graduate	Under Graduate	1.11241	.62556	.285
	Post Graduate	-.81477	.33697	.075
	Professional	-.51509	.76813	.908
Post Graduate	Under Graduate	1.92718*	.65478	.018
	Graduate	.81477	.33697	.075
	Professional	.29968	.79212	.982
Professional	Under Graduate	1.62750	.95143	.320
	Graduate	.51509	.76813	.908
	Post graduate	-.29968	.79212	.982

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.34 shows that in case of industry analysis, there is a significant difference between under graduate and post graduate investors (p value is 0.018).

From the result, it can be concluded that undergraduate investors are giving least importance on qualitative analysis. With the other groups, no significant difference has been found.

It can be seen from the analysis that almost all the dimensions of security analysis the investors educational category 'post graduate' give more importance and educational category 'professionals' give lesser importance than all other educational categories.

6.2.7 Annual Income Category-wise Comparison of the Use of Security Analysis

Annual income category may play important role in investment decision making and consequently in security analysis. They may have different perception about the importance of security analysis. Descriptive analysis has been carried to find out the means score of informants of each category of annual income. To test the statistical significance of the difference of these mean score F test has been done. Before doing the F test, homogeneity of variance has been checked by using Levene's test. The p value of the Levene's test is 0.000 which is less than .05. Since the homogeneity of variance is not assumed, Welch F test has been applied instead of ANOVA. The result of descriptive analysis and F test is exhibited in Table 6.35.

Table 6.35

Annual Income Category-wise Comparison of Security Analysis

Annual Income (in Rupees) Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Less than 5,00,000	129	107.35	12.94	145	8.031**	.000	Welch
5,00,000 - 10,00,000	143	104.96	21.84				
10,00,000 - 15,00,000	90	110.74	12.71				
More than 15,00,000	28	118.82	13.12				
Total	**390**	**108.08**	**17.09**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The annual income category ‘more than Rs.15,00,000’ is having the highest mean score (118.82) for the use of security analysis and the lowest score (104,96) is for the group having annual income category of ‘Rs.5,00,000 – 10,00,000’. Since the p value (0.000) is less than 0.05, the mean score is significantly different from others. To find out the exact difference among the pair of groups multiple comparisons have been done through post hoc analysis.

Tamhane’s T2 test has been applied to identify the pair wise differences since the equal variances are not assumed. The result is shown in table 6.36.

Table 6.36

Annual Income Category-wise Post Hoc Test: Security Analysis

Annual Income (in Rupees) Category (I)	Annual Income (in Rupees) Category (J)	Mean Difference (I-J)	Std. Error	p value
Less than 5,00,000	5,00,000 - 10,00,000	2.46539	2.07628	.802
	10,00,000 - 15,00,000	-3.19561	1.70644	.322
	More than 15,00,000	-11.13926**	2.70368	.001
5,00,000 - 10,00,000	Less than 5,00,000	-2.46539	2.07628	.802
	10,00,000 - 15,00,000	-5.66099	2.19070	.061
	More than 15,00,000	-13.60465**	3.03268	.000
10,00,000 - 15,00,000	Less than 5,00,000	3.19561	1.70644	.322
	5,00,000 - 10,00,000	5.66099	2.19070	.061
	More than 15,00,000	-7.94365*	2.79251	.040
More than 15,00,000	Less than 5,00,000	11.13926**	2.70368	.001
	5,00,000 - 10,00,000	13.60465**	3.03268	.000
	10,00,000 - 15,00,000	7.94365*	2.79251	.040

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.36 shows that in the case of use of security analysis in investment decision, there is significant difference in the annual income category between 'more than Rs.15,00,000' with 'less than Rs.5,00,000 (p value 0.001), Rs. 5,00,000 - 10,00,000 (p value 0.000) and Rs. 10,00,000 – 15,00,000 (p value 0.040) income categories. When we analyse the mean difference we realise that the investors income group 'more than Rs.15,00,000' gives more importance to overall security analysis while taking investment decision.

To get clear idea about how the annual income with classification of investors shows the difference among the different components of security analysis, component wise analysis has been done. First of all, Levene's test has been done to find out the homogeneity of variance. The results are as follows:

Table 6.37

Annual Income Category-wise Test of Homogeneity of Variances

Dimensions	Levene's Statistic	P Value
Quantitative Analysis	5.103	.002
Technical Analysis	.975	.405
Economic Analysis	3.642	.013
Qualitative Analysis	8.166	.000
Industry Analysis	3.016	.030

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.37 shows that all the dimensions except technical analysis show the heterogeneity.

Table 6.38

Annual Income Category-wise Comparison of Factors of Security Analysis

Dimensions	Income Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Quantitative Analysis	Less than Rs.5,00,000	129	30.09	5.75	40	9.817**	.000	Welch
	Rs.5,00,000 - 10,00,000	143	30.21	7.79				
	Rs.10,00,000 - 15,00,000	90	31.14	5.64				
	More than Rs.15,00,000	28	33.93	3.27				
	Total	**390**	**30.65**	**6.48**				
Technical Analysis	Less than Rs.5,00,000	129	26.14	5.73	35	3.199*	.023	ANOVA
	Rs.5,00,000 - 10,00,000	143	24.94	6.37				
	Rs.10,00,000 - 15,00,000	90	25.67	4.91				
	More than Rs.15,00,000	28	28.46	5.46				
	Total	**390**	**25.76**	**5.83**				
Economic Analysis	Less than Rs.5,00,000	129	22.76	4.44	30	2.215	.090	Welch
	Rs.5,00,000 - 10,00,000	143	22.34	6.07				
	Rs.10,00,000 - 15,00,000	90	3.61	4.89				
	More than Rs.15,00,000	28	24.64	4.84				
	Total	**390**	**22.94**	**5.24**				
Qualitative Analysis	Less than Rs.5,00,000	129	19.09	4.85	25	8.776**	.000	Welch
	Rs.5,00,000 - 10,00,000	143	17.57	5.06				
	Rs.10,00,000 - 15,00,000	90	20.22	3.00				
	More than Rs.15,00,000	28	20.14	4.31				
	Total	**390**	**18.87**	**4.65**				

Dimensions	Income Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Industry Analysis	Less than Rs.5,00,000	129	9.27	2.98	15	5.381**	.002	Welch
	Rs.5,00,000 - 10,00,000	143	9.91	3.16				
	Rs.10,00,000 - 15,00,000	90	10.10	2.56				
	More than Rs.15,00,000	28	11.64	2.91				
	Total	**390**	**9.87**	**3.00**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.38 shows the differences of various dimensions of security analysis among different annual income categories of investors. The result of one way ANOVA shows that in case of technical analysis the null hypothesis is rejected at 5% level of significance. The p value of technical analysis is 0.23 which is less than 0.05.

The result of Welch test shows that in case of economic analysis the null hypothesis has failed to reject as the p value (0.90) is more than 0.05. Whereas in case of quantitative analysis (p value 0.000), qualitative analysis (p value 0.000) and industry analysis (p value 0.002), the null hypothesis is rejected. Hence, it is concluded that there is a significant difference among the annual income categories with regard to dimensions of quantitative fundamental analysis, technical analysis, qualitative analysis and industry analysis. In order to find out the exact difference among the groups, post hoc test is done.

Annual Income Category-wise Multiple Comparisons – Factors of Security Analysis

The one way ANOVA result given in the previous analysis shows that there is a significant difference among the investors in different annual categories with regard to the use of quantitative analysis, technical analysis, qualitative analysis, industry analysis and security analysis. Hence, in order to explore the exact difference, researcher used Tukey HSD (if equal variances are assumed) and Tamhane's T2 (if equal variance are not assumed) test. The result is shown below.

1. **Quantitative Analysis**

As regards the Quantitative Analysis, investors with different annual income categories are differing, as the p value (0.000) shows a value which is less than 0.05. The result of post hoc for making the pair wise comparison is shown in the table 6.39

Table 6.39

Annual Income Category-wise Post Hoc Test - Quantitative Analysis

Annual Income (in Rupees) Category (I)	Annual Income (in Rupees) Category (J)	Mean Difference (I-J)	Std. Error	p value
Less than 5,00,000	5,00,000 - 10,00,000	-.04993	.72599	1.000
	10,00,000 - 15,00,000	-.85917	.69457	.771
	More than 15,00,000	-3.50997**	.69657	.000
5,00,000 - 10,00,000	Less than 5,00,000	.04993	.72599	1.000
	10,00,000 - 15,00,000	-.80925	.78449	.886
	More than 15,00,000	-3.46004**	.78626	.000
10,00,000 - 15,00,000	Less than 5,00,000	.85917	.69457	.771
	5,00,000 - 10,00,000	.80925	.78449	.886
	More than 15,00,000	-2.65079**	.75734	.005
More than 15,00,000	Less than 5,00,000	3.50997**	.69657	.000
	5,00,000 - 10,00,000	3.46004**	.78626	.000
	10,00,000 - 15,00,000	2.65079**	.75734	.005

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.39 shows that in case of quantitative analysis, there is significant difference among investors in the annual income category between 'more than Rs.

15,00,000’ with other income categories. From the above result, it can be concluded that the investors in income group ‘more than Rs. 15,00,000’ gives more importance to quantitative analysis than other income categories.

2. Technical Analysis

As regards the Technical Analysis, the annual income categories of investors are differing, as the p value (0.023) shows a value which is less than 0.05. The result of post hoc for making the pair wise comparison is shown in the table 6.40.

Table 6.40

Annual Income Category-wise Post Hoc Test - Technical Analysis

Annual Income (in Rupees) Category (I)	Annual Income (in Rupees) Category (J)	Mean Difference (I-J)	Std. Error	p value
Less than 5,00,000	5,00,000 - 10,00,000	1.20247	.70227	.319
	10,00,000 - 15,00,000	.47287	.79431	.933
	More than 15,00,000	-2.32475	1.20576	.218
5,00,000 - 10,00,000	Less than 5,00,000	-1.20247	.70227	.319
	10,00,000 - 15,00,000	-.72960	.77817	.785
	More than 15,00,000	-3.52722*	1.19519	.018
10,00,000 - 15,00,000	Less than 5,00,000	-.47287	.79431	.933
	5,00,000 - 10,00,000	.72960	.77817	.785
	More than 15,00,000	-2.79762	1.25148	.116
More than 15,00,000	Less than 5,00,000	2.32475	1.20576	.218
	5,00,000 - 10,00,000	3.52722*	1.19519	.018
	10,00,000 - 15,00,000	2.79762	1.25148	.116

Source: Survey Data

* Significant at 5% level

The table 6.40 shows that in case of quantitative analysis, there is a significant difference among investors in the annual income category between ‘more than Rs.15,00,000’ with income category ‘Rs.5,00,000 - 10,00,000’ (p value 0.018). When we analyse the mean difference it can be concluded that the income group ‘more than Rs.15,00,000’ gives more importance to quantitative analysis than income group Rs.5,00,000 – 10,00,000.

3. **Qualitative Analysis**

As regards the qualitative analysis, the annual income categories of investors are differing, as the p value (0.000) shows a value which is less than 0.05. The result of post hoc for making the pair wise comparison is shown in the table 6.41

Table 6.41

Annual Income Category-wise Post Hoc Test - Qualitative Analysis

Annual Income (in Rupees) Category (I)	Annual Income (in Rupees) Category (J)	Mean Difference (I-J)	Std. Error	p value
Less than 5,00,000	5,00,000 - 10,00,000	1.52659	.60079	.068
	10,00,000 - 15,00,000	-1.12920	.53108	.191
	More than 15,00,000	-1.04983	.91950	.836
5,00,000 - 10,00,000	Less than 5,00,000	-1.52659	.60079	.068
	10,00,000 - 15,00,000	-2.65579**	.52777	.000
	More than 15,00,000	-2.57642*	.91760	.044
10,00,000 - 15,00,000	Less than 5,00,000	1.12920	.53108	.191
	5,00,000 - 10,00,000	2.65579**	.52777	.000
	More than 15,00,000	.07937	.87355	1.000
More than 15,00,000	Less than 5,00,000	1.04983	.91950	.836
	5,00,000 - 10,00,000	2.57642*	.91760	.044
	10,00,000 - 15,00,000	-.07937	.87355	1.000

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.41 shows that in case of qualitative analysis, there is a significant difference among investors in the annual income category between Rs.5,00,000 - 10,00,000 with ‘Rs.10,00,000 – 15,00,000 (p value is 0.000) and ‘more than

Rs.15,00,000' income category. From the above result it can be concluded that Rs.5,00,000- 10,00,000 income group gives least importance to qualitative analysis than investors in the annual income category Rs.10,00,000 – 15,00,000 (p value is 0.000) and 'more than Rs.15,00,000'.

4. **Industry Analysis**

With regard to the industry Analysis, the annual income categories of investors are differing, as the p value (0.002) shows a value which is less than 0.05. The result of post hoc for making the pair wise comparison is shown in the table 6.42

Table 6.42

Annual Income Category-wise Post Hoc Test - Industry Analysis

Annual Income (in Rupees) Category (I)	Annual Income (in Rupees) Category (J)	Mean Difference (I-J)	Std. Error	p value
Less than 5,00,000	5,00,000 - 10,00,000	-.63777	.37244	.424
	10,00,000 - 15,00,000	-.82868	.37658	.161
	More than 15,00,000	-2.37154*	.60913	.002
5,00,000 - 10,00,000	Less than 5,00,000	.63777	.37244	.424
	10,00,000 - 15,00,000	-.19091	.37781	.997
	More than 15,00,000	-1.73377*	.60990	.041
10,00,000 - 15,00,000	Less than 5,00,000	.82868	.37658	.161
	5,00,000 - 10,00,000	.19091	.37781	.997
	More than 15,00,000	-1.54286	.61243	.091
More than 15,00,000	Less than 5,00,000	2.37154**	.60913	.002
	5,00,000 - 10,00,000	1.73377*	.60990	.041
	10,00,000 - 15,00,000	1.54286	.61243	.091

Source: Survey Data

The table 6.42 shows that in case of industry analysis, there is a significant difference in the annual income category between 'more than Rs.15,00,000' with 'less than Rs.5,00,000 (p value is 0.017) and Rs.5,00,000 - 10,00,000 income category. When we analyse the mean difference we infer that the income group 'more than Rs.15,00,000' gives more importance to qualitative analysis.

6.2.8 Marital Status-wise Comparison of Security Analysis and its Factors

The married and single investors may have different perceptions regarding the different factors of security analysis. Descriptive analysis has been done to find out the mean score of security analysis among married and single. To find out the statistical significance of the difference 't' also applied. The result is shown in table 6.43.

Table 6.43

Marital Status-wise Comparison of Security Analysis

Gender	N	Mean	SD	Max Score	t value	p value	Remarks
Married	343	104.23	16.88	145	-.284	.777	Equal variance assumed
Single	47	104.96	13.86				
Total	**390**	**108.08**	**17.09**				

Source: Survey Data

From the table 6.43, it can be observed mean score security analysis of married investors is 104.23 (16.88) differing from single investor 104.96 (13.86). The Independent sample t test is used to check the significance of the difference of the mean score among married and single investors.

In Independent sample t test, we get two sets of analysis, the first one assuming equal variance and the second one assuming unequal variance. If the p value of the Levene's test is less than .05, then we can conclude that the variance is heterogeneous. In that case second set of analysis (equal variance not assumed) has to be considered.

Since the p value of the 't' test more than .05, there no significant difference between married and single investors with regard to security analysis. Even though, there is no significant difference between married and single investors with regard to marital status, the researcher tests the difference among marital status with regard to the different factors of security analysis.

The equal variance assumed is rejected in the dimension of technical analysis and industry analysis. Therefore we consider data which assumes unequal variance.

The result is shown in table 6.44.

Table 6.44

Marital Status-wise Comparison of Dimensions of Security Analysis

Dimensions	Marital status	N	Mean	SD	Max Score	t value	p value	Remarks
Quantitative FA	Married	343	30.82	6.49	40	1.377	.169	Equal variance assumed
	Single	47	29.45	6.40				
	Total	**390**	**30.65**	**6.48**				
Technical	Married	343	25.39	5.82	35	-3.418**	.001	Equal variance not assumed
	Single	47	28.45	5.27				
	Total	**390**	**25.76**	**5.83**				
Economic	Married	343	23.04	5.36	30	1.098	.273	Equal variance assumed
	Single	47	22.15	4.26				
	Total	**390**	**22.94**	**5.24**				
Qualitative FA	Married	343	18.76	4.55	25	-1.312	.190	Equal variance assumed
	Single	47	19.70	5.29				
	Total	**390**	**18.87**	**4.64**				
Industry	Married	343	10.01	2.96	15	2.489*	.013	Equal variance Not assumed
	Single	47	8.85	3.11				
	Total	**390**	**9.87**	**3.00**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 6.44 makes clear that among the dimensions of security analysis, the variables like quantitative, qualitative, economic, have no significant difference among married and single investor since the p values are more than 0.05.

In case of technical and industrial factors of security analysis, there is difference between married and single investor, as the p value (0.001 and .013) is less than 0.05, so rejected the null hypothesis at the 5% level of significance. It can be seen that the mean score of the single investors are more than the married investors. Hence, it is clear that single investors give more importance to technical analysis.

Similarly, when the dimension of industry analysis is concerned, the mean score of married and single investors are significantly different. The null hypothesis is rejected at the 5% level of significance. Unlike the technical analysis, the mean score of married investor (3.17) is more than that of single investors. It is evidently clear from the result that married investors are more careful in industry analysis while they make the investment decision.

6.3 Conclusion

From the above analysis it can be concluded that on an average the investors do 75% security analysis while taking investment decisions. Through the factor analysis we have grouped the security analysis into five factors. The first factor is the Quantitative analysis as it contributes 29.71 % of the total variance. Technical analysis is the second factor, economic analysis, qualitative analysis and industry analysis are the third, fourth and fifth factor respectively.

In gender-wise comparison, even though, there is no significance between male and female investors with regard to total security analysis, they differ in factors of security analysis like technical, economic and industry analysis. Male are more prone to technical analysis and it substantiate the findings of Barber & Odean, (2001)[3], whereas in case of industry analysis, females are having higher mean score than their counterparts.

In age category wise comparison, there is significant difference among the investors in different age categories with regard to security analysis. The difference is in between the age category '41 – 50 years' with '18-30' and 'above 50 years' age categories. The age category 41 – 50 gives less importance to security analysis.

Regarding the components of security analysis, technical analysis, qualitative analysis and industry analysis show the significant difference.

In educational qualification wise comparison of security analysis, there is significance difference among the investors in different educational qualifications. It can be concluded from the result that 'post graduate' category gives more importance to security analysis. All the components of security analysis except technical analysis show the significance difference.

In annual income category wise comparison of security analysis, there is significant difference among the investors in different annual income categories. It can be concluded that the annual income group 'more than Rs.15,00,000' gives more importance to security analysis while taking investment decision. Regarding the components of security analysis, all components except economic analysis show the significant difference among different annual income categories.

In marital status-wise comparison of security analysis there is no significance among married and single while taking investment decision, but they differ in components of security analysis like technical analysis and industry analysis. Unmarried are having more mean score in technical analysis whereas married are having more mean score in industry analysis.

References:

1. Graham, B., & Dodd, D. L. (2008). *Security Analysis*. Ne York: Mc graw Hill.

2. Pandya, F. H. (2013). *Security Analysis and Portfolio Mnagement*. Mumbai: Jaico Publishing House.

3. Barber, B. M., & Odean, T. (2001). Boys will be Boys: Gender, Overconfidence and common stock investment. *The quarterky journal of economics , 16* (1), 261-292.

Chapter 7
Impact of Behavioural Bias and Emotional Intelligence in Investment Decision

7.1 Behavioural Bias

Most of the people invest in shares expecting periodic return in the form of dividends and terminal return in the form of capital appreciation. But it is the fact that many retail investors lose money in the stock market also. The reasons for the poor performance of retail investors are better explained by behavioural finance. Behavioural finance is a discipline that attempts to explain and increase understanding how the cognitive errors (mental mistakes) and emotions of investors influence the decision making process. It integrates the field of psychology, sociology and other behavioural sciences to explain individual behaviour, to examine group behaviour, and to predict financial markets (Ricciardi, 2008)[1]. Behavioural biases may be the reason for the poor performance of retail investors. The investors may deviate from the assumed rational decisions due to behavioural bias. Behavioural bias is the deviation from rational decisions. Behavioural biases can be broadly classified into Emotional and Cognitive biases. Emotional biases arise from impulse or intuition and may be considered from reasoning influenced by feelings. Emotion is a mental state that happens spontaneously rather than through conscious effort (Pompian, 2008)[2]. Emotional biases can be again classified into overconfidence, loss aversion, regret aversion and herd mentality biases. Cognitive biases arise from basic statistical, information processing, or memory errors. These biases arise either from subconscious mental procedures for processing information or from irrational perseverance in one's own beliefs. Cognitive biases are classified into belief perseverance biases and information processing biases. Belief perseverance is the tendency to cling to one's previously held or recently established beliefs irrationally or illogically. In belief perseverance biases the researcher considers representativeness, cognitive dissonance, conservation and illusion of control biases. Information processing biases arise in information being processed and used illogically or irrationally. Anchoring and adjustment, mental accounting, availability and self attribution biases are included in information processing biases. The different types of behavioural biases have been shown in figure 3.2 in chapter three.

To find out the extent of investor biases, a five point Likert scale is developed and the respondents were asked to rate the variables ranging from highly agree (5) to highly disagree (1). The statements BB1 to BB3 are asked to examine the representative biases, statements BB12 and BB13 to check cognitive dissonance, statements BB16 and BB17 to explore the illusion of control and statements BB18 and BB19 to examine the confirmation biases. All of these statements together constitute belief perseverance bias. The statements BB7 to BB9 are asked to examine anchoring bias, statements BB10 and BB11 to explore availability bias, BB14 and BB15 to check self attribution bias and BB26 and BB27 to examine mental accounting bias. These statements constitute information processing bias. The statements BB4 to BB6 are asked to check the over confidence bias, BB20 to BB22 to examine loss aversion bias, BB23 to BB25 to explore regret aversion bias and BB28 and 29 to examine herding bias. The mean values for these statements are given below with their respective standard deviations.

Table 7.1

Indicators of Behavioural Bias

Indicator code	**Indicators**	**Mean**	**Standard Deviation**
BB1	I consider the performance of market indices to make investment decisions in shares	3.6308	1.19212
BB2	I buy ‘hot’ stocks and avoid stocks that have performed poorly in the recent past	3.4949	1.12404
BB3	I believe, Good company means good stock to invest	3.4462	1.13641
BB4	I have sufficient knowledge of Indian stock market	3.1385	1.18096

Indicator code	Indicators	Mean	Standard Deviation
BB5	I believe, my skills and knowledge of stock market can help me to outperform the market.	3.1795	1.09619
BB6	I am confident of my ability to pick better stock than others	3.1513	1.08516
BB7	I place sell orders based on my entry price	3.2436	1.19538
BB8	I rely too heavily on one piece of information in investment decision	3.1872	1.19482
BB9	I forecast the changes in stock prices in the future based on the recent stock prices.	3.1026	1.18896
BB10	I take investment decision by using market tips	3.2462	1.28904
BB11	I give more importance to current information when I make the investment decision	3.3051	1.21123
BB12	I hold the shares when the price decreases, even it increases the loss	3.5667	1.12207
BB13	I invest again in securities which I have already own after its price goes down to justify my investment decision	3.4128	1.10448
BB14	I believe, I get profit on investment due to my skill	3.1692	1.13920
BB15	I believe, I lose money in my investment due to bad luck	3.1282	1.24358
BB16	When I throw a dice, I throw it in specific manner so that I get the number which I expect	3.4051	1.21895
BB17	I think I am more likely to win the lottery if I pick the numbers myself than a quick pick	3.3154	1.20859
BB18	I identify the company first and search for the information to make investment decision	3.3923	1.09565
BB19	When an investment is not going well I usually seek information that confirms I made the right decision about it.	3.4154	1.15697
BB20	After a prior gain, I am more risk seeking than usual.	3.2410	1.09138
BB21	After a prior loss, I become more risk averse	3.1641	1.12176
BB22	The pain of financial loss is more than the pleasure of financial gain	3.2051	1.09871

Indicator code	Indicators	Mean	Standard Deviation
BB23	I feel more sorrow about holding losing stocks too long than about selling winning stocks too soon.	3.1538	1.13687
BB24	I tend to hold on losing stock for too long hoping for a reversal	3.1205	1.09842
BB25	I book profits in a winning stock too soon and then felt I could have waited more.	3.1000	1.12816
BB26	I generally differentiate ‘main income’ & ‘extra income’	3.0077	1.19444
BB27	I am interested in stock’s individual gain/loss rather than total gain/loss of the portfolio	3.1923	1.19830
BB28	Trading volume of stock affect my investment decision	3.1205	1.16652
BB29	I seek signals from other investors in matters of financial knowledge and trading behaviour	3.1538	1.10009

Source: Field Survey

It can be seen from the table 7.1 that ‘I consider the performance of market indices to make investment decisions in shares’ having highest mean score of 3.6308 (SD 1.19212) followed by the statement ‘I hold the shares when the price decreases, even it increases the loss’ 3.5667 (SD 1.12207) and statement ‘I buy ‘hot’ stocks and avoid stocks that have performed poorly in the recent past’ 3.4949 (SD 1.12404). The statement ‘I generally differentiate ‘main income’ and ‘extra income’’ having the least mean score 3.0077 (SD 1.19444).

7.2 Factor Analysis of Behavioural Bias

Factor analysis is used for identifying the underlying factors and its structure in behavioural bias. It analyses the structure of correlation among large number of variables by defining group of variable that are highly correlated, called as factors. The number of statements included in the measurement instrument was 32; further, the statements were reduced to 29 based on the communalities in the extraction. Three statements were excluded from the analysis frame because of the low extraction values. It is seen that the communalities after deleting three statements show significantly large values suggesting that the statements are useful to analyse the bias of investors. In order to verify the adequacy or appropriateness of data for factor analysis, Kaiser- Meyer- Oklin Measure of sampling adequacy (KMO) and Bartlett's test of Sphericity are applied. The Kaiser-Meyer- Oklin measure of sampling adequacy is an index used for comparing the magnitudes of the observed correlation coefficients to the magnitudes of the partial correlation coefficients. KMO statistics vary between 0 and 1. A value of 0 indicates that the sum of partial correlation is large relative to the sum of correlation. Hence factor analysis is likely to be inappropriate. A value close to 1 indicates that patterns of correlation are relatively compact and hence the factor analysis should yield distinct and reliable results. The Bartlett's Test of Sphericity reveals the validity and suitability of the responses collected to the problem being addressed through the study. It is recommended that the Bartlett's Test of Sphericity must be less than 0.05 to be suitable in factor analysis. The following table shows the KMO and BTS results:

Table 7.2

KMO and Bartlett's Test – Behavioural Bias

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.940
Bartlett's Test of Sphericity	Approx. Chi-Square	7466.923
	Df	406
	Sig.	.000

Source: Field Survey

The correlation matrix showed sufficient items to justify the factorability data. The KMO and Bartlett's test of sphericity produces the Kaiser- Meyer- Olkin measure of sampling adequacy and Bartlett's test. KMO for overall matrix was found to be excellent (0.940) which is greater than 0.5 (Kaiser, 1974) and Barlett's test of sphericity (BTS) value is found significant ($p<0.000$) which meant that data is appropriate for Exploratory Factor Analysis (EFA). The details of factor analysis are given below:

Table 7.3

Total Variance Explained by variables of Behavioural Bias

Factor	Components	Initial Eigen values			Extraction Sums of Squared Loadings		
		Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	Emotional bias	9.621	33.174	33.174	9.621	33.174	33.174
2	Information Processing bias	5.464	18.843	52.017	5.464	18.843	52.017
3	Belief perseverance bias	2.936	10.124	62.141	2.936	10.124	62.141

Source: field Survey

Table 7.3 shows the percentage of variances and the Eigen values of the three components, (namely Emotional bias, Information processing bias and Belief perseverance bias) which explained the 62.14 % of total variances of behavioural bias. The first factor namely Emotional Bias explains 33.17 per cent of variance with the eigen value of 9.621. The second factor namely Information Processing Bias explains 18.84 per cent variance (eigen value of 5.464) followed by the third factor namely Belief Perseverance Bias which explains 10.12 per cent variance (eigen value 2.936). It is clear from the following scree plot.

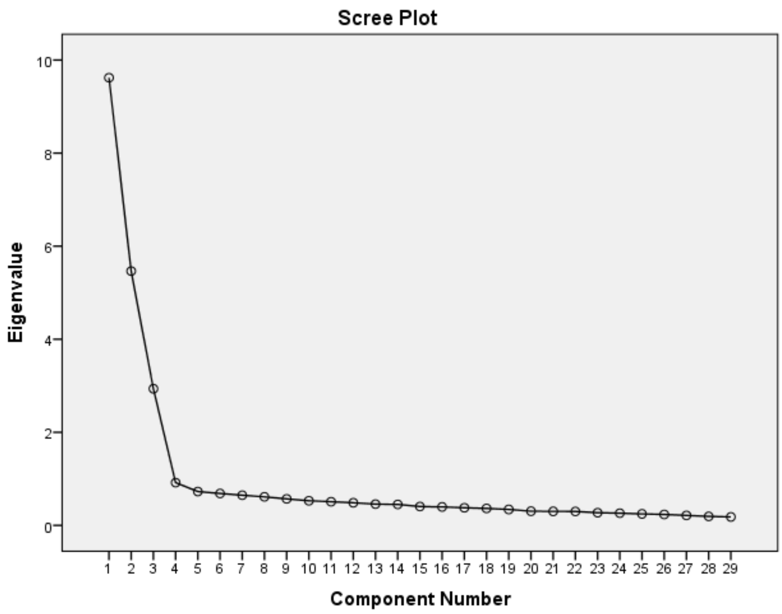


Figure 7.1 Scree Plot – Behavioural Bias

The diagram 7.2 makes it clear that all the 29 statements of are combined and split into three components.

The table presented below explains the rotated component factor loadings of behavioural bias.

Table 7.4

Rotated Component Matrix – Behavioural Bias

Indicator Code	Indicators	Components		
		1	2	3
BB1	Consider performance of market indices to make investment decisions			.745
BB2	Buy 'hot stock' and avoid poor performed stock			.698
BB3	Good company means good stock to invest			.693
BB4	Sufficient knowledge in Indian stock market	.822		
BB5	My skill & knowledge help me to outperform	.853		
BB6	Confident of my ability to pick better stock	.845		
BB7	Place sell orders based on my entry		.794	
BB8	Rely heavily one piece of information		.738	
BB9	Forecast stock price changes based on recent prices		.760	
BB10	Take investment decision by using market tips		.732	
BB11	Give more importance to current information		.736	
BB12	Hold shares when the price decreases			.741
BB13	Invest again in securities after its price go down			.721
BB14	I get profit on investment due to my skill		.725	
BB15	I lose money in my investment due to my bad luck		.769	
BB16	I throw dice in specific manner to get expected number			.711
BB17	I win the lottery if I pick the numbers myself			.764
BB18	I identify the company first, then search for information			.713
BB19	I seek information that confirms my decision is right			.700
BB20	After a prior gain, I am more risk seeking than usual	.805		
BB21	After a prior loss, I become more risk averse	.810		

Indicator Code	Indicators	Components		
		1	2	3
BB22	The pain of financial loss is more than pleasure of gain	.844		
BB23	Feel sorrow about holding losing stock too long than about selling winning stocks too soon	.846		
BB24	I hold on losing stock for too long hoping for a reversal	.855		
BB25	I book profits in a winning stock too soon and then felt I could have waited more.	.822		
BB26	I differentiate 'main income' & 'extra income'		.716	
BB27	I am interested in stock's individual gain/loss		.751	
BB28	Trading volume of stock affect my investment decision	.829		
BB29	I seek signals from other investors in trading behaviour	.832		

Source: Field Survey

The table 7.4 depicts the result of Principle Component Analysis of behavioural bias construct after rotated factor matrix. Variables with factor loadings near 0.70 are chosen for the study. After performing Varimax Rotation Method in Kaiser Normalization, factors of behavioural bias grouped into three factors as per the following:

- The first group is extracted 33.17 per cent. It consists of eleven items. They are 'I hold on losing stock for too long hoping for a reversal' with highest loading (0.855), followed by 'My skill & knowledge help me to outperform' (loading 0.853), 'Feel sorrow about holding losing stock too long than about selling winning stocks too soon' (loading 0.846), ' My skill and knowledge help me to outperform' (loading 0.845), 'The pain of financial loss is more than pleasure of gain' (loading 0.844), 'Trading volume of stock affect my investment decision' (loading 0.832), ''I seek signals from other investors in trading behaviour' (loading 0.829), 'I book profits in a winning stock too soon and then felt I could have waited more' (loading 0.822), 'Sufficient knowledge in Indian stock market' (loading 0.822), 'After a prior loss, I become more risk averse' (loading 0.810) and 'After a prior gain, I am more risk seeking than usual'(loading

0.805). These variables together constitute a common factor, whose characteristics are related to emotional bias which includes loss aversion, overconfidence, regret aversion and herd behaviour bias. Hence, it is named as **'Emotional Bias'. '**Emotional biases stem from impulse or intuition and may be considered to result from reasoning influenced by feelings' (Pompian, 2008)[3]. Since emotional biases stem from impulse or intuition, these biases are not easily corrected.

- Second group which is extracted 18.84 per cent of total variances included nine items. They are 'Place sell orders based on my entry' with the highest loading (0.794), followed by 'I lose money in my investment due to my bad luck' (loading 0.769), 'Forecast stock price changes based on recent prices' (loading 0.760), 'I am interested in stock's individual gain/loss' (loading 0.751), 'Rely heavily one piece of information' (loading 0.738), 'Give more importance to current information' (loading 0.736), 'Take investment decision by using market tips' (loading 0.732), 'I get profit on investment due to my skill' (loading 0.725) and 'I differentiate 'main income' and 'extra income''(loading 0.716). These variables together constitute a common factor, whose characteristics are related to cognitive bias that is based on processing information which includes anchoring and adjustment, mental accounting, availability and self contribution bias. Hence, it is named as **'Information Processing Bias'. '**The information processing biases result in information being processed and used illogically or irrationally' Pompian (2008)[4]**.**

- Third group is extracted 10.12 per cent of total variances included nine items. They are 'I win the lottery if I pick the numbers myself' with highest loading (0.764), followed by 'Consider performance of market indices to make investment decisions' (loading 0.745), Hold shares when the price decreases' (loading 0.741), 'Invest again in securities after its price go down' (loading 0.721), 'I identify the company first, then search for information' (loading 0.713), 'I throw dice in specific manner to get expected number' (loading 0.711), 'I seek information that confirms my decision is right' (loading 0.700), 'Buy 'hot stock' and avoid poor performed stock'(loading 0.698), 'Good company means good stock to invest' (loading 0.693). These variables together constitute a common factor, whose characteristics are related to cognitive bias based on belief which includes representativeness, cognitive dissonance, confirmation and illusion of control bias. Hence, it is named as **'Belief Perseverance Biases'.** **'**Belief perseverance behavioural biases are the tendency to cling to one's previously held or recently established beliefs irrationally or illogically. Investors continue to hold and justify the belief because of their bias towards belief in themselves or their own ideals or abilities' Pompian (2008)[5].

Thus, through exploratory factor analysis, 29 variables are split into three components, i.e, Emotional bias, Information processing bias and Belief perseverance bias. They are identified as the dimensions of investor behaviour bias in the present study. This findings are as expected by the theoretical aspects of behavioural finance, like loss aversion bias, overconfidence bias, regret aversion bias, herd mentality grouped under emotional bias, anchoring and adjustment bias, mental accounting bias, availability bias and self attribution bias grouped under information processing bias and representativeness bias, cognitive dissonance bias, confirmation bias and illusion control bias grouped under belief perseverance bias.

7.3 Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) is a measurement model of Structural Equation Modeling (SEM), which deals with the relationship between observed measures or indicator. This statistical technique tells us the suitability of theoretical specification of factors to the reality. It is used to confirm the factor structure of a set of observed variables. Structural Equation Modeling software is typically used for performing confirmatory factor analysis. The researcher used CFA as a first step to assess the proposed Measurement model in a structural equation model. The following figure shows the measurement model:

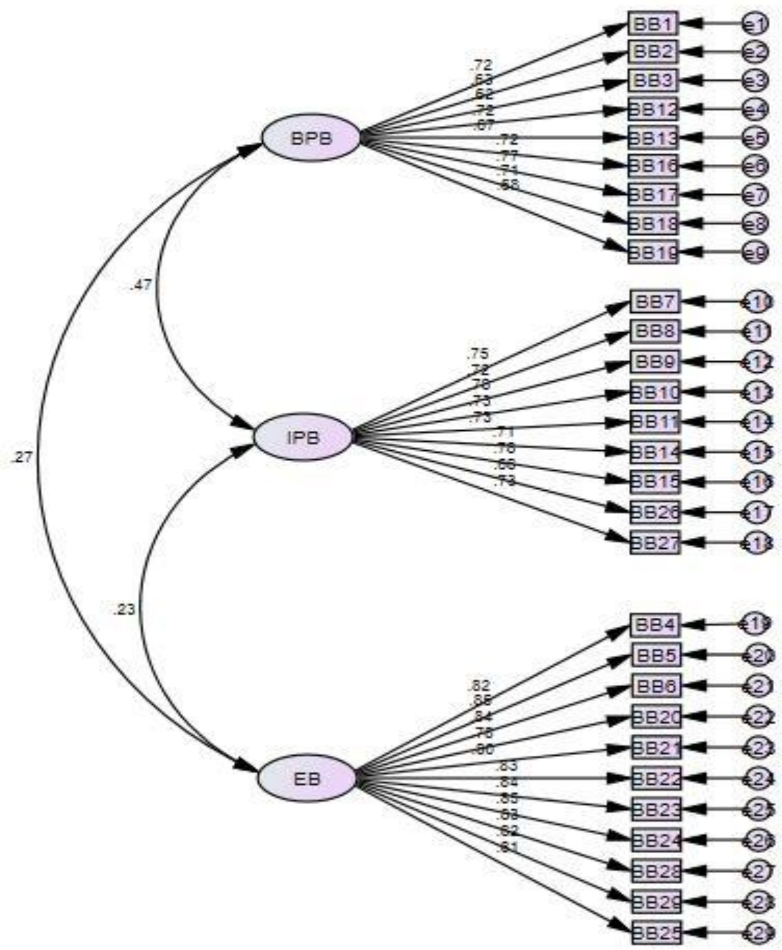


Figure 7.2 Confirmatory Factor Analysis - Behavioural Bias

Measurement model of behavioural bias is tested by a Confirmatory Factor Analysis by using Amos 21. Here measurement model is developed to test the attitude of investors towards different factors of behavioural bias with regard to different socio-economic variables, investment culture and personality types. Reliability of the scale developed for the study was tested by using Cronbanch's alpha value method and which is found to be significant. The structural equation model using Amos produces several indices of fit like measure of absolute fit, comparative fit and parsimonious fit. The following are the most commonly used fit indices:

Table 7.5

Model Fit Indices – Behavioural Bias

Sl. No	Indices of Common Fit	Value	Value of Good Fit
1.	CMIN/DF	1.875	<5
2.	RMR	0.049	<0.05
3.	Goodness of Fit Index (GFI)	0.948	>0.90
4.	Adjusted GFI (AGFI)	0.902	>0.90
5.	Comparative Fit Index (CFI)	0.955	>0.90
6.	Incremental Fit Index (IFI)	0.955	>0.90
7.	Tucker Leiws Index (TLI)	0.956	>0.90
8.	Normed Fit Index (NFI)	0.909	>0.90
9.	Root Mean Square Error of Approximation (RMSEA)	0.047	<0.08

Source: Field Survey

Table 7.5 shows the different model fit indices of confirmatory factor analysis. . The confirmatory factor analysis is good fit with Goodness of Fit Index (GFI) 0.948; Tucker Lewis Index (TLI) 0.956; Comparative Fit Index (CFI) 0.955; Root Mean Square Error of Approximation (RMSEA) 0.071; CMIN/df 1.875 and p-value 0.000. The present scale developed for the study was supported by the result of the Confirmatory Factor Analysis. Hence all the fit indices are satisfactory and appropriate for the scale, the Confirmatory Factor Analysis Confirms the structure of measurement scale.

To know the extent of behavioural biases while taking the investment decisions are estimated by calculating the values of mean of each variable. Following are the mean score of each bias.

Table 7.6

Descriptive of Different Factors of Behavioural Bias

Dimensions of Bias	Mean	Standard deviation
Emotional Bias	3.1571	.94143
Information Processing Bias	3.1758	.92629
Belief Perseverance Bias	3.4533	.84478

Source: Field Survey

From the above table it can be seen that all the biases are above 60% which means that investors in Kerala having above average bias while they take the investment decision.

The belief perseverance bias is having the highest mean score of 3.4533 (.84478), on an average it is having 69% influences among the investors in Kerala. Emotional bias is having the least mean score of 3.1571 (SD .94143).

7.4. Relation between Socio-Economic Variables with Factors of Behavioural Bias

The socio economic variable like gender, age, educational qualification, income and marital status are used for analyzing the variability of factors of behavioural bias among different categories of investors. The descriptive statistics of the socio economic variables in respect of factors of behavioural bias are presented below.

7.4.1 Gender-wise Analysis of Factors of Behavioural Bias

The male and female investors may have difference in the different factors of behavioural bias. To test the same, descriptive analysis has been done which shows the mean score of male and female investors with regards to behavioural bias. To find out the statistical significance of the difference in mean score 't test' is also applied. The result is shown in table 7.7.

Table 7.7

Gender-wise Analysis of Behavioural Bias

Gender	N	Mean	Max Score	SD	t value	p value	Remarks
Male	349	95.87	145	18.95	4.563	.000	Equal variance assumed
Female	41	81.83		15.62			
Total	**390**	**94.39**		**19.10**			

Source: Survey Data

From the table 7.7, it can be observed that on an aggregate mean score of men and women put together in this respect is 94.39 (SD 19.10) out of the maximum score of 145. This indicates that on an average, investors are affected 65% by behavioural bias while taking investment decision. The mean score of behavioural bias of male is 95.87 (17.70) differing from female 81.83 (15.62). The Independent sample t test is used to check whether the mean score difference is significant or not, among male and female with regard to behavioural bias.

Since the p value of the t test is less than .05, it can be inferred that there is significant difference between male and female investors with regard to behavioural bias. Since the average behavioural bias mean score of the male is more than female, it can be concluded that male investors are more influenced by behavioural bias than female.

The researcher also tests the difference among gender with regard to the different factors of behavioural bias. The equal variance assumed is rejected in the dimension of emotional bias. Therefore we consider the results which assume unequal variance. The results have been shown in the table 7.8.

Table 7.8

Gender-wise Analysis of Dimensions of Behavioural Biases

Dimensions of Bias	Gender	N	Mean	SD	t value	Max Score	p value	Remarks
Emotional	Male	349	34.99	10.52	1.673	55	.100	Equal variance not assumed
	Female	41	32.54	8.65				
	Total	**390**	**34.72**	**10.36**				
Information Processing	Male	349	29.17	8.32	4.119**	45	.000	Equal variance assumed
	Female	41	23.61	6.74				
	Total	**390**	**28.58**	**8.34**				
Belief Perseverance	Male	349	31.71	7.33	4.947**	45	.000	Equal variance assumed
	Female	41	25.68	7.85				
	Total	**390**	**31.07**	**7.60**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.8 makes clear that among the dimensions of Behavioural bias, the variables like emotional bias has no significant difference between male and female investor since the p value (0.100) is more than 0.05.

In case of information processing bias, there is difference between male and female investor, as the p value (0.000) is less than 0.05. The mean score of the information processing bias of male investor is 29.17 with the standard deviation 8.32 and the mean score of the female investor is 23.61 with standard deviation 6.74. Hence, it is clear that male investors are more affected than female investor in case of information processing bias. The scenario is same in the case of belief perseverance bias. In this case also the p value is less than .05 which denotes the existence of significant difference and mean score are more in the case of male investors. So it is very clear that male investors are more biased than their counterparts.

7.4.2 Age Category-wise Analysis of Behavioural Bias

Investors with different age category may have different level of behavioural bias. Hence the above data has been classified age wise and descriptive analysis has done to know the mean score of investors in different age category. It is found that there is different mean score for investors in different age category. Then ANOVA is applied to test the significance of difference among the mean of different age category.

Table 7.9

Age Category-wise Test of Homogeneity of Variances Behavioural Bias

Variable	Levene's Statistic	P Value
Behavioural bias	7.477**	.000

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

In this case, the p value of homogeneity test is 0.000 which means the equal variance is rejected. Then the researcher considers Welch's F value instead of ANOVA. The result is shown in the Table 7.10.

Table 7.10

Age Category-wise Analysis Factors of Behavioural Bias

Age Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
18 - 30 Years	68	98.00	19.58	145	3.698**	.013	Welch
31 - 40 Years	128	96.55	15.04				
41 - 50 Years	118	93.76	21.21				
Above 50 Years	76	88.50	20.24				
Total	390	94.39	19.10				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

From the above table it can be understood that the highest mean score is 98.00 (19.58) which is in the age category of '18 – 30 years' and the lowest mean is 88.50 (20.24) in age category 'Above 50 years'. This indicates that behavioural bias is more to young investors and less is in the case older investors. The p value is 0.013 which means there is significant difference among the mean score of different age categories. To know exact significant difference between different age groups one has to use the multiple analysis. In this case, researcher uses the Tamhane's T2 test to identify the pair wise differences since the equal variances are not assumed. The result is shown in table 7.11.

Table 7.11

Age Category-wise Post Hoc Test - Behavioural Bias

Age Category (I)	Age Category (J)	Mean Difference (I-J)	Std. Error	p value
18 – 30 Years	31 - 40 Years	1.45313	2.72076	.996
	41 - 50 Years	4.23729	3.07343	.673
	Above 50 Years	9.50000*	3.32069	.029
31 – 40 Years	18 - 30 Years	-1.45313	2.72076	.996
	41 - 50 Years	2.78416	2.36180	.807
	Above 50 Years	8.04688*	2.67565	.019
41 – 50 Years	18 - 30 Years	-4.23729	3.07343	.673
	31 - 40 Years	-2.78416	2.36180	.807
	Above 50 Years	5.26271	3.03356	.412
Above 50 Years	18 - 30 Years	-9.50000*	3.32069	.029
	31 - 40 Years	-8.04688*	2.67565	.019
	41 - 50 Years	-5.26271	3.03356	.412

Source: Survey Data
* Significant at 5% level

The result of Tamhane's T2 test shows that there is significant difference in investors in the age category of 'above 50 years' with '18 - 30 years' (p value .029) and '31 – 40 years'. It is clear from the result that aged investors are having less behavioural bias than young investors.

To be more specific, the researcher has done the descriptive analysis of the different factors of behavioural bias with regard to age category. To test the statistical significance ANOVA also is applied. The result of the Levene's test of homogeneity is presented in table 7.12

Table 7.12
Age Category-wise Test of Homogeneity of Variances
Dimensions of Behavioural Bias

Dimensions of Bias	Levene's Statistic	P Value
Emotional	1.118	.342
Information Processing	1.656	.176
Belief Perseverance	2.934*	.033

Source: Survey Data
*, ** statistically significant at the 5%, and 1% significant level

The table 7.12 shows that all the dimensions except belief perseverance bias and behavioural bias show the heterogeneity. Therefore, the researcher uses one way ANOVA for emotional bias and information processing bias factor and Welch's F for all other dimensions since the variances are heterogeneous.

Table 7.13

Age Category-wise Analysis of Factors of Behavioural Bias

Dimensions	Age Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Emotional	18 - 30 Years	68	33.31	10.63	55	1.529	.206	ANOVA
	31 - 40 Years	128	34.59	9.37				
	41 - 50 Years	118	36.29	10.98				
	Above 50 Years	76	33.82	10.57				
	Total	**390**	**34.72**	**10.36**				
Information Processing	18 - 30 Years	68	30.69	8.30	45	4.821**	.003	ANOVA
	31 - 40 Years	128	29.82	7.84				
	41 - 50 Years	118	27.19	8.29				
	Above 50 Years	76	26.78	8.64				
	Total	390	28.58	8.33				

Dimensions	Age Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Belief Perseverance	18 - 30 Years	68	34.00	7.68	45	9.303**	.000	Welch
	31 - 40 Years	128	32.14	6.40				
	41 - 50 Years	118	30.29	8.06				
	Above 50 Years	76	27.91	7.45				
	Total	**390**	**31.08**	**7.60**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.13 shows the differences of various dimensions of behavioural bias among different age categories of investors. The results show that in case of emotional bias there is no significant difference. The p value of emotional bias is 0.206. Hence there is no significance difference among investors in age categories with regard to emotional bias. Whereas, in case of information processing bias (p value 0.003) and belief perseverance bias (p value 0.000), the p value is below 0.05. Hence, it is concluded that there is a significant difference among the age categories with regard to dimensions of information processing bias and belief perseverance bias. In order to find out the exact difference among the groups, post hoc test is done.

Age Category-wise Multiple Comparisons: Behavioural Bias

The one way ANOVA result & Welch F tests show that there is significant difference among the different age categories with regard to information processing and belief perseverance bias. Hence, in order to explore the exact difference, Tukey HSD Test (equal variance assumed) and Tamhane's T2 test (equal variance not assumed) for multiple comparisons are done. The result is shown below.

1. **Information Processing Bias**

Regarding the information processing bias, the age categories of investor show significant difference since the p value (.003) is less than .05. The table 7.14 shows the pair wise comparison, which was done through the Tukey's HSD post hoc test to find out the exact difference.

Table 7.14

Age Category-wise Post Hoc Test - Information Processing Bias

Age Category (I)	Age Category (J)	Mean Difference (I-J)	Std. Error	p value
18 – 30 Years	31 - 40 Years	.87086	1.23296	.895
	41 - 50 Years	3.50474*	1.25096	.027
	Above 50 Years	3.91486*	1.37152	.023
31 – 40 Years	18 - 30 Years	-.87086	1.23296	.895
	41 - 50 Years	2.63387	1.04858	.060
	Above 50 Years	3.04400	1.18983	.053
41 – 50 Years	18 - 30 Years	-3.50474*	1.25096	.027
	31 - 40 Years	-2.63387	1.04858	.060
	Above 50 Years	.41012	1.20846	.987
Above 50 Years	18 - 30 Years	-3.91486*	1.37152	.023
	31 - 40 Years	-3.04400	1.18983	.053
	41 - 50 Years	-.41012	1.20846	.987

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.14 demonstrates the result of Tukey HSD test of multiple comparisons. In this case, there is a significant difference among 18-30 years of age category with '41 – 50' and 'above 50 years' age category. It is clear from the mean difference that the age category investors in the age 18 -30 are having more information processing bias than the investors in the age categories '41 – 50 years' and 'above 50 years'.

2. **Belief Perseverance Bias**

The perceptions of four categories of age differ with regard to the belief perseverance bias. Since the variance is not homogeneous in this case, the researcher used the Tamhane's T2 test which shows the pair wise comparison as shown in table 7.15.

Table 7.15

Age Category-wise Post Hoc Test - Belief Perseverance Bias

Age Category (I)	Age Category (J)	Mean Difference (I-J)	Std. Error	p value
18 – 30 Years	31 - 40 Years	1.85938	1.09008	.435
	41 - 50 Years	3.71186*	1.19095	.013
	Above 50 Years	6.09211*	1.26503	.000
31 – 40 Years	18 - 30 Years	-1.85938	1.09008	.435
	41 - 50 Years	1.85249	.93276	.257
	Above 50 Years	4.23273*	1.02565	.000
41 – 50 Years	18 - 30 Years	-3.71186*	1.19095	.013
	31 - 40 Years	-1.85249	.93276	.257
	Above 50 Years	2.38024	1.13228	.203
Above 50 Years	18 - 30 Years	-6.09211*	1.26503	.000
	31 - 40 Years	-4.23273*	1.02565	.000
	41 - 50 Years	-2.38024	1.13228	.203

Source: Survey Data

* Significant at 5% level

There is a significant difference in the belief perseverance bias among the age category '18-30 years' with '41-50 years' and 'above 50 years', as the p value is 0.003, 0.000 respectively. It is clear from the mean difference is that youngsters (18- 30, 31-40 age categories) are having more belief perseverance bias than aged investors.

7.4.3 Educational Qualification-wise Analysis of Behavioural Bias

The different education category may have different level of behavioural bias. The researcher has done the descriptive analysis to know the difference in mean score of different education category. To test the statistical significance of this difference ANOVA is applied. To do the same, homogeneity of variance is checked by using Levene's test. The p value of the Levene's test is 0.001(Levene's statistics 5.794) which is less than .05. Since the homogeneity of variance is not assumed, Welch F test has been applied instead of ANOVA. The result of descriptive analysis and F test is exhibited in Table 7.16.

Table 7.16

Educational Qualification-wise Analysis of Behavioural Bias

Qualification Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Under Graduate	25	98.88	16.54	145	4.647^{**}	.006	Welch
Graduate	232	96.00	18.29				
Post Graduate	117	91.44	21.25				
Professional	16	85.50	12.25				
Total	**390**	**94.39**	**19.10**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The under graduate is having the highest mean score 98.88 (16.54) of overall behavioural bias and the lowest score 85.50 (12.24) is among professional. Hence it is concluded that education wise behavioural bias is maximum for undergraduates and minimum among professionals. Since the p value (0.006) is less than 0.05, the mean score is significantly different from others. To find out the exact difference among the groups, multiple comparisons have been done through post hoc analysis. Tamhane's T2 test has been applied to identify the pair wise differences since the equal variances are not assumed. The result is shown in table 7.17.

Table 7.17

Educational Qualification-wise Post Hoc Test - Behavioural Bias

Educational Qualification (I)	Educational Qualification (J)	Mean Difference (I-J)	Std. Error	p value
Under Graduate	Graduate	2.87569	3.51958	.962
	Post Graduate	7.43556	3.84750	.310
	Professional	13.38000*	4.50770	.031
Graduate	Under Graduate	-2.87569	3.51958	.962
	Post Graduate	4.55987	2.30259	.260
	Professional	10.50431*	3.28908	.027
Post Graduate	Under Graduate	-7.43556	3.84750	.310
	Graduate	-4.55987	2.30259	.260
	Professional	5.94444	3.63784	.513
Professional	Under Graduate	-13.38000*	4.50770	.031
	Graduate	-10.50431*	3.28908	.027
	Post graduate	-5.94444	3.63784	.513

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.17 shows that in case of behavioural bias, there is a significant difference in the educational qualification category between professional with under graduate and graduate category of investors. When we analyse the mean difference we came to know that under graduate investors have the highest mean score followed by graduate investors. That means, the lower education categories are more prone to behavioural bias.

To get a vivid idea about how the education classification shows the difference among the factors of behavioural bias, factor wise analysis has been done. First of all, Levene's test has been done to find out the homogeneity of variance. The results are shown in the following table.

Table 7.18
Educational Qualification-wise Test of Homogeneity of Variances Factors of Behavioural Bias

Dimensions of Bias	Levene's Statistic	P Value
Emotional	2.510	.058
Information Processing	10.039**	.000
Belief Perseverance	3.503*	.016

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.18 shows that all the dimensions except belief perseverance bias show the homogeneity. Therefore, the researcher uses one way ANOVA for emotional and information processing bias and Welch's F for belief perseverance since the variances are heterogeneous.

Table 7.19
Educational qualification wise Analysis of Factors of Behavioural Bias

Dimensions of bias	Qualification Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Emotional	Under Graduate	25	36.20	9.82	55	2.456	.056	ANOVA
	Graduate	232	35.14	9.97				
	Post Graduate	117	34.51	11.28				
	Professional	16	28.06	7.71				
	Total	**390**	**34.72**	**10.36**				
Information processing	Under Graduate	25	28.88	5.27	45	3.389	.024	Welch
	Graduate	232	29.62	8.33				
	Post Graduate	117	26.44	8.91				
	Professional	16	28.75	4.60				
	Total	**390**	**28.58**	**8.33**				
Belief perseverance	Under Graduate	25	33.80	3.01	45	2.706	.055	Welch
	Graduate	232	31.25	5.35				
	Post Graduate	117	30.50	4.77				
	Professional	16	28.69	3.27				
	Total	**390**	**31.08**	**5.24**				

*, ** statistically significant at the 5%, and 1% significant level

The table 7.19 shows the differences of various dimensions of behavioural bias among different educational qualification categories of investors. The results of ANOVA and Welch F test show that in case of emotional and belief perseverance bias, the p values are more than 0.05; and hence there is no significance difference whereas in case of information processing bias, p value is .024. Hence, it is concluded that there is a significant difference among the educational qualification with regard to the dimension of information processing bias.

To find out the exact difference among the groups, multiple comparisons have been done through post hoc analysis. Tamhane's T2 test has been applied to identify the pair wise differences since the equal variances are not assumed. The result is shown in table 7.20.

Table 7.20

Educational Qualification-wise Post Hoc Test – Information Processing Bias

Educational Qualification (I)	Educational Qualification (J)	Mean Difference (I-J)	Std. Error	p value
Under Graduate	Graduate	-.74069	1.18759	.990
	Post Graduate	2.44410	1.33803	.365
	Professional	.13000	1.55946	1.000
Graduate	Under Graduate	.74069	1.18759	.990
	Post Graduate	3.18479*	.98922	.009
	Professional	.87069	1.27285	.985
Post Graduate	Under Graduate	-2.44410	1.33803	.365
	Graduate	-3.18479*	.98922	.009
	Professional	-2.31410	1.41424	.507
Professional	Under Graduate	-.13000	1.55946	1.000
	Graduate	-.87069	1.27285	.985
	Post graduate	2.31410	1.41424	.507

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.20 shows that in case of information processing bias, there is a significant difference in the educational qualification category between post graduates with graduate category of investors. When we analyse the mean difference we recognise that graduate investors are having the highest mean score which suggest that the graduates are more affected by information processing behavioural bias.

7.4.4 Annual Income Category-wise Analysis of Behavioural Bias

Investors with different category of annual income may have different level of behavioural bias while taking investment decision. The behavioural bias data have been arranged as annual income category wise and presented in the table 7.21. To test the statistical significance of the difference of these mean scores of behavioural bias ANOVA has been done. Before doing the ANOVA, homogeneity of variance has been checked by using Levene's test. The p value of the Levene's test is 0.000 (Levene's statistics 8.352) which is less than .05. Since the homogeneity of variance is not assumed, Welch F test has been applied instead of ANOVA. The result of descriptive analysis and F test is exhibited in Table 7.21.

Table 7.21

Annual Income Category-wise Analysis of Behavioural Bias

Annual income Category	**N**	**Mean**	**S D**	**Max Score**	**F Value/ Welch F**	**P Value**	**Remarks**
Less than Rs.5,00,000	129	99.13	16.29	145	9.266**	.000	Welch
Rs.5,00,000 - 10,00,000	143	93.98	19.35				
Rs.10,00,000 - 15,00,000	90	94.23	17.13				
More than Rs.15,00,000	28	75.14	23.86				
Total	**390**	**94.39**	**19.10**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The annual income category 'less than Rs.5,00,000' is having the highest mean score 99.13 (16.29) of behavioural bias and the lowest score 75.14(23.86) is for investors with an annual income category of 'more than Rs.15,00,000'. Since the p value (0.000) is less than 0.05, the mean score is significantly different from others. It can be understood that the low income category investors are more prone to behavioural bias than the high income category investors. To find out the exact difference among the pair of groups multiple comparisons have been done through post hoc analysis.

The result of Tamhane's T2 test is presented in table 7.22.

Table 7.22

Annual Income Category-wise Post Hoc Test - Behavioural Bias

Annual Income (in Rupees) Category (I)	Annual Income (in Rupees) Category (J)	Mean Difference (I-J)	Std. Error	p value
Less than 5,00,000	5,00,000 - 10,00,000	5.15276	2.16230	.103
	10,00,000 - 15,00,000	4.89845	2.30592	.192
	More than 15,00,000	23.98893*	4.73096	.000
5,00,000 - 10,00,000	Less than 5,00,000	-5.15276	2.16230	.103
	10,00,000 - 15,00,000	-.25431	2.42448	1.000
	More than 15,00,000	18.83616*	4.78987	.002
10,00,000 - 15,00,000	Less than 5,00,000	-4.89845	2.30592	.192
	5,00,000 - 10,00,000	.25431	2.42448	1.000
	More than 15,00,000	19.09048*	4.85640	.002
More than 15,00,000	Less than 5,00,000	-23.98893*	4.73096	.000
	5,00,000 - 10,00,000	-18.83616*	4.78987	.002
	10,00,000 - 15,00,000	-19.09048*	4.85640	.002

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.22 shows that in case of behavioural bias, there is a significant difference in the annual income category between 'more than Rs.15,00,000' with ‘less than Rs.5,00,000 (p value 0.000), Rs.5,00,000 – Rs.10,00,000 (p value 0.000) and Rs.10,00,000 – Rs.15,00,000 (p value 0.040) income categories. When we analyse the mean difference we understand that the income group ‘more than Rs.15,00,000’ is least affected by behavioural bias. From this, it can be concluded that when the income is decreasing, the level of behavioural bias is increasing.

To get clear idea about how the annual income classification shows the difference among the factors of behavioural bias, factor wise analysis has been done. First of all, Levene’s test has been done to find out the homogeneity of variance. The results are as follows:

Table 7.23

Annual Income Category-wise Test of Homogeneity of Variances Dimensions of Behavioural Bias

Dimensions	Levene’s Statistic	P Value
Emotional bias	4.771**	.001
Information processing bias	6.533	.147
Belief Perseverance bias	2.159	.092

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.23 shows that all the dimensions except emotional bias show the homogeneity. Therefore, the researcher uses Welch’s F for emotional factor and ANOVA for all other dimensions since the variances are homogeneous.

Table 7.24

Annual Income Category-wise Analysis of Factors of Behavioural Bias

Dimension	Income Category (in Rupees)	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Emotional	Less than 5,00,000	129	35.75	10.46	55	4.711	.004	Welch
	5,00,000 - 10,00,000	143	33.77	9.62				
	10,00,000 - 15,00,000	90	36.89	9.37				
	More than 15,00,000	28	27.96	13.30				
	Total	**390**	**34.73**	**10.36**				
Information Processing	Less than 5,00,000	129	30.20	7.97	45	6.406	.000	ANOVA
	5,00,000 - 10,00,000	143	29.29	8.16				
	10,00,000 - 15,00,000	90	26.36	8.64				
	More than 15,00,000	28	24.68	7.56				
	Total	**390**	**28.58**	**8.34**				
Belief Perseverance	Less than 5,00,000	129	33.18	6.51	45	17.068	.000	ANOVA
	5,00,000 - 10,00,000	143	30.92	7.85				
	10,00,000 - 15,00,000	90	30.99	7.17				
	More than 15,00,000	28	22.50	6.40				
	Total	**390**	**31.08**	**7.60**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.24 shows the differences of various dimensions of behavioural bias among different annual income categories of investors. The results of one way

ANOVA show that in case of information processing and belief perseverance biases the p values are less than .05 and hence the differences are significant.

The result of Welch test shows in case of emotional bias the p value less than 0.05. Hence, it is concluded that there is a significant difference among the annual income categories with regard to emotional biases of investors. In order to find out the exact difference among the groups, post hoc test is done.

Multiple Comparisons: Factors of Behavioural Biases

The one way ANOVA and Welch F results show that there is a significant difference among the different annual categories with regard to emotional, information processing, and belief perseverance biases. Hence, in order to explore the exact difference, researcher used Tukey HSD (if equal variances are assumed) and Tamhane's T2 (if equal variance are not assumed) test. The result is shown below.

1. **Emotional Bias**

With regard to the emotional biases, the annual income categories of investors are differing, as the p value (0.004) shows a value which is less than 0.05. Tamhane's T2 test has been applied to identify the pair wise differences since the equal variances are not assumed. The result of post hoc for making the pair wise comparison is shown in the table 7.25

Table 7.25

Annual Income Category-wise Post Hoc Test - Emotional Bias

Annual Income (in Rupees) Category (I)	Annual Income (in Rupees) Category (J)	Mean Difference (I-J)	Std. Error	p value
Less than 5,00,000	5,00,000 - 10,00,000	1.98271	1.22323	.490
	10,00,000 - 15,00,000	-1.13695	1.35050	.954
	More than 15,00,000	7.78765*	2.67672	.037
5,00,000 - 10,00,000	Less than 5,00,000	-1.98271	1.22323	.490
	10,00,000 - 15,00,000	-3.11966	1.27385	.088
	More than 15,00,000	5.80495	2.63887	.192
10,00,000 - 15,00,000	Less than 5,00,000	1.13695	1.35050	.954
	5,00,000 - 10,00,000	3.11966	1.27385	.088
	More than 15,00,000	8.92460*	2.70023	.013
More than 15,00,000	Less than 5,00,000	-7.78765*	2.67672	.037
	5,00,000 - 10,00,000	-5.80495	2.63887	.192
	10,00,000 - 15,00,000	-8.92460*	2.70023	.013

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.25 shows that in case of emotional bias, there is a significant difference in the annual income category between 'more than Rs.15,00,000' with 'less than Rs.5,00,000 (p value 0.037), and Rs.10,00,000 – Rs.15,00,000 (p value 0.013) income categories. When we analyse the mean difference, we came to know that the income group 'more than Rs.15,00,000' is least affected by emotional bias.

2. Information Processing Bias

In respect of the information processing bias, the annual income categories of investors are differing, as the p value (0.000) shows a value which is less than 0.05. Tukey HSD test has been applied to identify the pair wise differences since the equal variances are assumed. The result of post hoc for making the pair wise comparison is shown in the table 7.26.

Table 7.26

Annual Income Category-wise Post Hoc Test - Information Processing Bias

Annual Income (in Rupees) Category (I)	Annual Income (in Rupees) Category (J)	Mean Difference (I-J)	Std. Error	p value
Less than 5,00,000	5,00,000 - 10,00,000	.91484	.99184	.793
	10,00,000 - 15,00,000	3.84599*	1.12182	.004
	More than 15,00,000	5.52298*	1.70292	.007
5,00,000 - 10,00,000	Less than 5,00,000	-.91484	.99184	.793
	10,00,000 - 15,00,000	2.93116*	1.09902	.040
	More than 15,00,000	4.60814*	1.68799	.033
10,00,000 - 15,00,000	Less than 5,00,000	-3.84599*	1.12182	.004
	5,00,000 - 10,00,000	-2.93116*	1.09902	.040
	More than 15,00,000	1.67698	1.76750	.778
More than 15,00,000	Less than 5,00,000	-5.52298*	1.70292	.007
	5,00,000 - 10,00,000	-4.60814*	1.68799	.033
	10,00,000 - 15,00,000	-1.67698	1.76750	.778

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.26 shows that in case of information processing bias, there is a significant difference in the annual income category between ‘more than Rs.15,00,000’ with ‘less than Rs.5,00,000 (p value 0.007), and ‘Rs.5,00,000 – Rs.10,00,000’ (p value 0.013) income categories. When we analyse the mean difference we come to know that the income group ‘more than Rs.15,00,000’ is least affected by information processing bias and income group ‘less than Rs.5,00,000 is highly affected.

3. **Belief Perseverance Bias**

Regarding the belief perseverance bias, the annual income categories of investors are differing, as the p value (0.000) shows a value which is less than 0.05. Tukey HSD test has been applied to identify the pair wise differences since the equal variances are assumed. The result of post hoc for making the pair wise comparison is shown in the table 7.27

Table 7.27

Annual Income Category-wise Post Hoc Test - Belief Perseverance Bias

Annual Income (in Rupees) Category (I)	Annual Income (in Rupees) Category (J)	Mean Difference (I-J)	Std. Error	p value
Less than 5,00,000	5,00,000 - 10,00,000	2.25522*	.87085	.049
	10,00,000 - 15,00,000	2.18941	.98498	.119
	More than 15,00,000	10.67829*	1.49519	.000
5,00,000 - 10,00,000	Less than 5,00,000	-2.25522*	.87085	.049
	10,00,000 - 15,00,000	-.06581	.96496	1.000
	More than 15,00,000	8.42308*	1.48208	.000
10,00,000 - 15,00,000	Less than 5,00,000	-2.18941	.98498	.119
	5,00,000 - 10,00,000	.06581	.96496	1.000
	More than 15,00,000	8.48889*	1.55189	.000
More than 15,00,000	Less than 5,00,000	-10.67829*	1.49519	.000
	5,00,000 - 10,00,000	-8.42308*	1.48208	.000
	10,00,000 - 15,00,000	-8.48889*	1.55189	.000

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.27 shows that in case of information processing bias, there is a significant difference in the annual income category between 'more than Rs.15,00,000' with 'less than Rs.5,00,000 (p value 0.000), 'Rs.5,00,000 –

Rs.10,00,000' (p value 0.000) and Rs.10,00,000 – Rs.15,00,000 income categories. When we analyse the mean difference we came to know that the income group 'more than Rs.15,00,000' is least affected by belief perseverance bias and income group 'less than Rs.5,00,000 is highly affected. It can be concluded that when income is increasing the level of belief perseverance biases are decreasing.

7.4.5 Marital Status-wise Analysis of Behavioural Bias

Investors with different marital status may have different levels of behavioural bias. Descriptive analysis has been done to find out the mean score of behavioural bias among married and single investors and 't' test is applied to understand the statistical significance of the difference. Levene's test shows the p value 0.004 and hence, the homogeneity of variance cannot be assumed. The result is shown in table 7.28.

Table 7.28

Marital Status-wise Analysis of Behavioural Bias

Gender	N	Mean	SD	Max Score	t value	p value	Remarks
Married	343	93.27	19.48	145	-4.142	.000	Equal variance Not assumed
Single	47	102.57	13.61				
Total	**390**	**94.39**	**19.10**				

Source: Survey Data

From the table 7.28, it can be observed that the mean score of behavioural bias of married is 93.27 (19.48) and that of single investors is 102.57 (13.61). Since the p value of the t test less than .05, there is significant difference between single investors and married investors with regard to behavioural bias. The single investors are more prone to behavioural bias than the married investors.

To be more specific, the researcher tests the difference among marital status with regard to the different factors of behaviour bias. The equal variance assumed is rejected in all the dimension of behavioural bias. Therefore we consider the results which assume unequal variance. The result has been shown in table 7.29.

Table 7.29

Marital Status-wise Analysis of Factors of Behavioural Bias

Dimensions of Bias	Marital status	N	Mean	SD	Max Score	t value	p value	Remarks
Emotional	Married	343	34.54	10.47	40	-.997	.323	Equal variance not Assumed
	Single	47	36.04	9.52				
	Total	**390**	**94.39**	**19.10**				
Information Processing	Married	343	28.02	8.35	35	-4.099^{**}	.000	Equal variance not not assumed
	Single	47	32.66	7.11				
	Total	**390**	**94.39**	**19.10**				
Belief perseverance	Married	343	30.70	7.83	30	-3.801	.000	Equal variance not Assumed
	Single	47	33.87	4.94				
	Total	**390**	**94.39**	**19.10**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.29 makes clear that among the dimensions of behavioural bias, the emotional bias has no significant difference among married and single investor since the p values is more than 0.05.

In case of information processing and belief perseverance biases, there is difference between married and single investor, as the p values are less than 0.05. It can be seen that the mean score of the single investors is more than that of the married investors. Hence, it can be concluded that single investors are more prone to information and belief perseverance bias.

7.5. Relation between Socio-economic Variable with Various Behavioural Bias

For further detailed analysis, the elements of behavioural bias which is the components of the factors of behavioural biases as shown in the figure 3.2 in chapter three have been considered. The components of emotional biases are overconfidence, loss aversion, regret aversion and herd mentality bias. Information processing bias constitutes from anchoring, mental accounting, availability and self attribution bias. Belief perseverance bias composed of representativeness, cognitive dissonance, confirmation and illusion of control bias.

In the above section, we test the relation between socio economic variable with factors of behavioural bias, but in this section, the researcher analyse the relation between socio-economic variable with each individual bias. The socio economic variable like gender, age, educational qualification, income and marital status are used for analyzing the variability of each behavioural bias among different categories. Following are the details of different factors and their elements of behavioural bias.

Emotional Bias

Emotional biases arise from impulse or intuition and may be considered from reasoning influenced by feelings. Emotion is a mental state that happens spontaneously rather than through conscious effort (Pompian, 2008)[6]. Emotional biases can be again classified into overconfidence, loss aversion, regret aversion and herd mentality biases.

1. **Overconfidence**

'Overconfidence bias is a bias in which people demonstrate unwarranted faith in their own intuitive reasoning, judgements, and/or cognitive abilities. This may be the result of overestimating knowledge levels, abilities, and access to information' Pompian (2008)[7]. Overconfidence in individual investors results overestimate return and underestimate risk, trading too much believing that the stocks they themselves hold will perform better than others.

2. **Loss Aversion**

Individuals often show greater sensitivity to losses than to gains. i.e the 'mental' penalty they associate with a given loss is greater than the 'mental' reward from a gain of the same size. This called as loss aversion.

3. **Regret Aversion**

Human beings have the tendency to feel the pain or the fear of regret at having made errors. As such, to avoid the pain of regret, people tend to alter their behaviour, which may end up being irrational at times. Regret aversion arises because of people's desire to avoid feeling the pain of regret resulting from a poor decision.

4. **Herding**

Herding is the behaviour of investors to behave in the similar way as the market is behaving thereby we have many market participants behaving in similar fashion creating a trend.

Cognitive Bias

Cognitive biases arise from basic statistical, information processing, or memory errors. These biases arise either from subconscious mental procedures for processing information or from irrational perseverance in one's own beliefs. Cognitive biases are classified into information processing biases and belief perseverance biases.

Information Processing Biases

Information processing biases arise in information being processed and used illogically or irrationally. Anchoring, mental accounting, availability and self attribution biases are included in information processing biases.

1. **Anchoring**

When people form estimates, they often start with some initial, possibly arbitrary, value and then adjust away from it. However, experimental evidence shows that people often 'anchor' too much on their initial estimate and the adjustment is insufficient.

2. **Mental Accounting**

'Mental accounting bias is an information processing bias in which people treat one sum of money differently from another equal-sized sum based on which mental account the money is assigned to' (Pompian, 2008)[8].

3. Availability

Availability bias is the human cognitive bias that causes us to overestimate the probabilities of events associated with memorable or vivid occurrences. According to the availability bias people tend to heavily weigh their decisions toward more recent information, making any new opinion based toward that latest news.

4. Self Attribution

'Self attribution bias refers to the tendency of individuals to ascribe their success to innate aspects, such as talent or foresight, while more often blaming failures on outside influences, such as bad luck' (Pompian, 2008)[9]

Belief Perseverance Bias

Belief perseverance is the tendency to cling to one's previously held or recently established beliefs irrationally or illogically. In belief perseverance biases the researcher considers representativeness, cognitive dissonance, conservation and illusion of control biases.

1. Representativeness

Representativeness bias refers to the tendency of decision makers to view events as typical or representative of some specific class that is to see patterns where perhaps none exists. An important consequence of the representativeness bias is that investors tend to assume that recent event will continue in near future, and therefore seek to buy "hot" stocks and to avoid stocks which have performed poorly in the recent past.

2. Cognitive Dissonance

'When newly acquired information conflicts with pre-existing understanding, people often experience mental discomfort – a psychological phenomenon known as cognitive dissonance. The term cognitive dissonance encompasses the responses that arise when people struggle to harmonise cognition and thereby relieve their mental discomfort' (Pompian, 2008)[10].

3. Confirmation

Confirmation bias is a bias in which investor tend to notice and consider what confirms their beliefs, and to ignore what contradict their beliefs. It is a belief perseverance bias.

4. Illusion of control

Illusion of control bias is a 'bias in which people tend to believe that they can control or influence outcomes when, in fact they cannot' (Pompian, 2008)[11].

The table 7.30 shows the mean and standard deviation of the different types of behavioural bias.

Table 7.30

Descriptive of Various Behavioural Bias

Factors of Behavioural Bias	Elements of Behavioural Bias	Mean	Standard deviation
Emotional bias	Over confidence bias	3.1564	1.00571
	Loss aversion bias	3.2034	.97069
	Regret aversion bias	3.1248	1.00830
	Herding bias	3.1372	1.04206
Information processing bias	Anchoring bias	3.1778	1.01644
	Mental accounting bias	3.1000	1.07746
	Availability bias	3.2756	1.12704
	Self attribution bias	3.3603	1.09466
Belief perseverance Bias	Representativeness bias	3.5239	.92437
	Cognitive dissonance bias	3.4897	.97126
	Confirmation bias	3.1487	1.07001
	Illusion of control bias	3.4038	.98399

Source: Field Survey

As per the above table, it can be concluded that all the bias having above average influence level since the entire mean score is in between 3 to 4. Since the representativeness bias of belief perseverance bias is having the highest mean score of 3.5239 (SD 0.92437), it is having highest influence among the investors in Kerala followed by cognitive dissonance of having mean score of 3.4897(SD 0.97126) followed by illusion of control bias having the mean score of 3.4038(S.D 0.98399) (all are from belief perseverance bias). Mental accounting bias is having the least mean score of 3.1000 (SD 1.07746).

7.5.1 Gender-wise Analysis of Various Behavioural Biases

The gender wise analysis of different elements of behavioural bias and results of 't' test is presented in the table 7.31.

Table 7.31

Gender-wise Analysis of Various Behavioural Biases

Dimensions of bias	Gender	N	Mean	SD	Max Score	t value	p value	Remarks
Overconfidence	Male	349	10.70	2.70	15	3.279	.002**	Equal variances assumed
	Female	41	9.24	2.85				
	Total	**390**	**9.47**	**3.02**				
Loss aversion	Male	349	9.67	2.95	15	1.409	.165	Equal variances not assumed
	Female	41	9.07	2.53				
	Total	**390**	**9.61**	**2.91**				
Regret aversion	Male	349	9.46	3.06	15	1.550	.122	Equal variances assumed
	Female	41	8.68	2.61				
	Total	**390**	**9.37**	**3.02**				
Herding	Male	349	6.36	2.09	10	2.411	0.16	Equal variances assumed
	Female	41	5.54	1.86				
	Total	**390**	**6.27**	**2.08**				
Anchoring	Male	349	9.71	3.05	15	3.395	.001**	Equal variances assumed
	Female	41	8.02	2.65				
	Total	**390**	**9.53**	**3.05**				
Mental accounting	Male	349	6.34	2.14	10	3.674	.000**	Equal variances assumed
	Female	41	5.05	1.91				
	Total	**390**	**6.20**	**2.15**				

Dimensions of bias	Gender	N	Mean	SD	Max Score	t value	p value	Remarks
Availability	Male	349	6.67	2.25	10	3.156	.002**	Equal variances assumed
	Female	41	5.51	2.01				
	Total	**390**	**6.55**	**2.25**				
Self attribution	Male	349	6.45	2.17	10	6.036	.000**	Equal variances not assumed
	Female	41	5.02	1.31				
	Total	**390**	**6.30**	**2.14**				
Representativeness	Male	349	10.73	2.73	15	3.282	.001**	Equal variances assumed
	Female	41	9.24	2.84				
	Total	**390**	**10.57**	**2.77**				
Cognitive Dissonance	Male	349	7.15	1.87	10	5.193	.000**	Equal variances assumed
	Female	41	5.54	1.95				
	Total	**390**	**6.98**	**1.94**				
Confirmation	Male	349	6.95	1.91	10	4.208	.000**	Equal variances assumed
	Female	41	5.61	2.06				
	Total	**390**	**6.81**	**1.97**				
Illusion of control	Male	349	6.89	2.14	10	4.524	.000**	Equal variances assumed
	Female	41	5.29	2.12				
	Total	**390**	**6.72**	**2.19**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

As per the table 7.31, almost all the elements of behavioural biases except loss aversion and regret aversion show the significant difference between male and female investors.

Overconfidence bias shows significant difference among men and women. Although male investors and female investors are found to be overconfident, this study shows that male investors are more confident than female investors. This is in par with the findings of lot of researchers in this area. Barber & Odean (2001)[12] found that male investors are strongly affected by overconfident than the female investors. Lewellen, Lease, & Schlarbaum (1977)[13] found that male investors have strong tendency of overconfidence.

Herding bias also shows the significant difference among male and female investors. It can be concluded from the result that male investors are more affected than their counterparts.

Anchoring bias shows significance difference among male and female investors. Since the mean score of the male investors are high, they are more prone to anchoring bias. That means male investors rely heavily on the initial information while taking the investment decision.

Mental accounting bias shows the significant difference among male investors and female investors. The result shows that male investors are more affected by mental accounting bias than their counterparts.

Since the p-value is less than .05, availability bias shows significant difference among male and female investors. Male investors are more prone to availability bias than their counterparts. They give more probability of an event based on how easily the event comes to mind.

In self attribution bias, there is significant difference among male investors and female investors. Male investors are having more self attribution bias than their counterparts.

In representative bias, there is significant difference between among male and female investors. The result indicates that male investors are more affected by representative bias than female investors. That means male investors are giving more weight to the experience while making the investment decision.

Cognitive dissonance bias shows significance difference among male investors and female investors. It is found that male investors are more dissonant in their investment decisions. They hold on their belief that they have taken the correct investment decision.

Since the p value of confirmation bias is less than .05, there is a significant difference among male and female investors with regard to confirmation bias. Male investors are more affected by confirmation bias than female investors.

Illusion of control bias shows significance difference among male and female investors, male investors are more prone to illusion of control bias than female investors.

7.5.2 Age Category-wise Analysis of Various Behavioural Biases

The different age category may have differently affected by different behavioural bias. Descriptive analysis has done to know the mean score of investor bias in different age category. It is found that there is different mean score for different age category. Then ANOVA is applied to test the significance of difference among mean of different age category.

The result of the Levene's test of homogeneity is presented in table 7.32

Table 7.32
Age Category-wise Test of Homogeneity of Variances – Various Behavioural Biases

Dimensions of bias	Levene's Statistic	P Value
Overconfidence	.402	.752
Loss aversion	.294	.830
Regret aversion	1.195	.311
Herding	.350	.789
Anchoring	1.327	.265
Mental accounting	.169	.917
Availability	1.247	.292
Self attribution	2.113	.098
Representativeness	4.210**	.006
Cognitive Dissonance	1.749	.156
Confirmation	.977	.404
Illusion of control	3.375*	.019

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.32 shows that all the dimensions except representative bias and illusion of control bias show the heterogeneity. Therefore, the researcher uses one way ANOVA for the biases which show the homogeneity and Welch's F for the biases which show the heterogeneity.

Table 7.33
Age Category-wise Analysis of Various Behavioural Biases

Dimensions of bias	**Age Category**	**N**	**Mean**	**S D**	**Max Score**	**F Value/ Welch F**	**P Value**	**Remarks**
Overconfidence	18 - 30 Years	68	8.84	2.90	15	2.701*	.045	ANOVA
	31 - 40 Years	128	9.52	2.76				
	41 - 50 Years	118	10.02	3.19				
	Above 50 Years	76	9.11	3.15				
	Total	**390**	**9.47**	**3.02**				
Loss aversion	18 - 30 Years	68	9.28	3.00	15	1.333	.263	ANOVA
	31 - 40 Years	128	9.44	2.75				
	41 - 50 Years	118	10.04	3.03				
	Above 50 Years	76	9.53	2.90				
	Total	**390**	9.61	2.91				
Regret aversion	18 - 30 Years	68	9.07	3.12	15	.615	.606	ANOVA
	31 - 40 Years	128	9.45	2.79				
	41 - 50 Years	118	9.61	3.20				
	Above 50 Years	76	9.16	3.07				
	Total	**390**	**9.37**	**3.02**				
Herding	18 - 30 Years	68	6.12	2.11	10	1.643	.179	ANOVA
	31 - 40 Years	128	6.19	2.01				
	41 - 50 Years	118	6.62	2.13				
	Above 50 Years	76	6.03	2.08				
	Total	**390**	**6.27**	**2.08**				
Anchoring	18 - 30 Years	68	10.00	2.89	15	3.827*	.010	ANOVA
	31 - 40 Years	128	10.06	2.91				
	41 - 50 Years	118	8.92	3.08				
	Above 50 Years	76	9.17	3.21				
	Total	**390**	**9.53**	**3.05**				

Dimensions of bias	Age Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Mental accounting	18 - 30 Years	68	7.01	2.15	10	6.570**	.000	ANOVA
	31 - 40 Years	128	6.42	2.11				
	41 - 50 Years	118	5.79	2.08				
	Above 50 Years	76	5.74	2.12				
	Total	**390**	**6.20**	**2.15**				
Availability	18 - 30 Years	68	6.75	2.33	10	1.447	.229	ANOVA
	31 - 40 Years	128	6.77	2.16				
	41 - 50 Years	118	6.47	2.26				
	Above 50 Years	76	6.14	2.30				
	Total	**390**	**6.55**	**2.25**				
Self attribution	18 - 30 Years	68	6.93	1.94	10	5.365**	.000	ANOVA
	31 - 40 Years	128	6.57	1.97				
	41 - 50 Years	118	6.01	2.22				
	Above 50 Years	76	5.72	2.27				
	Total	**390**	**6.30**	**2.14**				
Representative-ness	18 - 30 Years	68	11.49	2.82	15	7.382**	.000	Welch
	31 - 40 Years	128	10.97	2.30				
	41 - 50 Years	118	10.29	2.96				
	Above 50 Years	76	9.53	2.81				
	Total	**390**	10.57	2.77				
Cognitive Dissonance	18 - 30 Years	68	7.56	1.87	10	5.365*	.011	ANOVA
	31 - 40 Years	128	7.09	1.79				
	41 - 50 Years	118	6.78	1.96				
	Above 50 Years	76	6.58	2.11				
	Total	**390**	**6.98**	**1.94**				
Confirmation	18 - 30 Years	68	7.25	2.05	10	5.452**	.001	ANOVA
	31 - 40 Years	128	7.08	1.85				
	41 - 50 Years	118	6.71	1.90				
	Above 50 Years	76	6.11	2.02				
	Total	**390**	**6.81**	**1.97**				
Illusion of control	18 - 30 Years	68	7.71	2.06	10	12.151**	.000	Welch
	31 - 40 Years	128	7.00	1.84				
	41 - 50 Years	118	6.51	2.29				
	Above 50 Years	76	5.70	2.23				
	Total	**390**	**6.72**	**2.19**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.33 shows the differences of elements of behavioural bias among different age categories of investors. All the behavioural biases except loss aversion, regret aversion, herding and availability, show the significant difference between different age categories.

In overconfidence, there is significant difference among investors in different age categories. Form the result, it is shown that the older investors are more overconfident than younger investors.

Anchoring bias shows significant difference among different age categories. The mean score of age category '18 – 30 years' is 10.00 (S.D 2.89) whereas mean score of above 40 years is 9.17 (S.D 3.21). This suggests that younger investor is more affected by anchoring bias than older investor.

Mental accounting also shows significant difference among different age categories. The mean score of the age category '18-30 years' is 7.01 (S.D 2.15) while the mean score of the age category 'above 50 years' is 5.74 (S.D 2.12). This implies that the younger investors are more affected by mental accounting bias than older investors.

Self attribution bias shows the significant difference among different age categories. The mean score is decreasing when age category increases. This means that younger investors are more affected by attribution bias than the older investors.

Representativeness bias shows significant difference among different age categories. It is found that youngsters are more prone to representative bias than the older investors. The mean score of the age group '18 – 30 years' is 11.49 (S.D 2.82) while mean score of the 'above 50 years' is 9.53 (S.D 2.81).

Since the p value is less than .05, cognitive dissonance bias is having the significance difference among different age categories. The mean score of age category '18 – 30 years' is 7.65 (S.D 1.87) whereas the mean score of age category 'above 50 years' is 6.58 (SD 2.11). This implies that younger investors are more dissonant than the older investors.

It is found that confirmation bias shows the significant difference among different age categories. The mean score of the age category '18 – 30 years' is 7.25 (S.D

2.05) whereas mean score of the age category 'above 50 years' is 6.11 (S.D 2.02). This indicates that younger investors are more prone to conversion bias than older investors.

Illusion control bias also have the significant difference among different age categories. The mean score of the age category '18 – 30 years' is 7.71 (S.D 2.06) while the mean score of 'above 50 years' is 5.70 (S.D 2.23). It can be understood that the younger investors are more prone to illusion control bias than the older investors.

7.5.3 Educational Qualification-wise Analysis of Various Behavioural Biases

The different education category may have difference in behavioural bias when they take investment decisions. The researcher has done the descriptive analysis to know the difference in mean score of different education category. To test the statistical significance of this difference ANOVA is applied. Since the homogeneity of variance is not assumed, Welch F test has been applied instead of ANOVA. The result of homogeneity is exhibited in Table 7.34.

Table 7.34

Educational Qualification-wise Test of Homogeneity of Variances – Various Behavioural Biases

Dimensions of bias	Levene's Statistic	P Value
Overconfidence	1.369	.252
Loss aversion	1.154	.327
Regret aversion	2.873*	.036
Herding	.652	.582
Anchoring	12.054**	.000
Mental accounting	.867	.458
Availability	8.689**	.000
Self attribution	7.726**	.000

Dimensions of bias	Levene's Statistic	P Value
Representativeness	2.845*	.038
Cognitive Dissonance	1.078	.358
Confirmation	2.004	.113
Illusion of control	6.538**	.000

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.34 shows that six of the behavioural biases show the homogeneity. Therefore, the researcher uses one way ANOVA for the same and Welch's F for other biases since the variances are heterogeneous.

Table 7.35

Educational Qualification-wise Analysis of Various Behavioural Biases

Dimensions of bias	Educational qualification	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Overconfidence	Under graduate	25	9.92	3.03	15	3.632*	.013	ANOVA
	Graduate	232	9.64	2.89				
	Post graduate	117	9.34	3.23				
	Professional	16	7.19	2.37				
	Total	**390**	9.47	3.02				
Loss aversion	Under graduate	25	10.32	2.58	15	2.293	.078	ANOVA
	Graduate	232	9.65	2.82				
	Post graduate	117	9.61	3.14				
	Professional	16	7.94	2.62				
	Total	**390**	9.61	2.91				
Regret aversion	Under graduate	25	9.56	3.18	15	3.080*	.036	Welch
	Graduate	232	9.52	2.91				
	Post graduate	117	9.28	3.24				
	Professional	16	7.63	2.36				
	Total	**390**	9.37	3.02				
Herding	Under graduate	25	6.40	1.87	10	1.211	.305	ANOVA
	Graduate	232	6.32	2.05				
	Post graduate	117	6.28	2.21				
	Professional	16	5.31	1.96				
	Total	**390**	6.27	2.08				

Dimensions of bias	Educational qualification	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Anchoring	Under graduate	25	9.76	1.90	15	5.364**	.002	Welch
	Graduate	232	9.91	3.06				
	Post graduate	117	8.64	3.21				
	Professional	16	10.25	1.34				
	Total	**390**	9.53	3.05				
Mental accounting	Under graduate	25	5.64	1.96	10	4.861**	.002	ANOVA
	Graduate	232	6.53	2.16				
	Post graduate	117	5.79	2.13				
	Professional	16	5.31	1.70				
	Total	**390**	6.20	2.15				
Availability	Under graduate	25	6.60	1.15	10	3.058*	.036	Welch
	Graduate	232	6.76	2.25				
	Post graduate	117	6.04	2.44				
	Professional	16	7.19	1.60				
	Total	**390**	6.55	2.25				
Self attribution	Under graduate	25	6.88	1.67	10	2.383	.079	Welch
	Graduate	232	6.42	2.16				
	Post graduate	117	5.97	2.26				
	Professional	16	6.00	1.21				
	Total	**390**	6.30	2.14				
Representative-ness	Under graduate	25	11.44	2.04	15	1.955	.132	Welch
	Graduate	232	10.64	2.72				
	Post graduate	117	10.31	3.07				
	Professional	16	10.19	1.97				
	Total	**390**	10.57	2.77				
Cognitive Dissonance	Under graduate	25	7.40	1.91	10	.539	.656	ANOVA
	Graduate	232	6.94	1.86				
	Post graduate	117	7.00	2.14				
	Professional	16	6.69	1.74				
	Total	**390**	6.98	1.94				
Confirmation	Under graduate	25	7.32	1.70	10	2.724*	.044	ANOVA
	Graduate	232	6.92	1.85				
	Post graduate	117	6.62	2.18				
	Professional	16	5.75	2.02				
	Total	**390**	6.81	1.97				
Illusion of control	Under graduate	25	7.64	1.55	10	3.514*	.022	Welch
	Graduate	232	6.75	2.03				
	Post graduate	117	6.56	2.57				
	Professional	16	6.06	1.91				
	Total	**390**	6.72	2.19				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.35 shows the differences of elements behavioural biases among different educational qualification categories of investors. All the behavioural biases except loss aversion, herding, self attribution, representative and cognitive dissonance show the significant difference between different educational qualification categories.

Overconfidence bias shows significance difference among different educational levels of investors. The mean score of 'under graduate' education level is 9.92 (S.D 3.03) while the mean score the 'professional' education level is 7.19 (S.D 2.37). This means that investors having low education level are more prone to overconfidence bias than investors having high education level.

Regret aversion bias also shows significant difference among different educational categories of investors. In this case also investors having lower education categories having higher regret aversion bias than the higher education categories.

Since the p value is less than 0.05 anchoring bias is having the significance difference among different education level of investors. Here, it is just reverse of the overconfidence. Investors having high education category is more prone to anchoring bias than investors having low education category.

Since the p value of mental accounting bias is less than 0.05, this bias also shows the significant different among different education categories. In this case, lower education categories are more prone to mental accounting bias than higher education category.

Availability bias shows significant difference among different education level of investors. The mean score of 'undergraduate' education level is 6.60 (S.D 1.15) where as 'professional' education level is 7.19 (S.D 1.60). This means that investors having high education level are more affected by availability bias than investors having low education category.

Confirmation bias shows the significance difference among different education categories. The mean score of 'undergraduate' educational category is 7.32 (S.D 1.93) whereas the mean score of 'professional' education category is 5.75 (S.D 1.74). It is found that the low educational category is more affected by confirmation bias than high educational category.

In illusion of control bias, there is significant difference among different education level of investors. The mean score of ‘undergraduate’ education level is 7.64 (S.D 1.55) where as ‘professional’ education level is 6.06 (S.D 1.91). This indicates that investors having low education category are more prone to illusion of control bias than investors of high education category.

7.5.4 Annual Income Category-wise Analysis of Various Behavioural Biases

Investors in different category of annual income may have different behavioural biases while taking investment decision. Descriptive analysis has been done to find out the mean score of each category of annual income. To test the statistical significance of the difference of these mean score ANOVA has been done. Before doing the ANOVA, homogeneity of variance has been checked by using Levene’s test. . The result of homogeneity of variance is exhibited in Table 7.36.

Table 7.36

Annual Income Category-wise Test of Homogeneity of Variances – Various Behavioural Biases

Dimensions of bias	Levene’s Statistic	P Value
Overconfidence	10.019	.558
Loss aversion	3.142*	.037
Regret aversion	2.854**	.008
Herding	2.371**	.000
Anchoring	.691	.311
Mental accounting	4.043	.070
Availability	1.195	.747
Self attribution	.205*	.034
Representativeness	5.302**	.000
Cognitive Dissonance	.409	.893
Confirmation	.869*	.025
Illusion of control	2.921	.457

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.36 shows that six of the behavioural biases have the homogeneity. Therefore, the researcher uses ANOVA for those who show homogeneity and for others Welch F.

Table 7.37

Annual Income Category-wise Analysis of Various Behavioural Biases

Dimensions of bias	Annual Income (in rupees)	N	Mean	S D	Max Score	F Value Welch F	P Value	Remarks
Overconfidence	Less than 5,00,000	129	9.75	3.00	15	7.451**	.000	Welch
	5,00,000 - 10,00,000	143	9.16	2.72				
	10,00,000 - 15,00,000	90	10.33	2.63				
	more than 15,00,000	28	6.96	4.10				
	Total	**390**	**9.47**	**3.02**				
Loss aversion	Less than 5,00,000	129	9.84	2.94	15	3.573*	.016	Welch
	5,00,000 - 10,00,000	143	9.38	2.76				
	10,00,000 - 15,00,000	90	10.16	2.67				
	more than 15,00,000	28	8.00	3.65				
	Total	**390**	**9.61**	**2.91**				
Regret aversion	Less than 5,00,000	129	9.67	3.03	15	3.802*	.012	Welch
	5,00,000 - 10,00,000	143	9.13	2.88				
	10,00,000 - 15,00,000	90	9.89	2.85				
	more than 15,00,000	28	7.64	3.61				
	Total	**390**	**9.37**	**3.02**				
Herding	Less than 5,00,000	129	6.50	2.05	10	3.044*	.029	ANOVA
	5,00,000 - 10,00,000	143	6.10	1.98				
	10,00,000 - 15,00,000	90	6.51	2.08				
	more than 15,00,000	28	5.36	2.50				
	Total	**390**	**6.27**	**2.08**				
Anchoring	Less than 5,00,000	129	9.92	2.95	15	4.947**	.002	ANOVA
	5,00,000 - 10,00,000	143	9.90	2.96				
	10,00,000 - 15,00,000	90	8.81	3.12				
	more than 15,00,000	28	8.21	3.13				
	Total	**390**	**9.53**	**3.05**				

Dimensions of bias	Annual Income (in rupees)	N	Mean	S D	Max Score	F Value Welch F	P Value	Remarks
Mental accounting	Less than 5,00,000	129	6.70	2.21	10	8.985**	.000	Welch
	5,00,000 - 10,00,000	143	6.34	2.10				
	10,00,000 - 15,00,000	90	5.61	2.09				
	More than 15,00,000	28	5.11	1.57				
	Total	**390**	**6.20**	**2.15**				
Availability	Less than 5,00,000	129	6.74	2.12	10	3.146**	.025	ANOVA
	5,00,000 - 10,00,000	143	6.81	2.25				
	10,00,000 - 15,00,000	90	6.01	2.36				
	More than 15,00,000	28	6.07	2.24				
	Total	**390**	**6.55**	**2.25**				
Self attribution	Less than 5,00,000	129	6.84	2.12	10	5.995**	.001	ANOVA
	5,00,000 - 10,00,000	143	6.24	2.02				
	10,00,000 - 15,00,000	90	5.92	2.19				
	More than 15,00,000	28	5.29	2.09				
	Total	**390**	**6.30**	**2.14**				
Representativeness	Less than 5,00,000	129	11.16	2.41	15	24.796**	.000	Welch
	5,00,000 - 10,00,000	143	10.45	2.91				
	10,00,000 - 15,00,000	90	10.99	2.39				
	More than 15,00,000	28	7.11	2.28				
	Total	**390**	**10.57**	**2.77**				
Cognitive Dissonance	Less than 5,00,000	129	7.41	1.76	10	8.036**	.000	ANOVA
	5,00,000 - 10,00,000	143	6.94	1.99				
	10,00,000 - 15,00,000	90	6.89	1.92				
	More than 15,00,000	28	5.50	1.88				
	Total	**390**	**6.98**	**1.94**				
Confirmation	Less than 5,00,000	129	7.40	1.78	10	12.916**	.000	ANOVA
	5,00,000 - 10,00,000	143	6.77	1.96				
	10,00,000 - 15,00,000	90	6.58	1.96				
	More than 15,00,000	28	5.04	1.64				
	Total	**390**	**6.81**	**1.97**				

Dimensions of bias	Annual Income (in rupees)	N	Mean	S D	Max Score	F Value Welch F	P Value	Remarks
Illusion of control	Less than 5,00,000	129	7.21	1.93	10	13.542**	.000	Welch
	5,00,000 - 10,00,000	143	6.76	2.18				
	10,00,000 - 15,00,000	90	6.53	2.38				
	More than 15,00,000	28	4.86	1.74				
	Total	**390**	**6.72**	**2.19**				

*, ** statistically significant at the 5%, and 1% significant level

The table 7.37 shows the differences of various elements of behavioural biases among different annual income categories of investors. All the behavioural biases show a significant difference between different annual income categories.

Since the p value is less than 0.05, the overconfidence bias shows the significant difference between various annual income categories. The mean score of annual income category 'Rs.10,00,000 than Rs.15, 00,000' is 10.33 (S.D 2.63) while the mean score of annual income category 'more than Rs.15, 00,000' is 6.96 (S.D 4.10). This indicates that low annual income investors are more prone to overconfidence bias than the high annual income investors.

In loss aversion bias, there is significant difference among various annual income categories. The mean score of annual income category 'Rs.10, 00,001 – 15, 00,000' is 10.16 (S.D 2.67) while the mean score of annual income category 'more than Rs.15, 00,000' is 8.00 (S.D 3.65). This indicates that low annual income investors are more affected by loss aversion bias than the high annual income investors.

Regret aversion bias shows significant difference among the investors in various annual income categories. . The mean score of annual income category 'Rs.10, 00,001 – 15, 00,000' is 9.89 (S.D 2.85) while the mean score of annual income category 'more than Rs.15, 00,000' is 7.64 (S.D 3.61). This indicates that low annual income investors are more prone to regret aversion bias than the high annual income investors.

Herding bias also shows significant difference among the investors in various annual income categories. The mean score of annual income category ‘Rs.10, 00,001 – 15, 00,000’ is 6.51 (S.D 2.08) while the mean score of annual income category ‘more than Rs.15, 00,000’ is 5.36 (S.D 2.50). This indicates that low annual income investors are more prone to herding bias than the high annual income investors.

In Anchoring bias, there is significant difference among the investors in various annual income categories. The mean score of annual income category ‘less than Rs.5, 00,000’ is 9.92 (S.D 2.95) while the mean score of annual income category ‘more than Rs.15, 00,000’ is 8.21 (S.D 3.13). This indicates that low annual income investors are more affected by anchoring bias than the high annual income investors.

Since the p value is less than 0.05, mental accounting bias shows the significant difference between the investors in various annual income categories. The mean score of annual income category ‘less than Rs.5, 00,000’ is 6.70 (S.D 2.21) while the mean score of annual income category ‘more than Rs.15, 00,000’ is 5.11 (S.D 1.77). This indicates that lower annual income investors are more affected by mental accounting bias than the higher annual income investors.

Availability bias shows significant difference among the investors in various annual income categories. The mean score of annual income category ‘Rs.5, 00,000 – 10, 00,000’ is 6.81 (S.D 2.12) while the mean score of annual income category ‘more than Rs.15, 00,000’ is 6.07 (S.D 2.14). This indicates that low annual income investors are more affected by availability bias than the high annual income investors.

In self attribution bias, there is significant difference among various annual income categories. The mean score of annual income category ‘less than Rs.5, 00,000’ is 6.84 (S.D 2.12) while the mean score of annual income category ‘more than Rs.15, 00,000’ is 5.89 (S.D 2.09). This implies that low annual income investors are more prone to self attribution bias than the high annual income investors.

Representativeness bias shows significant difference among various annual income categories. The mean score of annual income category ‘less than Rs.5, 00,000’ is

11.16 (S.D 2.41) while the mean score of annual income category ‘more than Rs.15, 00,000’ is 7.11 (S.D 2.28). This indicates that low annual income investors are more affected by representativeness bias than the high annual income investors.

Since the p value is less than 0.05, the cognitive dissonance bias shows the significant difference between various annual income categories. The mean score of annual income category ‘less than Rs.5, 00,000’ is 7.41 (S.D 1.76) while the mean score of annual income category ‘more than Rs.15, 00,000’ is 5.50 (S.D 1.88). This indicates that low annual income investors are more dissonant than the high annual income investors.

Since the p value is less than 0.05, the confirmation bias shows the significant difference between various annual income categories. The mean score of annual income category ‘less than Rs.5, 00,000’ is 7.40 (S.D 1.78) while the mean score of annual income category ‘more than Rs.15, 00,000’ is 5.04 (S.D 1.74). This indicates that low annual income investors are more prone to confirmation bias than the high annual income investors.

Illusion of control bias shows significant difference among various annual income categories. The mean score of annual income category ‘less than Rs.5, 00,000’ is 7.21 (S.D 2.41) while the mean score of annual income category ‘more than Rs.15, 00,000’ is 4.86 (S.D 1.94). This indicates that low annual income investors are more affected by illusion of control bias than the high annual income investors.

7.5.5 Marital Status-wise Analysis of Various Behavioural Biases

In order to examine whether there is a difference in the behavioural bias among married and single investors descriptive analysis has been done to find out the mean score of behavioural bias among the married and the single. To find out the statistical significance of the difference ‘t’ test is applied. The result has been shown in table 7.38.

Table 7.38

Marital Status-wise Analysis of Various Behavioural Biases

Dimensions of bias	Gender	N	Mean	SD	Max Score	t value	p value	Remarks
Overconfidence	Married	349	9.42	3.06	15	-1.011	.316	Equal variances not assumed
	Single	41	9.85	2.72				
	Total	**390**	**9.47**	**3.02**				
Loss aversion	Married	349	9.59	2.95	15	-.481	.632	Equal variances not assumed
	Single	41	9.79	2.65				
	Total	**390**	**9.61**	**2.91**				
Regret aversion	Married	349	9.32	3.05	15	-.946	.345	Equal variances assumed
	Single	41	9.76	2.81				
	Total	**390**	**9.37**	**3.02**				
Herding	Married	349	6.22	2.11	10	-1.430	.158	Equal variances not assumed
	Single	41	6.64	1.82				
	Total	**390**	**6.27**	**2.08**				
Anchoring	Married	349	9.35	3.06	15	-3.542**	.001	Equal variances not assumed
	Single	41	10.85	2.67				
	Total	**390**	**9.53**	**3.05**				
Mental accounting	Married	349	6.05	2.11	10	-3.560**	.000	Equal variances assumed
	Single	41	7.23	1.82				
	Total	**390**	**6.20**	**2.15**				
Availability	Married	349	6.43	2.29	10	-3.340**	.001	Equal variances not assumed
	Single	41	7.40	1.80				
	Total	**390**	**6.55**	**2.25**				
Self attribution	Married	349	6.18	2.12	10	-3.012**	.003	Equal variances assumed
	Single	41	7.17	2.07				
	Total	**390**	**6.30**	**2.14**				
Representativeness	Married	349	10.41	2.84	15	-4.427**	.000	Equal variances not assumed
	Single	41	11.77	1.82				
	Total	**390**	**10.57**	**2.77**				
Cognitive Dissonance	Married	349	6.88	2.00	10	-3.719**	.000	Equal variances not assumed
	Single	41	7.68	1.27				
	Total	**390**	**6.98**	**1.94**				

Dimensions of bias	Gender	N	Mean	SD	Max Score	t value	p value	Remarks
Confirmation	Married	349	6.72	2.00	10	-2.941**	.004	Equal variances not assumed
	Single	41	7.47	1.59				
	Total	**390**	**6.81**	**1.97**				
Illusion of control	Married	349	6.69	2.19	10	-.791	.430	Equal variances assumed
	Single	41	6.96	2.17				
	Total	**390**	**6.72**	**2.19**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 7.38 shows the mean score and t test results among various behavioural biases. All the behavioural biases except overconfidence, loss aversion, regret aversion, herding and illusion of control show the significant difference between different annual income categories.

Anchoring bias shows significant difference among married investor and single investor. The mean value of married investor is 9.35 (S.D 3.06) while the mean score of single investor is 10.85 (S.D 2.86). The result indicates that single investors are more affected by representative bias than the married investors.

Mental accounting bias also shows the significant difference among married investors and single investors. The mean score of the married investors is 6.05 (S.D 2.11) where as the mean score single investor is 7.23 (S.D 1.82). Single investors are more affected by mental accounting bias than the married investors.

Since p value of the availability bias is less than 0.05, this bias is significantly different among single and married investors. The mean value of married investor is 6.43 (S.D 3.06) while the mean score of single investor is 6.40 (S.D 1.80). This result implies that the single investors are more affected by availability bias than the married investors.

In self attribution bias, there is significant difference between single and married investors. The mean score of the married investors is 6.18 (S.D 2.12) where the mean score single investor is 7.17 (S.D 2.07). This means that the single investors are more prone to self attribution bias than the married investors.

In representative bias, there is significant difference between single and married investors. The mean score of married investor is 10.41 (S.D 2.84) while the mean score of single investor is 11.77 (S.D 1.82). The result indicates that the single investors are more affected by representative bias than the married investors.

Cognitive dissonance bias shows significance difference among single and married investors. The mean score of the married investors is 6.88 (S.D 2.00) where as the mean score single investor is 7.68 (S.D 1.27). This means that the single investors are more dissonant than the married investors.

Since the p-value is less than .05, confirmation bias shows the significant difference among married and single investors. The mean score of the married investors is 6.72 (S.D 2.00) where as the mean score single investor is 7.47 (S.D 1.49). The Single investors are more prone to availability bias than the married investors. They give more probability of an event based on how easily the event comes to mind.

Summary of Behavioural Bias

From the above analysis of behavioural bias, it can be concluded that on an average the investors are 65% affected by behavioural bias while taking the investment decisions. Through the factor analysis we have grouped the behavioural bias into three factors. The most important factor is the Emotional bias as it contributes 33.17 % of the total variance. Information processing bias is the second important factor (18.84%), and belief perseverance bias is the third factor (10.12%).

In gender-wise analysis, even though, there is significant difference between male and female investors with regard to behavioural bias, from the analysis we can conclude that male investors are more prone to behavioural bias than their female counterparts. In dimension wise analysis of behaviour biases male and female investors are equal in the case of emotional bias, but male investors are more influenced by information processing and belief perseverance bias while taking the investment decision.

There is significance difference among the investors in different age categories with regard to behavioural bias. The analysis indicates that behavioural bias is more to young investors and less in the case of older investors. In factor wise analysis, it can be understood that young investors are more prone to information processing and belief perseverance bias.

In educational qualification wise analysis of behavioural bias, it can be seen that behavioural bias is maximum for undergraduates and minimum among professionals. Only the information processing bias shows the significant difference among investors under different educational qualification.

In annual income category wise analysis of behavioural bias, there is significant difference among the investors in different annual income categories. It can be concluded that the low income investors are more influenced by behavioural bias than high income investors while taking investment decision. Regarding the components of behavioural bias, all components show the significant difference among different annual income categories.

In marital status-wise analysis of behavioural bias there is significance among married and single while taking investment decision, unmarried investors are highly influenced by behavioural bias when compared with the married investors. Factor wise analysis of behavioural bias shows all the factors having significant difference except emotional bias.

It can be concluded from the result that all the bias having above average influence level since the entire mean score are in between 3 to 4. Since the representativeness bias of belief perseverance bias is having the highest mean score of 3.5239 (SD 0.92437), it is having highest influence among the investors in Kerala followed by cognitive dissonance of having mean score of 3.4897(SD 0.97126) followed by illusion of control bias having the mean score of 3.4038(S.D 0.98399) (all are from belief perseverance bias). Mental accounting bias is having the least mean score of 3.1000 (SD 1.07746).

It can be concluded that all the elements of behavioural biases except loss aversion, regret aversion and herding show the significant difference between male and female investors.

Overconfidence bias shows significant difference among men and women. Although male investors and female investors are found to be overconfident, this study shown that male investors are more confident than female investors

Anchoring bias shows significance difference among male and female investors. Since the mean score of the male investors are high, they are more prone to anchoring bias.

Mental accounting bias shows the significant difference among male investors and female investors. The result shows that male investors are more affected by mental accounting bias than their counterpart.

Availability bias shows the significant difference among male and female investors. Male investors are more prone to availability bias than their counterparts.

In self attribution bias, there is significant difference among male investors and female investors. Male investors are having more self attribution bias than their counterparts.

Illusion of control bias shows significance difference among male and female investors, male investors are more prone to than female investors.

In representative bias, there is significant difference between among male and female investors. The result indicates that male investors are more affected by representative bias than female investors.

Cognitive dissonance bias shows significance difference among male investors and female investors. It is found that male investors are more dissonant in their investment decisions.

Illusion of control bias shows significance difference among male and female investors, male investors more prone to illusion of control bias than female investors.

The result shows that all the behavioural biases except availability, loss aversion, regret aversion and herding show the significant difference between different age categories.

In overconfidence, there is significant difference among different age categories. Form the result, it is shown that the older investors are more overconfident than younger investors.

Anchoring bias shows significant difference among different age categories. The younger investor is more affected by anchoring bias than older investors.

Mental accounting also shows significant difference among different age categories. The result implies that the younger investors are more affected by mental accounting bias than older investors.

Self attribution bias shows the significant difference among different age categories. The mean score is decreasing when the age category increases.

Representativeness bias shows significant difference among different age categories. It is found that youngsters are more prone to representative bias than the older investors

Cognitive dissonance bias is having the significance difference among different age categories. It can be concluded from the result that younger investors are more dissonant than the older investors.

There is a significant difference among male and female investors with regard to confirmation bias. Male investors are more affected by confirmation bias than female investors.

It is found that confirmation bias shows the significant difference among different age categories. The result indicates that younger investors are more prone to conversion bias than older investors.

Illusion control bias is having the significant difference among different age categories. It can be understood from the result that the younger investors are more prone to illusion control bias than the older investors.

The result shows that all the behavioural biases except loss aversion, herding, self attribution, representative and cognitive dissonance show the significant difference between different educational qualification categories.

Overconfidence bias shows significance difference among different educational level of investors. It shows that investors having low education level are more prone to overconfidence bias than investors having high education level.

Regret aversion bias also shows significant difference among different educational categories of investors. In this case also investors in lower education categories are having higher regret aversion bias than the higher education categories.

Anchoring bias has the significance difference among different education level of investors. Here, it is just the reverse of the overconfidence. Investors in the high education category are more prone to anchoring bias than investors in the low education category.

Since the p value of mental accounting bias is less than 0.05, this bias also shows the significant different among different education categories. In this case, lower education categories are more prone to mental accounting bias than higher education category.

Availability bias shows significant difference among different education level of investors.). Investors of high education level are more affected by availability bias than investors of low education category.

Confirmation bias shows the significance difference among different education categories. It is found that the low educational category is more affected by confirmation bias than high educational category.

In illusion of control bias, there is significant difference among different education level of investors. Investors in the low education category are more prone to illusion of control bias than the investors of high education category.

The result shows that all the behavioural biases show the significant difference among different annual income categories.

The overconfidence bias shows the significant difference among various annual income categories. The result indicates that low annual income investors are more prone to representativeness bias than the high annual income investors.

In loss aversion bias, there is significant difference among various annual income categories. The result indicates that low annual income investors are more affected by loss aversion bias than the high annual income investors.

Regret aversion bias shows significant difference among various annual income categories. . This result shows that low annual income investors are more prone to regret aversion bias than the high annual income investors.

Herding bias also shows significant difference among various annual income categories. The result shows that low annual income investors are more prone to herding bias than the high annual income investors.

In Anchoring bias, there is significant difference among various annual income categories. The result shows that low annual income investors are more affected by anchoring bias than the high annual income investors.

Mental accounting bias shows the significant difference among various annual income categories. The result indicates that low annual income investors are more affected by mental accounting bias than the high annual income investors.

Availability bias shows significant difference among various annual income categories. The result indicates that low annual income investors are more affected by availability bias than the high annual income investors.

In self attribution bias, there is significant difference among various annual income categories. The result implies that low annual income investors are more prone to self attribution bias than the high annual income investors.

Representativeness bias shows significant difference among various annual income categories. The result indicates that low annual income investors are more affected by representativeness bias than the high annual income investors.

Cognitive dissonance bias shows the significant difference among various annual income categories. The result implies that low annual income investors are more dissonant than the high annual income investors.

The confirmation bias shows the significant difference between various annual income categories. The result shows that low annual income investors are more prone to confirmation bias than the high annual income investors.

Illusion of control bias shows significant difference among various annual income categories. The result indicates that low annual income investors are more affected by illusion of control bias than the high annual income investors.

The result shows that all the behavioural biases except overconfidence, loss aversion, regret aversion, herding and illusion of control, show the significant difference between different annual income categories.

Anchoring bias shows significant difference among married investor and single investor. The result indicates that single investors are more affected by representative bias than married investors.

Mental accounting bias also shows the significant difference among married investors and single investors. Single investors are more affected by mental accounting bias than married investors.

Availability bias, it shows significant difference among single and married investors. The result implies that single investors are more affected by availability bias than married investors.

In self attribution bias, there is significant difference between among single and married investors. The result indicates that single investors are more prone to self attribution bias than married investors.

In representative bias, there is significant difference between among single and married investors. The result indicates that single investors are more affected by representative bias than married investors.

Cognitive dissonance bias shows significance difference among single and married investors. The result shows that single investors are more dissonant than married investors.

Confirmation bias shows the significant difference among the married and the single investors. Single investors are more prone to availability bias than the married investors. They give more probability of an event based on how easily the event comes to mind.

7.6 Emotional Intelligence

Emotional intelligence is a term created by two researchers – John Mayer, University of Hampshire and Yale's Peter Salavoy – and popularised by Daniel Goleman in his book 'Emotional Intelligence'. 'It is a person's ability to recognise and interpret emotions and to use and integrate them productively for optimal reasoning and problem solving.' Daniel Goleman explained the definition of emotional intelligence, expanding the same into five main domains:

1. **Self Awareness**. Recognising a feeling as it happens is the keystone of emotional intelligence. People with greater certainty about their feeling are better pilot of their lives.
2. **Managing Emotions**. People who are poor in this ability are constantly battling the feeling of distress, while those who excel in it can bounce back far more quickly from life's setbacks and upsets.
3. **Motivating Oneself**. People who have this skill tend to be more highly productive and effective in whatever they undertake.
4. **Empathy**. People who are empathetic are more attuned to the subtle social signals that indicate what others need.
5. **Social Skills**. These are the abilities that pave the foundation for popularity, leadership, and interpersonal effectiveness.

According to (Goleman, 2005)[14], emotional intelligence helps investor have better decision making. This aspect has been studied in the research and fifteen statements are given to informants to score ranging from one to five. The mean score for each statement is calculated and presented in table 7.39 below.

Table 7.39

Indicators of Emotional Intelligence

Indicator Code	Indicators	Mean	Standard deviation
SA1	I realise immediately when I lose my temper	3.6256	1.13752
SA2	I know when I am happy	3.6897	1.11251
SA3	I usually recognise when I am stressed	3.7333	1.06386
ME1	I can reframe bad situations quickly	3.4308	1.11732
ME2	I can consciously alter my frame of mind or mood	3.5026	1.03598
ME3	I rarely worry about wok or life in general	3.4308	1.09876
MO1	I am always able to motive myself to do difficult tasks	3.3513	1.09318
MO2	I believe in 'Action this Day'	3.3590	1.10589
MO3	I never waste time	3.3487	1.13665
EM1	I can see things from the other's point of view	3.2667	1.08539
EM2	I am excellent at empathising with someone else's problem	3.2231	1.07267
EM3	I can tell if someone is not happy with me	3.2359	1.04438
SSK1	I am an excellent listener	3.2000	1.23197
SSK2	I never interrupt other people's conversations	3.2538	1.23766
SSK3	I am good at adapting and mixing with a variety of people	3.2000	1.21516

Source: Field Survey

It can be seen from the table 7.39 that ''I usually recognise when I am stressed' having highest mean score of 3.7333 (SD 1.06386) followed by the statement 'I know when I am happy' 3.6897 (SD 1.11251) and statement 'I realise immediately when I lose my temper' 3.6256 (SD 1.13752). The statements 'I am an excellent listener' and 'I am good at adapting and mixing with a variety of people' having least mean score 3.2000 (SD 1.23197, 1.21516 respectively).

7.6.1 Factors of Emotional Intelligence

Factor analysis is used for identifying the underlying factors and its structure in Emotional Intelligence. It analyses the structure of correlation among large number of variables by defining group of variable that are highly correlated, called as factors. To find out the extent of investor bias, a five point Likert scale is developed and the respondents were asked to rate the variables ranging from highly agree (5) to highly disagree (1). The number of statements included in the measurement instrument was 17; further the statements were reduced to 15 based on the communalities in the extraction. Two statements were excluded from the analysis frame because of the low extraction values. It is seen that the communalities after deleting three statements show significantly large values suggesting that the statements are useful to analyse the bias of investors.

In order to verify the adequacy or appropriateness of data for factor analysis, Kaiser-Meyer- Oklin Measure of sampling adequacy (KMO) and Bartlett's test of Sphericity are applied. The Kaiser-Meyer- Oklin measure of sampling adequacy is an index used for comparing the magnitudes of the observed correlation coefficients to the magnitudes of the partial correlation coefficients. KMO statistics vary between 0 and 1. A value of 0 indicates that the sum of partial correlation is large relative to the sum of correlation. Hence, factor analysis is likely to be inappropriate. A value close to 1 indicates that patterns of correlation are relatively compact and hence the factor analysis should yield distinct and reliable factors. The Bartlett's Test of Sphericity reveals the validity and suitability of the responses collected to the problem being addressed through the study. It is recommended that the Bartlett's Test of Sphericity must be less than 0.05 to be suitable in factor analysis. The following table shows the KMO and BTS results:

Table 7.40

KMO and Bartlett's Test – Emotional Intelligence

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.748
Bartlett's Test of Sphericity	Approx. Chi-Square	2232.063
	Df	105
	Sig.	.000

Source: Field Survey

The correlation matrix showed sufficient items to justify the factorability data. The KMO and Bartlett's test of sphericity produces the Kaiser- Meyer- Olkin measure of sampling adequacy and Bartlett's test. KMO for overall matrix was found to be good (0.748) which is greater than 0.5 (Kaiser, 1974) and Barlett's test of sphericity (BTS) value is found significant (p = 0.000) which meant that data is appropriate for Exploratory Factor Analysis (EFA). The details of factor analysis are given below:

Table 7.41

Total Variance Explained by Variables of Emotional Intelligence

Factor	**Components**	**Initial Eigen values**			**Extraction Sums of Squared Loadings**		
		Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	Empathy	3.592	23.948	23.948	3.592	23.948	23.948
2	Motivating Oneself	2.469	16.458	40.406	2.469	16.458	40.406
3	Social Skills	2.136	14.239	54.645	2.136	14.239	54.645
4	Managing Emotions	1.519	10.124	64.769	1.519	10.124	64.769
5	Self Awareness	1.181	7.874	72.643	1.181	7.874	72.643

Source: Field Survey

Table given above shows the percentage of variances and the Eigen values of the five components, which explained the 72.64 percentage of total variances of emotional intelligence. With the principal component analysis, five components are extracted towards investor bias in the present context. The first component namely 'empathy' explains 23.95% per cent of variance with the eigen value of 3.592. The second component ‘motivating oneself’ explains 16.46% variance (eigen value of 2.469), third component ‘social skills’ explains 14.24% variance (eigen value 2.136), fourth component ‘managing emotion’ explains10.12% (eigen value 1.519) and fifth component ‘self awareness’ explains 7.87% (eigen value 1.18). It is clear from the following scree plot.

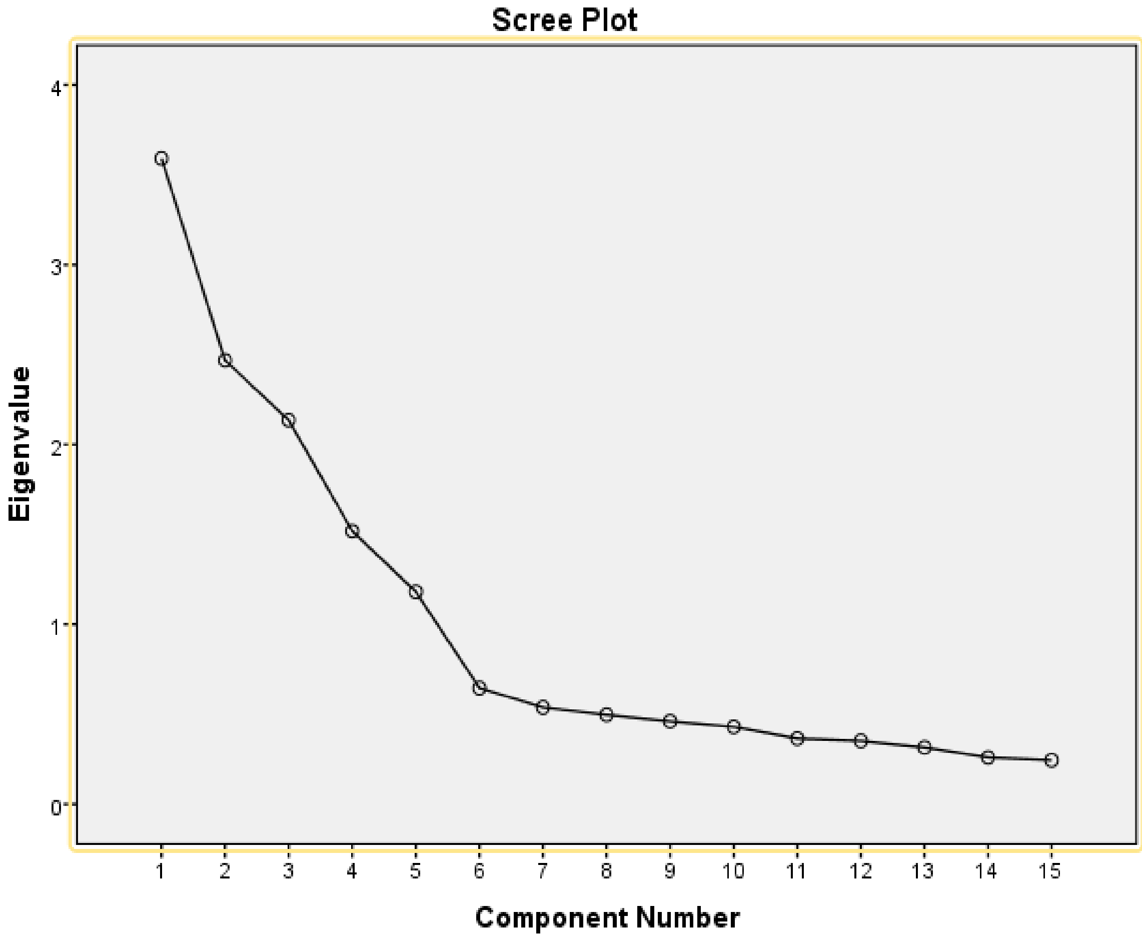


Figure 7.3 Scree Plot – Emotional Intelligence

The diagram 7.3 makes it clear that all the 15 statements are combined and split into five components.

The table presented below explains the rotated component factor loadings of security analysis.

Table 7.42

Rotated Component Matrix- Emotional Intelligence

Indicator Code	Indicators	Component				
		1	2	3	4	5
EM3	I can tell if someone is not happy with me	.887				
EM2	I am excellent at empathising with someone else's problem	.885				
EM1	I can see things from the other’s point of view	.835				
MO2	I believe in ‘Action this Day’		.849			
MO1	I am always able to motive myself to do difficult tasks		.830			
MO3	I never waste time		.827			
SSK1	I am an excellent listener			.892		
SSK2	I never interrupt other people's conversations			.842		
SSK3	I am good at adapting and mixing with a variety of people			.754		
ME2	I can consciously alter my frame of mind or mood				.843	
ME3	I rarely worry about wok or life in general				.826	
ME1	I can reframe bad situations quickly				.780	
SA3	I usually recognise when I am stressed					.832
SA2	I know when I am happy					.803
SA1	I realise immediately when I lose my temper					.799

Source: Field Survey

The table depicts the result of Principle Component Analysis of emotional intelligence constructed after rotated factor matrix. Variables with factor loading more than 0.70 are chosen for the study. After performing Varimax Rotation Method in Kaiser Normalization, factors of emotional intelligence grouped into five factors as per the following:

- The first group is extracted 23.95 %. It consists of three items. They are ‘I can tell if someone is not happy with me’ with highest loading (0.887), followed by ‘I am excellent at empathising with someone else's problem’ (loading 0.885), ‘I can see things from the other's point of view' (loading 0.835). These variables together constitute a common factor, whose characteristics are related to Empathy. Hence, it is termed as **'Empathy'.**

- Second group which is extracted 16.46 per cent of total variances included three items. They are 'I believe in 'Action this Day'' with highest loading (0.849), followed by 'I am always able to motive myself to do difficult tasks' (loading 0.830), 'I never waste time' (loading 0.827). These variables together constitute a common factor, whose characteristics are related to the motivating oneself. Hence, it is called as **'Motivating Oneself'.**

- Third group is extracted 14.24 per cent of total variances included three items. They are 'I am an excellent listener' with highest loading (0.892), followed by 'I rarely worry about wok or life in general' (loading 0.842), 'I am good at adapting and mixing with a variety of people' (loading 0.754). These variables together constitute a common factor, whose characteristics are related to social skills. Hence, it is named as **'Social Skill'.**

- Fourth group which is extracted 10.12 per cent of total variances included three items. They are 'I can consciously alter my frame of mind or mood', (0.842), followed by 'I rarely worry about wok or life in general' (loading 0.826), 'I can reframe bad situations quickly' (loading 0.780). These variables together competitive constitute a common factor, whose characteristics are related to managing emotions. Hence, it is termed as **'Managing Emotions'.**

- Fifth and last group is extracted 7.87 per cent of total variances included three items. They are 'I usually recognise when I am stressed' (loading0.832), followed by 'I know when I am happy' (loading 0.803) and 'I realise immediately when I lose my temper' (loading 0.799). These variables together constitute a common factor, whose characteristics are related to the self awareness. Hence, it is named as **'Self Awareness'.**

Thus, through exploratory factor analysis, 15 variables are split into five components, i.e, Empathy, Motivating oneself, Social skill, Managing emotions, Self awareness. They are identified as the dimensions of security analysis in the present study.

7.6.2 Confirmatory Factor Analysis of Emotional Intelligence

Confirmatory Factor Analysis (CFA) is a measurement model of Structural Equation Modeling (SEM), which deals with the relationship between observed measures or indicator. This statistical technique tells us of the suitability of theoretical specification of factors to the reality. It is used to confirm the factor structure of a set of observed variables. Structural Equation Modeling software is typically used for performing confirmatory factor analysis. The researcher used CFA as a first step to assess the proposed Measurement model in a structural equation model. The following figure shows the measurement model:

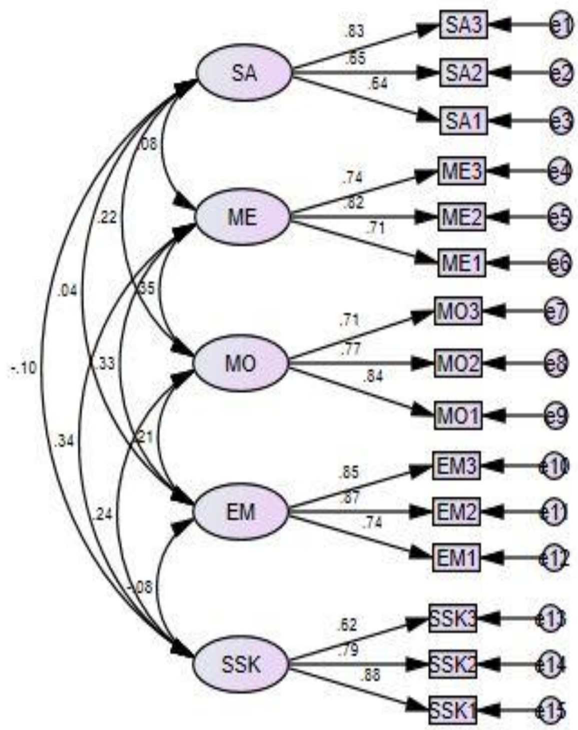


Figure 7.4 Confirmatory Factor Analysis - Emotional Intelligence

Measurement model of emotional intelligence is tested by a Confirmatory Factor Analysis by using Amos 21. This measurement model is developed to test the attitude of investors towards different factors of emotional intelligence with regard to different socio-economic variables. Reliability of the scale developed for the study was tested by using Cronbanch's alpha value method and which is found to be significant. The structural equation model using Amos produces several indices of fit like measure of absolute fit, comparative fit and parsimonious fit etc. The following are the most commonly used fit indices:

Table 7.43

Model Fit Indices – Emotional Intelligence

Sl. No	Indices of Common Fit	Value	Value of Good Fit
1.	CMIN/DF	1.394	<5
2.	RMR	0.043	<0.05
3.	Goodness of Fit Index (GFI)	0.963	>0.90
4.	Adjusted GFI (AGFI)	0.945	>0.90
5.	Comparative Fit Index (CFI)	0.985	>0.90
6.	Incremental Fit Index (IFI)	0.986	>0.90
7.	Tucker Leiws Index (TLI)	0.981	>0.90
8.	Normed Fit Index (NFI)	0.951	>0.90
9	Root Mean Square Error of Approximation (RMSEA)	0.032	<0.08

Source: Field Survey

Table 7.43 shows the different model fit indices of confirmatory factor analysis The confirmatory factor analysis is good fit with Goodness of Fit Index (GFI) 0.963; Tucker Lewis Index (TLI) 0.981; Comparative Fit Index (CFI) 0.985; Root Mean Square Error of Approximation (RMSEA) 0.032; CMIN/df 1.394 and p-value 0.011. The present scale developed for the study was supported by the result of the Confirmatory Factor Analysis. Since all the fit indices are satisfactory and appropriate for the scale, the Confirmatory Factor Analysis Confirms the structure of measurement scales.

To know the extent of the different dimensions of emotional intelligence of investors the mean score are calculated. Following are the mean score of each Factor.

Table 7.44

Descriptive of the Different Factors of Emotional Intelligence

Factors of Emotional Intelligence	Mean	Standard deviation
Empathy	3.2419	.94306
Motivating Oneself	3.3521	.78379
Social Skills	3.5043	.67675
Managing Emotions	3.4393	.66978
Self Awareness	3.6829	.90099

Source: Field Survey

From the above table, it can be concluded that all the dimensions of emotional intelligence is above average level since the entire mean score is in between 3 to 4. It is found that self awareness is having the highest mean score 3.6829 (S.D .90099) followed by managing emotions 3.4393 (S.D .66978). Empathy is having the least mean score 3.2419 (S.D 94306)

7.6.3 Socio-economic Variables with Emotional Intelligence

The socio economic variable like gender, age, educational qualification, income and marital status are used for analyzing the perception of investors towards factors of behavioural bias. The descriptive statistics of the socio economic variables in respect of factors of behavioural bias are presented below.

7.6.4. Gender-wise Analysis of Emotional Intelligence

The male and female may have different level of emotional intelligence. To test the same descriptive analysis has been done which shows the mean score of male female with regards to emotional intelligence. To find out the statistical significance of the difference in mean score ‘t test’ is applied. The result is shown in table 7.45.

Table 7.45

Gender-wise analysis of Emotional Intelligence

Gender	N	Mean	Max Score	SD	t value	p value	Remarks
Male	349	50.41	75	7.68	-3.265	.001	Equal variance assumed
Female	41	54.61		8.73			
Total	**390**	**50.85**		**7.87**			

Source: Survey Data

From the table 7.45, it can be observed that on an average the investors are having the mean emotional intelligence of 50.85 (SD 7.87) out of the maximum score of 75. To be more specific, on an average, investors are having 67.8% emotional intelligence while taking investment decision. The mean score emotional intelligence of male is 50.41 (7.68) differing from female 54.61 (8.73). The Independent sample ‘t’ test is used to check whether the mean score difference is significant or not, among male and female with regard to emotional intelligence.

Since the p value of the t test is less than .05, there is significant difference between male and female with regard to emotional intelligence. Since the average of mean score of emotional intelligence of female is more than male, female is having more emotional intelligence than male.

7.6.5 Age Category-wise Analysis of Emotional Intelligence

The different age category may have different level of emotional intelligence. Descriptive analysis has been done to know the mean score of different level of age category. It is found that there is different mean score for different age category. Then ANOVA is applied to test the significance of difference among mean of different age category.

In ANOVA, there is an assumption that the variance of outcome is homogeneous. This assumption can be tested by using Levene’s test. The null hypothesis of this test is that the variance of the group is homogeneous. If the p value of the Levene’s test is less than .05, then we can conclude that the variance is heterogeneous. Then we should adjust the F test to correct this problem. The researcher uses Welch's F to correct the heterogeneity.

In this case, the p value of homogeneity test is 0.000 which means that equal variance is rejected. Then the researcher considers Welch's F value instead of ANOVA. The result is shown in the Table 7.46.

Table 7.46

Age Category-wise Analysis of Emotional Intelligence

Age Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
18 - 30 Years	68	51.54	9.15	75	.317	.813	Welch
31 - 40 Years	128	50.41	6.69				
41 - 50 Years	118	51.03	9.08				
Above 50 Years	76	50.68	6.52				
Total	390	50.85	7.89				

Source: Survey Data

From the above table it can be understood that the highest mean score is 51.54 (9.15) which is in the age category of '18 – 30 years' and lowest mean is 50.68 (6.52) in age category 'Above 50 years'. The p value is 0.813 which means there is no significant difference among the mean score of different age categories.

7.6.6 Educational Qualification-wise Analysis of Emotional Intelligence

The different education category may have different level of emotional intelligence. The researcher has done the descriptive analysis to know the difference in mean score of different education category. To test the statistical significance of this difference ANOVA is applied. To do the same, homogeneity of variance is checked by using Levene's test. The p value of the Levene's test is 0.000 which is less than .05. Since the homogeneity of variance is not assumed, Welch F test has been applied instead of ANOVA. The result of descriptive analysis and F test is exhibited in Table 7.47

Table 7.47

Educational Qualification-wise Analysis of Emotional Intelligence

Qualification Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Under Graduate	25	48.88	6.25	75	11.337**	.000	Welch
Graduate	232	52.33	7.85				
Post Graduate	117	48.75	8.11				
Professional	16	47.81	2.66				
Total	**390**	**50.85**	**7.89**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The graduate is having the highest mean score 52.33 (7.85) of emotional intelligence and the lowest score 47.81 (2.66) is among professional. Since the p value (0.000) is less than 0.05, the emotional intelligence of graduate is more than the professionals.

7.6.7 Annual Income Category-wise Analysis of Emotional Intelligence

The different categories of annual income may have different levels of emotional intelligence while making investment decision. Descriptive analysis has been done to find out the means score of each category of annual income. To test the statistical significance of the difference of these mean score ANOVA has been done. Before doing the ANOVA, homogeneity of variance has been checked by using Levene's test. The p value of the Levene's test is 0.106 which is more than .05. Since the homogeneity of variance is assumed, ANOVA has been applied. The result of descriptive analysis and F test is exhibited in Table 7.48.

Table 7.48

Annual Income Category-wise Analysis of Emotional Intelligence

Annual income Category (in rupees)	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Less than 5,00,000	129	51.53	7.70	75	2.875*	.036	ANOVA
5,00,000 - 10,00,000	143	51.55	8.09				
10,00,000 - 15,00,000	90	48.74	8.05				
More than 15,00,000	28	50.93	6.17				
Total	**390**	**50.85**	**7.89**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The annual income category 'Rs.5,00,000 - 10,00,000' is having the highest mean score 51.55(8.09) of emotional intelligence and the lowest score 48.74(8.05) is in annual income category of 'Rs. 10,00,000 - 15,00,000'. Since the p value (0.000) is less than 0.05, the emotional intelligence of the investors in annual category 'Rs.10,00,000 - 15,00,000' lower than the annual income category of 'Rs.5,00,000 - 10,00,000'.

7.6.8 Marital Status-wise Analysis of Emotional Intelligence

The married and single may have different level of emotional intelligence. Descriptive analysis has been done to find out the mean score of behavioural bias among married and single. To find out the statistical significance of the difference 't' test is applied. Levene's test shows the p value 0.359 and hence the homogeneity of variance is assumed. The result is shown in table 7.49.

Table 7.49

Marital Status-wise Analysis of Emotional Intelligence

Gender	N	Mean	SD	Max Score	t value	p value	Remarks
Married	343	50.69	8.05	75	-1.085	.275	Equal variance assumed
Single	47	52.02	6.53				
Total	**390**	**50.85**	**7.89**				

Source: Survey Data

From the table 7.49, it can be observed that the mean score emotional intelligence of the married is 50.69 (8.05) differing from single 52.02(6.53). Since the p value of the t test is more than .05, there is no significant difference between married and single with regard to emotional intelligence.

Summary of Emotional Intelligence

From the above analysis it can be concluded that on an average the investors are having 67.8% emotional intelligence while taking the investment decisions. Through the factor analysis we have grouped the emotional intelligence into five factors. The most important factor is the Empathy as it contributes 23.95 % of the total variance of emotional intelligence. Motivating oneself is the second important factor (16.46%), social skill (14.24%), managing emotions (10.12%), self awareness (7.87%) are the third, fourth and fifth factor respectively.

In gender-wise analysis, there is significance between male and female investors with regard to emotional intelligence. From the analysis we can conclude that female investors are having more emotional intelligence than their counterparts.

There is no significance difference among the investors in different age categories with regard to emotional intelligence. This indicates age is not a factor which determines emotional intelligence.

In educational qualification wise analysis of emotional intelligence, it can be seen that there is significant difference among investors different levels of educational qualification.

In annual income category wise analysis of emotional intelligence, there is significant difference among the investors in different annual income categories.

In marital status-wise analysis of emotional intelligence there is no significance among married and single investors.

References:

1. Ricciardi, V. (2008). The Psychology of Risk: The Behavioural Finance Perspective. (F. J. Frank, Ed.) *Handbook of finance , 2*, 85-111.

2. Pompian, M. M. (2008). *Behavioral Finance and Wealth Management.* New Jersey: John Wiley & Sons.

3. Ibid
4. Ibid
5. Ibid
6. Ibid
7. Ibid
8. Ibid
9. Ibid
10. Ibid
11. Ibid

12. Barber, B. M., & Odean, T. (2001). Boys will be Boys: Gender, Overconfidence and common stock investment. *The quarterky journal of economics , 16* (1), 261-292.

13. Lewellen, W. G., Lease, R. C., & Schlarbaum, G. G. (1977). Patter of Investment Strategy and Behaviour among Individual Investors. *Journal of Business , 50* (3), 296-333.

14. Goleman, D. (2005). *Emotional Intelligence, Why It Can Matter More Than IQ.* New York: Bantam Books.

Chapter 8

Factors Influencing Investment Performance – An Empirical Analysis

Investment performance is the performance of return on the investment. Performance is calculated over a specific period of time. Investor gets return in the form of regular income or periodic returns in the form of interest or dividend and terminal return in the form of capital appreciation. Capital appreciation is also called as price return which the return that comes from the difference of purchase price and selling price. Return can be Nominal return or Real return. Nominal return is the return generated by an investment. Real return is nominal return minus inflation. Investor has to consider the positive real return while making investment decision. In the previous chapters, a detailed analysis of security analysis, behavioural bias and emotional intelligence have been done. However the work will not be a complete one without the analysis on the investment performance of investors. It is also relevant to examine the influence of security analysis, behavioural bias and emotional intelligence on investment performance. Therefore the present chapter attempts to fulfil this gap.

In this study, the researcher asks the respondent to assess their own investment performance. The rate of return of equity investment is assessed by demanding the respondent to compare their current rate of return to both expected rate of return and average return of the stock market. Satisfaction level of investment decision is also taken as the criteria to measure the investment performance.

If the rate of return is more than the expected rate of return, the investment performance is good, otherwise vice versa. To capture the dimension of investment performance a five point likert scale is used ranging from highly disagrees to highly agree. The investors were asked to express their response which best described their perception against each of the indicator. Following are the indicators used to measure the investment performance and the mean score obtained.

Table 8.1

Indicators of Investment Performance

Indicator code	Name of the Indicator	Mean	Standard Deviation
IP1	The rate of return of my recent stock investment meets my expectation	2.2026	1.09568
IP2	My rate of return is equal to or higher than the average rate of return of the market	2.0923	1.06193
IP3	I feel satisfied with my investment decision in the last year	2.2846	1.05797
IP	Investment performance (aggregate score)	6.5795	2.82799

The mean score of the investment performance is low 6.58 (SD 2.79) out of the maximum score of 15 which implies that investor satisfaction level is 43.86%. 'The rate of return of my recent stock investment meets my expectation' is having the mean score of 2.20 (1.10). This indicates that most of the investors are not satisfied with their rate of return. 'My rate of return is equal to or higher than the average rate of return of the market' shows lowest mean score of 2.09 (1.06). This means that most of the investors don't even get the average return of the market. The mean score of 'I feel satisfied with my investment decision in the last year' is 2.28 (1.06). This shows that most of the investors are not satisfied with their investment decision in the last year. From the above, it can be inferred that most of the individual investors are not satisfied with the return from their equity investment.

In order to accomplish the objective of measuring the investment performance, aggregate and the socio economic wise comparisons have been attempted based on the selected variables. The statistical tools like Mean, Standard deviation, Independent sample t test, one way ANOVA and Multiple regression analysis have been used for analysis purposes. The chapter also introduces various research models and in the final model behavioural bias is considered as a mediating variable. Structural Equation Modelling has been used for the fixing the research model.

8.1 Socio-economic wise Comparison of Investment Performance

The socio economic variable like gender, age, educational qualification, income and marital status are used for analyzing the performance of investors towards their investment in equity shares. The descriptive and inferential statistics of the socio economic variables in respect of investment performance are presented below.

8.1.1 Gender-wise Analysis of Investment Performance

In this section, the researcher tries to find out the investment performance among the male and the female investors. To know the difference, the researcher has done the descriptive analysis. To find out the statistical significance of the difference in mean score t-test also applied. In this case levene's test homogeneity shows p-value as 0.000, i.e, equal variance is not assumed. So we consider the t-value of equal variance not assumed. The result is shown in table 8.2

Table 8.2

Gender-wise Comparison of Investment Performance

Gender	N	Mean	Max Score	SD	t value	p value	Remarks
Male	349	6.30	15	2.77	-5.986	.000	Equal variance not assumed
Female	41	8.98		2.12			
Total	**390**	**6.58**		**2.83**			

Source: Survey Data

From the table 8.2, it can be observed that aggregate investment score of male investor is 6.30 as against the maximum score of 15. This shows that in percentage terms the performance is only 42%. In the case of female investors the aggregate score is 8.98 out of 15.   In percentage terms the performance level is 60%. The difference is also significant as the 'p' value for the 't' test conducted is less than 0.05. From this it can be concluded that in investment performance female investors are in a better position than male investors.

8.1.2 Age Category-wise Analysis of Investment Performance

The above data relating to investment performance has been classified age wise and presented in the table 8.3. to understand whether the investment performance is different among the investors in different age category. The mean difference is also tested with ANOVA and F value is also given in the table.

Table 8.3

Age Category-wise Comparison of Investment Performance

Age Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
18 - 30 Years	68	6.32	3.11	15	4.863^{**}	.002	ANOVA
31 - 40 Years	128	6.25	2.69				
41 - 50 Years	118	6.37	2.69				
Above 50 Years	76	7.67	2.82				
Total	**390**	**6.58**	**2.83**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

From the above table it can be seen that the highest mean score of investment performance is 7.67 (2.61) which is in the age category of 'above 50 years' and lowest mean is 6.32 (3.11) in age category '18-30 years'. The p value is 0.002 which means that mean score of different age categories are significantly different. It can be inferred from the result that the older investor have the better investment performance than the younger ones. The age of the category and investment performance is having the direct relationship. Investors in the lower age category have a lower investment performance and higher ager category have a higher investment performance. It may be due to the experience and maturity of aged investors.

To know the exact significant difference between different age groups one has to use multiple comparisons. In this case, researcher uses the Tukey HSD to identify the pair wise differences since the equal variances are assumed. The result is shown in table 8.4.

Table 8.4

Age Category-wise Post Hoc Test - Investment Performance

Age Category (I)	Age Category (J)	Mean Difference (I-J)	Std. Error	p value
18 – 30 Years	31 - 40 Years	.06572	.41819	.999
	41 - 50 Years	-.04935	.42429	.999
	Above 50 Years	-1.34752*	.46518	.021
31 – 40 Years	18 - 30 Years	-.06572	.41819	.999
	41 - 50 Years	-.11507	.35565	.988
	Above 50 Years	-1.41324**	.40356	.003
41 – 50 Years	18 - 30 Years	.04935	.42429	.999
	31 - 40 Years	.11507	.35565	.988
	Above 50 Years	-1.29817**	.40988	.009
Above 50 Years	18 - 30 Years	1.34752*	.46518	.021
	31 - 40 Years	1.41324**	.40356	.003
	41 - 50 Years	1.29817**	.40988	.009

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The result shows that age category 'above 50 years' is significantly different from all other age categories. Since mean difference of age category '50years' is positive, this category has the better investment performance than the other age categories.

8.1.3 Educational Qualification-wise Analysis of Investment Performance

In order to understand the variability of investment performance among investors in different education categories, the above data relating to investment performance has been rearranged education category wise and presented in the table 8.5. F test is applied to find out the statistical significance of the mean difference. The p value of the Levene's homogeneity test is 0.000 which is less than .05. Since the homogeneity of variance is not assumed, Welch F test has been applied. The result of and F test is also exhibited in the following table.

Table 8.5

Educational Qualification-wise Comparison of Investment Performance

Qualification Category	N	Mean	S D	Max Score	F Value/ Welch F	P Value	Remarks
Under Graduate	25	3.72	2.44	15	34.398^{**}	.000	Welch
Graduate	232	6.57	2.72				
Post Graduate	117	7.21	2.53				
Professional	16	6.56	2.10				
Total	**390**	**6.58**	**2.83**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

Form the above table it can be seen that investors with 'post graduate' educational level is having the highest mean score of 7.21(2.53) and the 'undergraduate' having the lowest score of 3.72 (2.44). The 'graduate' and professional is having almost the same score. Since the p value (0.000) is less than 0.05, the mean score of the investment performance in different educational level is significantly different from others. It can be concluded that under graduates are having weak investment performance.

To find out the exact difference among the groups multiple comparisons have been done through post hoc analysis. Tamhane's T2 test has been applied to identify the pair wise differences since the equal variances are not assumed. The result is shown in table 8.6.

Table 8.6

Educational Qualification-wise Post Hoc Test - Investment Performance

Educational Qualification (I)	Educational Qualification (J)	Mean Difference (I-J)	Std. Error	p value
Under Graduate	Graduate	-2.84897**	.57294	.000
	Post Graduate	-3.49368**	.59970	.000
	Professional	-2.84250**	.87140	.007
Graduate	Under Graduate	2.84897**	.57294	.000
	Post Graduate	-.64471	.30862	.159
	Professional	.00647	.70352	1.000
Post Graduate	Under Graduate	3.49368**	.59970	.000
	Graduate	.64471	.30862	.159
	Professional	.65118	.72548	.806
Professional	Under Graduate	2.84250**	.87140	.007
	Graduate	-.00647	.70352	1.000
	Post graduate	-.65118	.72548	.806

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

The table 8.6 shows that 'under graduate' education level is significantly different from all other education level in case of investment performance and from the mean difference it can be found that 'undergraduate is having lower investment performance than the other educational categories.

8.1.4 Annual Income Category-wise Analysis of Investment Performance

In order to understand the variability of investment performance among investors in different annual income category, the above data relating to investment performance has been rearranged annual income category wise and presented in the table 8.7.

Analysis of variance is carried out to find out the statistical significance of the mean difference and F value is calculated and presented in the table.

Table 8.7

Annual Income Category-wise Analysis of Investment Performance

Annual income Category (in rupees)	**N**	**Mean**	**S D**	**Max Score**	**F Value/ Welch F**	**P Value**	**Remarks**
Less than 5,00,000	129	5.57	2.70	15	19.893**	.000	ANOVA
5,00,000 - 10,00,000	143	6.48	2.53				
10,00,000 - 15,00,000	90	7.28	2.81				
More than 15,00,000	28	9.50	2.33				
Total	**390**	**6.58**	**2.83**				

Source: Survey Data

* statistically significant at the 5%

From the above table it can be observed that annual income category 'more than Rs.15, 00,000' is having the highest mean score 9.50 (2.33) and the annual income category 'Less than Rs.5, 00,000' is having lowest score 5.57 (2.70). Since the p value 0.000 which is less than 0.05, the mean score of annual income categories is significantly different from others. It can be observed from the result that annual income categories are having direct relation with investment performance. Lower income level is having the low investment performance and vice-versa. To find out the exact difference among the pair of groups multiple comparisons have been done through post hoc analysis.

Tamhane's T2 test has been applied to identify the pair wise differences since the equal variances are not assumed. The result is shown in table 8.8.

Table 8.8

Annual Income Category-wise Post Hoc Test - Investment Performance

Annual Income (in Rupees) Category (I)	Annual Income (in Rupees) Category (J)	Mean Difference (I-J)	Std. Error	p value
Less than 5,00,000	5,00,000 - 10,00,000	-.91663*	.32082	.023
	10,00,000 - 15,00,000	-1.71189**	.36287	.000
	More than 15,00,000	-3.93411**	.55083	.000
5,00,000 - 10,00,000	Less than 5,00,000	.91663*	.32082	.023
	10,00,000 - 15,00,000	-.79526	.35549	.115
	More than 15,00,000	-3.01748**	.54600	.000
10,00,000 - 15,00,000	Less than 5,00,000	1.71189**	.36287	.000
	5,00,000 - 10,00,000	.79526	.35549	.115
	More than 15,00,000	-2.22222**	.57172	.001
More than 15,00,000	Less than 5,00,000	3.93411**	.55083	.000
	5,00,000 - 10,00,000	3.01748**	.54600	.000
	10,00,000 - 15,00,000	2.22222**	.57172	.001

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

From the table 8.8, it can be found that in case of investment performance, there is a significant difference between all income categories except the income categories between 'Rs.5,00,000 -10,00,000 and Rs.10,00,000 – 15,00,000 (p value 0.115).

8.1.5 Marital Status-wise Analysis of Investment Performance

In order to understand the investment performance among the married and the single investors, the data has been classified according to marital status and presented in table 8.9. To find out the statistical significance of the difference of mean score 't test' is applied. Homogeneity of variance is tested by Levene's test. The p value of

Levene's test is 0.000 which means homogeneity is rejected. The result is shown in table 8.9.

Table 8.9

Marital Status-wise Comparison of Investment Performance

Gender	N	Mean	SD	Max Score	t value	p value	Remarks
Married	343	6.77	2.87	15	4.905^{**}	.000	Equal variance not assumed
Single	47	5.17	1.97				
Total	**390**	**6.58**	**2.83**				

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

From the table 8.9, it can be observed that the mean score of investment performance of married investors is higher 6.77 (2.87) and the single is lower 5.17 (1.97). It can be concluded from the result that married investors are having more investment performance than the single investors.

Since the p value of the t test is less than .05, the mean score difference between investors in married and single is significant, with regard to investment performance.

8.2 Impact of Security Analysis, Behavioural Bias and Emotional Intelligence on Investment Performance

One of the research aims is to know the impact of security analysis, emotional intelligence and behavioural bias on investment performance. Multiple regression analysis has been done for the same. Multiple regression analysis is a 'statistical technique used to analyse the relationship between a single dependent variable and several independent variables' (Hair, Black, Babin, & Anderson, 2015)[1].

8.2.1 Impact of Security Analysis on Investment Performance

From the literature, it can be inferred that security analysis is important to have a better investment performance. Although the investor may not have the better investment performance only with security analysis, it can be assured that investor cannot have consistent investment performance without security analysis. Here the researcher tests the impact of the different factors of security analysis on investment performance.

As discussed earlier, the attributes of security analysis is grouped into five factors namely quantitative analysis, technical analysis, economic analysis, qualitative analysis and industry analysis. The researcher tests the impact of these factors on investment performance through multiple regression analysis by using Eviews software. The dependent variable is investment performance and independent variables are factors of security analysis.

Since the correlation matrix for independent variable, as shown in table 8.10 shows weak correlation, multicollinearity among the independent variables is not significant.

Since heteroskedasticity has been detected using Breusch-Pagan-Godfrey test, the model has been re-estimated by using White heteroskedasticity-consistent standard errors. The results are given below.

Table 8.10
Multiple Regression Analysis of Factors Security Analysis on Investment Performance

Variable	Co-efficient	Standard error	t-statistic	Prob.
Intercept	0.379776	0.806386	0.47096	0.6379
Economic	0.078225	0.030806	2.539258*	0.0115
Qualitative	0.030656	0.030897	0.9922	0.3217
Quantitative	0.077592	0.023458	3.3077**	0.0010
Industry	0.268231	0.048723	5.505168**	0.0000
Technical	-0.0465	0.024923	-1.8658	0.0628
F- statistic	19.27063**			
Prob (F-statistic)	0.000			
R-squared	0.200558			
Adjusted R^2	0.190179			

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

From the table 8.10 it can be seen that the co-efficient of the independent variables like Economic, Quantitative and Industry analysis are significant at 5% significant level and all the co-efficient are positive. This indicates that Economic, Quantitative and Industry analysis have the positive impact on investment performance. Technical analysis is significant at 10% significant level and its coefficient is negative. So it makes negative impact on investment performance. From this, it can be assumed the investors who are trading on short-term by using technical analysis are not satisfied with their rate of return and their investment decision.

The overall significance of the estimated model given by the F statistic is 19.27 and its P value is 0.000. It means that the independent variables taken together are highly significant in explaining the dependent variable. R^2 of the model is 0.20 which means that all the independent variables (Economic, Qualitative, Quantitative, Industry and Technical analysis) taken together explains 20% of the total variation of the dependent variable (Investment Performance). Adjusted R^2 is 19.02%. Adjusted R^2 is a measure of the loss of predictive power or shrinkage in regression. It tells us how much variance in the outcome would be accounted for if the model had been derived from the population from which the sample was taken (Field, 2014)[2].

8.2.2 Impact of Behavioural Bias on Investment Performance

From the literature, it can be inferred that behavioural biases have adverse impact on investment performance. Here the researcher tests the impact of the different factors of behavioural bias on investment performance.

As discussed earlier, the attributes of behavioural bias is grouped into three factors through factor analysis. The three factors are emotional bias, information processing bias and belief perseverance bias. The researcher tests the impact of these factors on investment performance through multiple regression analysis. The dependent variable is investment performance and independent variables are factors of behavioural bias.

Since the correlation matrix for independent variables show weak correlation, multicollinearity among the independent variable is not significant.

Heteroskedasticity is checked in the sample data and it is not significant. The results are given below.

Table 8.11

Multiple Regression Analysis of Factors Behavioural Bias on Investment Performance

Variable	Co-efficient	Standard error	t-statistic	Prob.
Intercept	12.03686	0.676626	17.78953**	0.000
Emotional bias	-0.05499	0.013345	-4.12058**	0.000
Belief perseverance bias	-0.06837	0.019606	-3.48723**	0.0005
Information processing bias	-0.04978	0.017695	-2.81337**	0.0052
F- statistic	22.71305**			
Prob (F-statistic)	0.0000			
R-squared	0.150040			
Adjusted R^2	0.143434			

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

From the table 8.11 it can be found that the co-efficient of all the three independent variables are significant at 1% significant level and the co-efficient are negative. This indicates that all the factors of behavioural bias have inverse impact on investment performance.

The overall significance of the estimated model given by the F statistic is 22.71 and its P value is 0.000. It means that the independent variables taken together are highly significant in explaining the dependent variable. R^2 of the model is 0.15 which means that all the independent variables (emotional, belief perseverance and information processing bias) taken together explains 15% of the total variation of the dependent variable (Investment Performance). Adjusted R^2 is 14.34%.

8.2.3 Impact of Emotional Intelligence on Investment Performance

It can be inferred that emotional intelligence is one of the important factor to have a better investment performance. Here the researcher tests the impact of the different factors of emotional intelligence on investment performance.

As discussed earlier, the attributes of emotional intelligence is grouped into five factors through factor analysis. The five factors are empathy, managing emotions, managing oneself, social skills and self awareness. The researcher tests the impact of these factors on investment performance through multiple regression analysis. The dependent variable is investment performance and independent variables are factors of emotional intelligence.

Since the correlation matrix for independent variables show weak correlation, multicollinearity among the independent variables is not significant.

Since heteroskedasticity has been detected using Breusch-Pagan-Godfrey test the model has been re-estimated by using White heteroskedasticity-consistent standard errors. The results are given below.

Table 8.12
Multiple Regression Analysis of Factors Emotional Intelligence on Investment Performance

Variable	Co-efficient	Standard error	t-statistic	Prob.
Intercept	3.62751	0.948089	3.826129	0.0002
Empathy	0.045749	0.054815	0.83461	0.4045
Managing emotions	0.085042	0.055064	1.544419	0.1233
Managing Oneself	0.08624	0.061177	1.409682	0.1594
Social skills	0.127933	0.048696	2.627189**	0.009
Self awareness	-0.04316	0.055487	-0.77787	0.4371
F- statistic	4.513075**			
Prob (F-statistic)	0.000521			
R-squared	0.055502			
Adjusted R^2	0.043204			

Source: Survey Data

*, ** statistically significant at the 5%, and 1% significant level

From the table 8.12 it is found that the co-efficient of only one independent variable social skill is significant at 5% significant level and the co-efficient is positive. All other factor's p-value is more than .05, hence not significant. This indicates social skill has the positive impact on investment performance. From this, it can be assumed that the investors who are having better social skill may have easy access to information and he can use that information to have right investment.

The overall significance of the estimated model given by the F statistic is 5.51 and its P value is 0.000. It means that the independent variables taken together are highly significant in explaining the dependent variable. R^2 of the model is 0.05 which means that all the independent variables (empathy, managing emotions, managing oneself, social skills and self awareness) taken together explains 5% of the total variation of the dependent variable (Investment Performance). Adjusted R^2 is 4.32%.

8.3 Combined Effect of Security Analysis, Emotional Intelligence and Behavioural Bias on Investment Performance.

The main aim of the present study is to examine the combined impact of security analysis, behavioural bias and emotional intelligence on investment performance. A number of studies have been conducted so far to analyse the relationship between security analysis, emotional intelligence and behavioural bias on investment performance individually. In this study the researcher attempts to analyse the combined relationship between security analysis, emotional intelligence and behavioural bias on investment performance as a whole.

In the present study, the researcher made an attempt to analyse the impact of security analysis and emotional intelligence on investment performance of equity investors in Kerala. There is an important role for behavioural bias on the above relation. Hence, the study made an effort to prove the role of behavioural bias as mediation in between the relationship of security analysis and emotional intelligence on investment performance.

Structural Equation Modelling (SEM) is used to depict the relationships among variables. SEM can examine a series of dependence relationship simultaneously. It is useful in testing theories that contain multiple equations involving dependence relationship (Hair, Black, Babin, & Anderson, 2015). It combines confirmatory factor analysis and multiple regressions into one model. Confirmatory factor analysis helps to confirm the factors and their variables are suitable for structural model whereas, multiple regression estimate the regression weights between security analysis, emotional intelligence (independent variables), behavioural bias (mediating variable) and investment performance (dependent variable).

The proposed research model developed for the study is given in figure 8.3. In the research model, security analysis and emotional intelligence are considered as independent variables, investment performance is considered as dependent variable and behavioural bias as mediating variable. Each path between constructs in the research model was indicted as hypotheses to be tested in the study.

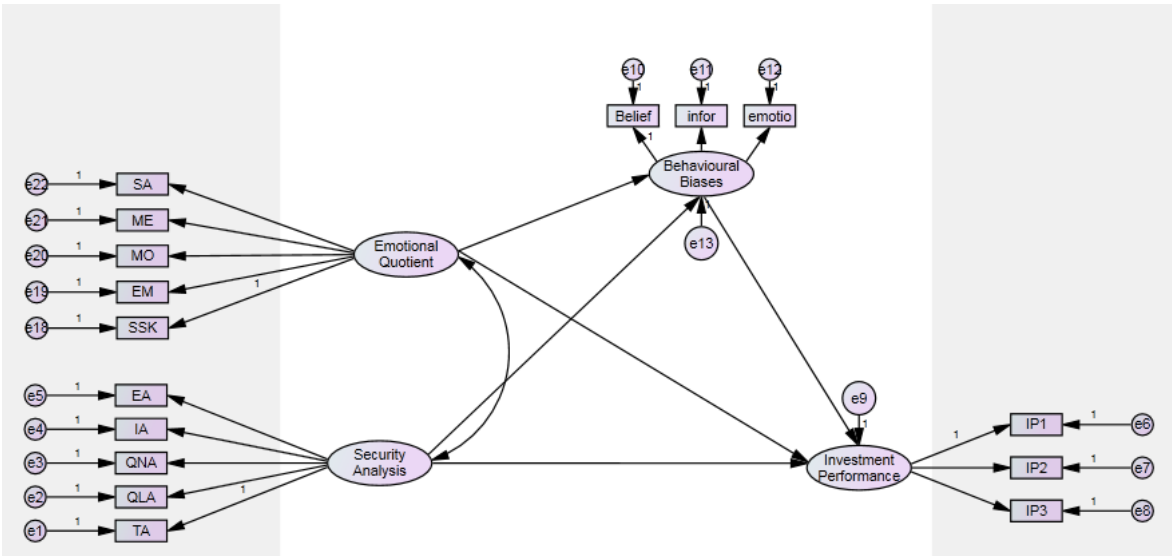


Figure 8.1 Proposed Research Model

For the purpose of analysis of research model, the statistical technique called Structural Equation Modeling (SEM) using Partial Least Square was used. SEM is a powerful second generation multivariate technique for examining the construct.

SEM assesses how well the predicted interrelationships between the variables match the actual or observed variables.

8.3.1 Model without Mediation

The direct influence of security analysis and emotional intelligence towards investment performance is presented in figure 8.2.

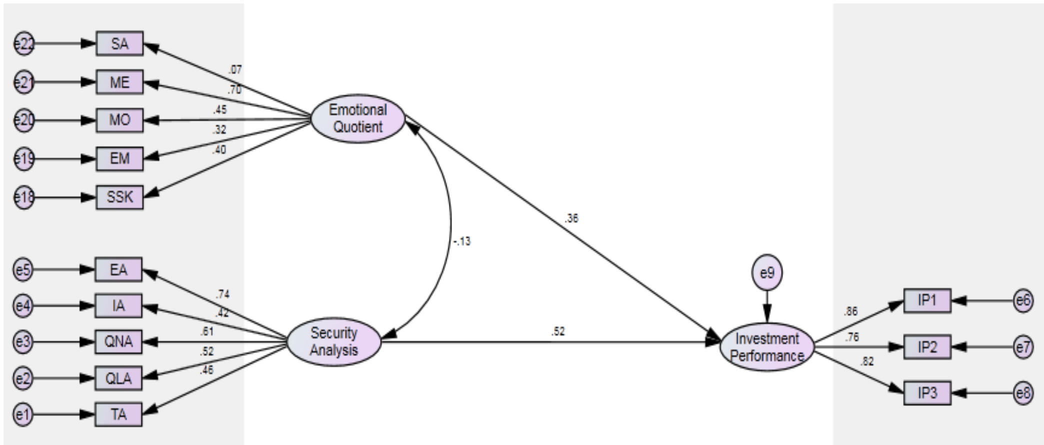


Figure 8.2 Research Model without Mediation

The structural equation model using Amos produces several indices of fit like measure of absolute fit, comparative fit and parsimonious fit etc. The following are the most commonly used fit indices:

Table 8.13

Model Fit Indices – Research Model without Mediation

Sl. No	Indices of Common Fit	Value	Value of Good Fit
1.	CMIN/DF	3.020	<5
2.	RMR	0.047	<0.05
3.	Comparative Fit Index (CFI)	0.953	>0.90
4.	Goodness of Fit Index (GFI)	0.954	>0.90
5.	Adjusted GFI (AGFI)	0.932	>0.90
6.	Incremental Fit Index (IFI)	0.953	>0.90
7.	Tucker Lewis Index (TLI)	0.960	>0.90
8.	Normed Fit Index (NFI)	0.932	>0.90
9.	Root Mean Square Error of Approximation (RMSEA)	0.07	<0.08

Source: Field Survey

Table 8.13 shows the different model fit indices of the structural model. The structural model fit is good with Goodness of Fit Index (GFI) 0.954; Tucker Lewis Index (TLI) 0.960; Comparative Fit Index (CFI) 0.953; Root Mean Square Error of Approximation (RMSEA) 0.07; CMIN/df 3.020 and p-value 0.000. These indexes indicate a strong predictive validity of the research model.

The model without mediation shows the relationship between security analysis on investment performance. The relationship between security analysis and investment performance shows a beta value 0.52 and it is significant at 1% level ($p<.01$). Hence one can conclude that the security analysis has a significant impact on investment performance, i.e one unit change in security analysis will make 0.52 changes in investment performance. By considering all the aspects of security analysis the investors can achieve the better investment performance level.

The relationship between emotional intelligence and investment performance shows a beta value 0.36 and it is significant at 1% level ($p<.01$). Hence one can conclude that the emotional intelligence also has a significant impact on investment performance. By increasing emotional intelligence the investors can achieve the better investment performance level.

When we compare these two exogenous variable (security analysis and emotional intelligence) the security analysis is having more impact ($\beta = 0.52$) than the emotional intelligence ($\beta = 0.36$) on endogenous variable namely investment performance.

8.3.2 Model with Mediation

The mediation model seeks to discover and make clear the underlying mechanism of an observed relationship existing between a dependent and an independent variable through including a third explanatory variable, which is normally known as a the mediator variable. The hypothesis of a mediation model is not related to a direct causal relationship between the dependent and independent variable, but the hypothesis assumes that the independent variable as the main cause of the mediator variable, which, consequently, results in the dependent variable.

In the present research, behavioural bias has an important role in investment decision making and consequently in investment performance. Therefore, the researcher decided to put the behavioural bias as a mediator between security analysis, emotional intelligence and investment performance.

The research model is presented in Figure 8.3.

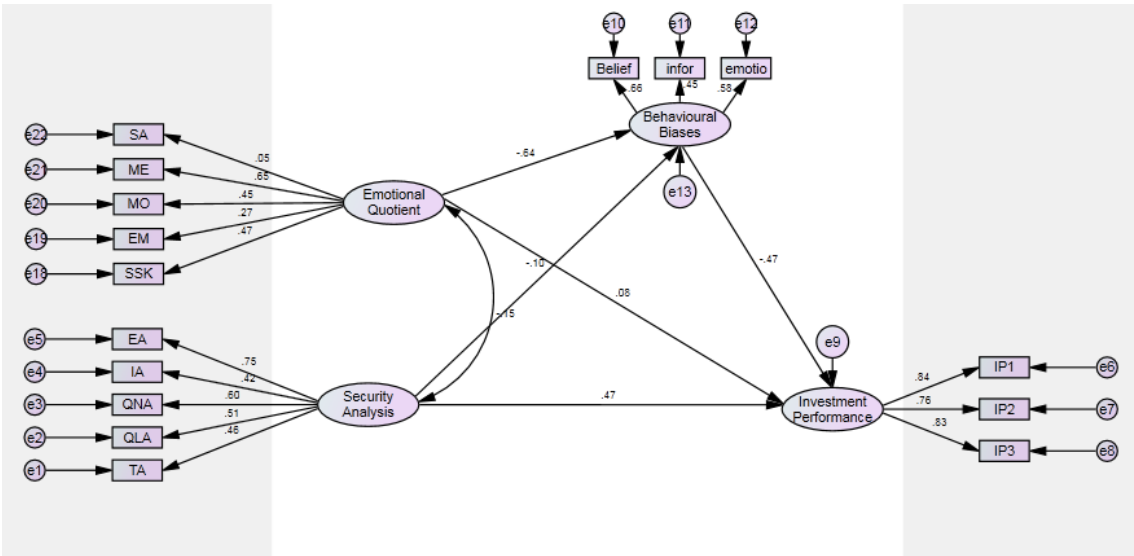


Figure 8.3 Research Model with Mediation

The structural equation model using Amos produces several indices of fit like measure of absolute fit, comparative fit and parsimonious fit etc. The following are the most commonly used fit indices:

Table 8.14

Model Fit Indices – Model with Mediation

Sl. No	Indices of Common Fit	Value	Value of Good Fit
1.	CMIN/DF	3.661	<5
2.	P-value	0.000	<0.05
3.	RMR	0.049	<0.05
4.	Comparative Fit Index (CFI)	0.918	>0.90
5.	Goodness of Fit Index (GFI)	0.923	>0.90
6.	Adjusted GFI (AGFI)	0.903	>0.90
7.	Incremental Fit Index (IFI)	0.913	>0.90
8.	Tucker Leiws Index (TLI)	0.930	>0.90
9.	Normed Fit Index (NFI)	0.938	>0.90
10.	Root Mean Square Error of Approximation (RMSEA)	0.078	<0.08

Source: Field Survey

Table 8.14 shows the different model fit indices of the structural model. The structural model fit is good with Goodness of Fit Index (GFI) 0.923; Tucker Lewis Index (TLI) 0.930; Comparative Fit Index (CFI) 0.918; Root Mean Square Error of Approximation (RMSEA) 0.078; CMIN/df 3.020 and p-value 0.000. These indexes indicate a strong predictive validity of the research model.

The research model proves the meditation effect of Behavioural bias in between the Investment performance (outcome variable) and the Security analysis (predictor variable). 'Mediation refers to a situation when the relationship between a predictor variable and an outcome variable can be explained by their relationship to a third variable (mediator)' (Field, 2014).

According to Baron & Kenny[3] (1986), Mediation can occur when it fulfils some conditions. They are:

1. The independent variable must significantly affect the mediator,
2. The independent variable must significantly affect the dependent variable in the absence of the mediator,
3. Mediator must affect the dependent variable.
4. The effect of the independent variable on the dependent variable gets smaller upon the addition of the mediator to the model.

Chiefly there are two types of mediation; full mediation and partial mediation. Full mediation or complete mediation occurs when the independent variable applies its total influence through the mediating variable. But the partial mediation is the situation where the independent variable applies some of its influence on the dependent variable through the mediating variable, and it also applies some of its influence directly on the dependant variable, not through the mediating variable (Baron & Kenny, 1986)[4].

Mediation exists if the coefficient of the direct path between the independent variable and the dependent variable is reduced when the indirect path via the mediator is introduced into the model (Bontis, Booker, & Serenko, 2007)[5].

In this model, it is clear that there is a significant relationship between security analysis on investment performance (β=0.47 and $p<.01$) and also emotional intelligence on investment performance (and β=0.08 and $p<.05$). At the same time, there is a significant relationship between security analysis and behavioural bias (β = -.10 and $p<.05$) and between emotional intelligence and behavioural bias (β= -0.64 and $p<.01$). There is also significant relation between behavioural bias and the investment performance (β= -0.47 and $p<.01$). When the mediator, behavioural bias introduced in the model, the influence of independent variable (security analysis & emotional intelligence) on the dependent variable (investment performance) gets reduced, i.e the beta value reduced from 0.52 to 0.47 in the case of security analysis and 0.36 to 0.08 in the case of emotional intelligence.

In both the situations, there is partial mediation, because all the paths show significant influence. That is security analysis and emotional intelligence exercises some of its influence on investment performance through the mediating variable behavioural bias and it also applies some of its influence directly on investment performance.

The result of hypotheses used in the model is shown in the table 8.15.

Table 8.15

Result of Hypotheses Testing - Research Model

Sl No	Hypotheses	β value	P value	Result
1	H0: There is no significant relationship between security analysis and investment performance	0.47	<.01	Reject H0
2	H0: There is no significant relationship between emotional intelligence and investment performance	0.08	0.016	Reject H0
3	H0: There is no significant relationship between security analysis and behavioural bias	-0.10	0.046	Reject H0
4	H0: There is no significant relationship between emotional intelligence and behavioural bias	-0.64	<.01	Reject H0
5	H0: There is no significant relationship between behavioural bias and investment performance.	-0.47	<.01	Reject H0

Note: All the relationship was significant at 5% level.

It is clear from the table 8.15 that entire hypotheses are rejected. And all the paths have a significant relationship. Since the p value of covariance is 0.066, it is not significant.

Thus the model proves that in the equity capital market, behavioural bias has a mediating role between security analysis and investment performance and between emotional intelligence and investment performance. Here, the mediation analysis proved the inevitable role of behavioural bias in the investment performance.

8.4 Conclusion

This chapter covers the influence of behavioural bias on investment performance among retail investors in Kerala. The chapter also points out the research model analysis, which shows the influence of security analysis and emotional intelligence on investment performance, by considering behavioural bias as a mediator.

From the above analysis it can be concluded that the investment performance of the individual investors in Kerala is quite low. On an average the mean score of the investment performance is 6.58 out of 15. It indicates that investors are not satisfied with their rate of return and investment decisions.

In the case of gender, the mean score investment performance given by male investors is 6.30 (2.77) and mean score of female investors is 8.98 (1.35), there is significant difference between male and female with regard to investment performance. Since the mean investment performance of the female is more, they are having more investment performance than male investors.

In age category, it is found that the highest mean score is 7.67 (2.61) which is in the age category of 'above 50 years' and lowest mean is 6.32 (3.11) in age category '18-30 years'. It can be inferred from the result that the older investor is having better investment performance than the younger ones. The age of the category and investment performance is having the direct relationship. It may due to the experience and maturity of aged investors.

In educational level, the 'post graduate' educational level is having the highest mean score of 7.21(2.53) and the 'undergraduate' having the lowest score of 3.72 (2.44). The 'graduate' and professional are having almost the same score. Since the p value

(0.000) is less than 0.05, the mean score of the investment performance in different educational level is significantly different from others. It can be concluded that under graduates are having lower investment performance than other educational categories.

The annual income category ‘more than Rs.15, 00,000’ is has the highest mean score 9.50 (2.33) and the annual income category ‘Less than 5, 00,000’ is having lowest score 5.57 (2.70). Since the p value 0.000 which is less than 0.05, the mean score of annual income categories is significantly different from others. It can be observed from the result that annual income categories are having direct relation with investment performance. Lower income level is having the low investment performance and vice-versa.

In case of marital status, it can be observed that the mean score of investment performance of married is higher 6.77 (2.87) and the single is lower 7.12 (1.66). It can be concluded from the result that married investors are having more investment performance than the single investors.

In case of the impact of dimensions of security analysis to investment performance, it can be found that the co-efficient of the independent variables like Economic, Quantitative and Industry analysis are significant at 5% significant level and all the co-efficient are positive. This indicates that Economic, Quantitative and Industry analysis have the positive impact on investment performance. Technical analysis is significant at 10% significant level and its coefficient is negative. So it makes negative impact on investment performance. From this, it can be assumed that the investors who are trading on short-term by using technical analysis are not satisfied with their rate of return and their investment decision.

In case of the impact of dimensions of emotional intelligence to investment performance, it can be found that the co-efficient of only one independent variable social skill is significant at 5% significant level and the co-efficient is positive. All other factor’s p-value is more than .05, hence not significant. This indicates social skill has the positive impact on investment performance. From this, it can be assumed that the investors who are having social skill may have easy access to information and they can use that information to have the right investment.

In case of the impact of dimensions of behavioural to investment performance, it can be found that the co-efficient of all the three independent variable are significant at 1% significant level and the co-efficient are negative. This indicates, as discuss in the earlier literature, all the factors of behavioural bias reduces the investment performance.

At last, the research model proves that in the equity capital market, behavioural bias has a mediating role between security analysis and investment performance, and between emotional intelligence and investment performance. Here, the mediation analysis proved the inevitable role of behavioural bias in the investment performance.

References:

1. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2015). *Multivariate Data Analysis.* Noida: Pearson India Education Service Pvt Ltd.
2. Field, A. (2014). *Discovering statistics using IBM SPSS Statistics.* New Delhi: Sage Publication India Pvt Ltd.
3. Baron, R. M., & Kenny, D. A. (1986). The Moderator-Mediator Variable Distiction in Social Psychological Research: Conceptual , Strategic and Statistical Considerations. *Journal of Personality and Social Psychology , 51* (6), 1173-1182.
4. Ibid
5. Bontis, N., Booker, L. D., & Serenko, A. (2007). *The mediating effect of organizational reputation on customer royalty and service recommendation in the banking industry*. Bingley: Emerald Management Decision.

Chapter 9

Summary, Findings and Recommendations

9.1 Introduction

Savings are the excess of income over expenses. People who save can invest the same in some investment avenues. Investment means the commitment of fund with the expectation of positive return. Return, risk, time and liquidity are the four dimensions of investment. The objective of investment is to maximise the return and minimise the risk involved in it. Through long term investment one can experience the magic of compounding, increase in the aggregate return and reduction in volatility, risk and the burden of cost.

Volatility is the degree of variation in asset price over time. If a security has sudden high price movement, the security has high volatility. If security price is relatively stable, the security has low volatility. It is a measure of risk, i.e., high volatility implies high risk and vice versa. Some factors are held responsible for the volatility and risk. In some studies micro variables like dividend per share, earnings per share, company size and book value per share have got prominence and in others macro variables like bank rate of interest, index of industrial growth, union budget, inflation rate and foreign currency value, rainfall etc, have been highlighted. Changes in local or global economic and political environment also influence the share price movements. If these are the only reason for the change in share price, the share price doesn't change minute by minute and even second by second as they do in the stock market. In practice, the behaviour of the investor affects largely the share price movements which can be explained in behavioural finance.

Behavioural Finance

Behavioural Finance is the application of psychological element in financial decision making. It is the study of how human psychology affects the investment decisions- and how these decisions affect the individual stock prices and broad market movements. As stated by the Meir Statman, "Investors are human beings and human beings aren’t perfectly rational, they are normal always. When they buy on emotion, they not only risk their own investment plans, but also create opportunities for others in the market.”

Significance of the Study

The Indian equity market is one of best among the world stock market in terms of returns. But only 2% of population is having demat account in NSDL and CDSL. The equity culture is not spread among the individual investor because of several reasons such as lack of awareness, absence of efficient regulatory system, non-availability of floating stocks, absence of variety of capital market instruments, high degree of stock market volatility etc. Stock market volatility is the major reason attributed to the refrainment of the individual investors from the stock market.

Statement of the Problem

Investors presume equity investment as highly risky due to its volatility. An increase in stock market volatility brings a large stock price change of advances or declines. Investors interpret a raise in stock market volatility as an increase in the risk of equity investment and consequently they shift their funds to less risky assets. It has an impact on business investment spending and economic growth through a number of channels. Changes in local or global economic and political environment influence the share price movements and show the state of stock market to the general public. Moreover the behavioural and psychological aspects also contribute to the stock market volatility.

To study this phenomenon, the researcher has to identify the extent and pattern of volatility in the stock market and the anomalies existing in the stock market, which shows deviations from the standard financial theories. Usually when the investor takes the investment decision he does the security analysis. But the investors doing the same level of security analysis are not getting the same gain due to their difference in the level of behavioural bias and emotional intelligence. Socio-economic variables of each investor are considered as the basis of difference among behavioural bias and emotional intelligence of the investors.

In this background the researcher investigates the following major issues:-

1. What is the extent and pattern of stock price volatility in Indian capital market?
2. Whether the Indian stock market is efficient at weak form and semi-strong form of the Efficient Market Hypothesis?
3. How the security analysis, behaviour bias and emotional intelligence change according to investor's gender, age, education, annual income and marital status?
4. What is the role and impact of security analysis, behavioural bias and emotional intelligence on investment performance?

Objectives of the Study

Based on the research question mentioned above, the specific objectives set for the research are given below:

1. To identify the extent and pattern of stock price volatility in Indian capital market.
2. To test the stock market efficiency at its weak form and semi-strong form with regard to Efficient Market Hypothesis in Indian Stock Market.
3. To assess the level of security analysis, behavioural bias and emotional intelligence of the individual investors in Kerala and their variability with regard to their gender, age, educational qualification, annual income and marital status.
4. To find out the role and impact of security analysis, behavioural bias, emotional intelligence on investment performance.

Hypotheses

Based on the above mentioned objectives the following hypotheses are formulated and tested in this study.

- There is no stock price volatility in Indian stock Market

- Indian stock market follows a random walk/ weak form of Efficient Market hypothesis.
- Average abnormal return (cumulative abnormal return) being generated by the stocks on or around the event day is not significantly different from zero. / Indian stock market is efficient in its semi-strong form of Efficient Market Hypothesis.
- There is no significant difference between security analysis, behavioural biases and emotional intelligence in Kerala with regard to their gender, age, educational level, annual income and marital status.
- There is no significant relation between various security analysis, behavioural biases and emotional intelligence upon the investment performance of individual investors.

Conceptual Model

The conceptual model (Fig: 1.3) of this study is based on four latent variable namely security analysis, emotional intelligence, behavioural bias and investment performance. The model seeks to identify the relationship between two independent variables (security analysis and emotional intelligence) and dependent variables (investment performance) and to check whether the behavioural bias is acting mediating or moderating variable.

Research Methodology

This research design is descriptive in nature. Both secondary and primary data were collected for the study.

Sampling Design

Sampling design consists of sampling method and sample size of secondary and primary data.

Selection of Companies

The companies which have declared bonus share and stock split of the share during the period from 01/01/2014 to 31/12/2016 are treated as the population for the secondary data analysis. The population consists of companies selected from three categories, firstly the companies which had declared bonus share (152 companies), secondly which had declared stock split (235 companies) and thirdly which had declared bonus share as well as stock split simultaneously (12 companies). The total number of the above three categories are 399 companies.

The statistical equation is used to calculate the sample size of investors. The highest standard deviation among variables was taken. After applying finite population correction factor the sample size is calculated as 16. Then sample size of companies calculated for the study has been rounded to 20.

Simple random sampling method is used to select the companies. Samples are selected through computer generated random numbers. The data of indices (Nifty and Sensex) collected from their respective website and daily closing price for the selected shares are collected from Bombay Stock Exchange website during the period 01/01/2002 to 31/12/2016. But some of the stocks are listed after 01/01/2002; in that case observations are collected from the date of listing of the stock.

Selection of Investors

The target population of the micro level analysis of this study comprises of individual investors in Kerala who are buying and selling the shares in any of the stock exchanges in India. An official data of equity investors in Kerala and their geographical distribution are not available; the scholar has to take the assistance of share broking firms such as Karvy, Vertex Securities, Geojit PNB Paribas, JRG Securities and Motilal Oswal to identify investors.

The exact data regarding the number of equity investors in Kerala and their geographical distribution is not available. The statistical equation is used calculate the sample size of investors. The highest standard deviation among variables from the pilot study was taken. The sample size so calculated is 385 and it has been rounded to 390.

Since the population of the study comprises Individual (Retail) investors in Kerala who are buying and selling the equity shares through their demat account, a two stage cluster sampling (Area Sampling) technique has been used for selecting sample investors.

In the initial stage, three districts have been selected from the fourteen districts in Kerala by using lottery method for the investigation. Accordingly Ernakulam, Kozhikode and Thiruvananthapuram are selected. In the second stage, one Corporation, one Municipality and one Gramapanchayath were selected from each sample district by adopting the random sampling method by employing computer generated random numbers. Accordingly, from Ernakulam District - Cochin corporation, Aluva Municipality out of 13 Municipalities and Edathala Gramapanchayath out of 82 Gramapanchayath from Thiruvanthapuram District- Thiruvanathapuram Corporation, Attingal Municipality out of 5 Municipalities, and Vellarada Gramapanchayath out of 78 Gramapanchayaths and from Kozhikode District- Kozhikode Corporation, Ramanattukara Municipality out of seven Municipalities and Kadalundi Gramapanchayath out of 70 Gramapanchayaths were chosen.

The assistance of share broking firms has been sought to identify the investors. As such, the list of demat account holders were collected from the leading stock market brokers of the three selected districts. From these lists the scholar has prepared the comprehensive list of investors in these districts. Duplication has also been removed in this stage from the lists supplied by different broking firms.

Not all brokers in all the selected locations were ready to spare the full list of investors with them. From the list given by these brokers, sample investors have been selected through random numbers generated by computer. Then they were personally met in undisguised format with a schedule to collect data for the study.

Research Instrument

Pre-tested Structured interview schedule is used as the instrument for the purpose of collecting primary data for the study. A detailed interview schedule consisting of every aspects of the present study was prepared in consultation with experts in the field of finance and behavioural finance.

Variables of the Study

The present study aims to examine the influence of security analysis, behavioural bias and emotional intelligence towards investment performance. To fulfil these objectives the following variables are used.

1. Security Analysis
2. Behavioural Bias
3. Emotional Intelligence
4. Investment Performance

The security analysis further classified into quantitative analysis, Technical analysis, economic analysis, qualitative analysis and industry analysis. Behavioural bias is further classified into emotional bias, information processing bias and belief perseverance bias. Emotional intelligence also classified into empathy, motivating oneself, social skills, managing emotions and self awareness.

The study also uses the socio economic variables like gender, age, educational level, annual income and marital status to classify the investors.

Scaling Technique

The scaling technique is used to alter the qualitative data into quantitative one. Scaling is a method which changes attributes (a series of qualitative facts) into variables (a quantitative series). It is a procedure for assignment of numbers or symbols to subjective abstract concepts. Hence, the researcher used a five-point Likert's scale on the measuring instrument.

Tools for Data Analysis

The tools used for the analysis are statistical tools like percentage, arithmetic mean, Standard deviation, independent sample t test, one way ANOVA/Welch F, kTukey HSD/ Tamhane's T2 Post Hoc Test for Multiple Comparisons and multivariate techniques like Multiple regression, Exploratory Factor Analysis, Confirmatory Factor Analysis, Structural Equation Modeling (SEM), Dickey-Fuller, Philip-Perron, Autocorrelation and econometrics tools like exponential generalised autoregressive conditional heteroskedasticity (EGARCH) and event study to test the semi-strong form of efficient market hypothesis.

Limitations of the Study

The present study is subject to the following limitations.

- Only two events (stock split and bonus issue) were taken for the event study. Moreover, the event 'stock split' and 'bonus issue' which were announced within the period of 1st January 2014 to 31st December 2016 were chosen, the period of three years only was considered.

- The human behaviours are complex and difficult to be understood as they vary according to situations, so it is not possible to ensure 100% accuracy in the result. However efforts have been made to ensure as much as accurate as possible.

- Samples are not taken from the full fledged sample frame. It is collected from stock brokers; some of the brokers are hesitant to provide the details of investors. It may affect sampling even though the researcher has taken all the efforts to make the sample frame comprehensive.

- The researcher finds it difficult to get data on investor's real return and investment performance; so the researcher uses the subjective assessment. It is made by asking them to compare their current real return to expected return and rate of return of the market. Moreover, satisfaction level of investment decision also used as criteria to measure the investment performance.

- The study is limited to only the area of security analysis, behavioural bias and emotional intelligence.

Structure of the Thesis

The report of the study has been presented in nine chapters as Introduction, Review of Literature, Theoretical Framework, Extent and Pattern of Indian Stock Market Volatility, Market Efficiency of the Indian Stock Market, Role of Security Analysis on Investment Decision, Impact of Behavioural Bias and Emotional Intelligence on Investment Decision, Factors Influencing the Investment Performance – an Empirical Analysis, and the last chapter presents the Summary, Findings and Recommendations.

9.2 Review of Literature

Many scholars have undertaken studies on the topic during the past six decades. All these studies have been broadly classified into stock market volatility, stock market efficiency, security analysis, emotional intelligence, behavioural bias and investment performance. There are lots of researches which explain these variables individually. Most of the research discussed volatility, extent and pattern of volatility in different stock market, reasons of volatility, comparison of volatility in different stock markets in different countries, sectors and different asset classes. Now a days, researchers use more sophisticated econometrics tools to evaluate the volatility than the other statistical tools. There are lot of other studies which have discussed the different forms of market efficiency in relation to efficient market hypothesis in different stock markets in the world. Some researcher have studied about the security analysis and their different approaches like fundamental analysis, technical analysis, techno-fundamental analysis, their effectiveness and their impact on return on investment. Recently lots of studies have occurred in the emerging area in finance, namely behavioural finance. Some studies also discussed the relation of emotional intelligence on return on investment.

The present study is entirely different from past researches conducted in these areas in the sense that this study considers all these variable together. Firstly it studies the extent and pattern of Indian stock market volatility since the individual investors are very concerned about the same. Secondly, the researcher tests the market efficiency of Indian stock market; thirdly, an attempt is made to check the combined effect of security analysis, behavioural bias and emotional intelligence on investment performance. Security analysis and emotional intelligence act as independent variable on investment performance which is the dependent variable whereas behavioural bias acts as mediating variable. The study also illuminates the relationship between the key variables like gender, age, educational qualification, annual income and marital status on security analysis, behavioural bias, emotional intelligence and investment performance.

9.3 Theoretical Framework

This part of the study aims to formulate a theoretical framework regarding volatility, stock market efficiency, security analysis, behavioural bias, emotional intelligence and investment performance.

Volatility

The volatility of a share indicates the variability of its expected return. Volatility of the share price hampers individual investment, as a result it also affects the economy as a whole. It creates more uncertainty in the market and adversely affects the flow of fund to productive investment. To some extent, volatility is the normal part of the process whereas the excess volatility caused by the irrational behaviour of the investors is detrimental which will affect the smooth functioning of financial system and economic performance.

Efficient Market Hypothesis

As per Efficient Market Hypothesis security prices are expected to move randomly in an efficient market. In efficient market, everybody has access to all information simultaneously without any cost, who interprets it similarly and behaves rationally. So nobody can make abnormal return from the market. The efficient market argues that in an efficient market, new information is processed and interpreted as it arrives, and prices at the same time adjust to new levels. Consequently, an investor cannot always earn abnormal returns by doing fundamental analysis or technical analysis.

The efficient Market Hypothesis is divided into three forms.

1. **Weak Form**: It holds the view that past sequence of the securities prices cannot predict the future price of the same security. It is the direct refusal of technical analysis. Tools to test weak form market efficiency are auto correlation test, run test, filter test and unit root test.
2. **Semi-strong Form**: The semi-strong form implies that the current share price reflects all publicly available information about the company. Whenever the information becomes public the share price changes and imbibes the full information. Examples for this are announcement of dividends, stock splits, corporate annual reports etc. As weak form repudiates technical analysis, semi strong form refuses fundamental analysis as it says that fundamental analyst cannot make superior gains. Event study is generally used to test semi strong efficiency of the market.
3. **Strong Form**: This implies that the current price of a share absorbs all information, both publicly available and insider information. This means that nobody can make abnormal return by using public as well as privet information. Persons occupying key post in the corporate have access to much information that is not available to the public. This is called as insider information. Mutual funds and other professional analyst with large research facilities may gather private information regarding the different stocks which is not available to the public. The strong form of efficiency can be tested by comparing the market return and the return generated by mutual fund.

Behavioural Finance

Behavioural finance is to replace the efficient markets hypothesis as the most widely accepted paradigm; it is not sufficient to simply find flaws with the EMH, it finds out the reasons of stock market anomalies by justifying them with explanation of various investor biases while taking investment decisions. It is an open-minded finance. Kahneman and Tversky have shown empirically that people are irrational in a consistent and correlated manner. They have started this revolution at the beginning of 1970s.

Investment Decision Making

Decision making is the most complex and challenging activity of investors. Every investor differs from the others in all aspects due to various factors like demographic factor, socioeconomic background, educational level, sex, age and race. An optimum investment decision plays an active role and is a significant consideration.

Investor is a rational being who will always act to maximize his financial gain. Yet we are not rational being; we are human being; an integral part of this humanness is the emotion within us. Indeed, we make most of our life decisions on purely emotional considerations.

Investment performance depends mainly on the quality of investment decision they take. Most of the investors may take the investment decision through the security analysis. But, even without the knowledge of themselves, their decision may affect their behavioural bias and level of emotional intelligence.

Security Analysis

Security analysis is the first step of the portfolio management. In this step, investors analyse the risk-return characteristics of each security under consideration. The law of the market is 'buy underpriced securities and sell the overpriced securities'. Security analysis is all about identifying underpriced and overpriced securities. Basically there are two approaches; fundamental analysis and technical analysis. The third one is the blend of these two, namely, techno fundamental analysis.

Fundamental Analysis

Fundamental analysis is also called as EIC analysis where E stands for economic, I for Industry and C for Company analysis. Economic analysis aims at determining whether the economic climate is conducive and is capable of encouraging the growth of the business sector in a country. Industry analysis demands insight into (1) the key sectors or subdivisions of overall economic activity that influence particular industries, and (2) the relative strength or weakness of particular industry or other groupings under specific set of assumptions about economic activity. Company analysis deals with the estimation of return and risk of individual stock.

Technical Analysis

Investment timing is crucial as the market is continuously jolted by waves of buying and selling. Prices are moving in trends and cycles, and are never stable. Technical analysis helps us to take the decision when to buy and sell. Entry and Exit decision is very important as it decides the profits or losses of investment. The purpose of "chart analysis" is to determine the probable strength of demand versus pressure of supply at various price levels, and thus to predict the probable direction in which a stock will move, and where it probably will stop. Apart from price charts, the analyst uses mathematical indicator also to know the underlying trend of a stock. Mathematical indicators are used to project future financial or economical trend. It helps to identify momentum, trends, volatility etc. Mathematical indicators like moving averages smoothen out the apparent erratic movements of share prices and highlight the underlying trend. Market indicators help the investor gauge changes in all shares within a specified market. Relative Strength Index (RSI), Exponential Moving Average (EMA), Moving Average Convergence and Divergence (MACD) are also used by technical experts for predicting future price. Indicators used by technical analyst to study the trend of the market as a whole is known as market indicators.

Behavioural Bias

There are three financial decisions taken by individuals in stock trading: buy, sell, and hold. Many authors have identified the following pattern of individual behavioural biases while taking their investment decisions. A bias is a systematic error in the way we process information of the world. Biases are irrational financial decisions caused by faulty cognitive reasoning or reasoning influenced by emotions. Behavioural biases fall into two broad categories, cognitive and emotional.

Cognitive Bias

Cognitive bias deals with the way one thinks. It arises from basic statistical, information processing, or memory errors. It is the result of the faulty reasoning so that the better information and advice can correct them. Cognitive biases are again classified into two categories, Belief Perseverance and Information Processing.

Belief Perseverance Bias is the tendency to cling to once previously hold or recently established belief irrationally or illogically. Investors continue to hold and justify the belief because of their bias toward belief in themselves or their own ideals or abilities. Confirmation, representativeness, illusion of control and cognitive dissonance are the examples of belief perseverance bias.

Information processing bias arises when information is being processed and used illogically and irrationally in financial decision making. It includes anchoring, mental accounting, availability and self attribution.

Emotional Bias

Emotional bias deals with the way one feels. It arises from the impulse or intuition rather than conscious calculations. It is rather difficult to correct the emotional bias, because emotion is a mental state that acts spontaneously than through conscious effort. Actually, the investors need to control their emotions, but often they fail to control. It includes loss aversion, overconfidence, regret aversion and herding.

The dictionary meaning of emotional intelligence is the capacity to be aware of, control and express one’s emotions, and to handle interpersonal relationships judiciously and empathetically. Daniel Goleman explained the definition of emotional intelligence, expanding the same into five main domains. They are self awareness, managing emotions, motivating oneself, empathy and social skills.

Investment Performance

Investment performance is the rate of return (dividend plus capital appreciation) received from the investment. Usually the rate of return is high, high performance is attributed, otherwise vice versa.

9.4 Findings of the Study based on Secondary Data Analysis.

Based on the analysis of the data consists the two prominent Indian stock market indices – BSE Sensex, S&P CNX Nifty and 20 individual stocks listed on Bombay Stock exchange which are selected randomly for event analysis, the study turns up some valuable findings, which are shown under different heads in the following pages.

9.4.1 Extent and Pattern of Volatility in Indian Stock Market

The study shows the Indian stock market volatility, the result bring based on EGARCH (1,1) models. When we compare the period 2002 – 2016 and the period 2012 – 2016, the volatility is increasing at higher rate when the period comes shorter. When period comes to one year (2016) the volatility increases at alarming rate (only three stocks give different results due to company specific reasons). With this, we can conclude that volatility is very high in shorter period and the same can be minimised if one is prepared to invest in long term.

According to the results we can find that the leverage effects γ are negative in almost all cases including Sensex and Nifty at 5% significant level and it means that good news generates less volatility than bad news in Indian stock Market. It is interesting to note that the negative coefficients of γ in the period 2012 to 2016 are not at all significant at 5% significant level for the selected individual stocks. That means this period of bad and good news makes the same extent of volatility. But, in the period 2016, again the γ shows negative co-efficient which is significant at 5% significant level. So we might be able to say that the shareholders of Indian stock market preferred to hear good news than bad news, especially when they suffer the bad time because they feel scarier for bad news. With this result, it is reliable to announce that Indian stock market is more sensitive to bad news.

To all stocks and indices during the year 2016, the symmetric effect α which is a little bit different than it was in the previous period in EGARCH model in which all are significant at even 1% significant level. In most of the cases when the period comes shorter, the volatility increases, but in some cases it is vice versa, depending on the nature of the stocks. With the present study, we can conclude that the volatility exists in the whole period in Indian stock market.

The parameter δ measures the persistence in conditional volatility irrespective of anything happening in the market. In almost all the stocks and indices (except some in the period 2016) , parameter δ are all positive and relatively large, e.g. above 0.9, then volatility takes long time to die out following an event in the Indian stock market. Also, according to the relative scale of the coefficients, the leverage effect or the symmetric effects dominated. In order to find the long term volatility, we first have to find the long term variance in the EGARCH model.

The researcher considers the modeling of the daily stock returns volatility in Indian stock market during the periods 2002 to 2016, 2012 to 2016 and 2016. In model comparison, the results indicate that it is important to specify the EGARCH model which is sufficiently flexible to accommodate these data. Empirical evidences suggest that the EGARCH model provides a better description and more parsimonious representation than the traditional GARCH model. The finding is that like any other emerging market, the volatility exists in the whole period in Indian stock market, leverage effect is negative in almost all stocks and indices and markets have long memory so that it will take long time to die out the volatility effect after an event. This is the pattern of Indian stock market. The extent of volatility will be very high in shorter period and the same can be reduced if one is ready to invest in long term.

9.4.2 Weak Form Efficiency

In the present study, the researcher uses three statistical methods, namely Augmented Dickey-Fuller unit root test, Phillip-Perron unit root test and Autocorrelation test.

Result from the study shows that all the selected stock prices are non stationary at 5% significance, but become stationary in first differences. The augmented Dickey-

Fuller test fails to reject the null hypothesis for all log stock prices, thereby implying that all stock prices are non stationary. After taking the log first difference in the price of the stocks, (i.e. the return of the stock), the null hypothesis of unit root is rejected at the 1% significance level. The test statistics are more negative than the critical value in all cases. That means Indian stock markets are not a weak form efficient.

Result from the study shows that all the selected stocks prices are non stationary in log levels at 5% significance, but becomes stationary in log first differences. The Phillip-Perron test fails to reject the null hypothesis for all stock prices, thereby implying that all stock prices are non stationary. Whereas, after taking the log first difference on the price of the stocks, (i.e. the return of the stock), the null hypothesis of unit root is rejected at the 1% significance level. The test statistics are more negative than the critical value in all cases. It means that the stock returns in Indian stock markets are not a weak form efficient. The result given by Augmented Dickey-Fuller test and Phillip-Perron are same in this case.

Autocorrelation at lag one is highest for Sunil Hi-tech Engineers (0.107) followed by Tech Mahindra (0.106) and the lowest for HCL Technologies (0.005). Out of the selected twenty stocks, only two stocks - ITC Limited (-0.26), Chamanlal Setia (-0.009) – shows negative autocorrelation at lag one, but they are not significant. Positive auto correlation denotes predictability of returns in the short run, which is the general evidence against weak form efficiency whereas negative autocorrelation indicates mean-reversion in return. There are lots of significant positive and negative autocorrelation for different stocks at different lags. Overall, almost all the stock returns except for very few lags, the auto correlation co-efficient are non-zero at 1%, 5%, 10 % significance levels.

Q statistics also give the evidence for possible dependence in the first and higher order of the return distributions. It shows that the null hypothesis of auto correlation is rejected for almost all returns on all selected stocks at lag one through fifteen at 1% , 5%, 10% level of significance. The non-zero autocorrelation of the series associated with Q statistics, which are jointly significant at 1%, 5%, 10% significant level at one and fifteen degrees of freedom, clearly suggest that all return series do not follow a random walk model. The results exhibit that the Indian stock market is not efficient in its weak form.

All the above-mentioned tests give the same result that the Indian stock market is not efficient in its weak form.

9.4.3 Semi-Strong Form Efficiency - Event Study

The study attempts to examine the semi-strong form of pricing efficiency of the Indian Stock Market in relation to the impact of special events such as bonus issue and stock split announcements on the price behaviour of the related stock, using a sample of 20 stocks which were listed in the Bombay Stock Exchange that witnessed the bonus issue and stock split announcement at different times in the period from 01/01/2003 to 31/12/2006. The market model of event study methodology is applied to calculate the return of the sample stocks in the window of 61 days. The analysis based on the average abnormal return and cumulative average abnormal return of the stocks clearly reveals that no abnormal return which is statistically significant is created on and around the event day. This result clearly shows the existence of semi-strong efficiency in Indian stock market.

9.5 Findings of the study based on Primary Data Analysis.

9.5.1 Descriptive Statistics of the Respondents

Based on the analysis of the data collected from the individual equity investors in Kerala, the study turns up some valuable findings, which are shown under different heads in the following pages.

The summary of the demographic profile of the respondents was listed below:

1. The study found that 349 (89.5%) of the sample investors are male and the remaining 41 (10.5%) are female. Even though the female population in Kerala outnumbered male population, very less of them are active in the field of corporate security investment.

2. It shows that 165 (42.3%) of the sample investors reside in Corporation area, 125 (32.1%) in Municipality area and 100 (25.6%) Gramapanchayath area. From the above distribution it can be inferred that majority of the investors in the sample belongs to urban areas of Kerala.

3. It is found that 45.6 % of the sample investors are Hindus, 28.7% are Christians and 25.6% are Muslims. This is a fare representation of the state's population.

4. The study shows that out of 390 investors 68 (17.4%) are in the age category 18-30 years, 128 (32.8%) from 31-40 years, 118 (30.3%) from 41-50 years and 76 (19.5%) from the above 50 years age category. The mean age of the sample investors is approximately 42 years which indicates that middle aged are more involved in corporate investment.

5. It is found that out of 390 sample investors, 25 (6.4%) are under graduates, 232 (59.5%) are graduates, 117 (30%) are post graduates and 16 (4.1%) are having professional qualification. Hence it can be concluded that the informants selected for the study are reasonably educated and low educated investors are less intense to the corporate savings than the high educated investors.

6. It shows that out of 390 respondents, 267 (68.5%) are employed in private or government sector, 16 (4.1%) are in profession, 48 (12.3%) are in business and 59 (15.1%) are retired from their job. Hence it can be concluded that most of the investors are from fixed income group.

7. It can be seen that 87.9% (343) of the sample investors are married and the rest are unmarried.

8. It is found that out 390 of the sample investors, 129 (33.1%) belongs the annual income category 'less than Rs.5,00,000', 143 (36.7%) belongs to 'Rs.5,00,000 – 10,00,000', 90 (23.1%) belongs to Rs.10,00,000 to 15,00,000 and 28 (7.2%) belongs to 'More than Rs.15,00,000' income category. The mean annual income of sample investors is Rs.7,71,794. This shows that middle income people are more involved in the stock market investment.

9. Most (87.7%) of the sample investors are first generation investors, only 12.3% of investors are second generation investors. Hence it can be concluded that family investment culture in corporate securities is less in Kerala.

10. In case of experience in the equity investment, one third (33.3%) of the investors is having the experience of less than 5 years, 32.6% is having the experience of 5-10 years, 10.5% is having the experience of 11 - 15 years and 23.6% having 'more than 15 years' experience. The mean experience in equity investment of the sample investors is 9.81 years.

11. Period wise analysis of holding securities shows that almost half (49%) of the investors are holding the equity shares below one year, 43.1% of investors holding 1 to 3 year, only 7.9% of investors are holding for more than 4 years. The mean average of the holding period of the sample investor is 1.09 years. Hence it can be deduced that majority of the sample investors are short term or medium term investors. Long term and very long term investors are lesser in figure.

9.5.2 Security Analysis

Regarding the elements of security analysis 'growth of the economy' is having highest mean score of 4.0538(SD 1.12904) followed by 'debt equity ratio' 3.9128(SD 1.06479) and 'past performance of company's share' 3.9103 (SD 1.01386) out of the 29 attributes. That means investors give more importance to the above attributes while they take the investment decision. The 'industry growth relative to GDP' is having the least mean score of 3.2179 (1.16336).

The study identified the dimensions of security analysis through Exploratory Factor Analysis and confirmed it through Confirmatory Factor Analysis. The dimensions are quantitative analysis, technical analysis, economic analysis, qualitative analysis and industry analysis. It shows that quantitative analysis is having highest mean score 3.8314 (SD 0.81050) followed by economic analysis having mean score of 3.8226 (SD 0.87351) which are more than the mean score of overall security analysis 3.7269 (SD 0.58914). This means that investors give more importance to quantitative and economic analysis mostly while they take the investment decision. The least mean score is for industry analysis 3.2889 (SD 1.00087). This indicates that investors are not that much bothered about the industry in which they invest. On average investors attach 74.53% importance to security analysis while taking investment decision. Mean score in this respect is 108.08 (SD 17.09) out of the maximum score of 145.

1. In gender wise analysis, mean score security analysis of male is 107.92 (17.70) differing from female 109.43 (10.60). But the difference of male and female investors is not significant. Among the dimensions of security analysis, the factors like quantitative analysis and qualitative analysis have no significant difference between male and female investor, whereas technical, economical and industry analysis shows the significant difference between male and female.

The mean score of the technical analysis of male investor is 25.99 (74.25%) and the mean score of the female investor is 23.73 (67.8%). From this result, it is clear that the male investors are very much concerned in technical analysis as they are having more trading mentality than female investors.

In economic and industry analysis, the score of female is more than the male which shows that female are more careful in investment decision than their male counterpart.

2. In age wise comparison, it can be understood that the highest mean score is 112.69 (13.37) which is in the age category of '18 – 30 years' and lowest mean is 102.96 (20.88) in age category '41-50 years'. The p value is 0.003 which means there is significant difference among the mean score of different age categories.

The study shows the differences of various dimensions of security analysis among different age categories of investors. The result shows that in case of quantitative and economic analysis, no significant difference among different age categories whereas, in case of technical analysis, qualitative analysis and industry analysis, there is significant difference among the investors.

In the case of technical analysis, there is a significant difference in investors in the age category ‘18-30 years’ with all other age categories. From the analysis, it can be seen that investors in the age category ‘18 -30 years’ give more importance to technical analysis showing that most of the youngsters act as short-term traders, not as long term investors.

From the analysis, it can be concluded that in all dimensions of security analysis, investors in the age category ‘41-50 years’ are having lower mean score. It means that investors in the age category ‘41-50 years’ are giving lesser importance to security analysis.

3. In education wise analysis, post graduate is having the highest mean score (108.75) of security analysis and the lowest score (93.50) is among professional. Since the p value (0.000) is less than 0.05, at least one of the mean score is significantly different from others. In case of security analysis, there is a significant difference in the educational qualification category between professional with all other educational categories of investors. Since the mean score of the post graduate investors is higher than all other educational categories, this educational category gives more importance to security analysis, and investors in professional category give least importance to security analysis when compared to other educational categories.

The study shows the differences of various dimensions of security analysis among the different educational qualification categories of investors. The result shows that in case of technical analysis, there is no significant difference among investors in different categories of educational qualification. Whereas, in case of quantitative analysis, economic analysis, qualitative analysis and industry analysis, the researcher finds the significant difference among different level of educational qualification.

It can be seen that almost in all the dimensions of security analysis the investors educational category ‘post graduate’ gives more importance and educational category ‘professional’ gives less importance than all other educational categories. Professionals are giving lesser importance to security analysis which may be due to their busy involvement in their profession.

4. In annual income wise comparison, investors in the annual income category ‘more than Rs.15,00,000’ is having the highest mean score (118.82) for the use of security analysis and the lowest score (104.96) is for investors in the annual income category of ‘Rs.5,00,000 – 10,00,000’. Since the p value (0.000) is less than 0.05, the mean score is significantly different from others. In case of use of security analysis in investment decision, there is significant difference in the mean score of investors in the annual income category between ‘more than Rs.15,00,000’ with investors in the all other income categories. When we analyse the mean difference we came to know that the investors in income group ‘more than Rs.15,00,000’ give more importance to overall security analysis while taking investment decision.

The study shows that technical analysis, quantitative analysis, qualitative analysis and industry analysis show the significant difference among the annual income categories.

In case of quantitative analysis, qualitative analysis and industry analysis, investors in annual income category ‘more than Rs.15,00,000’ gives more importance than investors in the other categories of annual income.

5. In marital status wise analysis, mean score for security analysis of married investors is 104.23 (16.88) differing from single investors 104.96 (13.86). Since the p value of the ‘t’ test is more than .05, it can be considered that there is no significant difference between married and single investors with regard to security analysis.

In the dimensions of security analysis, the variables like quantitative, qualitative, economic analysis have no significant difference among married and single investor.

In case of technical and industrial factors of security analysis, there is difference between married and single investor. It can be seen that the mean score of the single investors are more than the married investors. Hence, it is clear that single investors give more importance to technical analysis.

Similarly, the dimension of industry analysis is concerned; the mean score of married and single investors are significantly different. Unlike the technical analysis, the mean score of married investors is more than that of single investors. It is evidently clear from the result that married investors give more importance to industry analysis than single investors in making the investment decision.

9.5.3 Factors of Behavioural Bias

The study identified the dimensions of behavioural bias through Exploratory Factor Analysis and confirmed it through Confirmatory Factor Analysis. The dimensions are emotional bias, information processing bias and belief perseverance bias. This findings are as expected by the theoretical aspects of behavioural finance, like loss aversion bias, overconfidence bias, regret aversion bias, herd mentality grouped under emotional bias, anchoring & adjustment bias, mental accounting bias, availability bias and self attribution bias grouped under information processing bias and representativeness bias, cognitive dissonance bias, confirmation bias and illusion control bias grouped under belief perseverance bias.

The study shows that on an aggregate mean score of the behavioural biases of investors is 94.39 (SD 19.10) out of the maximum score of 145. This indicates that on an average, investors are affected 65% by behavioural bias while taking investment decision.

1. In gender wise analysis, mean score of behavioural bias of male is 95.87 (17.70) differing from female 81.83 (15.62). It shows significant difference between male and female investors with regard to behavioural bias. Since the mean score of the male is more than female, male investors are more influenced by behavioural bias than female.

Among the dimensions of Behavioural bias, the dimension like emotional bias has no significant difference between male and female investor. In case of information processing bias and belief perseverance bias, there is difference between male and female investor. Hence, it can be inferred that male investors are more affected than female investor in case of information processing and belief perseverance bias.

2. In age wise comparison, It can be understood that the highest mean score is 98.00 (19.58) for investors in the age category of '18 – 30 years' and lowest mean is 88.50 (20.24) for investors in the age category 'Above 50 years'. This indicates that behavioural bias is more to young investors and less is in the case older investors. The result shows the significant difference among the mean score of different age categories

In case of emotional bias, there is no significant difference among different age categories, whereas in case of information processing bias and belief perseverance bias, it shows the significant difference among the age categories. In the case of information processing bias and belief perseverance bias there is a significant difference among age categories.

3. In educational qualification wise analysis, 'under graduate' investors are having the highest mean score 98.88 (16.54) of overall behavioural bias and the lowest score 85.50 (12.24) is among 'professional' investors. Since the p value is less than .05, there is a significant difference among the various educational qualification categories of investors. It shows that the lower education categories are more prone to behavioural bias than the higher education categories.

The detailed study shows that in case of emotional and belief perseverance bias, significant difference doesn't exist among different educational categories whereas in case of information processing bias, significant difference exists among the different levels of educational qualification.

4. In annual income wise comparison, investors in the annual income category 'less than Rs.5,00,000' is having the highest mean score 99.13 (16.29) of

behavioural bias and the lowest score 75.14(23.86) is investors in the annual income category of 'more than Rs.15,00,000'. The mean score is significantly different from others. It can be understood that the low income category investors are more prone to behavioural bias than the high income category investors.

The detailed analysis among various dimensions of behavioural bias among different annual income categories of investors shows that in case of emotional, information processing and belief perseverance biases, the differences are significant.

It can be inferred from the result that when income is increasing the level of all dimensions of biases are decreasing.

5. In marital Status wise analysis, It can be observed that the mean score of behavioural bias of married investors is 93.27 (19.48) and that of single investors is 102.57 (13.61). It shows the significant difference between male and female with regard to behavioural bias. It can be inferred that single investors are more prone to behavioural bias than the married investors.

The detailed analysis shows among the dimensions of behavioural bias that the emotional bias has no significant difference among married and single investors.

In case of information processing and belief perseverance biases, there is difference between married and single investor. It can be seen that the mean score of the single investors is higher than the married investors. Hence, it can be concluded that single investors are more prone to information and belief perseverance bias.

9.5.4 Components of Behavioural Bias

The study shows that investors in Kerala is affected by all the elements of behavioural bias above average level since the entire mean score is in between 3 to 4. Since the representativeness bias is having the highest mean score of 3.5239 (SD 0.92437), it is having highest influence among the investors in Kerala followed by cognitive dissonance having mean score of 3.4897(SD 0.97126) followed by illusion of control bias having the mean score of 3.4038(S.D 0.98399). Mental accounting bias is having the least mean score of 3.1000 (SD 1.07746).

1. In gender wise analysis, the results show that all the behavioural biases except loss aversion, regret aversion and herding show the significant difference between male and female investors. In all other elements of bias which show the significant difference like overconfidence, anchoring, mental accounting, availability, self attribution, representativeness, cognitive dissonance, confirmation and illusion of control male investors are more affected than the female investor.
2. In age category wise analysis, all the behavioural biases except loss aversion, regret aversion, herding and availability bias show the significant difference between different age categories.

In all other bias which are having significant difference in the mean scores among different age categories like overconfidence, anchoring, mental accounting self attribution, representativeness, cognitive dissonant, confirmation and illusion control show that the lower age categories (younger investors) are more prone to these behavioural biases than the higher age categories (older investors).

3. In educational qualification wise analysis, all the behavioural biases except loss aversion, herding, self attribution, representative and cognitive dissonance show the significant difference between different educational qualification categories.

Behavioural biases like overconfidence, anchoring, regret aversion, mental accounting, availability, confirmation and illusion of control show significance difference among different educational level of investors. In case of the biases like overconfidence, regret aversion, mental accounting, confirmation and illusion of control it can be seen that investors having lower educational level are more prone to these biases than investors having higher educational level while the anchoring bias is just reverse, i.e., investors having higher education level are more prone to anchoring bias than the investors having lower educational qualification.

In availability bias, investors having high education level are more affected by availability bias than investors having low education category except the educational category ‘post graduates’.

4. In annual income wise comparison, all the behavioural biases show the significant difference between different annual income categories. Almost all biases show the same result that low annual income investors are more prone to respective bias than the high annual income investors. The slight differences are shown by overconfidence bias where annual income category ’10,00,000 than Rs.15, 00,000’ is more prone to overconfidence bias than other annual income categories. Likewise in loss aversion and regret aversion, the annual income category ‘Rs.10, 00,001 – 15, 00,000’ is more prone to respective biases than the other annual income categories.
5. Marital Status wise analysis shows that all the behavioural biases except overconfidence, loss aversion, regret aversion, herding and illusion of control have significant difference among married and single investors. The biases which show the significant difference like anchoring, mental accounting, availability, self attribution, representativeness, cognitive dissonance and confirmation indicate that single investors are more prone to respective bias than married investors.

9.5.5 Emotional Intelligence

From the analysis, it can be concluded that all the dimensions emotional intelligence variables are above the average level since the entire mean score is in between 3 to 4. It is found that self awareness is having the highest mean score 3.6829 (S.D .90099) followed by managing emotions 3.4393 (S.D .66978). Empathy is having the least mean score 3.2419 (S.D 94306)

The study identified the dimensions of behavioural bias through Exploratory Factor Analysis and reconfirmed it through Confirmatory Factor Analysis. Empathy, motivating oneself, social skills, managing emotions and self awareness are the first, second, third, fourth and fifth factors respectively.

It can be seen that on an average the investors are having the mean emotional intelligence of 50.85 (SD 7.87) out of the maximum score of 75. To be more specific, on an average, investors are having 67.8% emotional intelligence while taking investment decision.

1. In gender wise analysis, mean score emotional intelligence of male is 50.41 (7.68) differing from female 54.61 (8.73). The result shows the significant difference between male and female with regard to emotional intelligence. Since the average of mean score of emotional intelligence of female is more than male, female is having more emotional intelligence than male.
2. In age category wise comparison, it can be understood that the highest mean score is 51.54 (9.15) which is in the age category of '18 – 30 years' and lowest mean is 50.68 (6.52) in age category 'Above 50 years'. The result shows that there is no significant difference among the mean score of different age categories.
3. In educational qualification wise analysis the educational category 'graduate' is having the highest mean score 52.33 (7.85) of emotional intelligence and the lowest score 47.81 (2.66) is among professional. The difference is significant since the p value is less than .05. It can be inferred from the result that emotional intelligence of the graduate is higher than that of the professionals.
4. In annual income wise classification, annual income category 'Rs.5,00,000 - 10,00,000' is having the highest mean score 51.55(8.09) of emotional intelligence and the lowest score 48.74(8.05) is in annual income category of 'Rs. 10,00,000 - 15,00,000'. It can be concluded from the result that emotional intelligence of the investors in annual category 'Rs.10,00,000 - 15,00,000' is lower than the annual income category of 'Rs.5,00,000 - 10,00,000'.
5. In marital status wise comparison, It can be observed that the mean score of the emotional intelligence of the married is 50.69 (8.05) differing from the single 52.02(6.53). But the result shows that there is no significant difference between married and single with regard to emotional intelligence.

9.5.6 Investment Performance

The mean score of the investment performance is low 6.58 (43.8%), which implies that investors are not satisfied with their rate of return from the investment decisions. ‘The rate of return of my recent stock investment meets my expectation’ is having the mean score of 2.20 (1.10). This indicates that most of the investors are not satisfied with their rate of return. ‘My rate of return is equal to or higher than the average rate of return of the market’ shows lowest mean score of 2.09 (1.06). This means that most of the investors don’t even get the average return of the market. The mean score of ‘I feel satisfied with my investment decision in the last year’ is 2.28 (1.06). This shows that most of the investors are not satisfied with their investment decision in the previous year.

1. In gender wise analysis, it can be seen that aggregate investment score of male investor is 6.30 as against the maximum score of 15. This shows that in percentage terms the performance is only 42%. In the case of female investors the aggregate score is 8.98 out of 15. In percentage terms the performance level is 60%. The difference is also significant as the ‘p’ value for the ‘t’ test conducted is less than 0.05.
2. In age category wise analysis, It can be found that the highest mean score is 7.67 (2.61) which is in the age category of ‘above 50 years’ and lowest mean is 6.32 (3.11) in age category ‘18-30 years’. The p value is 0.002 which means that mean score of different age categories are significantly different. It can be inferred the higher age category is having higher returns than the lower age category.
3. In educational qualification wise analysis, ‘post graduate’ educational level is having the highest mean score of 7.21(2.53) and the ‘undergraduate’ is having the lowest score of 3.72 (2.44). The ‘graduate’ and professional owns up almost the same score. The result shows that the mean score of the investment performance in different educational level is significantly different from others. It can be concluded that under graduates are having less investment performance than other educational categories.

4. In annual income wise comparison, the annual income category ‘more than Rs.15, 00,000’ is having the highest mean score 9.50 (2.33) and the annual income category ‘Less than 5, 00,000’ is having lowest score 5.57 (2.70). It can be derived from the result that the mean score of annual income categories is significantly different from others. Further it is observed from the result that annual income categories are having direct relation with investment performance. Lower income level is having the low investment performance and vice-versa.
5. Marital status wise analysis shows that the mean score of investment performance of the married is higher 6.77 (2.87) and the single is lower 5.17 (1.97). It can be concluded from the result that married investors are having more investment performance than the single investors. The mean score difference between married investors and single investors is significant with regard to investment performance.

9.5.7 Impact of Security Analysis, Behavioural Bias and Emotional Intelligence on Investment Performance

1. The impact of security analysis on investment performance indicates that Economic, Quantitative and Industry analysis have the positive impact on investment performance. Technical analysis is significant at 10% level and its coefficient is negative. So it makes negative impact on investment performance. From this, it can be concluded that the investors who are trading on short-term by using technical analysis is not satisfied with their rate of return and their investment decision.
2. The impact of behavioural bias on investment performance implies that the co-efficient of all dimensions of bias like emotional, information processing and belief perseverance bias are significant at 5% significant level and the co-efficient is negative. This indicates that all the factors of behavioural bias have inverse impact on investment performance.
3. Impact of emotional intelligence on investment performance indicates that the co-efficient of only one independent variable social skill is significant at

5% significant level and the co-efficient is positive. All other factors' (empathy, motivating oneself, managing emotions, self awareness) p-value is more than .05, hence not significant. This indicates that social skill has the positive impact on investment performance.

9.5.8 Combined Effect of Security Analysis, Emotional Intelligence and Behavioural Bias on Investment Performance.

The model without mediation shows the relationship between security analysis on investment performance. The relationship between security analysis and investment performance shows a beta value 0.52 and it is significant at 1% level ($p<.01$). Hence it can be concluded that the security analysis has a significant impact on investment performance. By considering all the aspects of security analysis the investors can achieve the better investment performance level. The relationship between emotional intelligence and investment performance shows a beta value 0.36 and it is significant at 1% level ($p<.01$). Hence it can be concluded that the emotional intelligence also has a significant impact on investment performance. By increasing emotional intelligence the investors can achieve the better investment performance level. When we compare these two exogenous variables (security analysis and emotional intelligence) the security analysis is having more impact ($\beta = 0.52$) than the emotional intelligence ($\beta = 0.36$) on the endogenous variable namely investment performance.

The model with mediation, it is clear that there is a significant relationship between security analysis on investment performance ($\beta=0.47$ and $p<.01$) and emotional intelligence on investment performance (and $\beta=0.08$ and $p<.05$). At the same time, there is a significant relationship between security analysis and behavioural bias ($\beta = -.10$ and $p<.05$) and between emotional intelligence and behavioural bias ($\beta= -0.64$ and $p<.01$). There is also significant relation between the behavioural bias and the investment performance ($\beta= -0.47$ and $p<.01$). When the mediator, behavioural bias is introduced in the model, the influence of independent variable (security analysis and emotional intelligence) on the dependent variable (investment performance) gets reduced, i.e the beta value is reduced from 0.52 to 0.47 in the case of security analysis and 0.36 to 0.08 in the case of emotional intelligence. In both the situations, there is partial mediation, because all the paths show significant influence. That is security analysis and emotional intelligence do exercise some of their influence on investment performance through the mediating variable behavioural bias; and it also applies some of its influence directly on investment performance.

9.6 Conclusions

The major conclusions based on the findings of the study are explained below:

BSE Sensex, S&P CNX Nifty and 20 selected stocks prices exhibit volatility clustering. It can be seen that the leverage effects are negative in almost all cases including Sensex and Nifty which are significant at 5% significant level which means that good news generates less volatility than bad news in Indian stock Market. To all stocks and indices during the 2016, the symmetric effect is different than it was in the previous period in EGARCH model in which all are significant at even 1% significant level. That means, in most of the cases when the period comes shorter, the volatility increases. The persistence in conditional volatility, irrespective of anything happening in the market, are all positive and relatively large, so the volatility takes long time to die out following an event in the Indian stock market. According to the relative scale of the coefficients, the leverage effect or the symmetric effects dominates.

All the three tests - augmented Dickey-Fuller test, Phillip-Perron test and auto correlation test – reject the null hypothesis of return series and it shows that Indian stock market is not efficient in its weak form.

The market model of event study methodology is applied to calculate the return of the sample stocks in the window of 61 days. The analysis based on the average abnormal return and cumulative average abnormal return of the stocks clearly reveals that no abnormal return which is statistically significant is created on and around the event day. This result clearly shows the existence of semi-strong efficiency in Indian stock market.

On average, individual investors are doing 75% security analysis while taking investment decisions. On average, individual investors are 65% prone to behavioural bias while taking investment decision. On average, investors are having 67.8% emotional intelligence.

The dimensions of Security Analysis like Economic, Quantitative and Industry analysis have the positive impact on investment performance. All the factors of behavioural biases like emotional bias, information processing bias and belief perseverance bias have inverse impact on investment performance. Only one dimension like social skill has the positive impact on investment performance.

The study proves that security analysis and emotional intelligence have the significant influence on investment performance. The result shows the partial mediation effect of behavioural finance between the security analysis and investment performance, and between emotional intelligence and investment performance. Hence the role of behavioural bias is highly projected in this context for having better investment performance along with security analysis and emotional intelligence.

9.7 Recommendations

Based on the findings and of the study, the researcher put forward the following recommendations to enhance the investment performance among investors in Kerala.

To the Investors

This study and its findings would be useful to individual investors as it gives indication of volatility in Indian stock market. Investor's objective is to make more return with less risk. Hence they have to study and analyse volatility in stock market before making investment decisions. It is found in this study that each stock is having its own different extent of volatility. Some stocks are more volatile and others are defensive. Apart from that, some stocks give more weight on negative news (leverage effect) than positive news. Moreover, volatility takes long time to die out following an event in the Indian stock market. Therefore, an investor should check the extent and pattern volatility of each stock individually and choose the stock according to his risk tolerance and the conditions of stock market. To reduce the volatility investor has to plan their investment in long-term. Investors have to be very careful about bad news since the bad news creates more volatility. Investor has to be more patient since the volatility takes long time to die out following an event in the Indian stock market.

The results given by Augmented Dickey-Fuller test, Phillip-Perron and Autocorrelation exhibit that Indian stock market is not efficient in its weak form. This indicates that it is possible to predict future trend and price movements on the basis of past price and volume data.

The analysis based on the event study which relies on average abnormal return and cumulative average abnormal return of the stocks, clearly reveals that no abnormal return which is statistically significant is created on and around the event day. This result clearly shows the existence of semi-strong efficiency in Indian stock market. Therefore, investor cannot make superior return by using publicly available information.

Since Economic, Quantitative and Industry analysis of security analysis have the positive impact on investment performance; the investor should try to enhance the same to have better investment performance.

All the dimensions of behavioural bias like emotional, information processing and belief perseverance bias show the negative impact on investment performance. So the investors should take the measures to reduce the adverse effects of behavioural bias. Investors should also make constant efforts to enhance their awareness on behavioural bias. Learning about the behavioural biases themselves will help them have better self-understanding of the manner in which how they get influenced by cognitive and emotional bias while making investment decisions. If the investors practise to control the behavioural bias, they can reduce the wrong investment decisions so that they may have better investment performance. It is important for them to understand the behaviour themselves so that they can manage their perceptions, and thereby, control the volatility of the share price due to their irrational actions.

Even after awareness, it is proposed that they themselves have to be conscious about the behavioural biases they are likely to be sensitive to. This should be analysed periodically in order to revive and rejuvenate their memory, thus giving themselves a better chance to make improved financial performance in the stock market.

There will be negativity in the market; however investors have to engage in investment decisions with more sensibility and patience. Investors have to keep in mind that investing in equity shares is not a gambling and an easy way to amass quick wealth; rather it is a rational risk taking domain with a decent return.

Similarly, social skills of emotional intelligence are also having a positive impact on investment performance, so the investor can increase the investment performance by enhancing the social skills through investor clubs and other social get-togethers.

To the Policy Makers and Regulatory Agencies

Stock market volatility is not unnatural or unwanted, whereas hyper volatility caused by behavioural bias of investors is not desirable. Investors may consider hyper volatility with higher risk and may change their investment due to hyper volatility. The stock market volatility may affect to the real economy and adversely affect the economic performance. In the past, episodes of hyper volatility led to bubbles and crashes leaving millions of investors deprived of their hard earned savings and making the investors insolvent. This concern has focussed upon the need of measuring and predicting the stock market volatility so that stock market mechanism can be developed to avoid the dangers of excessive volatility. Otherwise, the investors will abstain from the market, which adversely affect in the capital formulation.

- Introduce a well articulated syllabus to improve the financial literacy at high school level. Financial education instruction in schools has a significant and positive impact on investment decision making.

- College level financial education programmes may be implemented to all students irrespective of their subjects in order to educate them of the corporate investment and impact of behavioural biases on it.

- Behavioural Finance should be given more importance in the Academic Curriculum. If the students are equipped with excellent awareness in Behavioural Finance, the psychological aspect of the behavioural finance would have guided them to accomplish better self-awareness, and hence decision making in hectic situation might not be as problematic to them.

- Investor workshops may be conducted to give the idea of security analysis and most importantly about behavioural biases in rural and semi urban areas.

9.8 Scope for Further Research

In case of volatility, this study is restricted itself to the two major stock market indices and twenty stocks which have used for event study (i.e. the stocks that have declared bonus share and stock split during the period 2004 – 2016) to check the volatility clustering and the existence of volatility in short-term, middle term and long term, leverage effect of volatility, persistence of conditional volatility of Indian stock market. This study attempts to find out the extent and pattern of volatility in Indian Stock Market. But there are number of avenues of research which can explore in the terrain of volatility in Indian Stock Market.

- Research can be conducted in order to establish the volatility with frequency of trade and trading volume by using high frequency data.

- Market co-integration can be studied to find out the extent of integration of Indian stock market with other financial markets like money market and even with other stock markets in the world.

- Comparison of leverage effect with other stock markets and the reasons of difference in leverage effect and the relation of leverage effect with behavioural bias can be studied.

- Comparison of persistence of conditional volatility with other stock markets and the reasons of difference in persistence of conditional volatility and the relation of persistence of conditional volatility with behavioural bias can also be studied.
- In Behavioural finance, research can be done about each individual bias with different socio-economic context. The impact of awareness of investors about behavioural biases on the market efficiency can be researched.

Bibliography

Abarbanell, J. S., & Bushee, B. J. (1997). Fundamental Analysis, Future Eanings and Stock Prices. *Journal of accounting research , 35* (1), 1-24.

Ackert, L. F., & Deaves, R. (2011). *Understanding Behavioural Finance.* Delhi: Cengage Learning India Private Limited.

Aczel, A. D., Sounderpandian, J., Saravanan, P., & Joshi, R. (2012). *Complete Business Statistics.* New Delhi: McGraw Hill Education.

Ahamed S, A. Z. (2011). Volatility Spillover Effects in Emerging MENA Stock Market. *Review of Applied Economics , 7* (1-2), 107-127.

Ahamed, M., & Samajpati, U. (2010). Evaluation of Stock Selection Skills and Market Timing Abilities of Indian Mutual Fund Managers. *Management Insight* , 71-82.

Ahamed, N., Ahamed, Z., & Khan, S. K. (2011). Behavioural finance: Shaping the Decisions of Small Investors of Lahore Stock Exchange. *Interdisciplinary Journal of Research in Business , 1* (2), 38-43.

Ahmed, A. E., & Suliman, Z. S. (2011). Modeling Stock Market Volatility using GARCH models, Evidence from Sudan. *International Journal of Business and Social Science , 2* (23), 114-128.

Alexander, C. (2008). *Practical Financial Econometrics.* New York: John Wiley & Sons.

Al-Qaisi, K. (2011). Predicting the Profit per Share Using Financial Ratios. *Asian Journal of Finance and Accounting , 3* (1), 162-173.

Alsedrah, I., & Ahamed, N. (2014). Behavioural Finance: The Missing Piece in Modern finance. *First Middle East Conference on Global Business,* *Economics, Finance and Banking* (p. 1 to 13). Dubai: www.globalbizresearch.org.

Al-Tamimi, H. A., & Kalli, A. A. (2009). Financial Literacy and Investment Decisions of UAE investors. *The Journal of Risk Finance , 10* (5), 500-516.

Ameriks, J., Warnik, T., & Salovey, P. (2009). Emotional Intelligence and Investor Behaviour. *The Research Foundation of CFA institute* .

Asquith, P. (1983). Merger Bids, Uncertainty and Stockholder Returns. *Journal of Financial Economics* , 51-83.

Avadhani, V. A. (2011). *Security Analysis and Portfolio Management* (10th Revised Edition ed.). Mumbai: Himalaya Publishing House Pvt. Ltd.

Azzopardi, P. V. (2012). *Behavioural Technical Analysis.* Delhi: Vision Books Pvt. Ltd.

Bachelier's, L. (1900). *The Theory of Speculation.* PhD Thesis, Parris: Gauthier-Villaras.

Baillie, R. T., & DeGennaro, R. P. (1990). Stock Returns and Volatility. *Journal of Financial and Quantitative Analysis , 25* (2), 203-214.

Bajpai, N. (2011). *Business Research Methods.* Delhi: Pearson Education in South Asia.

Bakar, s., & Chui Yi, A. N. (2016). The Impact of Psychological Factors on Investors' Decision Making in Malaysian Stock Market, A Case of Klang Valley and Pahang. *Procedia Economics and Finance* , 319-328.

Banarjee, A. V. (1992). A Simple Model of Herd Behavior. *The Quarterly Journal of Economics, 107* (3), 797-817.

Baradi, N. K., & Mohapatra, S. (2014). The Use of Technical and Fundamental Analyses by Stock Exchange Brokers: Indian Evidence. *Journal of Empirical Evidence , 2* (4), 19o-203.

Barber, B. M., & Odean, T. (2000). Trading is Hazardous to Your Wealth: The common Stock Investment Performance of Individual Investors. *Journal of Finance , LV* (2), 773-806.

Barber, B. M., & Odean, T. (2001). Boys will be Boys: Gender, Overconfidence and common stock investment. *The quarterky journal of economics , 16* (1), 261-292.

Baron, R. M., & Kenny, D. A. (1986). The Moderator-Mediator Variable Distiction in Social Psychological Research: Conceptual , Strategic and Statistical Considerations. *Journal of Personality and Social Psychology , 51* (6), 1173-1182.

Beers, M. (2005). Emotion Regulation Abilities and the Quality of Social Interaction. *Emotion, 5* (1), 113-118.

Bentler, P., & Bonnet, D. (1980). Significance Test and Goodness of Fit in the analysis of Covariance Structures. *Psychological Bulletin , 88* (3), 588-606.

Berenson, M. L., Levine, D. M., & Szabat, K. A. (2016). *Basic Business Statistics: Concepts and application.* New Jersey: Pearson.

Bhalla, V. (2011). *Investment Management* (17th edition ed.). New Delhi: S. Chand & Company Ltd.

Bhowmik, D. (2013). Stock Market Volatility: An Evaluation. *International Journal of Scientific and Research Publications , 3* (10), 1-17.

Black, F. (1986). Noise. *The Journal of Finance , XLI* (3), 529-543.

Bodie, Z., Kane, A., Marcus, A. J., & Mohanty, P. (2016). *Investments.* New Delhi: McGraw Hill Education.

Bollen, K. (1989). *Structural Equations with Latent Variables.* New York: John Wiley & Sons, Inc.

Bollerslev, T. (1986). Generalized Autoregressive Conditional heteroscedasticity model. *Journal of Econometrics* , 307-327.

Bollerslev, T., & Mikkelsen, H. O. (1996). Modeling and pricing long memory in stock market volatility. *Journal of Econometrics , 73* (1), 151-184.

Bontis, N., Booker, L. D., & Serenko, A. (2007). *The mediating effect of organizational reputation on customer royalty and service recommendation in the banking industry.* Bingley: Emerald Management Decision.

Boobalan, C. (2014). Technical Analysis in Select Stocks of Indian Companies. *International Journal of Business and Administration Research Review , 2* (4), 26-36.

Brealey, R. A., Myres, C. S., Allen, F., & Mohanty, P. (2014). *Principles of Corporate Finance.* Chennai: Mc Graw Hill Education.

Brigham, E. F., & Houston, J. F. (2013). *Fundamentals of Financial Mangement.* New Delhi: Cengage learning India Pvt. Ltd.

Brock, W., Lakonishok, J., & Lebaron, B. (1992). Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *The Journal of Finance , 47* (5), 1731-1764.

Brooks, C. (2008). *Introductory Econometrics for Finance.* New York: Cambridge University Press.

Brown, S. J., & Warner, J. B. (1980). Measuring Security Price Performance. *Journal of Financial Economics , 8* (3), 205-258.

Brown, S. J., & Warner, J. B. (1985). Using Daily Stock Returns: The case of Event Studies. *Journal of Financial economics , 14* (1), 3-31.

Burlakanti, K., & Chiruvoori, R. (2013). Performance Evaluation of Selected Equity Fund in India. *International Journal of Social Science & Interdisciplinary research , 2* (5), 69-78.

Byrne, B. M. (2010). *Structural Equation Modeling with AMOS.* New York: Routledge.

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (2007). *The Econometrics of Financial Markets.* New Delhi: New Age International .

Chakraborty, P. (2011). Semi- Strong of Pricing Efiiciency of Indian Stock Market - An Emiprical Test in the Context of Stock-Split Announcement. *EXCEL International Journal of Multidisciplinary Management Studies , 1* (2), 1-13.

Chaudhary, A. K. (2013). Impact of Behavioural Finance in Investment Decisions and Strategies - A Fresh Approach. *International Journal of Mnangement Research and , 2* (2), 85-92.

Chitra, R. (2011). Technical Analysis on Selected Stocks of Energy Sector. *Inetrnational Journal of Managment & Business Studies , 1* (1), 42-46.

Chou, C.-P., & Bentler, P. M. (1995). Etimates and Test in Structural Equation Modelling. In R. H. Hoyle, *Structural Equation Modelling: Concepts, Issues and Applications* (pp. 37-55). Thousand Oaks, CA, US: Sage Publications.

Christie, A. A. (1982). The Stochastic Behavior of Common Stock Variances: Value, leverage and interest rate effects. *Journal of Financial Economics , 10* (4), 407-432.

Christos, A. (1992). *An Empirical Investigation of the Efficient Market Hypothesis: The Case of The Athens Stock Exchange.* York: Department of Economics and Related Studies, University of York.

Chung, H. Y. (2006). *Testing Weak Form Efficiency of the Chinese Stock Market.* Karhula: Lappeenranta University of Technology.

Coffie, W. (2013). *Behavioural Finance Theories Effecting on Individual Investor's Decision-Making.* Essi Leppinen: University of Wolverhampton.

Damodaran, A. (2012). *Investment Valuation.* NewJersey: John Wiley & Sons.

Danquah, E. (2014). Analysis of the Impact of Emotional Intelligence on Organisational Performance: A Banking Perspective. *British Journal of Marketing Studies , 2* (3), 34-50.

Day, T. E., & Lewis, C. M. (1992). Stock Market Volatility and the Information Content on Stock index Option. *Journal of Econometrics , 52*, 267-287.

De Souza, M. J., Ramos, D. g., Pena, M. G., Sobreiro, V. A., & Kimura, H. (2018). Examination of the Probability of Technical Analysis based on moving average strategies in BRICS. *Financial Innovation , 4* (3), 2-18.

Debjiban, M. (2007). Comparative Analysis of Indian Stock Market with International Markets. *Great Lakes Herald , 1* (1), 39-71.

Degutis, A., & Novickytė, L. (2014). The Efficient Market Hypotheis: A Critical Review of Literature and Methodology. *Ekonomica , 93* (2), 7-23.

Dhiman, B., & Rajeha, S. (2018). Do Personality Traits and Emotional Intelligents of Investors determine thier Risk Tolerance. *Managemnt and Labour Studies , 43* (1&2), 88-99.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Eestimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistics Association , 74* (366), 427-431.

Dolley, J. C. (1933). Characteristics and Procedure of Common Stock Split-Ups. *Harvard Business Review , 37* (5), 316-326.

Dyckman, T., Philbrick, D., & Stephen, J. (1984). A Comparison of Event Study Methodologies Using Daily Stock Returns: A Simulation Approach. *Journal of Accounting Research , 22*, 1-33.

Edelen, R. M., & Warner, J. B. (2001). Aggregate price effects of institutional trading: A study on mutual fund flow and market return. *Journal of inancial economics* , 195-220.

Elton, E. J., & Gruber, M. J. (1994). *Modern Portfolio Theory and Investment Analysis* (4th ed.). New York: John Wiley & Sons.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity withthe Estimates of the Variance of United Kingdom Inflation. *Econometrica , 50* (4), 987-1008.

Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of Conditional Variance. *Econometric Reviews , 5* (1), 1-50.

Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating Time Varying Risk Premia in the Term Structure: The Arch-M Model. *Econometrica , 55* (2), 391-407.

Ezadinea, N., Fathi, S., & Salami, S. (2011). The Effect of Emotional Intelligence on Portfolio Performance of Stakeholders: Empirical Evidence from Iran. *Interdisciplinary Journal of Contemporary Research in Business , 3* (5), 679-685.

Fama, E. (1970). Efficient Capital Market: A Review of Theory and Empirical Work. *Journal of Finance , 25* (2), 382-417.

Fama, E. F. (1990). Efficient Capital Market II. *The journal of Finance , 46* (5), 1575-1617.

Fama, E. F. (1998). Market Efficeincy, Long Term Returns and Behavioral Finance. *Journal of Financial Economics* , 283-306.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics , 49*, 283-306.

Field, A. (2014). *Discovering statistics using IBM SPSS Statistics.* New Delhi: Sage Publication India Pvt Ltd.

Fischer, D. E., & Jordan, R. J. (1995). *Security Analysis and Portfolio Management.* Noida: Pearson Education in South Asia.

Fischer, D. E., & Jordan, R. J. (2006). *Security analysis and Portfolio Management.* Neelhi: Pearson Education in South Asia.

Fisher, D. E., & Jordan, R. J. (2006). *Security Analysis and Portfolio Management.* Noida: Pearson Education.

Forbes, W. (2009). *Behavioural finace.* New Delhi: John Wiley & Sons.

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equations Models with Unobservable Variables and Mesurement Error. *Journal of Marketing Research* , 39-50.

Franses, P. H. (1988). *Time series Model for business and Economic Forecasting.* New York: Camebridge University Press.

French, K., & Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. *Journal of Financial Economics , 17* (1), 5-26.

Fromlet, H. (2011). Behavioral Finance- Theory and Practical Application. *Business Economics, 36* (3), 18-28.

Gal, D. (2006). A Psychological Law of Inertia and the Illusion of Loss aversion. *Judgement and Decision Making , 1* (1), 23-32.

Gang, L., & Zhu, J. (2014). Research on Effectiveness of Technical Indicators with the Volume. *International Confereance on Education, Management and Computing Technology* (pp. 436-439). Shanghai: Atlantis press.

Garson, D. (2012). *Testing Statistical Assumptions.* USA: G David Garson and Statistical Associate Publishing.

Ghelichi, M. A., Nakhjavan, B., & Gharehdaghi, M. (2016). Impact of Psychological Factors on Investment Decision Making in Stock Exchange Market. *Asian Journal of Management Sciences and Education , 5* (3), 36-44.

Gimba, V. K. (2010). Testing Weak Form Efficiency Market Hypothesis: Evidence from Nigerian Stock Market. *CBN Journal of Applied Statistics , 3*, 117-136.

Ginblatt, M., Keloharju, M., & Linnainmaa, J. T. (2011). IQ, Trading Behaviorand Performance. *Journal of Financial Economics* , 1-24.

Givoly, D., & Palmon, D. (1985). Insider Trading and Exploitation of Insider Information: Some Empirical Evidence. *Journal of Business* , 58-71.

Glosten, L. R., Jaganathan, R., & Runkle, D. E. (1993). On the Relation Between the Expected Value and the Volatility of the Nominal excess return of the stock. *The Journal of Finance , 48* (5), 1779-1801.

Goleman, D. (2005). *Emotional Intelligence, Why It Can Matter More Than IQ.* New York: Bantam Books.

Graham, B., & Dodd, D. L. (2008). *Security Analysis.* Ne York: Mc graw Hill.

Grinblatt, M., & Keloharju, M. (2000). The investment behaviourand performance of various investor types: A study of Finnland's unique data set . *Journal of Financial Economics* , 43-67.

Gujarati, D. (2011). *Econometrics by Example.* New York: Palgrave Macmillan.

Gujarati, D. N., Porter, D. C., & Gunasekar, S. (2012). *Basic Econometrics.* New Delhi: McGraw Hill Education.

Gunathilaka, C. (2017). Investor Sentiment and Asset Pricing: A Review. *VJM , 3* (1), 77-91.

Gupta, R. K. (2014). Weak Form Efficiency of Indian Stock Market with Reference to BSE. *International Journal of Research in Business Management , 2* (9), 15-20.

Gupta, S. K., & Joshi, R. (2015). *Security Analysis & Portfolio Management.* New Delhi: Kalyani Publishers.

Guptha, R., & Basu, P. K. (2007). Weak Form Efficiency in Indian Stock Markets. *International Business and Economics Research Journal , 6* (3), 57-64.

Hadi, F. (2017). Effects of Emotional Intelligence on Investment Decision Making with a moderating role of Financial literacy. *China-USA Business Review* , *16* (2), 53-62.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2015). *Multivariate Data Analysis*. Noida: Pearson India Education Service Pvt Ltd.

Hassan, T. R., Khalid, W., & Habib, A. (2014). Overconfidence and Loss Aversion in Investment Decisions: A Study of the Impact of Gender and Age in Pakitani Perspective. *International SAMANM Journal of Finance and Accounting* , *2* (3), 44-61.

Hooper, D., Coughlan, J., & Mullen, M. R. (2008). Structural Equation Modelling: Guidelines for determining model Fit. *The Electronic Journal of Business Research Methods* , *6* (1), 53-60.

Impact of Cognitive Biases in Investment Decisions of Individual Investors in Stock Market. (2017). *International Journal of Engineering Technology, Managment and Applied Sciences* , *5* (6), 531-538.

Irshad, S., Badshah, W., & Hakam, U. (2016). Effects of Representativeness Bias on Investment Decision Making. *Management and Administrative Sciences Review* , *5* (1), 26-30.

Islam, S. (2012). Behavioral Finance of an Inefficient Market. *Global Journal of Management and Business Research* , *12* (14), 13-34.

Jaffe, J. F. (1974). Special Information and Insider Trading. *Journal of Business* , 47-59.

Jagadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Loosers: Implication for Stock Market Efficiency. *Journal of Finance* , *48* (1), 65-91.

Jagongo, A., & Mutswenje, V. S. (2014). A Survey of the Factors Influencing Investment Decisions: The Case of Individual Investors at the NSE. *International Journal of Humanities and Social Science , 4* (4), 92-102.

Jonsson, R., & Radeschnig, J. (2014). *From Market Efficiency to Event Study Methodology*. Sweden: Malardalen University.

Joshi, D. J. (2012). Testing Market Efficiency of Indian Stock Market. *International Journal of Scientific and Research Publications , 2* (6), 1-4.

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica , 47* (2), 263-291.

Kalsie, A., & Kalra, J. K. (2015). An Empirical Study on Efficient Market Hypothesis of Indian Capital Markets. *Journal of Management Research and Analysis , 2* (2), 108-114.

Kalyanaraman, R. (2017, May 21). *E paper: Livemint*. Retrieved May 2017, 25, from Livemint: http://www.livemint.com/Money/1obvYAc2YiDhWSbBtaYG3J/24-million-new-demat-accounts-opened-last-year-highest-sin.html

Kamath, R., & Wang, Y. (2006). The Casuality Between Stock Index Returns and Volumes in the Asian Equity Market. *Journal of International Business Research , 5* (2), 63-74.

Karmakar, M. (2005). Modeling conditional volatility of Indian Stock Markets. *Vikalpa , 30* (3), 21-37.

Karthikeyan, V., & Lalwani, S. (2017). Emotional Intelligence in Banking Sector - An Integrative Literature Review. *IOSR Journal of Business and Management , 19* (10), 9-14.

Kaur, H. (2002). *Stock Market Volatility in India.* New Delhi: Deep & Deep Publications Pvt. Ltd.

Kavitha, C. (2015). Investors Attitude towards Stock market Investment. *International Journal of Scientific Research and Management , 3* (7), 3356-3368.

Kendall, M. (1953). The analysis of economic time series. *Journal of the Royal Statistical Society, Series A , 96*, 11-25.

Kevin, S. (2011). *Security Analysis and Portfolio Management.* New Delhi: PHI Learning Private Limited.

Khan, A. Q., Ikram, S., & Mehtab, M. (2011). Testing Weak Form Market Efficiency of Indian Capital Market: A Case of National Stock Exchange (NSE) and Bombay Stock Exchange (BSE). *A. Q. Khan1,2, Sana Ikram3 , 3* (6), 115-127.

Khan, A., & Ikram, S. (2010). Testing Semi-Strong Form of Efficient Market Hypothesis in Relation to the Impact of Foreign Institutional Investors' (FII's) Investments onIndian Capital Market. *International Journal of Trade, Economics and Finance , 1* (4), 373-379.

Khan, A., & Ikram, S. (2011). Testing Strong Form Market Efficiency of Indian Capital Market: Performance Appraisal of Mutual Funds. *International Journal of Business & Information Technology* , 15-161.

Khan, E., & Gedamkar, P. (2015). Performance Evaluation Equity Shares and Mutual funds with respect to their Risk and Return. *MIT-SOM PGRC KJIMRP1ST International Conference* (pp. 149-155). Maharashtra: MIT School of managment.

Khan, M. Z. (2015). Impact of Avilability Bias and Loss Aversion Bias on Investment Decision Making, Moderating Role of Risk Perception. *Impact Journal of Research in Business Mangement , 1* (2), 1-12.

Kishore, R. M. (2015). *Financial Management.* New Delhi: Taxmann's.

Kline, R. B. (2011). *Principles and Practicce of Structural Equation Modeling* (3rd ed.). New York: The Guilford Press.

Kubilay, B., & Bayrakdaroglu, A. (2016). An Empirical Research on Investor Biases in Financial Decision-Making, Financial Risk Tolerance and Financial Personality. *International Journal of financial research , 7* (2), 171-183.

Kurt, S. (1991). Hyper Volatility of Securities Market. *The Bombay Stock Exchange Review* , 1-9.

Langer, E. (1975). The Illusion of Control. *Journal of Personality and Social Psychology* , 311-328.

Lewellen, W. G., Lease, R. C., & Schlarbaum, G. G. (1977). Patter of Investment Strategy and Behaviour among Individual Investors. *Journal of Business , 50* (3), 296-333.

Linter, G. (1998). Behavioural Finance: Why Investors make bad decisions. *The Planner , 13* (1), 7-8.

Ljung, G., & Box, G. (1978). On a Measure of Lack of Fit in Time Series Models. *Biometrica , 67* (2), 297-303.

Loomba, J. (2012). Do FIIS Imapct Volatility of Indian Stock Market? *International Journal of Marketing, Financial Services & Management Research , 1* (7), 80-93.

Lubnau, T., & Todorova, N. (2014). Technical Trading Revisited: Evidence from the Asian Stock Markets. *Corporate Ownership and Control* , 511-532.

Lumely, T., Diehr, P., Emerson, S., & Chen, L. (2002). *The Importance of the Normality Assumption in Large Public Health Data Sets.* Washington: Annual Reviews.

Luong, L. P., & Thu Ha, D. T. (2011). *Behavioral Factors Influencing Individual Investors' Decision-making and Performance.* Vietnam: Umeå School of Business.

Luong, L. P., & Thu Ha, D. T. (2011). *Behavioural Factors Influencing Individual Investor's Decision-Making and Performance.* Sweden: Umea School of Business, Umea University.

MacCallum, R., Browne, M., & Sugawara, H. (1996). Power Analysis and Determination of Sample Size for Covariance Structure Modeling. *Psychological Methods , 1* (2), 130-149.

MacKinlay, A. C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature , 35* (1), 13-39.

Mallikarjunappa, T., & Afsal, E. M. (2008). The impact of derivatives on stock market volatility: Astudy of the NIFTY index. *Asian Academy of Management Journal of Accounting and Finance , 4* (2), 43-65.

Mallikarjunappa, T., & Manjunath, T. .. (2009). Stock Price Reactions to Dividend Announcements. *Journal of Management & Public Policy , 1* (1), 43-56.

Manuel, J., & Mathew, G. (2017). Impact of Cognitive Biases in Investment Decision of Individual Investors in Stock Market. *International Journal of Engineering Technology, Management and Applied Sciences , 5* (6), 531-538.

Mehndiratta, N., & Gupta, S. (2010). Impact of Dividend Announcement on Stock Prices. *International Journal of Information Technology and Knowledge Management , 2* (2), 405-410.

Mehra, R. (1998). On the Volatility of Stock Prices: An Exercise in Quantitative theory. *International Journal of System Science , 29* (11), 1203-1211.

Metghalchi, M. (2008). Are Moving Average Trading Rules Profitable? Evidence from the Mexican Stock Market. *The Journal of Applied Business Research , 24* (1), 115-128.

Miller, M. H. (1991). *Financial Innovation & Market Volatility.* New York: Blackwell.

Mukhhopadhyaya, J. N. (2011). An Analytical Study of Indian Stock Market Volatility and Its Linkage. *International Journal Of Business Management, Economics And Information Technology , 3* (1), 91-109.

Nalina, K., & Karthik, N. (2013). Volatility in Indian Stock Market- A Case Study of Selected Indices. *Advances in Management , 6* (7), 32-42.

Nawazish, M., & Sara, S. M. (2012). Time Varying Stock Market Volatility: The Case of an Emerging Market. *Research Journal of Recent Sciences , 1* (11), 41-46.

Neeraj, G., & Ashiwn, G. (2014). Testing of Efficient Market Hypothesis: astudy on indan stock Market. *IOSR Journal Business and Mangement , 16* (8), 28-38.

Nelson, D. B. (1991). Conditional Heteroscedasticity in Asset Returns: A new Approach. *Econometrica* , 347-370.

Nishad, T. M., & Thomachan, K. (2015). How volatile Indian Stock Market ? A Study Based on Selected Sectoral Indices. *International Journal of Research - Granthalaya , 3* (12), 142-149.

Nithya, J., & Thamizhchelvan, G. (2014). Effectiveness of Technical Analysis in Banking Sector of Equity Market. *IOSR journal of Business and Management , 16* (7), 20-28.

Obamuyi, T. M. (2013). Factors Influencing Investment Decisions in Capital Market: A Study of Individual Investors in Nigeria. *Organizations and Markets in Emerging Economies , 4* (1(7)), 141-161.

Pandya, F. H. (2013). *Security Analysis and Portfolio Mnagement.* Mumbai: Jaico Publishing House.

Parikh, P. (2010). *Value Investing and Behavioral Finance.* New Delhi: Tata McGraw Hill Education Pvt. Ltd.

Pathade, V. K. (2017). Equity Research: Fundamental anlysis for long term investment. *International Journal of Applied Research , 3* (4), 678-682.

Phillips, P. C., & Perron, P. (1988). Testing for Unit Root in Time Series Regression. *Biometrika , 75* (2), 335-346.

Pirayesh, R. (2004). A Study on the Effects of Emotional Intelligence on Retail Investor's Behaviour. *Managemenr Science Letters* , 43-48.

Pompian, M.M (2012). *Behavioural finace and wealth management.* New Jersey: John wiley & Sons.

Pompian, M. M. (2006). *Behavioral Finance and Wealth Management.* New Jersey: John Wiley & Sons, Inc.

Pompian, M. M. (2008). *Behavioral Finance and Wealth Management.* New Jersey: John Wiley & Sons.

Pompian, M. M. (2008). *Behavioral Finance and Wealth Management.* New Jersey: John Wiley & Sons.

Qadri, S. U., & Mohsin, S. (2014). An Empirical Study of Overconfidence and Illusion of Control Biases, Impact on Investor's Decision Making: An Evidence from ISE. *European Journal of Business Management , 6* (14), 38-45.

Raheja, S., & Dhiman, B. (2017). Role of Emotional Intelligence on Investment Decision of Individuals. *International Journal of Applied Business and Economic Research , 15* (22(2)), 1-9.

Rahman, M. T., & Moazzem, K. G. (2011). Capital Market of Bangladesh: Volatility in the Dhaka Stock Exchange (DSE) and Role of Regulators. *International Journal of Business and Management , 6* (7), 86-93.

Raja, M., & Sudhahar, J. C. (2010). An Empirical Test of Indian Stock Market Efficiency in Respect of Bonus announcement. *Asia Pacific Journal of Finance and Banking Research , 4* (4), 1-14.

Rajan, G. S., & Parimala, S. (2013). Stock Price Movement through Technical Analysis: Empirical Evidence from the Fast Moving Consumer Goods (FMCG Sector). *Indian Journal of research , 2* (2), 142-45.

Raju, M. T., & Ghosh, A. (2004). *Stock Market Volatility – An International Comparison.* Mumbai: Securities and Exchange Board of India Working Paper Series with number 8.

Ramesh, K., & Devendar, V. (2017). Technical Analysis: Price behavior of Select Indian Equities. *International Journal of Business and Management Invention , 6* (7), 35-42.

Ranganatham, M., & Madhumathi, R. (2012). *Security Analysis and Portfolio Management* (2nd Edition ed.). Noida: Pearson Education in South Asia.

Ranganathan, R., & Madhumathi, R. (2015). *Security Analysis and Portfolio Management.* New Delhi: Pearson Education in South Asia.

Ranjbar, H. M., Abedini, B., & Jamali, M. (2014). Analyzing the Effect of Behavioral Factors on the Investors Performance in Tehran Stock Exchange. *International Journal of Technical Research and Applications* , 80-86.

Rao, S. N., & Sreejith, U. (2014). Event Study Methodology: A Critical Review. *The Macrotheme Review , 3* (1), 40-53.

Ricciardi, V. (2008). The Psychology of Risk: The Behavioural Finance Perspective. (F. J. Frank, Ed.) *Handbook of finance , 2,* 85-111.

Ross, S. A., Westerfield, R. W., & Jordan, B. D. (2008). *Fundamentals of Corporate Finance.* New Delhi: Tata McGraw Hill.

Rostami, M., & Dehaghani, Z. A. (2015). Impact of Behavioral Biases(Overconfidence, Ambiquity-Aversion and Loss Aversion) on Investment Making Decision in Tehran Stock Exchange. *Journal of Scientific Research and Development , 2* (4), 60-64.

Roy, S. G. (2015). Equity Research: Fundamental and Technical Analysis. *International Journal of Science and Research , 4* (9), 272-275, Retrieved on 26/09/2016 from https://www.ijsr.net/archive/v4i9/SUB157950.pdf.

Sachin, K., & sanningammanavara, K. (2014). The Efficiency Testing of Weak Form of Indian Stock Market. *International journal of Engineering and Management Research , 4* (4), 44-53.

Sahni, D. (2012). Behavioral Finance: Testing Applicability on Indian Investors. *Shiv Shakti International Journal of Multidisciplinary and Academic Research , 1* (2), 1-12.

Salovey, P., & Mayer, J. D. (1990). Imagination, Cognition and Personality. *Emotional Intelligence , 9* (3), 185-211.

Sarmiento-Sabogal, J., Hatemi-J, A., & Cayón-Fallon, E. (2016). A test of the efficient market hypothesis with regard to the exchange rates and the yield to maturity in Colombia. *WSEAS Transactioons on Business and Economics , 13*, 321-329.

Satish, D. V., & Nayia, M. (2012). Stock Return, Volatility and the Global Financial Meltdown:. *International Journal of Arts and Commerce , 1* (7), 166-178.

Schwert, W. (1990). Stock Market Volatility. *Financial analyst journal* , 23-34.

Seng, D., & Hancock, J. R. (2012). Fundamental Analysis and the Prediction of Earnings. *International Journal of Business and Management , 7* (3), 32-46.

Sewell, M. (2012). The Efficient Market Hypothesis: Empirical Evidence. *International Journal of Statistics and Probability , 1* (2), 164-178.

Seyhun, H. N. (1986). Insiders' Profits, Costs of Trading and Market Efficiency'. *Journal of Financial Economics* , 16-29.

Shalit, H., & Shlomo, Y. (2002). Estimating Beta. *Review of Quantitative Finance and Accounting , 18* (2), 95-118.

Sharma, A. K., & Seth, N. (2011). Recent Financial Crisis and Market Efficiency: An Empirical Analysis of Indian Stock Market. *Indore Management Journal , 2* (4), 27-39.

Shashikala, V., & Chitramani, P. (2017). A Review on Emotional Intelligence and Investment Behaviour. *International Journal of Management , 8* (3), 32-41.

Shefrin, H. (2002). *Beyond Greed and Fear- Understanding Behavioural Finance and Psychology of Investing.* New York: Oxford University Press.

Shefrin, H. (2008). *A behavioural approch to Asset pricing.* New York: Elsevier.

Shefrin, H. M., & Statman, M. (1985). The Disposition to Sell Winners too Early and Ride Losers too long. *The Journal of Finance , XL* (3), 777-790.

Shiller, R. J. (1981). Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *The American Review , 71* (3), 421-436.

Shiller, R. J. (1990). Speculative Prices and Popular Models. *Journal of Economic Perspectives, 4* (2), 55-65.

Shleifer, A. (2000). *Inefficinet Markets - An introduction to Behavioural Finance.* New York: Oxford University Press.

Shusha, A. A., & Touny, M. A. (2016). The Attitudinal Determinants of Adopting the Herd Bahavior:An Applied Study on the Egyptian Exchange. *Journal of Finance and Investment Analysis , 5* (1), 55-69.

Singh, S., & Bahl, S. (2015). *Behavioural Finance.* New Delhi: Vikas Publishing House Pvt Ltd.

Standard, B. (2016, March 8). *Home: Business Standard*. Retrieved January 14, 2017, from Business Standard: http://www.business-standard.com/article/pti-stories/investor-accounts-in-nsdl-cdsl-recorded-at-2-5-crore-116030800936_1.html

Statman, M. (1999). Behavioral Finance: Past Battles and future engagements. *Financial Analyst Journal , 55* (6), 18-27.

Su, C. (2010). *Application of EGARCH Model to Estimate Financial Volatility of Daily Returns.* Sweden: University of Gothenburg.

Subash, R. (2012). *Role of Behavioral Finance in Portfolio Investment Decisions: Evidence from Indai.* Prague: Institute of Economic Studies, Chales University.

Sulphey, M. (2014). *Behavioral Finance.* Delhi: PHI Learning Private Limited.

Tabachnick, B. G., & Fidell, L. (2007). *Using Multivariate Statistics (5th ed.).* New York: Allyn and Bacon.

Tahir, A. (2011). Capital Market Efficiency: Evidence from Pakistan. *Interdisciplinary Journal of Contemporary Research in Business , 3* (8), 947-953.

Tanvir, M., Sufyan, M., & Ahsan, A. (2016). Investor's Emotional Intelligence and Impact on Investment decision. *International Journal of Academic research in Economics and Management Sciences , 5* (3), 12-28.

Thaler, R., & Johnson, E. (1990). Gambling with the house money and trying to break even: The effects of prior outcomes on risky choice. *Management Science , 36*, 643-660.

Titan, A. G. (2015). The Efficient Market Hypothesis: Review of Specialized Literature. *Procedia Economics and Finance* (32), 442-449.

Tripathi, V. (2015). *Security Analysis and Portfolio Management.* New Delhi: Taxmann Publicatons.

Usman, D. I., Muturi, W. M., & Memba, F. S. (2017). Influence on Anchoring Bias on Investors' Decision Making in Property Market in Plateau state, Nigeria. *International Journal of Management and Commerce Innovations , 5* (1), 49-59.

Venketesh, C., & Ganesh, L. (2011). Fundamental Analysis as a Method of Share Valuation in Comparison with Technical Analysis. *International Economics & Finance Journal , 6* (1), 27-37.

Wafi, A. S., Hassan, H., & Mabrouk, A. (2015). Fundemental Analysis Model in Financial Markets - Review Study. *Procedia Ecnomics and Finance , 30*, 939-947.

Welch, I. (2000). Herding among security analysts. *Journal of Financial Economics , 58*, 369-396.

Westerholm, J., & Kuuskoski, M. (2003). Do Direct Stock Market Investments Outperform Mutual Funds? A Study of Finnish Retail investors and Mutual Funds. *LTA* , 197-212.

Wheaton, B., Muthen, B., D.F, A., & Summers, G. (1977). Assessing Reliability and Stability in Panel Models. *Sociological Methodology , 8* (1), 84-136.

Worldometers. (2007, December 27). *population, worldometers*. Retrieved march 31, 2017, from Worldometers: www.worldometers.info/world-population/india-population/

Zalane, S. (2015). Behavioral biases of Individual Investors: The Effects of Anchoring. *Eurasian Journal of Social Sciences , 3* (1), 13-19.

Websites

http://www.bseindia.com

http://www.nseindia.com

http://www.moneycontrol.com

http://www.economictimes.indiatimes.com

http://www.jstor.org

http://www.ndtv.com

http://www.shodhganga.inflibnet.ac.in

http://www.thehindu.com

Appendix 1

Behavioural Aspects of Equity Share Investors in Kerala
Structured Interview Schedule

Serial No.

Please ✓ for each question

District : Trivandrum ☐ Ernakulam ☐ Kozhikode ☐

Residential Location : Corporation ☐ Municipality ☐ Panchayath ☐

Gender : Male ☐ Female ☐

Age (As on 01/04/2015) : ....years

Religion : Hindu ☐ Christian ☐ Muslim ☐

Educational Qualification : Under Graduate ☐ Graduate ☐
Post Graduate ☐ Professional ☐

Occupation : Employed ☐ Professional ☐
Business ☐ Retired ☐

Marital Status : Married ☐ Single ☐

Annual Income : Less than Rs.5,00,000 ☐ Rs.5,00,000 – 10,00,000 ☐
10,00,001 – 15,00,000 ☐ More than 15,00,000 ☐

Type of investor : 1st generation investor ☐ 2nd generation ☐

investor

Experience in investment in Stock : .... years

Your average holding period of Shares : Below 1 year ☐ 1 – 3 years ☐
Above 6 years ☐

Please tick mark (✓) the following variables to the extent of its use while making the investment decision.

HS =Highly used, U = Used, N = Neutral, NS=Not used NAU = Not at all used

1	Growth rate of the economy	HS	U	N	NU	NA
2	Inflation rate	HS	U	N	NU	NA
3	Interest rate	HS	U	N	NU	NA
4	Exchange rate	HS	U	N	NU	NA
5	Infrastructure	HS	U	N	NU	NA
6	Economic & political stability	HS	U	N	NU	NA
7	Industry growth relative to the GDP	HS	U	N	NU	NA
8	Permanence – need for a particular industry	HS	U	N	NU	NA
9	Cost structure – fixed cost to variable cost	HS	U	N	NU	NA
10	Business plan of the company	HS	U	N	NU	NA
11	Quality of the management	HS	U	N	NU	NA
12	Debt Equity ratio	HS	U	N	NU	NA
13	Competitive edge	HS	U	N	NU	NA
14	Promoter's holdings in shares	HS	U	N	NU	NA
15	Company's market share	HS	U	N	NU	NA
16	Past performance of the company's share	HS	U	N	NU	NA
17	Analysis of financial statement	HS	U	N	NU	NA
18	Earnings Per Share	HS	U	N	NU	NA
19	Price Earnings ratio	HS	U	N	NU	NA
20	Price to Book ratio	HS	U	N	NU	NA
21	Dividend payout ratio	HS	U	N	NU	NA
22	Return on equity	HS	U	N	NU	NA
23	Volume of trade	HS	U	N	NU	NA
24	52 weeks high and low	HS	U	N	NU	NA
25	stock Charts	HS	U	N	NU	NA
26	Moving Averages	HS	U	N	NU	NA
27	Breadth of the market = advances - declines	HS	U	N	NU	NA
28	Market indices	HS	U	N	NU	NA
29	Relative strength index	HS	U	N	NU	NA

Read each statement and √ the following according to your agreement / Disagreement

SA= Strongly agree A=Agree N=Neutral D=Disagree SD= Strongly Disagree

1	I consider the performance of market indices to make investment decisions in shares	SA	A	N	D	SD
2	I buy 'hot' stocks and avoid stocks that have performed poorly in the recent past	SA	A	N	D	SD
3	I believe, Good company means good stock to invest	SA	A	N	D	SD
4	I have sufficient knowledge of Indian stock market	SA	A	N	D	SD
5	I believe, my skills and knowledge of stock market can help me to outperform the market.	SA	A	N	D	SD
6	I am confident of my ability to pick better stock than others	SA	A	N	D	SD
7	I place sell orders based on my entry price	SA	A	N	D	SD
8	I rely too heavily on one piece of information in investment decision	SA	A	N	D	SD
9	I forecast the changes in stock prices in the future based on the recent stock prices.	SA	A	N	D	SD
10	I take investment decision by using market tips	SA	A	N	D	SD
11	I give more importance to current information when I make the investment decision	SA	A	N	D	SD
12	I hold the shares when the price decreases, even it increases the loss	SA	A	N	D	SD
13	I invest again in securities which I have already own after its price goes down to justify my investment decision	SA	A	N	D	SD
14	I believe, I get profit on investment due to my skill	SA	A	N	D	SD
15	I believe, I lose money in my investment due to bad luck	SA	A	N	D	SD
16	When I throw a dice, I throw it in specific manner so that I get the number which I expect	SA	A	N	D	SD
17	I think I am more likely to win the lottery if I pick the numbers myself than a quick pick	SA	A	N	D	SD
18	I identify the company first and search for the information to make investment decision	SA	A	N	D	SD

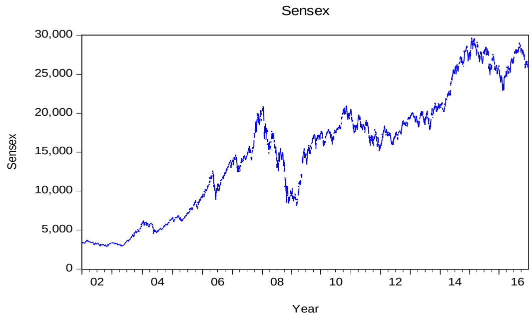
19	When an investment is not going well I usually seek information that confirms I made the right decision about it.	SA	A	N	D	SD
20	After a prior gain, I am more risk seeking than usual.	SA	A	N	D	SD
21	After a prior loss, I become more risk averse	SA	A	N	D	SD
22	The pain of financial loss is more than the pleasure of financial gain	SA	A	N	D	SD
23	I feel more sorrow about holding losing stocks too long than about selling winning stocks too soon.	SA	A	N	D	SD
24	I tend to hold on losing stock for too long hoping for a reversal	SA	A	N	D	SD
25	I book profits in a winning stock too soon and then felt I could have waited more.	SA	A	N	D	SD
26	I generally differentiate ‘main income’ & ‘extra income’	SA	A	N	D	SD
27	I am interested in stock’s individual gain/loss rather than total gain/loss of the portfolio	SA	A	N	D	SD
28	Trading volume of stock affect my investment decision	SA	A	N	D	SD
29	I seek signals from other investors in matters of financial knowledge and trading behaviour	SA	A	N	D	SD
30	The rate of return of recent stock investment meets my expectation.	SA	A	N	D	SD
31	My rate of return is equal to or higher than the average return rate of the market.	SA	A	N	D	SD
32	I feel satisfied with my investment decisions in the last year.	SA	A	N	D	SD
33	I realise immediately when I lose my temper	SA	A	N	D	SD
34	I can 'reframe' bad situations quickly	SA	A	N	D	SD
35	I am always able to motive myself to do difficult tasks	SA	A	N	D	SD
36	I can see things from the other’s point of view	SA	A	N	D	SD
37	I am an excellent listener	SA	A	N	D	SD
38	I know when I am happy	SA	A	N	D	SD
39	I can consciously alter my frame of mind or mood	SA	A	N	D	SD
40	I believe in ‘Action this Day’	SA	A	N	D	SD
41	I am excellent at empathising with someone else's problem	SA	A	N	D	SD
42	I never interrupt other people's conversations	SA	A	N	D	SD

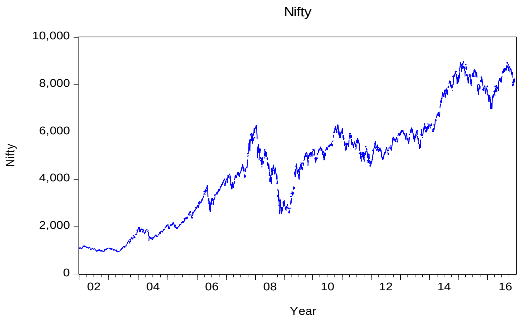
43	I usually recognise when I am stressed	SA	A	N	D	SD
44	I rarely worry about work or life in general	SA	A	N	D	SD
54	I never waste time	SA	A	N	D	SD
46	I can tell if someone is not happy with me	SA	A	N	D	SD
47	I am good at adapting and mixing with a variety of people	SA	A	N	D	SD

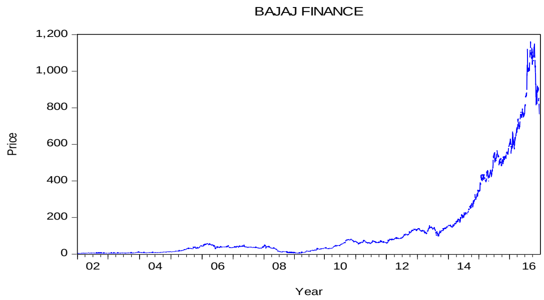
Thank you for your Kind Co-operation

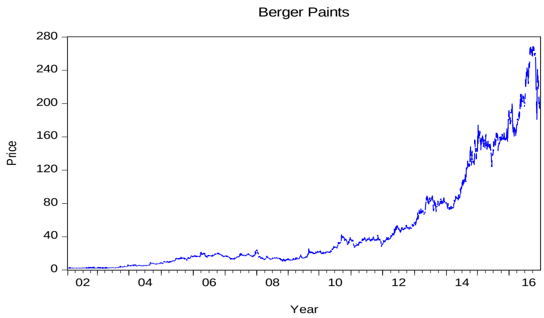
Appendix 2

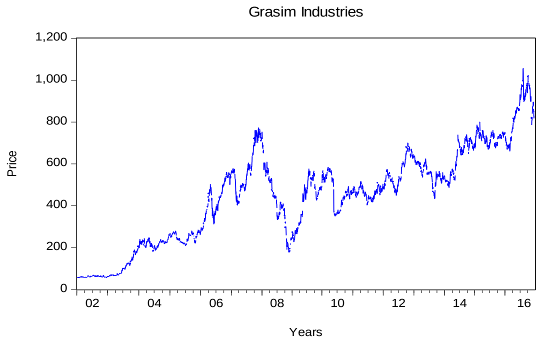
Closing Price of Indices & Various Selected Stocks

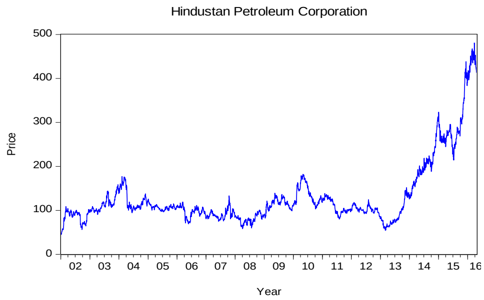


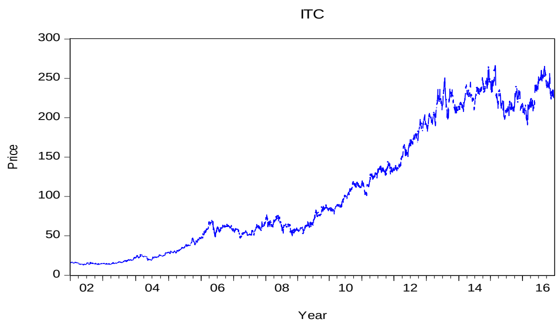


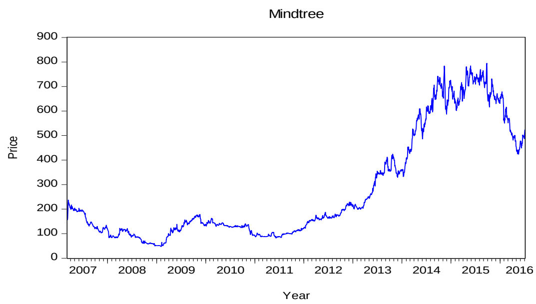


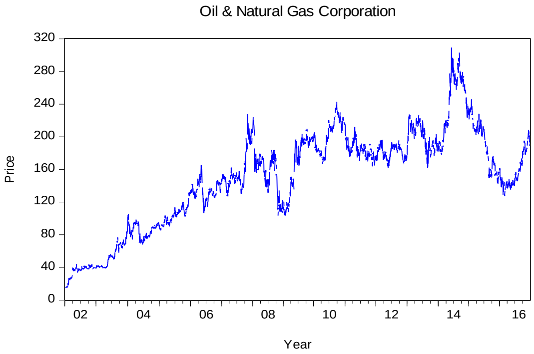








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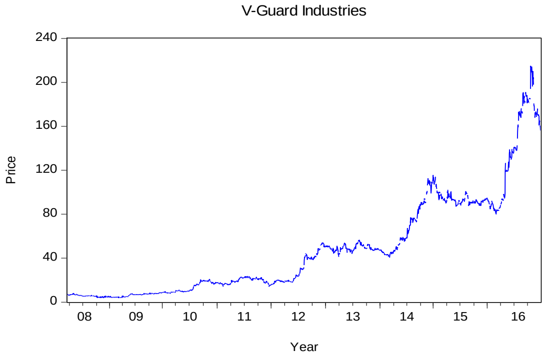
Price
0 40 80 120 160 200 240 280 320
02 04 06 08 10 12 14 16
Year


V-Guard Industries
Price
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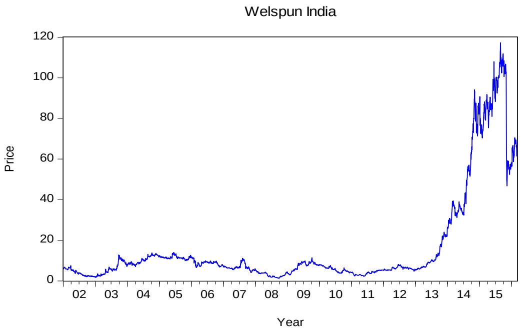
08 09 10 11 12 13 14 15 16
Year


Welspun India
Price
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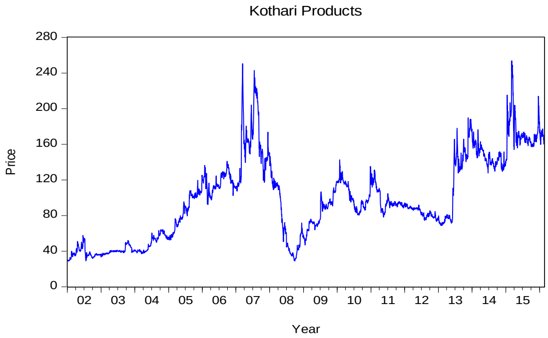
02 03 04 05 06 07 08 09 10 11 12 13 14 15
Year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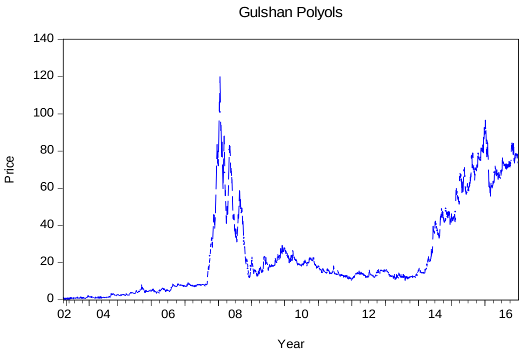
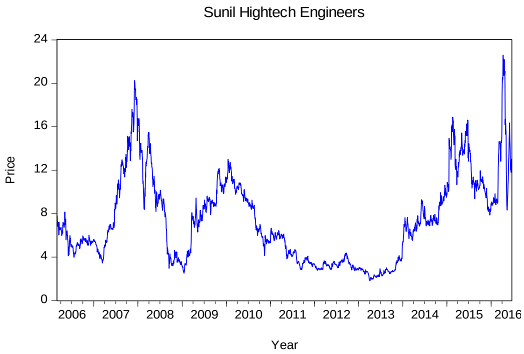
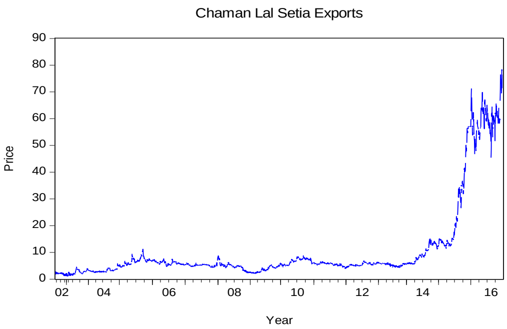
Price
0 40 80 120 160 200 240 280
02 03 04 05 06 07 08 09 10 11 12 13 14 15
Year


Gulshan Polyols
Price
0 20 40 60 80 100 120 140
02 04 06 08 10 12 14 16
Year


Sunil Hightech Engineers
Price
0 4 8 12 16 20 24
2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016
Year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Price
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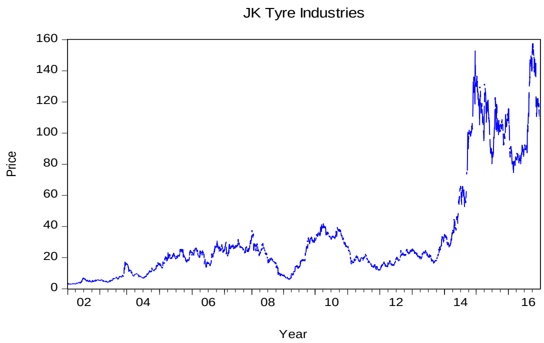
02 04 06 08 10 12 14 16
Year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Price
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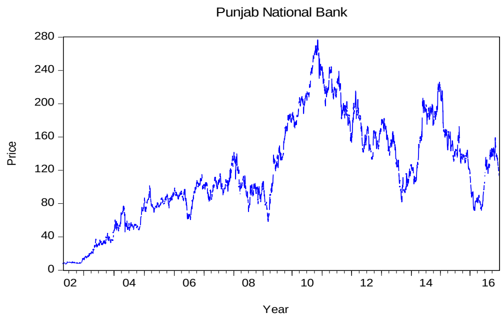
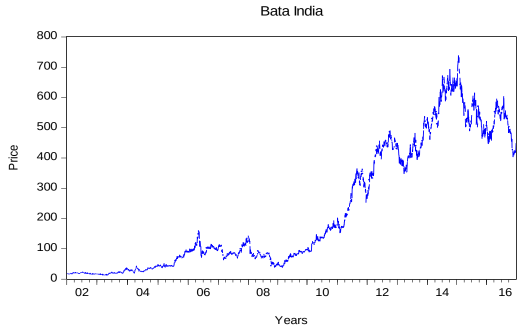
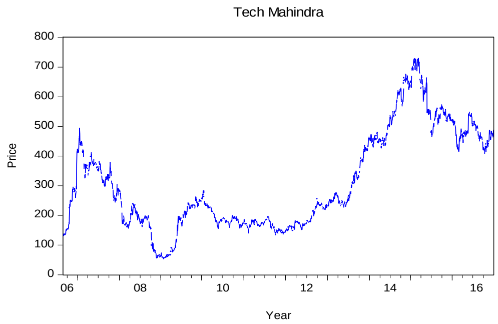
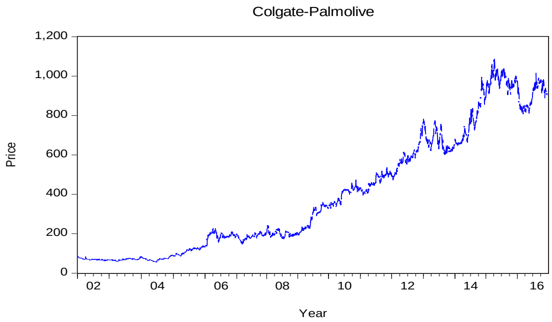
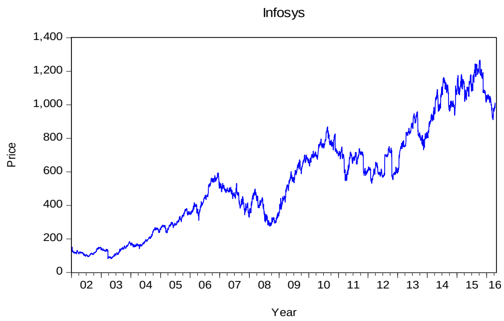
Year

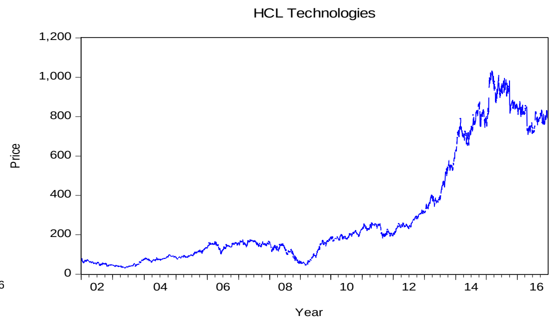

Punjab National Bank
Price
Year


Bata India
Price
Years


Tech Mahindra
Price
Year

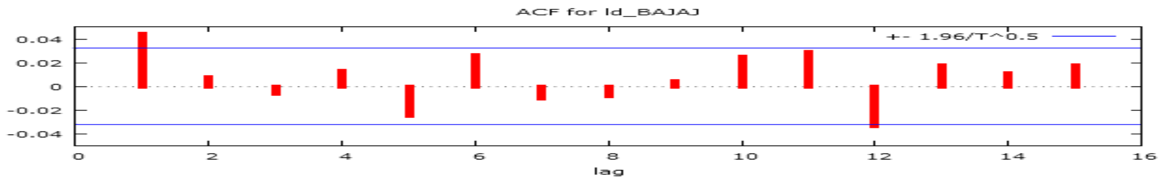

Colgate-Palmolive
Price
Year

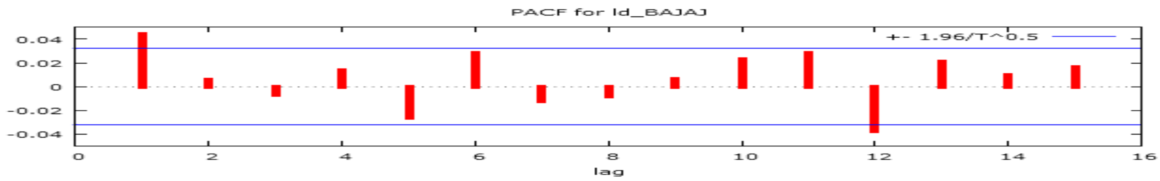

Infosys
Price
Year

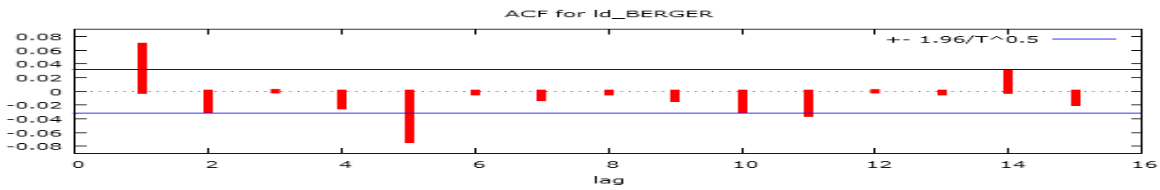

HCL Technologies
Price
Year

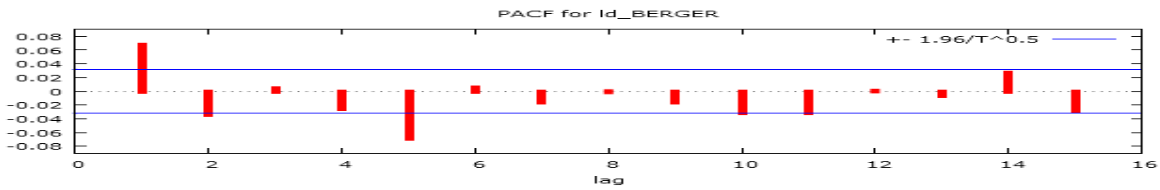
Appendix 3

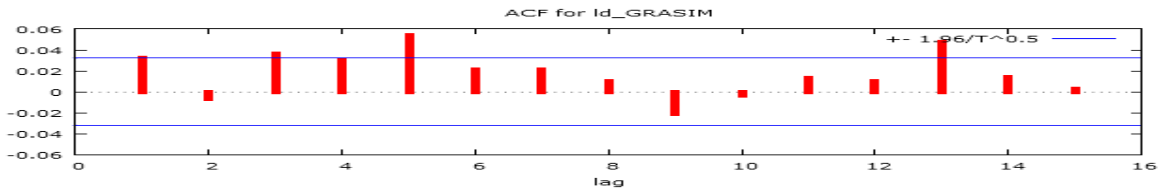
ACF and PACF Chart of Twenty Selected Stocks

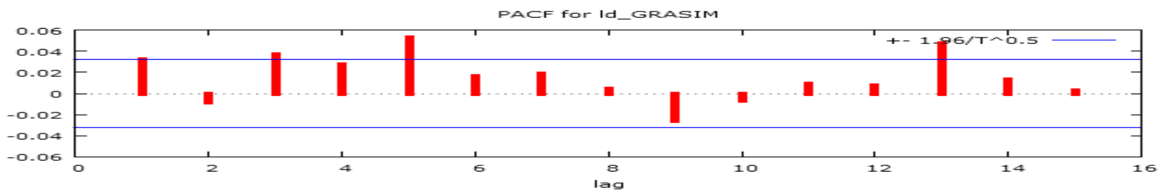


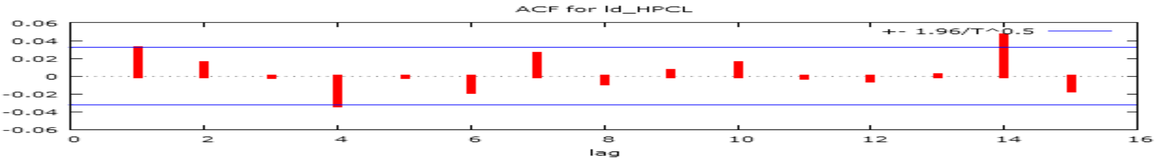








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+- 1.96/T^0.5
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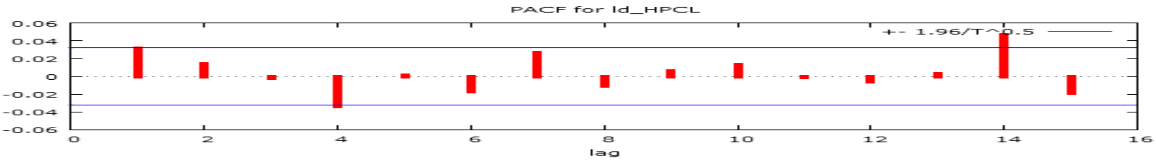
0.04
0.02
0
-0.02
-0.04
-0.06
0 2 4 6 8 10 12 14 16
lag


PACF for ld_HPCL
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0.04
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-0.04
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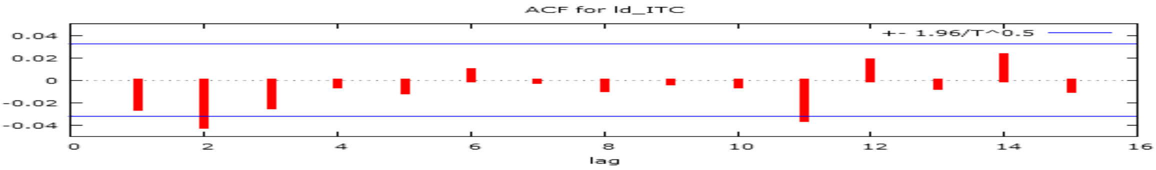
0 2 4 6 8 10 12 14 16
lag


ACF for ld_ITC
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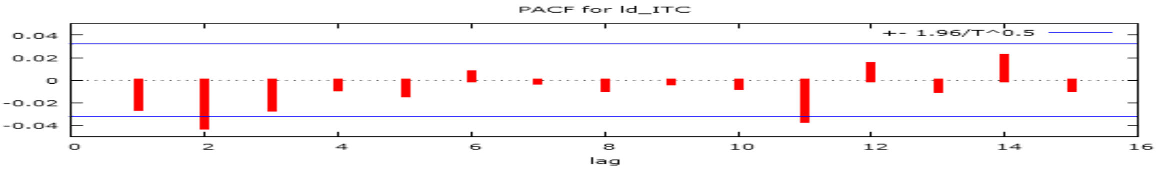
0.02
0
-0.02
-0.04
0 2 4 6 8 10 12 14 16
lag


PACF for ld_ITC
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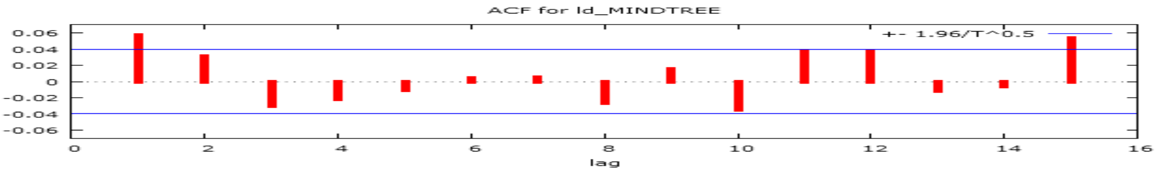
0.02
0
-0.02
-0.04
0 2 4 6 8 10 12 14 16
lag


ACF for ld_MINDTREE
+- 1.96/T^0.5
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0.04
0.02
0
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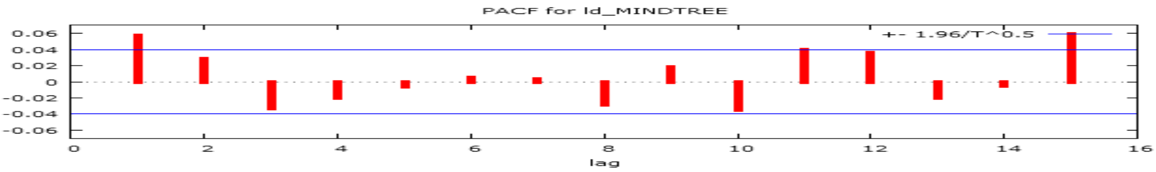
-0.06
0 2 4 6 8 10 12 14 16
lag


PACF for ld_MINDTREE
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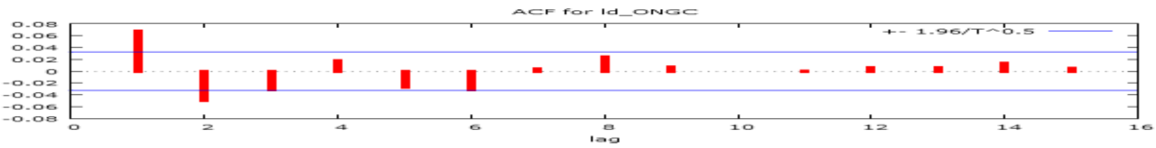
0.04
0.02
0
-0.02
-0.04
-0.06
0 2 4 6 8 10 12 14 16
lag


ACF for ld_ONGC
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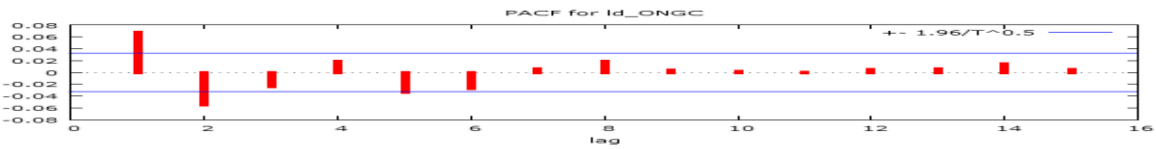
0.08
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
0 2 4 6 8 10 12 14 16
lag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+- 1.96/T^0.5
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0.06
0.04
0.02
0
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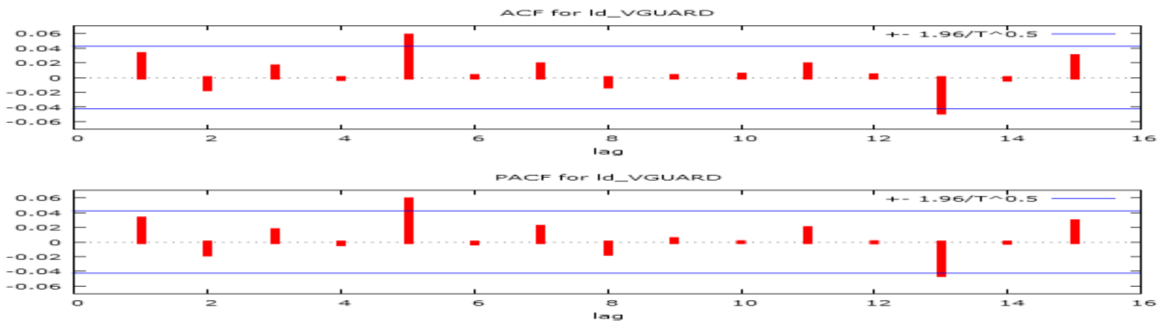
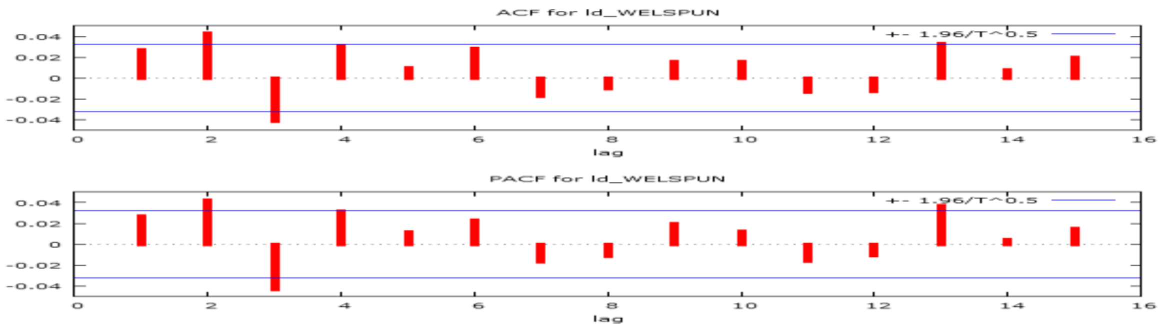
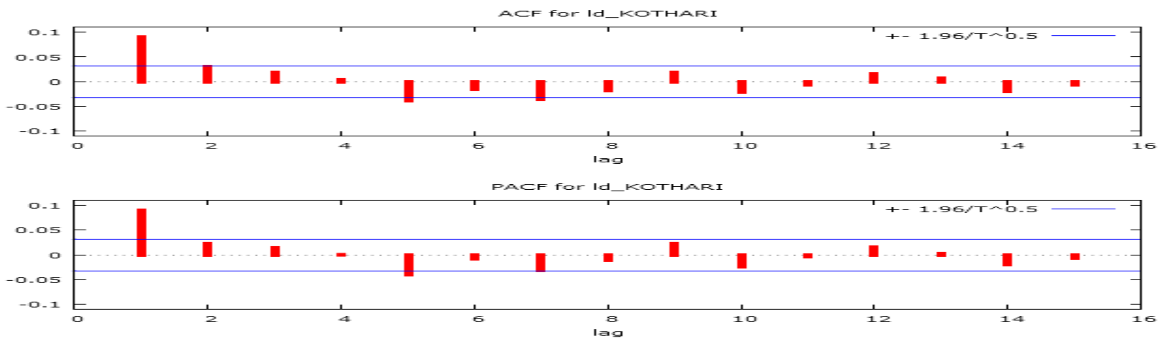
-0.04
-0.06
-0.08
0 2 4 6 8 10 12 14 16
lag


ACF for ld_VGUARD
+- 1.96/T^0.5
lag
PACF for ld_VGUARD
+- 1.96/T^0.5
lag


ACF for ld_WELSPUN
+- 1.96/T^0.5
lag
PACF for ld_WELSPUN
+- 1.96/T^0.5
lag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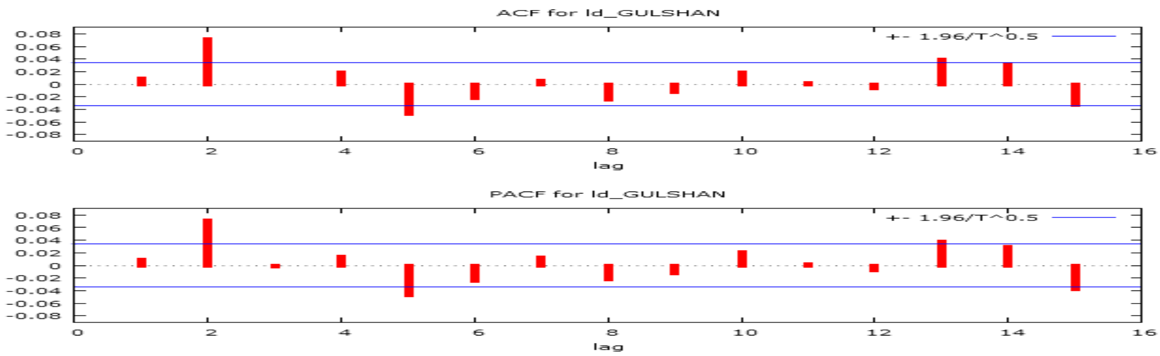
lag
PACF for ld_KOTHARI
+- 1.96/T^0.5
lag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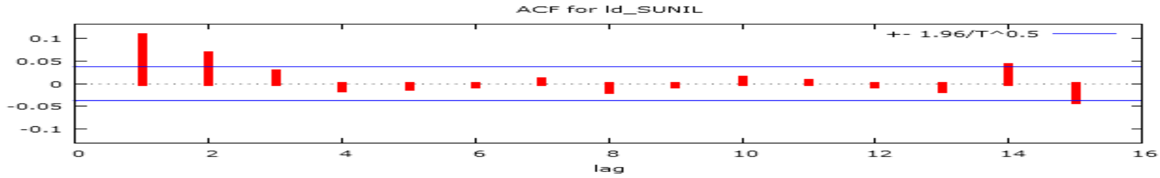
+- 1.96/T^0.5
lag
PACF for ld_GULSHAN
+- 1.96/T^0.5
lag


ACF for ld_SUNIL
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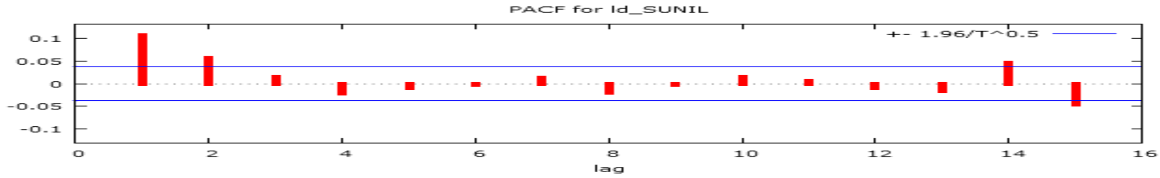
lag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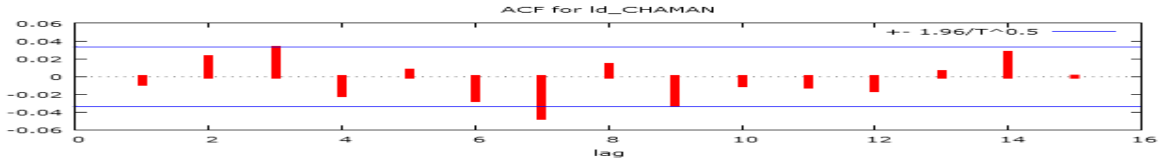
lag


ACF for ld_CHAMAN
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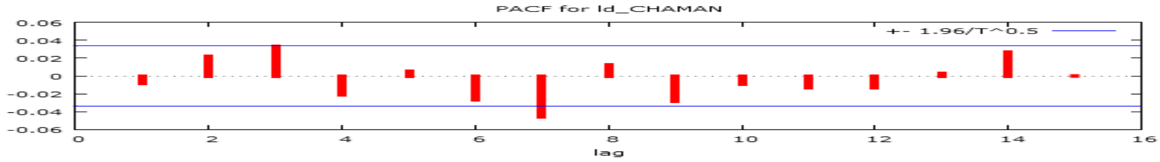
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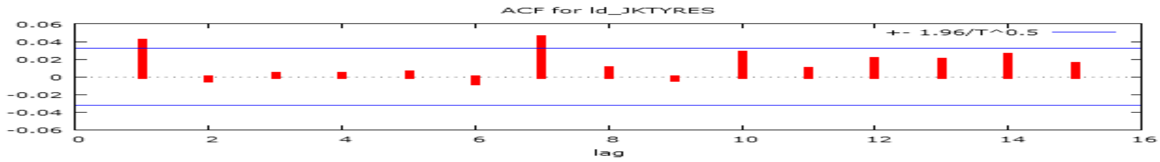
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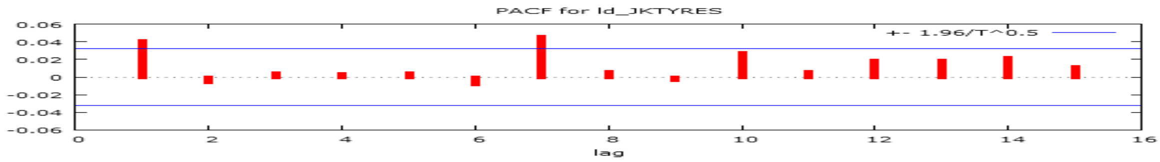
lag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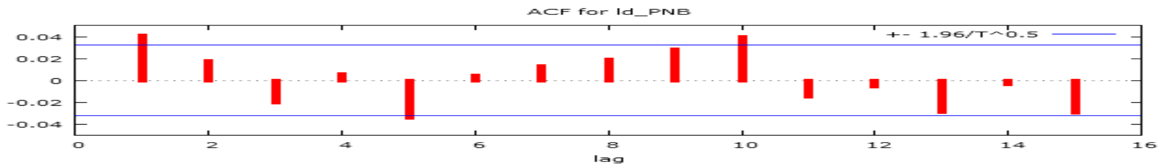
lag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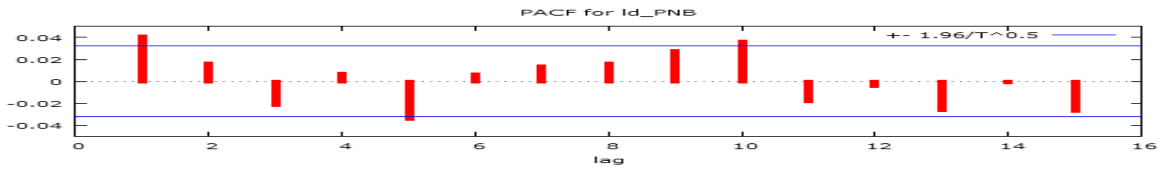
PACF for ld_PNB
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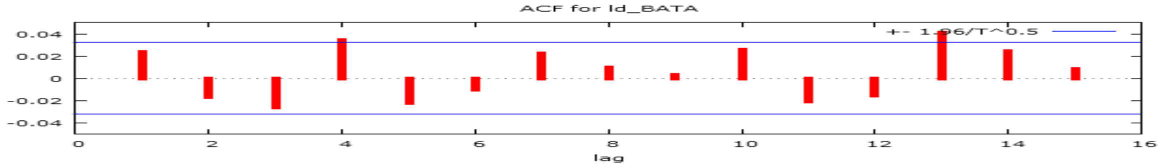
lag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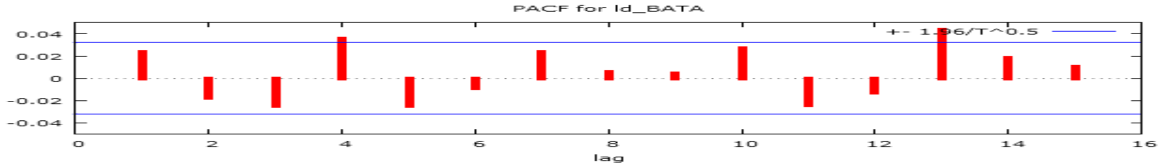
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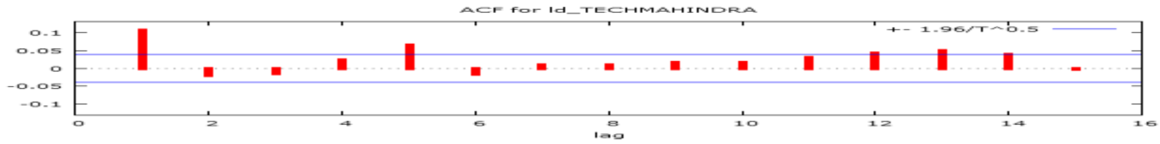
lag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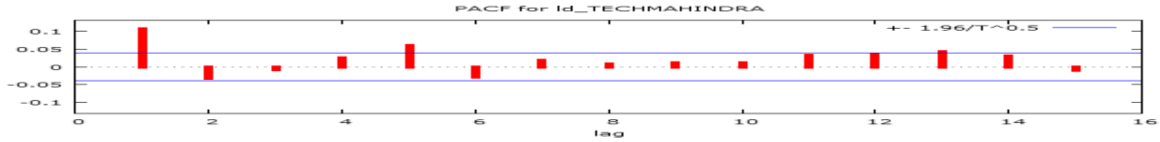
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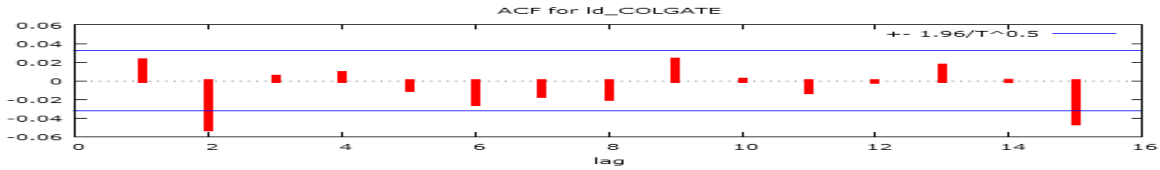
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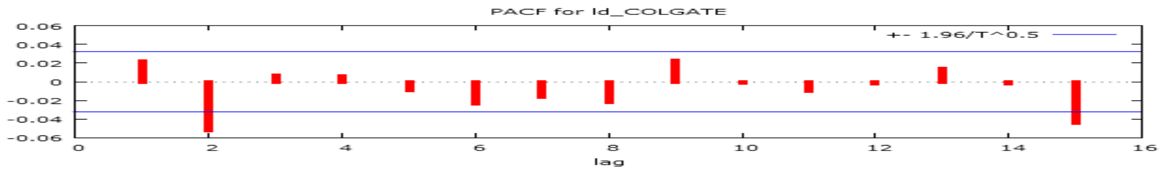
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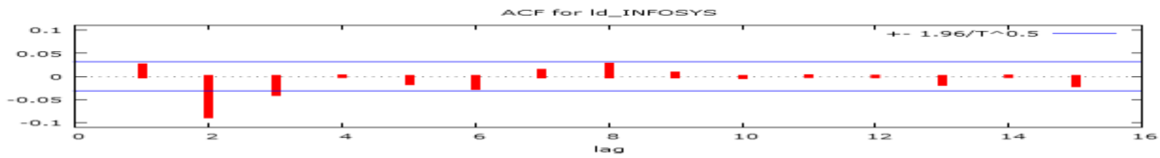
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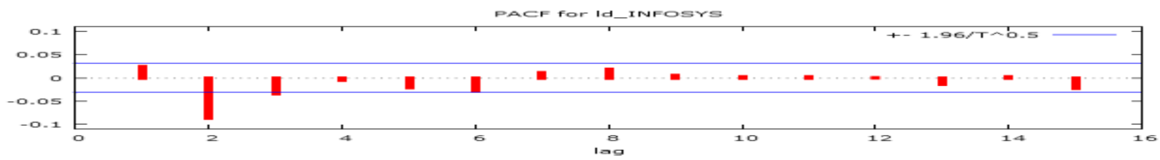
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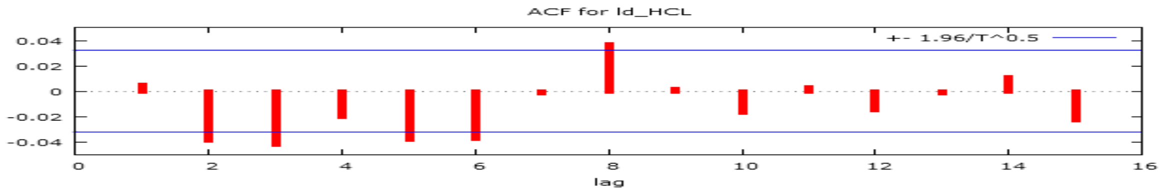
ACF for ld_HCL
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0
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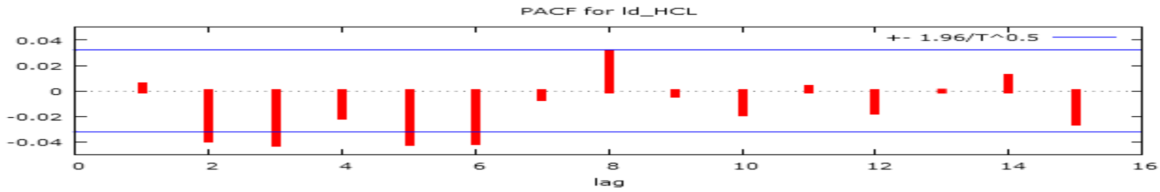
-0.04
0
2
4
6
8
10
12
14
16
lag


PACF for ld_HCL
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0.02
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-0.04
0
2
4
6
8
10
12
14
16
lag