An Analysis of Behavioural Bias and Investment Performance among Equity Mutual Fund Investors in Kerala

Thesis submitted to the

UNIVERSITY OF CALICUT

For the award of degree of

DOCTOR OF PHILOSOPHY IN COMMERCE

Under the Faculty of Commerce and Management Studies

By

DARSANA SUDHARSAN

Under the Supervision of

Dr. BIJU JOHN M

Professor and Head

Research and PG Department of Commerce

St. Thomas' College (Autonomous)

Thrissur-680001

February 2023

UNIVERSITY OF CALICUT

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Dr. Biju John M.
Dean, Professor and Head
Research Department of Commerce
St Thomas College Autonomous
Thrissur, Kerala-680001
9447448568
drbijujohnm@gmail.com

Member of the Senate
University of Calicut

Certificate

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Dr. Biju John M

Supervising Teacher

Dr. Biju John M.
Dean, Professor and Head
Research Department of Commerce
St Thomas College Autonomous
Thrissur, Kerala-680001
9447448568
drbijujohnm@gmail.com

Member of the Senate
University of Calicut

Certificate

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Supervising Teacher

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I hereby declare that this thesis entitled '***An Analysis of Behavioural Bias and Investment Performance among Equity Mutual Fund Investors in Kerala***', submitted to the University of Calicut, for the award of the Degree of Doctor of Philosophy in Commerce, is a record of the bonafide research work done by me under the supervision and guidance of Dr. Biju John M, Professor and Head, Research and PG Department of Commerce, St. Thomas' College (Autonomous) Thrissur. I also declare that, this thesis has not been formed the basis for the award of any degree, diploma, associateship, fellowship or any other title of recognition from any university or institution and to the best of my knowledge and belief, it contains no material previously published by any other person, except where due references are made in the text of the thesis.

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Thrissur

Date

Acknowledgement

Ph.D has been a truly life changing experience for me, and it would not have been possible to do without the support and guidance that I received from many people.

Words fall short in my lexicon to express my heartfelt admiration and gratitude to my research supervisor and mentor, Dr. Biju John M, Professor and Head, Research Department of Commerce, St. Thomas' College (Autonomous), Thrissur, who has offered the inspirational guidance, support and encouragement during my research work. The subject knowledge and experience he possesses, was phenomenally stimulating for me. I feel much fortunate to have pursued my Ph.D under his benign supervision. I am deeply indebted to him for giving me an opportunity to pursue Ph.D under his guidance.

I express my deep gratitude to the University Grants Commission for the financial assistance (JRF/SRF) extended for my research work. I express my sincere thanks to the former Head of the Department, Dr. Thomas Paul Kattookkaran and the entire faculty of the Research Department of Commerce for their valuable support and sincere co-operation throughout the period of my research work. I am extremely grateful to the former Principals, Dr. Joy K L, Dr. Ignatius Antony, Dr. Jenson P.O and the present Principal-in-charge Fr. Dr. Martin K A for arranging all facilities in the college for my research work.

I owe much to Dr. V M Chacko-Research Council Coordinator, Dr. Xavier Joseph, VC Nominee and Associate Professor, Department of Physics, Christ College, Irinjalakkuda and all other doctoral committee members for their constant support.

I am very thankful to Dr. Aparna Sajeev, Expert Member of the Doctoral Committee, Dr. B Johnson, Dean of the Department of Commerce and Management Studies and Dr. M A Joseph, Former Head, Department of Commerce and Management Studies, University of Calicut for the valuable directions and comments given during my research work. A special thanks to Dr. Vinod V. M., Librarian, C.H.M.K., for all the facilities and guidance provided for the plagiarism checking of my thesis. I also thank all other faculties in the Department of Commerce, University of Calicut. I express my gratitude to the Director of Research of University of Calicut and the whole team, for all the facilities provided for undertaking the research.

I am extremely grateful to Dr. Sindhu K P, Principal-in-charge NSS College Parakkulam for her valuable suggestions and being a guiding light in my research. I also thank Dr. Sam Thomas, Professor, Cochin University of Science and Technology for the encouragement and support given during my research.

I would like to specially mention the selfless efforts of Dr. Tom Jacob, Assistant professor, Christ College (Autonomous), Irinjalakuda and Dr. Nishija Unnikrishnan whose guidance and suggestions enhanced the quality of my research work. I wish to extend my sincere thanks to the Librarian Mr. Sanjo Jose and all other administerial staff of St Thomas' College (Autonomous), Thrissur for all the facilities given during my research.

I would like to thank my friends, Dr. Anoop K G, Remya R, Urmila R Menon, Athira J, Harishma C, Choondal Alfred Deepthi and Midhunlal M M for their unconditional support and motivation.

My study would not have been completed without the blessings of my parents Mr. Sudharsan N P and Mrs. Seena V C. I remember with love my sisters Nimisha Sudharsan and Drisya Sudharsan who constantly encouraged me throughout my research. I would like to remember gratefully the love and support of my father in law Mr. Wilson P, mother in law Mrs. Valsa Wilson, brother-in-law Mr. Arun Paul, sister-in-law Mrs. Anisha Vincent E and my loving niece Alaida Paul.

I am extremely thankful to my husband, Mr. Ajith K W, who stood by me during the ups and downs of my journey and without his love, support and tolerance, this work would not have been possible.

Above all, I express my unlimited gratefulness to the Lord Almighty for the endless blessings showered upon me for the successful completion of my research work.

Darsana Sudharsan

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Abbreviations

ADF	Augmented Dickey Fuller
AIC	Akaike Information Criterion
AMC	Asset Management Company
AMFI	Association of Mutual Funds in India
ANOVA	Analysis of Variance
ARIMA	Auto Regressive Integrated Moving Average
AUM	Assets Under Management
BIC	Bayesian Information Criterion
BSE	Bombay Stock Exchange
CAGR	Compound Annual Growth Rate
COVID-19	Coronavirus Disease of 2019
CRISIL	Credit Rating Information Services of India Limited
ECM	Error Correction Model
ECT	Error Correction Term
ELSS	Equity Linked Savings Scheme
EMH	Efficient Market Hypothesis
ETF	Exchange Traded Fund
FDI	Foreign Direct Investment
FIIs	Foreign Institutional Investors
FoF	Fund of Fund
GDP	Gross Domestic Product
HQ	Hannan-Quinn's Information Criterion
IDBI	Industrial Development Bank of India
IMF	International Monetary Fund
KMO	Kaiser-Meyer-Olkin
LR	Log Likelihood Ratio
MF	Mutual Fund
MOSPI	Ministry of Statistics and Programme Implementation
NAV	Net Asset Value
NDA	National Democratic Alliance

NPA	Non-Performing Asset
NSE	National Stock Exchange
RBI	Reserve Bank of India
RERA	Real Estate (Regulation and Development) Act
S.E	Standard Error
SBI	State Bank of India
SD	Standard Deviation
SEBI	Securities Exchange Board of India
SIC	Schwarz Information Criteria
SIP	Systematic Investment Plan
SPSS	Statistical Package for Social Science
VAR	Vector Auto Regression
VECM	Vector Error Correction Model
UTI	Unit Trust of India

Chapter 1

INTRODUCTION

Contents

1.1 Introduction

A strong financial system significantly accelerates a country's economic growth. The Indian government's 1991 liberalisation strategy led to a new definition of the Indian financial system. The Indian capital market has seen a number of financial breakthroughs throughout this time (Mishra, 2009). These developments helped India's capital market expand, which in turn increased resource mobilisation and capital formation in the nation. Due to economic advancement, the disposable income of the investors increases with more scope for savings. With growing financialization, household savings in India have been shifting from physical assets to financial assets and within that, from bank deposits to investments in securities (RBI, 2021). Equity shares are attractive investment options for individuals as they deliver higher returns compared to conventional financial assets. However, high return in equity shares is backed by the element of high risk.

Mutual funds have emerged as the most convenient way to invest in equity instruments by enabling individuals to invest in securities with the professional expertise of fund managers (Debasish, 2009). Robust capital inflows and strong retail participation fostered the Indian mutual fund industry magnificently over the years. The mutual fund industry has become one of the fastest growing sectors in the Indian financial market (Turan & Bodla, 2004). Mutual funds have gained significant popularity among retail investors over the past decade. Strong growth in capital markets, increasing penetration across geographies, technological progress, and regulatory efforts boost the advancement of mutual funds in India. Additionally, the gaining popularity of Systematic Investment Plans (SIPs) in mutual funds augmented retail investor participation.

The majority of the industry's assets were held by institutional investors until 2017 (AMFI, 2021). However, this situation changed and individual investors' participation in mutual fund investments, particularly in equity funds, increased drastically. 55% of the industry's assets were held by individuals in 2021 (CRISIL Research, AMFI). Furthermore, individual-held AUM grew at a CAGR of 21%, while institutional AUM grew at a CAGR of only 15% (CRISIL Research, AMFI).

Minimizing risks and maximising returns are the major goals of any investor. But every investor is not able to earn a return as per their expectations. Investor psychology plays a dominant role in their investment decisions, which would affect their investment performance (Bakar & Yi, 2016). Exploring investor psychology helps in designing more schemes with a well-diversified portfolio catering to their needs, thereby improving their returns.

1.1.1 Mutual Funds

A mutual fund is a type of investment vehicle that pools money from numerous investors and invests in various securities with the expertise of professional fund managers. Mutual fund schemes are managed by Asset Management Companies (AMCs). To invest in a mutual fund, one must purchase a unit of the fund, which turns them into the fund's owner. The income and capital appreciation from the fund are shared among the unit holders based on the number of units held by them, after deducting applicable expenses, as calculated by a scheme's Net Asset Value (NAV). A small fee is charged in return by the mutual fund.

Mutual fund investments are ideal for investors who:

- lack knowledge regarding stock market investment
- like to grow their wealth, but lack time to study the stock market
- would like to invest only a small amount.

1.1.2 Growth of the Mutual Fund Industry in India

The Indian mutual fund industry is one of the fastest-growing industries with promising future growth. In India, mutual funds are established as a trust under the Indian Trust Act, 1882, under the SEBI (Mutual Funds) Regulations, 1996.

The history of the Indian mutual fund industry can be traced back to 1963, with the setting up of the Unit Trust of India (UTI) by the government of India under the regulatory control of the RBI. In 1978, the administrative control of UTI was shifted from the RBI to the Industrial Development Bank of India (IDBI). UTI launched the first mutual fund scheme, the UTI Scheme, in 1964. At the end of 1988, the Assets Under Management (AUM) held by UTI stood at Rs. 6,700 crores.

In 1987, public sector banks and insurance companies entered the mutual fund industry. The first non-UTI fund, the SBI mutual fund, was set up in the same year. Further, five more mutual funds were introduced by the public sector. By the end of 1993, the AUM held by the industry had reached Rs. 47,004 crores.

In 1992, SEBI was established to protect the interests of investors and promote the development of the capital market. SEBI formulated the (Mutual Funds) Regulations 1993 to establish a comprehensive regulatory framework for the mutual fund industry. In the same year, the first private sector mutual fund was formed, the Kothari Pioneer Fund, which thereafter merged with Franklin Templeton. The Association of Mutual Funds in India (AMFI) was incorporated on

August 22, 1995, as the regulator of the mutual fund industry in India. In 1996, the mutual fund regulations were revised. Moreover, many mergers and acquisitions took place in the industry during this phase. By the end of January 2003, the AUM held by the industry reached Rs. 1,21,805 crore.

In 2003, UTI was bifurcated into two separate entities, the Specified Undertaking of the UTI and the UTI Mutual Fund. After the global economic recession in 2009, the financial markets all over the world were at an all-time low and India was no exception. Furthermore, the removal of the entry load by SEBI also affected the mutual fund industry adversely. Consequently, the growth of mutual fund AUM was sluggish during the period 2010–2013.

Since May 2014, the Indian mutual fund industry has witnessed constant advancement and an increase in AUM and the number of investor accounts. The industry's AUM reached Rs. 10 lakh crore during the year. Within three years, the industry had witnessed a growth of more than twofold in the size of AUM, which crossed Rs. 20 lakh crore in 2017. Demonetization, the implementation of the Real Estate (Regulation and Development) Act, 2016, (RERA) and the Benami Transactions (Prohibition) Amendment Act, 2016, played a crucial role in shifting the savings of households from physical to financial assets, which in turn stimulated the growth of the mutual fund industry in India. The growth continued steadily, which helped it reach Rs. 30 lakh crore in 2020.

In 2021, the mutual fund AUM registered a growth of 22% and stood at Rs. 37.6 lakh crore. Equity-oriented schemes were the highest-contributing category to the growth of the mutual fund industry. Mutual funds' deployment in equity instruments stood at 53.37 percent in 2021-2022. Progressively, a wide variety of schemes have been launched by the industry to cater to the needs of investors with different preferences. Considering the significant changes in the industry, many initiatives were launched to ensure transparency and protect investors.

Despite the significant developments taking place, penetration of the mutual fund industry in India is quite low when compared to the global average.

However, the country's high savings propensity and increasing regulations in the industry have brightened the industry's outlook.

1.1.3 Structure of Mutual Funds in India

In India, mutual funds are organised into a three-tiered structure consisting of trustees, the sponsoring firm, and the Asset Management Company (AMC).

1. **Sponsor**

   The company that sets up the mutual fund to earn money through fund management is known as the sponsor. Fund management is done through an associate company. The sponsor has to seek the permission of SEBI to set up a mutual fund and meet certain criteria laid down by SEBI, which are as follows:

   1) The sponsor must have at least 5 years of experience in financial services with a positive net worth over all those years.
   2) The sponsor should show profits in at least 3 out of 5 years, including the immediately preceding year.
   3) The sponsor must have at least a 40% share of the total net worth of the asset management company.

2. **Board of Trustees**

   The sponsor creates a trust through an agreement called a trust deed. Trustees are appointed to manage the trust. Their primary responsibility is to protect the interests of mutual fund investors. They appoint asset management companies to float mutual fund schemes. They monitor the operations of various schemes to safeguard the interests of investors. Asset management firms cannot introduce a new scheme into the market without the trust's approval.

3. **Asset Management Company (AMC)**

   The asset management company manages the funds of various mutual fund schemes. The AMC floats various schemes in the market according to the needs of investors. The AMC acts as a fund manager for the trust and employs professionals to make investments, carry out research, and serve the investors. The AMC is responsible for all fund-related activities, such as launching the scheme and managing it. In return, AMCs charge a fee for the management of mutual funds. Moreover, the success of a mutual fund depends on the efficiency of the AMC.

1.1.4 Advantages of Mutual Fund Investment

1. **Professional Management**

   Many people who even have a substantial amount of income to save are also disinterested in investing in the stock market. Lack of knowledge regarding the financial market is one of the reasons for this hesitation. Mutual funds are suitable for those who do not have any knowledge regarding the financial markets and who lack the time to track the market's performance in order to invest in financial securities, as they are managed by professional fund managers.

2. **Diversification of Portfolio**

   Asset diversification is critical for managing investment risk. A mutual fund pools the money of investors and invests it in various securities. Hence, the investor doesn't have to worry since all his money is not invested in a single asset.

3. **Affordability**

   Mutual funds are affordable for people belonging to lower income brackets, as one could start investing in them even with a small amount. To purchase shares in blue-chip companies, an investor will have to pay a huge amount. But mutual funds make it possible to purchase the shares of these companies, as they collect small amounts from many investors and invest them in these shares. Furthermore, the fee for asset management services has been lowered.

4. **Convenience**

   Investors have options to invest in mutual funds either by investing the whole amount in a lump sum or by opting for systematic investment plans (SIPs), i.e., investing a fixed amount systematically. Mutual funds also offer a plethora of schemes, such as children's plans, retirement plans and industry-specific schemes. As a result, investors do not have to waste valuable time selecting stocks.

5. **Liquidity**

   Investors can sell their mutual funds at any time, except in the case of the Equity Linked Savings Scheme (ELSS), which has a 3-year lock-in period. However, closed-end funds can be redeemed only on maturity.

6. **Transparency**

   Mutual funds present their daily net asset values, which help investors monitor the performance of their funds. They also send quarterly reports of their schemes, which provide details of the portfolio, the performance of the schemes and so on.

7. **Return Potential**

   Mutual funds deliver high returns when they are invested for a longer period. Their level of risk is low when compared to direct investment in shares since they consist of a diversified portfolio.

8. **Well Regulated**

   Mutual funds are required to be registered with SEBI, and they work within the regulatory framework of SEBI. The operations of mutual funds are regularly monitored to protect the interests of investors.

9. **Innovative Schemes**

   Mutual funds offer a variety of schemes that suit an individual's risk tolerance level and investment horizon. Mutual funds have been designed to cater to investors' specific goals, such as retirement planning, children's education and so on. Some schemes that invest in international securities are also popular now.

10. **Tax Benefits**

    Mutual funds are tax-efficient investment options when they are held by investors for a longer period. Equity Linked Savings Schemes (ELSS) provide tax benefits for investors as they are qualified for tax deductions under Section 80 C. However, the maximum amount eligible for deduction is Rs. 1.5 lakh.

1.1.5 Categorisation of Mutual Fund Schemes by SEBI

As per SEBI guidelines on the categorisation and rationalisation of schemes issued in October 2017, mutual funds are classified as follows:

1. **Equity schemes**

   An equity mutual fund is a mutual fund that mainly invests in equity and equity-related instruments. The major objective of equity mutual funds is to seek capital appreciation over the long term. Such funds could be volatile in the short run, making them suitable for highly risk-taking investors who are ready to invest for a longer investment period.

2. **Debt schemes**

   A debt fund invests mainly in bonds or other debt securities. Their major objectives include income generation and capital preservation.

3. **Hybrid schemes**

   Hybrid funds are mutual funds that invest in both equity and debt instruments. They provide a balance between growth and income.

4. **Solution-oriented schemes**

   These mutual funds are designed to achieve a specific goal, such as a child's education planning, retirement planning and so on.

5. **Index Funds**

   Index funds are designed in a way that imitates the composition and performance of a market index. The securities in the portfolio and their weights will be the same as those in the index. They are passively managed funds.

6. **Exchange Traded Funds (ETFs)**

   ETFs are marketable securities that track an index or a basket of assets, similar to index funds.They are listed on stock exchanges. They are passively managed funds. There are gold ETFs that hold gold as the underlying asset.

7. **Fund of Funds (FoFs)**

   Fund of funds are pooled investment fund that invest in other schemes of mutual funds.

8. **International funds**

   International funds are mutual funds that invest in the stocks of companies listed outside India.

1.1.6 Net Asset Value (NAV)

Net asset value is the market value of securities held by a scheme. It represents a fund’s intrinsic value per share. The NAV of a mutual fund scheme represents its performance. The NAV of a scheme changes every day as the market value of securities varies daily. The NAV of a scheme is computed by dividing the market value of securities held by the scheme by the total number of units of those securities on a particular date. When the value of securities in a fund increases, the

NAV increases and when the value of securities in a fund decreases, the NAV decreases.

1.1.7 Behavioural Finance

Behavioural finance is a branch of finance that studies how investors' cognitive errors and emotions influence their decision-making. It involves the integration of various fields such as Sociology, Psychology and Finance. Linter (1988) defines behavioural finance as "the study of how human beings interpret and act on information to make informed investment decisions."

According to the theory of behavioural finance, investors are not always rational, many of them do not diversify their investments properly and they tend to sell winning stocks while holding the losing ones. The study of how investors make systematic errors in judgement is known as behavioural finance. Moreover, it focuses on how investors interpret information and act on it to implement their investment decisions.

Investor psychology, according to proponents of behavioural finance, has the power to drive market prices and fundamental values far apart. Behavioural finance provides insight into how investor psychology influences financial markets.

1.1.8 History and Growth of Behavioural Finance

Traditional finance theory was globally accepted until the mid-20th century. The Bounded Rationality Theory of Herbert Simon is considered the founding stone of behavioural finance. In 1956, the theory of cognitive dissonance was propounded by Leon Festinger. In the 1960s and 1970s, researchers started to investigate the role of psychological factors in the financial decision-making process. In 1965, Eugene Fama proposed the Efficient Market Hypothesis (EMH) theory, in which the author suggested that if stocks function in a market where the data regarding the prices are available, then the stock prices precisely reflect the intrinsic value of the stock. Fama also proposed the Random Walk Hypothesis

(RWH), which assumed that future stock price levels were not predictable other than by a series of random numbers (Fama, 1965). Moreover, the author argued that any attempt to predict the future prices of stocks based on past trends was completely irrelevant.

Fama proposed a three-fold approach to the efficient market hypothesis theory in 1970, as a continuation of his previous work. The proposed approach is comprised of three layers, where every layer builds upon the notion in the previous layer to make the concept more comprehensive. The first layer is termed the "weak layer," which assumes that future stock prices cannot be predicted based on past values. The second layer, which is called the "semi-strong layer," suggested that the stock prices adjust themselves to new information in an equitable manner, leaving zero possibility for the investor to beat the market. The third, which is the "strong layer," proposed that the stock prices reflect private information along with all the public information. Hence, the theory rejects the possibility of any competitive advantage for insider trading.

In 1973 and 1974, Kahneman and Tversky introduced behavioural biases such as representativeness, availability, anchoring and adjustment. In 1979, Kahneman and Tversky developed the prospect theory, which challenged the efficient market hypothesis theory. Prospect theory describes how people select between two different outcomes that involve risk and are aware of the probabilities of the outcomes. They also pointed out that the tendency of people to avoid risk while making financial decisions is one of the problems people exhibit in their approach to analysing risk. This was one of the initial studies on the possibility of the interference of psychological bias in individual financial decisions. Loss of aversion bias was also discovered in the same year.

In 1980, Thaler argued that rational decision-making is not completely true and recognised various mistakes individuals make in making decisions, such as regret aversion, underweighting opportunity costs and failing to ignore sunk costs. These findings laid the foundation stone for the concept of behavioural finance. In 1981, framing bias was discovered (Kahneman & Tversky, 1981). In 1985, the concept of mental accounting was introduced (Thaler, 1985). Thaler and De Bondt (1985) proposed that an individual's cognitive bias can result in the predictable mispricing of equities. Furthermore, they stated that individuals often overreact to unforeseen events to gain portfolio returns. Their findings indicate that prior losers' portfolios steadily outperform portfolios of prior winners since people usually overreact to depressing news and this overreaction further impacts their investment decisions. Andreassen and Kraus (1988) also challenged the efficient market hypothesis theory by indicating that people always tend to extrapolate past prices during a market trend and permit it to affect their investment decisions.

In 1996, Robert Shiller's book titled "Irrational Exuberance" was published and discussed the sudden loss of value of an investment when investors predict the rise in the share prices and become overconfident about the increase in the share values. The investor sentiment model for overreaction and underreaction of stock prices was explained by Thaler and Barberis (1998).

Thaler (1999) successfully predicted the downfall of the stock market using behavioural finance and criticised the EMH theory for the collapse. In the same year, behavioural asset pricing theory and behavioural portfolio theory were discovered by Statman, M. (1999). The linkage of behavioural finance with the efficient market was discussed by Shleifer A. in “Inefficient Markets.”

In 2000, Hersh Shefrin authored the book "Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing," which explains how psychology impacts the entire field of finance. He has also classified behavioural biases into heuristics and frame-dependent biases.

Robert J. Shiller has also made significant contributions to the field of behavioural finance. Shiller (2003) indicated that the emotions of individuals play a crucial role in the rise and fall of the market and further criticised the media for spreading false sentiment regarding the upward market movement, which in turn influences the public highly. Currently, behavioural finance is used to identify the possible causes of stock rallies and crashes and their relationship with human actions.

1.1.9 Important Contributors

Many academicians, economists and psychologists have immensely contributed to the field of behavioural finance. A few of them are mentioned below:

- **Daniel Kahneman and Amos Tversky**

  Daniel Kahneman and Amos Tversky are regarded as the fathers of behavioural finance. Both of them worked on contrasting ideas during the 1960s and thereafter they decided to work together in the 1970s to make major contributions that became the yardstick in this field. Daniel Kahneman received the Nobel Prize in Economics in 2002 for integrating insights from psychology into economics.

- **Richard H. Thaler**

  The concept of mental accounting was introduced by Richard Thaler. He has written a classic book, "Can the Market Add and Subtract? Mispricing in Tech Stock Carve-Outs." Richard Thaler was awarded the 2017 Nobel Prize in Economics for his contributions to behavioural economics.

- **Robert J Shiller**

  From the 1980s on, Shiller was a pioneer in the field of behavioural finance. Shiller was awarded the Nobel Prize in Economics in 2013 along with Eugene Fama and Lars Peter Hansen for the empirical analysis of stock prices. His most notable work is "Irrational Exuberance," in which he accurately predicted the stock market crash in 2000.

- **Hersh M. Shefrin**

  Shefrin and Statman together introduced the concept of the "disposition effect." Shefrin, along with Richard Thaler, developed an economic theory of self-control. His notable work is "Beyond Greed and Fear: Understanding Behavioural Finance and the Psychology of Investing."

- **Vernon L. Smith**

  Vernon Smith is recognised as the father of experimental economics. In 2002, he was awarded the Nobel Prize along with Daniel Kahneman.

1.1.10 Standard Finance versus Behavioural Finance

- Standard finance assumes that investors are rational while investing. As per behavioural finance, investors possess certain biases that lead them to commit errors in making investment decisions.
- According to standard finance, people take every decision after considering the elements of risk and return. On the other hand, behavioural finance assumes frame dependence. It suggests that investors' perceptions of risk and return are affected by how decision problems are framed.
- Standard finance assumes that markets are efficient and the price of a security is an unbiased estimate of its intrinsic value. In contrast, behavioural finance believes that there will be a mismatch between a security's market price and its intrinsic value due to various investor biases and errors.
- According to standard finance, investors are guided by logic and independent judgment, whereas in behavioural finance, emotions and a herd mentality influence their investment decisions.
- As per the views of the efficient market hypothesis, stock prices follow a random walk, i.e., even though there are fluctuations in prices, they are corrected and bought back in time, while behavioural finance suggests that investors push the prices of securities to unsustainable levels in both directions.

1.1.11 Behavioural Theories

The major theories that play a dominant role in behavioural finance are:

1. **Prospect Theory**

The prospect theory is a behavioural model formulated by Daniel Kahneman and Amos Tversky in 1979. According to it, investors admire gains and losses differently and take decisions based on anticipated gains rather than anticipated losses. It demonstrates how investors chose between risky and uncertain alternatives. Prospect theory reveals that investors are loss averse, and if two equal options are given to them, one in terms of probable gains and the other in terms of probable losses, the former option will be preferred.

2. **Behavioural Asset Pricing Model**

Shefrin and Statman (1994) proposed the behavioural asset pricing model, which assumed a market in which investors interact with information traders. Those who commit cognitive errors were referred to as "noise traders," while those who do not commit cognitive errors are "information traders." The theory suggests that capital market investors are not only affected by risk but also by their moral sentiment.

3. **Behavioural Portfolio Theory**

The behavioural portfolio theory was developed by Shefrin and Statman (Behavioral portfolio theory, 2000). According to the theory, investors have many goals, and portfolios are created to meet those goals. This theory explains portfolios in terms of behavioural frontiers. The theory further states that investors construct their portfolios as a pyramid of assets with well-defined roles.

4. **Behavioural Efficient Market Hypothesis**

The behavioural efficient market hypothesis theory was developed as an alternative to the efficient market hypothesis theory by Shleifer (2000). The theory focuses on irrational investors. It states that in the actual financial markets, irrational investors trade against arbitrageurs whose resources are limited by short horizons, risk aversion and agency problems. In this theory, behavioural models are presented to explain market anomalies. As per this theory, most investors react to irrelevant information or trade on noise rather than information.

1.1.12 Behavioural Bias

Behavioural bias is defined as a predisposition towards error by Shefrin (2007). It refers to the propensity to make decisions while being influenced by an underlying belief. Investor biases are mainly divided into cognitive biases and emotional biases.

Cognitive Biases

Cognitive biases are systematic errors in thinking that occur when people process and interpret information around them and affect the decisions they make. A cognitive bias arises as a result of one's brain's attempt to simplify information processing. The concept of cognitive bias was first introduced by Tversky and Kahneman in 1972.

Belief Perseverance Bias

Belief perseverance bias refers to the tendency of individuals to stick on to their previously held beliefs irrationally. Investors tend to hold securities to justify their beliefs because they believe in themselves or their own abilities (Pompain, 2006). The different types of belief perseverance biases are representativeness, confirmation, cognitive dissonance and illusion of control.

Representativeness Bias

Representativeness bias refers to the tendency of individuals to form judgements based on stereotypes (Shefrin, 2000). It is heuristic-driven. Investors who are prone to representative bias often become highly optimistic about past winners and highly pessimistic about past losers. They assume that the stocks of a good company will also be good, which cannot always be true. Investors may be attracted to mutual funds with a good track record as they believe that these funds are representative of high-performing funds.

Confirmation Bias

People usually pay more attention to the information that supports their views while ignoring the rest. Confirmation bias is about interpreting the available evidence in a way that aligns with one's own beliefs or views (Shefrin, 2007). Investors who are exposed to confirmation bias seek information that supports their original views on that particular investment, avoiding information that contradicts their views. As a result, confirmation bias causes investors to make poor investment decisions. Furthermore, it can cause investors to hold onto their under-diversified portfolio.

Cognitive Dissonance Bias

Cognitive dissonance refers to the mental conflicts experienced by people when they come across evidence that their assumptions or beliefs are wrong (Shiller, 1998). Cognitive dissonance theory was proposed by Festinger in 1957. The theory suggests that discrepancies between past choices and empirical evidence cause distress among individuals and to support their past decisions, they alter their existing beliefs. Moreover, people who are prone to cognitive dissonance bias will jump through mental hoops to avoid or reduce inconsistencies.

Illusion of control Bias

Investors who are prone to the illusion of control bias tend to think that they have control over the outcomes, which they actually don't have (Pompain, 2006). Investors who are affected by the illusion of control bias would maintain under-diversified portfolios. Many studies suggest that the illusion of control often leads to overconfidence among investors.

Information Processing Bias

Information processing biases are cognitive biases in which individuals make errors in thinking while processing information related to a financial decision. Information processing bias occurs when people process information irrationally or illogically (Pompain, 2006).

Anchoring Bias

Tversky and Kahneman (1974) suggested that when forming estimates, people start with some initial arbitrary value and make adjustments to it. The initial value may be suggested as a result of a partial calculation. In the financial market, investors often refer to the initial purchase price when selling or analysing. Moreover, it is the mindset of individuals to hold on to a notion and then consider it as a reference point for making decisions in the future.

Availability Bias

Availability bias refers to the mentality of individuals to rely upon information that is readily available instead of examining other alternatives (Tversky & Kahneman, 1974). There are instances where people assess the probability of a particular event by the ease with which the occurrence of that event can be brought to mind.Investors affected by availability bias would selectthe funds based on the information they have rather than analysing the fund.

Self-Attribution Bias

Self-attribution bias refers to the tendency of individuals to attribute success to innate factors while attributing failures to situational factors. This concept was proposed by Heider in 1958. Individuals tend to take credit for their successes and blame external factors for their failures (Bradley, 1978). Investors who are prone to self-attribution bias tend to take credit for profits from their investments and blame their losses on situational factors. They tend to take high risks due to overconfidence in their attitude.

Mental Accounting Bias

Mental accounting bias refers to the intentions of individuals to place their invested assets in different categories and attribute separate functions to these categories (Kivetz, 1999). This categorisation and assignment of functions may be illogical, which would lead them to make improper investment decisions. It leads investors to make illogical distinctions between the return on income and the return on capital gain. Many investors spend their dividends while retaining the principal. This is due to the different weights assigned by them to these two.

Emotional Bias

Emotion is a mental state that acts spontaneously. Emotional bias arises from intuition or impulse rather than conscious calculations. It deals with the way one feels. Emotional bias consists of overconfidence, loss aversion, regret aversion and herding bias.

Overconfidence

Overconfidence refers to an overly optimistic assessment of one's knowledge or control over a situation. According to Michael Pompain (2006), overconfidence refers to unwarranted faith in one’s intuitive reasoning, judgments and cognitive abilities. Investors who are prone to overconfidence bias tend to trade excessively, as they believe that they have more knowledge than other investors. They also underestimate their downside risk, resulting in poor fund performance.

Loss Aversion

Loss aversion is the tendency of individuals to avoid losses in exchange for acquiring equivalent gains. Daniel Kahneman and Amos Tversky coined this term in 1979 while working on the prospect theory. The theory suggests that the pain caused by a loss would be greater than the joy created by an equivalent gain.

Investors with loss aversion tend to hold the losing funds too long, which in turn diminishes the returns generated from the funds. On the other hand, they tend to sell the winning ones too early. As a result, it restricts the upside potential of the fund.

Regret Aversion

Individuals tend to avoid actions that have the potential to cause discomfort over faulty investment decisions (Kahneman & Tversky, 1979). The underlying cause of this bias is human beings' inherent fear of failure. Investors with a regret aversion bias are hesitant to sell losers for fear that the price will rise, causing them mental pain. However, they tend to sell the winning stocks too soon as they think that the price might decrease in the future. Such investors frequently engage in herding behaviour to alleviate the pain of regret because they feel safer in popular investments. Moreover, they underestimate themselves and rely on others' recommendations.

Herd Behaviour

Herd behaviour refers to the tendency of individuals to follow the crowd. Investors with a herd mentality follow the investment decisions of the market majority (Shefrin, 1996). In a bullish market, they tend to buy more shares since others are doing so, whereas in a bearish market, they sell their shares as others are doing so. Investors who resort to herd behaviour make easy investment decisions because they do not need to properly analyse because they are imitating others. It could also reduce feelings of regret, even if it leads to loss.

1.1.13 Investment Decisions

Decision-making refers to the process of selecting the best alternative from several alternatives. Investment decisions are concerned with the allocation of financial resources to obtain the maximum return. Decision-making is the most challenging activity for investors. The decisions taken by investors differ according to various factors such as their gender, age, education level, income and so on. Moreover, emotional factors also exert an influence on their investment decisions.

The quality of investment decisions taken by investors affects their investment performance.

1.1.14 Investment Performance

Investment performance refers to the rate of return obtained from the investment made. It is measured during a specific period of time. In the case of mutual funds, the rate of return can take the form of dividends, interest, or capital appreciation. The performance of a mutual fund is represented by its NAV. Performance is said to be high when the NAV of the fund is higher than its NAV in the previous period. When the investor has an expectation about the return on his investment and the actual return is higher than his expectation, the investment performance is said to be high. Furthermore, when the return delivered by a fund is higher than the market return, the investment performance is high.

1.2 Statement of the Problem

The Indian economy is the sixth largest economy in the world in terms of nominal GDP (World Bank, 2022). According to the World Economic Outlook published by the IMF, India's GDP grew at a rate of 9% in 2021, making it one of the fastest-growing economies in the world. Economic growth resulting from domestic savings is more sustainable than the growth achieved from borrowed capital (Patra et al., 2017). According to the World Bank's reports, India’s domestic savings rate is 28.9%, higher than the world average of 26.16% in 2020. A remarkable shift is witnessed in individuals' savings from physical assets to financial assets. The net savings in financial assets increased at a CAGR of 15.7% between 2014 and 2021 (MOSPI, 2022).

A developed financial market plays a crucial role in the overall economic development of a nation. A bi-directional causal relationship exists between economic growth and stock market development in India (Deb & Mukherjee, 2008). By analysing economic history, it is obvious that stocks have provided huge returns in the long run. Investing in equity shares enables even common men to participate in the economic growth of the nation. But to invest directly in equity shares, one must have appropriate knowledge regarding the financial markets.

Investment in equity through mutual funds provides professional expertise and diversification among various asset classes.

Equity mutual funds have emerged as an attractive investment option for investors. In 2021, 77% of individual mutual fund investors' assets were invested in equity mutual funds (AMFI, 2021). The average AUM of equity mutual funds grew at a CAGR of 27.5% as of December 2021. Even though India's mutual fund AUM as a percentage of GDP grew from 4.3% in 2002 to 16.6% in 2021, it is still significantly lower than the world average of 75% (World Economic Outlook, IMF).

There are different types of equity mutual funds in India with different market capitalisations. They have exhibited hikes and dips in their performance based on market movement. Many equity mutual funds have outperformed the market barometer. However, the lower investment rate in equity mutual funds makes it evident that people are highly reluctant to invest in equity mutual funds.

Kerala is the state with the highest literacy rate in India (Census Report, 2011). But it lags far behind in terms of mutual fund investment. Despite the high returns provided by equity mutual funds in the long run, investors in Kerala are reluctant to make a higher share of their investment in equity mutual funds. The percentage of AUM to GDP accounts for only 5% of the state's GDP, which is quite low (AMFI, 2021). Lack of financial knowledge stood as a stumbling block to the growth of mutual funds in Kerala.

The investment decisions of investors play an important role in defining the trend of the market. The investment decisions of individuals are influenced by various socio-economic factors such as their gender, age, education, occupation, annual income, investment experience and so on. Furthermore, investment decisions are also driven by various behavioural biases, which would influence their investment performance.

Thus, it is important to assess the types of behavioural biases that exist among equity mutual fund investors in Kerala and their variability in accordance with different socio-economic variables. Moreover, it would be essential to examine whether the behavioural biases of investors exert any impact on their investment performance.

1.3 Research Questions

The present study is undertaken to resolve the following research questions:

- Is there a relationship between the stock market and equity mutual funds in India?
- What is the trend of the performance of equity mutual funds in India?
- To what extent does the behavioural bias of equity mutual fund investors in Kerala change according to their gender, age, education level, occupation, marital status, annual income and investment experience?
- Does the behavioural bias of equity mutual fund investors in Kerala exert any influence on their investment performance?

1.4 Objectives of the Study

The present study is undertaken with the following specific objectives:

1. To examine the relationship between the stock market and equity mutual funds in India.
2. To evaluate the trend of the performance of equity mutual funds in India.
3. To assess the nature and extent of behavioural bias among equity mutual fund investors in Kerala and its variability with regard to the identified socio-economic variables.
4. To examine the influence of behavioural bias among equity mutual fund investors in Kerala on their investment performance.

1.5 Hypotheses of the Study

Based on the objectives, the following hypotheses are formulated:

- H1: There exists a long-run relationship between equity mutual funds and the stock market in India.
- H2: The performance of equity mutual funds in India would progress in the future.

- H3: There is a significant difference between behavioural biases with regard to their gender, age, education level, occupation, marital-status, annual income and investment experience.
- H4: There is a significant difference between the investment performance of investors with regard to their gender, age, education level, occupation, marital status, annual income and investment experience.
- H5: There is a significant relation between behavioural biases and the investment performance of equity mutual fund investors.

1.6 Scope of the Study

The present study focuses on analysing the relationship between equity mutual funds and the stock market in India, the trend of the performance of equity mutual funds, the influence of investors' socio-economic factors on various behavioural biases, and the influence of these behavioural biases on the investment performance of equity mutual fund investors in Kerala.

In order to study the relationship between equity mutual funds and the stock market, the net asset values of four types of equity mutual funds and the Sensex for the period 2011–2021 have been considered for the study. For analysing the performance, the daily net asset values of these equity mutual funds for the same period have been used. The study of behavioural biases and investor performance has been limited to equity mutual fund investors in Kerala. Furthermore, the scope of the study is limited to the influence of selected cognitive and emotional biases among equity mutual fund investors in Kerala.

1.7 Significance of the Study

The economic development of a nation depends upon the mobilisation of savings and the flow of these savings to companies. Individuals would benefit from these savings only if they gained profits from their investments. Equity shares are the highest return-generating asset class and their profit from them could beat inflation. However, a great level of knowledge regarding the financial market is required for investors in order to make a profit from it. Investing in equity mutual funds enables them to invest in equity shares with the professional expertise of fund managers and thereby reap the benefits. Hence, it is of paramount importance to examine the relationship between the stock market and mutual funds in India. To assist investors and fund managers in making decisions regarding the selection of funds, it is significant to explore the trend of the performance of equity mutual funds in India.

Kerala is the state with the highest literacy rate in India. However, it is one of the least penetrated states in terms of mutual fund investment. Many investors would be hesitant to invest in mutual funds due to their ignorance of financial markets and the information about losses incurred by their peers. Different behavioural biases may exist among the investors, which may prevent them from earning profits. Therefore, it is imperative to examine the behavioural biases that exist among investors and their variability in accordance with different socio-economic variables.

The returns earned by investors vary from one person to another. Some investors obtain profit from their investments while others incur losses. The investment performance of investors is influenced by many variables. Profits being the key motive for investment, the factors affecting the equity funds' performance have to be analysed. Hence, the influence of investors' socio-economic factors and behavioural biases on their investment performance has to be examined.

1.8 Operational Definitions

Investors

Investors are individuals who make an investment in equity mutual funds with the objective of gaining returns.

Cognitive Bias

Cognitive biases are systematic errors incurred in the way of thinking that lead people to make wrong decisions.

Emotional Bias

Emotional biases occur when the decision-making power of an individual is distorted by his emotions.

Belief Perseverance Bias

Belief perseverance bias refers to an individual's tendency to stick on to his previously held beliefs irrationally or illogically.

Information Processing Bias

Information processing biases are the biases that are incurred when people process information irrationally or illogically.

Investment Performance

Investment performance is the performance of the return (increase or decrease in NAV with respect to NAV on the date of purchase) on the investment.

1.9 Limitations of the Study

The present study is subjected to the following limitations:

- The researcher considers only four types of equity mutual funds and within that, the most performing fund from each category was selected as the sample and the data pertaining to the period 1st January 2011 to 31st December 2021 were considered.
- The study does not cover the entire equity mutual fund investors in Kerala. Data were collected from investors with the help of various stock brokers. Some of the brokers were hesitant to provide the details. It may affect the sampling even though the researcher has taken maximum efforts to make the sample frame comprehensive.
- The researcher used subjective assessment to assess the investors' investment performance. It is done by asking them to compare their current return to the average return of equity mutual funds in the market.
- The present study has not been conducted over an extended period of time having positive and negative movements in the stock market which would

be the key influencer on investors' decision-making. Hence, the investors' opinions regarding theirinvestment performance may not be the same always.

1.10 Structure of the Thesis

The whole thesis is divided into nine chapters which are as follows:

Chapter 1: Introduction

The chapter includes a brief introduction of the topic, scope and significance of the study, statement of the problem, research questions, objectives of the study, major hypotheses, operational definitions of important variables, and limitations of the study.

Chapter 2: Literature Review

The chapter includes the existing literature reviews based on the topic under study.

Chapter 3: Research Methodology

The chapter elucidates the detailed methodology adopted for the study, including the research design, sampling design and a brief explanation of the tools adopted for analysis.

Chapter 4: Relationship between the Stock Market and Equity Mutual Funds in India

The chapter includes the analysis regarding the existence of relationship between the stock market and equity mutual funds in India using various econometric analyses.

Chapter 5: Trend of the Performance of Equity Mutual Funds in India

The chapter explains the trend of the performance of equity funds in India using trend analysis and Auto Regressive Integrated Moving Average (ARIMA) model.

Chapter 6: Nature and Extent of Behavioural Bias of Equity Mutual Fund Investors

The chapter covers the profile of investors, various behavioural biases and how it varies among investors with regard to different socio-economic factors.

Chapter 7: Behavioural Bias and Investment Performance among Equity Mutual Fund Investors

The chapter discusses the influence of behavioural bias among investors on their equity fund performance in Kerala.

Chapter 8: Findings and Conclusions

The chapter presents the findings and conclusions emerging from the present study.

Chapter 9: Recommendations

The chapter includes the recommendations, implications and scope for further research.

Chapter 2

REVIEW OF LITERATURE

Contents

2.1 Introduction

Equity mutual funds are regarded as the best investment avenue for long-term investment. Despite the higher returns they provide, investment in mutual funds is low in India when compared to other investment options. Several studies have been conducted in the field of mutual fund investment, covering its different aspects. The findings, analytical framework and policy proposals developed by the researchers are remarkable. Although some of the studies are comprehensive, some gaps still persist. An extensive literature review has been done to understand the various studies conducted in this field and to find out the research gap.

2.2 Review of Literature

The existing literature reviews made for the present study are presented as follows:

2.2.1 Relationship between the Stock Market and Mutual Funds

Despite the fact that there have been numerous studies on mutual funds in India, research on the relationship between mutual funds and the stock market is limited.

Gupta, Mathur, and Singh (2021) have examined the long-run relationship between returns of equity mutual funds and stock market indices in India. Johansen's cointegration test and Engle-Granger cointegration test have been used to analyse the linkage between them. A strong long-run relationship has been found between equity mutual funds and stock market indices.

Ardhani, Effendi, and Irfany (2020) studied the short-term and long-term relationship of Islamic mutual funds' net asset values with the inflation rate, exchange rate, money supply and gross domestic product in Indonesia. It was found that none of the variables influenced the net asset values of mutual funds in the short run. Inflation, money supply and GDP influence the net asset values in the long term, whereas the exchange rate has no significant effect on the mutual funds' net asset values.

Agarwal and Khan (2019) studied the effect of macroeconomic variables such as exchange rate, gold price, crude oil price, silver price, money supply, interest rate, foreign exchange reserves and stock market indices on gold mutual funds and energy mutual funds. Interest rates and foreign exchange reserves have had a greater effect on gold funds. There was a low degree of cointegration between macroeconomic variables and the energy funds.

Qureshi, Kutan, Ismail, and Gee (2017) examined the relationship between stock market volatility and mutual fund flows in emerging markets in Asia by employing a panel VAR model. A positive relationship was found to exist between equity fund flows and market volatility, whereas market volatility moves inversely with movements in balanced fund flows.

Othman, Kameel, and Aziz (2015) studied whether there exists a causal relationship between the prices of Islamic equity unit trust funds and certain macro-economic variables of the Malaysian economy, such as the consumer price index, industrial production index, treasury bill rate, money supply, crude oil price, foreign exchange rate, national political elections and corruption index. VECM and Granger causality tests have been employed for the study. It has been found that political elections, the industrial production index and the financial crisis have a unidirectional causal relationship with fund unit prices. The results imply that a bi-directional causal relationship exists between crude oil prices and fund unit prices. There was no causality among the Treasury bill rate, money supply, foreign exchange rate, corruption index and fund unit prices.

Aydogan, Vardar, and Tunc (2014) have studied the dynamic relationship between mutual fund flows and stock returns in the Turkish stock market. Their study revealed the existence of a long-run relationship between all categories of mutual fund flows and stock returns. Results of the Granger Causality test indicate that bidirectional causality exists between mutual fund flows and stock returns.

Deo (2014) analysed the cointegration among four Indian stock market indices, namely, CNX Mid-cap, CNX Small-cap, CNX Nifty and CNX Nifty 500. Johansen's cointegration test and the Engle-Granger cointegration test have been used to test whether a long-term relationship exists between the variables. At least one cointegrating equation has been found among the indices, which indicates the presence of a long-run relationship.

Jebran (2014) explored the dynamic linkage between the stock market of Pakistan and the stock markets of India, Indonesia, China, Malaysia and Sri Lanka. He used correlation matrix to find an association between stock markets and evidence of integration between the Indian and Indonesian equity markets was found. The long-run relationship between the variables was examined using the Johansen and Juselius co-integration approach. Only one cointegrating equation was found. Srilankan stock market was found to be granger caused by Indian, Malaysian and Indonesia stock markets. The study revealed that there is no long-term relationship between the Pakistan stock market and other stock markets.

Pojanavatee (2014) examined the dynamic linkage between the stock market and equity funds in Australia using Johansen's cointegration and VECM-based causality tests. The evidence of cointegration and causality indicates the possibility of gaining from arbitrage. A causal relationship was found to run from mid-cap and small-cap funds to large-cap equity funds. The long-run pricing of Australian equity funds is cointegrated with the stock market index.

Al-Jafari, Salameh, and Asil (2013) examined the relationship between mutual funds and the Amman stock exchange index in Jordan. Error correction model and Granger causality tests have been applied for the study. The results indicate that the Amman Stock Exchange Index exerts influence on mutual funds. However, mutual funds did not exert influence on the Amman stock exchange index.

Alexakis, Dasilas, and Grose (2013) examined whether there exists a causal relationship between Japanese mutual fund flows and stock index prices. They used hidden cointegration approach and crouching error correction model for analysis. Mutual funds and stock prices were found to be cointegrated. Bi-directional causality was found in the case of positive movements, whereas causality was found to move from funds to stock prices in the case of negative movements.

Bose (2012) examined the dynamic relationship between mutual fund flows and FIIs in India, on the basis of post-crisis data for the period 2008–2012. Granger causality analysis within a VAR framework has been employed to investigate the relationship between them. From the empirical results, it is evident that net investments by FIIs exert a causal influence on stock market returns.

Mishra (2011) examined the causal relationship between mutual fund investment flows and stock market returns in India. Augmented Dickey-Fuller test has been used to check for the presence of unit root. They applied the Toda and Yamamoto procedures of the Granger causality test. They found that a unidirectional causality runs from stock market returns to mutual fund investments in India.

Ben-Rephael, Kandel, and Wohl (2011) explored the relationship between mutual fund flows and stock market returns. The findings suggest that fund flows are positively autocorrelated with market returns. Moreover, one-half of the price change was found to be reversed within 10 trading days.

Burucu and Contuk (2011) analysed whether there exists any long-term relationship between investment fund flows and stock returns in Turkey. A long-term relationship was found between them by conducting Johansen's cointegration tests. The Granger causality test showed no evidence of causality between investment flows and stock returns.

Ho, Ernst, and Zhang (2011) examined the size effect of large-cap stocks and small-cap stocks over long-term investment. The macroeconomic variables, such as industrial production and 3-month Treasury bill rates, have been used along with the stock prices for the study. Multivariate cointegration results showed the presence of one long-run cointegrating vector. Large-cap and small-cap stock prices exhibited a negative long-run relationship. They concluded that the size effect exhibited predictable reversals in the case of long-run investment.

Chu (2010) employed a cointegration test to examine whether long-run linkage exists between equity funds of the Hong Kong Mandatory Provident Fund (MPF) and benchmark indices of the Hong Kong Investment Fund Association. They used the Granger causality test to analyse the short-run relationship between the variables. More than half of the equity funds are found to be cointegrated with the stock market index and some of the funds exhibited short-run linkage with the stock market.

Hossain, Rahman, and Rajib (2009) have examined the relationship between mutual funds' returns and the stock market index of the Dhaka stock exchange using Johansen's cointegration and the variables were found to be cointegrated. Bi-directional causality was found between DSE general index turnover and mutual fund returns. A unidirectional causality was found to move from mutual funds' return to DSE general index return, mutual funds' return to mutual funds' turnover and DSE general index turnover to mutual funds' turnover.

Rakowski and Wang (2009) explored the relationship between mutual fund returns and daily fund flows within a VAR framework. A positive relationship was found between past fund flows and future fund returns. However, no relationship exists between fund flows and future fund returns when monthly data is used.

Mukherjee and Bose (2008) investigated the movement of the Indian stock market with other stock markets in Asia and the USA by applying cointegration, VECM, vector autoregression and Granger causality. The Indian stock market is influenced by the US stock index and that of other Asian countries and more significantly Indian market returns highly influence the pricing of other Asian markets.

Oh and Parwada (2007) studied the relationship between mutual fund flows and stock market returns in Korea. The Granger causality test has been employed for analysing the data. A positive relationship was found to exist between mutual fund flows and stock market returns. Further, the empirical evidence suggests that stock purchases granger-cause returns.

Alexakis, Niarchos, Patra, and Poshakwale (2005) examined the causality between mutual funds and stock returns in Greece. The Granger causality test has been employed in the study. They found that there was a bi-directional causality between mutual funds and stock returns. The results of cointegration implied that mutual funds cause stock returns to fall or rise.

Matallin and Nieto (2002) analysed whether Spanish stock funds can be used as an alternative to direct investing in the stock exchange through investing in the stock index Ibex 35. Cointegration was used to determine the long-run relationship between the funds and Ibex 35. 11 funds out of 63 were found to be cointegrated with Ibex 35. Hence, it was found that those funds could be used as a passive investment strategy.

Edelen and Warner (2001) have examined the relationship between returns and fund flows into US equity mutual funds. A strong association has been found between fund flows and returns on the previous day. Investors have been found to take an overnight period to react to market information.

Gregoriou and Rouah (2001) examined whether cointegration exists between hedge funds and stock market indices in Zurich. The monthly net asset values of the 10 largest hedge funds and the closing values of stock market indices were collected and analysed. While two hedge funds were found to be cointegrated with stock market indices, the rest of them were not found to be cointegrated with the market indices.

Bailey and Lim (1992) examined the correlation between the US stock market returns and country returns. Daily and weekly returns of 19 country funds have been used for the study. The results indicated the presence of a correlation between stock returns and fund returns. In addition to the above, the prices of country funds exhibit similar behaviour to domestic stocks compared to the foreign stocks in which these funds were invested.

2.2.2 Trend of the Performance of Mutual Funds

Pastor and Vorsatz (2020) explored the performance and flows of actively managed mutual funds in the USA during the COVID-19 crisis period of 2020. Regression analysis has been employed in the study. The empirical evidence suggests that most active funds underperformed the benchmarks during the period. Moreover, funds with high sustainability ratings performed well. The investors seemed to focus on sustainability during the crisis period.

Alam (2019) explored the stock selection and market timing abilities of fund managers in India from April 2000 to March 2018. They employed the CAPM, Fama-French and Cahart models for analysis. The results revealed that, for a small number of equity funds, the fund managers exhibit positive stock selection skills by using single and multifactor models. They concluded that the fund managers have limited stock selection and market timing abilities.

Li, Yang, and Li (2017) have used the ARIMA model to analyse and predict the Shanghai Composite Index. The results indicate that the index will rise in the future, providing investors with a basis for anticipating the future of the market.

Petrevska (2017) has identified a model that best describes and forecasts future international tourism demand. Box–Jenkins ARIMA methodology has been used for modelling the data. He advocated that even though the accuracy of the proposed ARIMA model can be regarded as good, valid and satisfactory, the model is still not highly accurate due to the presence of several structural outbreaks during the sample period.

Rapoo and Xaba (2017) studied the forecasting performance of Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Network (ANN) models with published exchange rates obtained from South African Reserve Bank (SARB). The forecasting performance of the models has been measured using MSE and MAE. The superiority of the ARIMA model over the ANN model has been revealed in the study.

Baral and Das (2016) analysed the growth trend of the Indian mutual fund industry. The sector-wise analysis revealed that the share of public sector mutual funds decreased from 2003–04 to 2014–15, whereas, the share of private sector mutual funds increased, which indicates the significant role played by private sector funds in the industry.

Guha and Bandyopadhyay (2016) have employed the ARIMA model in order to forecast the price of gold in India. Data for the period November 2003 to January 2014 were used. ARIMA (1,1,1) has been selected as the best model that enables forecasting the future prices of gold.

Gowri and Deo (2015) used the ARIMA methodology to model selected funds of mutual funds. The daily NAVs of four growth-oriented schemes were taken for the study. The validity of the models was tested by comparing the future NAVs of the funds with those of the forecasted data. No significant difference was found in their returns and the forecasts showed sustainable returns.

Panda, Mahapatra, and Moharana (2015) examined the risk-return performance of mutual funds, market timing ability and stock selection ability of the fund managers in India from January 2008 to December 2013. Treynor ratio, Jensen’s Alpha and Henriksson-Merton models were used for measuring the performance and fund managers' abilities. The results indicated that the managers with very few funds exhibited superior returns. The fund managers exhibited average stock selection skills. Furthermore, no market timing abilities were present among them.

Adebiyi, Adewumi, and Ayo (2014) have used the ARIMA model of forecasting for the prediction of stock prices. The results obtained demonstrated the potential of ARIMA models for stock price prediction which enables investors to make profitable investments. They concluded that ARIMA models have the capability to compete with emerging forecasting techniques in short-term prediction.

Pal and Chandani (2014) evaluated the performance of selected equity mutual funds in India. They have employed CAGR, expense ratio, standard deviation, Sharpe ratio, Beta and R-squared for analysis. The HDFC Mid-cap Opportunities Fund was found to be the best-performing fund among the other funds considered for the study.

Plantier (2014) documented the global growth of long-term mutual funds. It is implied that the mutual fund industry has witnessed notable growth during the period 1993–2013 in the USA, Asia-Pacific, Europe and the rest of the world. The cross-country statistical analysis results indicate that the ratio of long-term mutual funds tends to grow with the increase in per-capita income.

Rodriguez (2014) examined the ability of world fund managers in forecasting the funds. Domestic differential exposure and assertion rates were used to examine the forecasting ability. The average forecasting ability was found to be negative, which revealed that fund managers have failed to effectively manage their funds.

Anish and Majhi (2013) presented a FLANN-based net asset value technique for prediction to dig out the patterns hidden in the mutual funds. In this paper, a trigonometric expansion-based financial model has been developed for NAV prediction. They suggested that FLANN exhibited better results in terms of complexity, convergence, MAPE and RMSE.

Bollapragada, Savin, and Kerbache (2013) forecasted the prices of exchange-traded funds using simple linear regression, multiple regression, single exponential smoothing, Holt's exponential smoothing, and Box-Jenkins (ARIMA) models. They inferred that multiple regression had provided the best results in forecasting the prices of exchange-traded funds.

Devi, Sundar, and Alli (2013) have estimated the best model for the four top Nifty Midcap 50 companies. The accuracy of the models was predicted using the Akaike information criterion and the Bayesian information criterion. The trend predictions recommend that investors make investments in the index with a lower percentage of error.

Priyadarshini and Babu (2012) evaluated the interaction effects of various economic factors that influence the net asset values of mutual funds in India and forecasted the future net asset values using regression analysis and an artificial neural network and compared the performance of the two methods. The results indicated that artificial neural networks outperformed regression analysis in forecasting the net asset values of the funds.

Soongswang and Sanohdontree (2011) analysed the performance of open-ended mutual funds in Thailand and investigated whether their returns outperformed the market. Data Envelopment Analysis (DEA) and Pearson's correlation coefficients have been used for analysis. The results imply that the open-ended mutual funds outperform the market and their performance has sustained for at least three months.

Tripathy (2006) evaluated the market timing abilities of fund managers of 31 tax planning schemes in India from December 1995 to January 2004. The Jensen andMazuy model and the Henriksson and Merton model have been employed in order to find out the market timing abilities of the fund managers. They inferred that the fund managers were timing the market in the wrong direction, which means that they failed to earn better returns.

Redman, Gullett, and Manakyan (2000) explored the performance of international mutual funds in the US market using Sharpe's index, Treynor's ratio and Jensen's alpha. The study period was 1985–1994, 1985–1989, and 1990–1994. The results imply that during 1985–1994, the international mutual funds outperformed the stock market index as per Sharpe's index and Treynor's ratio. Further, the international mutual funds outperformed the US market and domestic portfolio during 1985–1989, whereas the returns declined below the US market and domestic mutual funds during the period 1990–1994.

Jayadev (1996) explored the performance of two growth mutual funds, namely, Mastergain and Magnum Express, based on their monthly returns. Sharpe's ratio, Treynor's ratio, and Jenson's measures were used for evaluating their performance. The results revealed that Mastergain performed better as per Treynor and Jenson's measures, whereas it underperformed as per the Sharpe ratio. Further, Magnum Express exhibited poor performance according to all three measures.

Hurcich and Tsai (1989) have studied the regression and time series model selection in small samples, of which the primary focus was the Akaike Information Criteria (AIC). The study also discussed the applications of non-stationary autoregressive and moving average time series models and they inferred that AIC is the best model selection criteria when compared to its competitors.

2.2.3 Behavioural Finance

Ainia and Lutfi (2019) analysed the effect of risk perception, risk tolerance, loss aversion and overconfidence on investment decision-making. Risk perception has been found to have a negative effect on investment decision-making, whereas risk tolerance and overconfidence have a positive effect. On the other hand, loss aversion does not have an effect on investment decision-making.

Cheng (2019) investigated whether investors exhibit selective information acquisition, which is a source of confirmation bias. The findings of the study indicate the evidence for information preference that is consistent with confirmation bias exists among investors. However, there was no direct evidence of confirmation bias.

Niessen-Ruenzi and Ruenzi (2019) examined whether gender bias exists among mutual fund investors. They found that investors invest less money in female managed funds. Female fund managers are found to follow more reliable investment styles and their investment performance seems to be more stable compared to male managers. Their results imply that gender bias affects investment decisions, which further contributes to the lower participation of women in the mutual fund industry.

R and Christie (2019) explored the influence of investors' annual income on the behavioural biases exhibited by them, such as anchoring, availability, mental accounting, gambler's fallacy, regret aversion, loss aversion, representativeness and overconfidence. Data for the study were collected from 436 equity investors in Chennai through pre-structured questionnaires. ANOVA and correlation analysis were used for analysing the data. The empirical evidence suggests that the annual income of investors had a significant effect on all the biases except regret aversion and gambler's fallacy. Further, the results imply that, in the case of overconfidence bias, investors with higher annual income were prone to overconfidence bias than those having lower income, whereas for rest of the significant biases, investors with lower annual income were more affected.

Antony and Joseph (2017) examined the effect of behavioural factors on the investment decisions of investors in Kerala. Representativeness bias, overconfidence, mental accounting, regret aversion and herd behaviour were the factors considered for the study. They concluded that overconfidence exerts the greatest impact on the investment decisions of investors, whereas herd behaviour has the least effect.

Hadi (2017) examined the effect of emotional intelligence on investment decisions with a moderating role of financial literacy. Financial literacy facilitates investors having better control over their emotions and investors who have more control over their emotions are found to be better decision-makers. A positive relationship was found between the financial literacy of investors and their investment decision making.

Jonson, Soderberg, and Wilhelmsson (2017) analysed the impact of financial literacy, risk attitude, and saving motives of mutual fund investors on the attenuation of their disposition bias by employing ordinal logistic regression. It has been found that mutual fund and market knowledge had an impact on investors' dispositions. They also conclude that men are less susceptible to disposition bias than women.

Ghelichi, Nakhjavan, and Gharehdaghi (2016) explored the influence of psychological factors such as confidence, beliefs, a sense of remorse and regret and snake bites on investment decisions by investors in the Tehran stock exchange. Data were collected from 384 investors through pre-structured questionnaires. Structural equation modelling was employed for the analysis of the data. The results imply that confidence and belief positively influence investment decisions, whereas, sense of remorse and snake bites negatively influence investment decisions.

Gupta and Sharma (2016) analysed the investors' satisfaction level with mutual fund companies and the risk minimization level of these companies. Data were collected from 90 investors in Jaipur city through questionnaires. They found that risk bearing capacity was higher in the case of investors with higher income and they highly tend to invest in mutual funds.

Irshad, Badshah, and Hakam (2016) examined the effect of representativeness bias on investment decisions among investors in the Islamabad stock exchange. Data were collected from 120 investors through pre-structured questionnaires. Regression analysis was used in the study. The results suggest that representativeness bias has a positive effect on investment decisions among investors.

Kubilay and Bayrakdaroglu (2016) studied the relationship between personality traits of investors, psychological biases and their financial risk tolerances. The study was conducted among individual investors trading in Istanbul. A chi-square test and logistic regression were used for analysing the data. It was found that a significant relationship exists between the personality traits of investors and their psychological biases. They also claimed that the financial risk tolerance of investors was affected by their personality traits.

Kumar and Goyal (2016) examined the relationship between rational decision making and behavioural biases among individual investors and how demographic variables influence the rational decision making process. They found that male investors are more prone to herding bias. Investors in higher income group are found to be less confident than investors in low income group. Furthermore, older investors are found to be less susceptible to the disposition effect.

Bodnaruk and Simonov (2015) studied the effect of financial expertise on investment. They found that the financial experts were not making better investment decisions. They do not outperform others, do not diversify risks and do not exhibit lower behavioural biases. They conclude that financial expertise does not influence investment decisions.

Daniel and Hirshleifer (2015) discussed the role of overconfidence in financial markets. They reviewed two sets of empirical findings, which were that the trading volumes were excessive and the security returns were predictable. They have used models of investor trading and security prices that consist of different aspects of overconfidence. The results indicated that investors who neglect information for trading would trade excessively; hence, such neglect would influence the prices.

Geetha and Vimala (2014) explored the influence of gender, age, education, occupation and income of investors on their risk-taking abilities. The data were collected from 500 investors in Chennai city. Descriptive statistics along with chi-square tests have been employed in the study. A significant relationship was found between income level and the risk-taking ability of investors.

Mishra and Metilda (2015) studied the impact of investment experience, education level and gender on behavioural biases such as self-attribution bias and overconfidence bias. Investment experience had a significant impact on self-attribution bias and overconfidence bias. The study revealed that overconfidence and self-attribution bias increase as the level of education increases. Men were found to be more overconfident than women. But there is no statistically significant difference in self-attributive bias between male and female investors. However, no significant association was found between self-attribution bias and overconfidence bias.

Mobarek, Mollah, and Keasey (2014) explored country-specific herding behaviour in the European stock market. They included continental Europe (France and Germany), the Nordic countries (Sweden, Denmark, Finland and Norway), and the PIIGS countries (Portugal, Italy, Greece and Spain) as samples in the study. Daily stock returns for a panel of European markets are used in the study. Regression analysis was used for analysing the data. They found evidence for herd behaviour across many markets in Europe. The findings imply that herd behaviour was significant in Europe during crises and extreme market conditions.

Onsomu (2014) examined whether the investors at the Nairobi Securities Exchange are affected by various behavioural biases. They also analysed whether these biases had any significant relationship with the gender of the investors. No significant correlation was found to exist between representativeness bias, overconfidence bias, availability bias, the disposition effect, confirmation bias and gender.

Zindel, Zindel, and Quirino (2014) demonstrated that behavioural finance contributes to a better understanding of the decision-making process. Cognitive illusions, heuristics and cognitive biases lead to faulty decisions rather than rational ones. Understanding and letting the investors know about the cognitive illusions would help them make investment decisions more appropriately.

Lakshmi, Visalakshmi, Thamaraiselvan, and Senthilarasu (2013) analysed the relationship between investment decisions of long-term and short-term Indian investors and certain behavioural traits such as herding, representative heuristics, social contagion, overconfidence, the disposition effect, risk aversion and cognitive dissonance. They found that long term investors exhibited low levels of overconfidence and weak herding behaviour, whereas short-term investors exhibited a high level of overconfidence and strong herding behaviour. Short-term investors possess low levels of risk aversion, the disposition effect and cognitive dissonance, whereas they are high in the case of long-term investors.

Rekik and Boujelbene (2013) examined the impact of demographic and behavioural factors on the investment decisions of investors in the Tunisian stock market. Factor analysis has been employed in the study. They found that representativeness, loss aversion, herding attitude, mental accounting and anchoring have significant influence on the investors' decision-making. Moreover, it was concluded that gender, age and experience exerted influence on their investment decisions.

Bailey, Kumar, and Ng (2011) examined the effect of the behavioural biases of mutual fund investors on fund choices. They considered disposition effect, narrow framing, overconfidence, local bias, lottery stock preference, inattention to earnings news, inattention to macroeconomic news, fund-level local bias, and fund-level inattention to analyse the effect of biases on investment decisions. Factor analysis revealed that the biased investors conform to five types of stereotypes such as gambler, smart, overconfident, narrow framer and mature. Highly biassed investors tend to invest in funds with higher expense ratios and higher loads, resulting in poor investment performance.

Sadi, Asl, Rostami, Gholipour, and Gholipour (2011) examined the relation between investors' personalities and perceptual errors in the Tehran stock market.

Data were collected from 200 investors through pre-structured questionnaires. Parametric analysis and correlation were used for analysis. Direct correlation was found between extroversion and openness with hindsight bias and overconfidence, while, reverse correlation was found between conscientiousness and randomness with openness and availability bias.

Dash (2010) explored the factors that affect an individual's investment decision and how these factors impact the risk tolerance levels and investment decisions of investors belonging to different gender and age groups. A pre-structured questionnaire was used for data collection. Factor analysis has been employed for the analysis of the data. The results suggest that age and gender have an influence on the risk-taking ability of investors.

Al-Tamimi and Kalli (2009) examined the relationship between financial literacy and the factors affecting investment decisions. The most influencing factors on investment decisions were found to be religious reasons, perceived ethics of the firm, diversification purpose and reputation of the firm, whereas, the least influencing factors were found to be rumours, the ease of obtaining borrowed funds, opinions of family members and recommendations from friends.

Glaser, Langer, and Weber (2007) attempted to test the trend recognition and forecasting abilities of financial professionals. Probability estimates and confidence intervals were the two methods of trend prediction used in the study. It has been found that the degree of overconfidence was positively correlated for the experimental subjects. Furthermore, the results imply that professional traders have been more overconfident than students in trend prediction tasks.

Agnew (2006) examined the individual characteristics of behavioural biases with a view to determining whether propensities to follow biases vary across individuals. They found that higher-salaried employees tend to make significantly better decisions. Women were found to make better decisions in 401(k) participation and investment in company stocks. The study also found the evidence of mental accounting.

Brozynski, Menkhof, and Schmidt (2006) investigated the impact of experience on overconfidence, risk-taking, and the herding of fund managers. Data were collected from 117 fund managers in Germany. Their analysis regarding the impact of experience on overconfidence yields mixed results. Further, experienced fund managers were less affected by herding bias and the degree of risk taking has also been found to decrease with experience.

Massa and Simonov (2003) examined the ways in which investors react to prior gains or losses. They found that on a yearly horizon, investors do not behave according to loss aversion. They behave according to the house money effect and the standard utility theory. Their study also found that the investors are not affected by mental accounting bias.

Barber and Odean (2001) examined whether overconfidence among investors leads to excessive trading based on the gender to which they belong. They proved that men are more overconfident than women and trade more. They also established that overtrading causes men to perform worse and earn lower returns than women.

Donkers, Melenberg, and Soest (2001) examined the factors that affect the risk attitude of an individual. The data were collected from Dutch households. A strong relationship was found to exist between risk aversion and income level. Furthermore, the individuals with high income levels were found to be less risk averse.

Hirshleifer (2001) categorised the various cognitive errors of investors. They explained that self-deception occurs due to the tendency of people to think that they are better than they really are, heuristic simplification occurs due to the limited attention and processing capabilities of individuals and the individuals affected by the disposition effect are prone to sell winning stocks too soon and hold on to losing stocks for too long.

Camerer and Lovallo (1999) explored whether optimistic behaviour influences entry into competitive markets. They explained that frequent failures are due to the limited opportunities to make money and bounded rationality. From their experimental research, they arrive at the conclusion that overconfidence leads to excessive entry into markets.

Barberis, Shleifer, and Vishny (1998) proposed a model of investor sentiment that is consistent with the heuristic of representativeness. They found that stocks underreacts to good news such as earings announcements. On the other hand, investor sentiment displays an overreaction of stock prices to consistent good or bad news.

Grinblatt, Titman, and Wermers (1995) examined the extent to which stocks are purchased by mutual funds based on their past returns and their tendency to exhibit herd behaviour. They found that 77 percent of the funds bought stocks which are past winners. They also found evidence of herding in the mutual funds.

Eagly and Carli (1981) explored whether men and women differ in the way they are influenced. Meta-analysis has been employed in the study. The results suggest that females are more conforming and persuadable than their male counterparts. Due to a lower level of confidence among females, they were found to be more prone to herding bias than males.

Bradley (1978) analysed the evidence related to self-serving biases in the attributions of causality. In the works reviewed by him, it was found that individuals tended to accept responsibility for the positive outcomes, whereas they denied responsibility for the negative outcomes. Evaluations made by others of one's performance are found to be the central theoretical factor underlying the effects of publicity.

2.2.4 Influence of Behavioural Bias on Investment Performance

Lebdaoui, Chetioui, and Ghechi (2021) explored the impact of behavioural biases and financial literacy on investment performance. Data were collected from a sample of 196 Moroccan investors. Financial literacy was found to be negatively related to overconfidence and positively related to representativeness.

Overconfidence and representativeness were the most significant biases among the Moroccan investors. The results also indicate that overconfidence and representativeness exert a significant impact on investment performance.

Keswani, Dhingra, and Wadhwa (2019) examined the impact of behavioural factors on investors' investment decisions and on their investment performance at the National Stock Exchange. Heuristic theory, prospect theory, market factors and the herding effect were the behavioural factors used in the study. Exploratory factor analysis and multiple regression tests have been used for analysis. The variables are found to have greatly influenced the investment decision and return on investment.

Alrabadi, Al-Abdallah, and Aljarayesh (2018) examined whether behavioural biases exist among investors at the Amman Stock Exchange and their effect on their investment performance. They also studied whether these biases differ between male and female investors. The results indicate that overconfidence bias, loss aversion bias, familiarity bias, disposition bias, representativeness bias, confirmation bias, availability bias and herding bias have a significant effect on investment performance. No significant difference was found between males and females.

Ibrahim and Umar (2017) analysed the effects of behavioural factors on the investment performance of investors in the Nigerian capital market. Multiple regression has been used for analysing the data. It was found that behavioural factors, including prospect factors, herding factors, heuristic factors and rationality factors, have a positive and significant influence on investment performance.

Javed, Bagh, and Razzaq (2017) examined the effect of herding bias, overconfidence, representativeness and availability bias on the perceived investment performance of investors in the Pakistan stock exchange. The judgmental sampling technique has been used for sampling purposes. Regression has been used to analyse the data collected through questionnaires. The results imply that herding bias, overconfidence, representativeness and availability bias had a significant positive impact on perceived investment performance.

Kumari and Sar (2017) investigated whether herd behaviour, overconfidence and risk tolerance influence the investment performance of investors in East India. Data were collected using pre-structured questionnaires from 106 investors. Descriptive statistics, followed by multiple regression, have been applied for data analysis. The results indicate that market-wide herding under herding bias, unrealistic optimism and dispositional optimism under overconfidence and speculative risk and calculative risk under and risk tolerace influence the investment performance of investors.

Aziz and Khan (2016) analysed the behavioural biases that influenced the investment decisions and performance of investors at the Pakistan Stock Exchange. Variables were taken on the basis of heuristics and prospect theory. Regression was used to analyse the data collected from the investors. Biases based on heuristics had a positive relationship with investment performance, while biases based on prospect theory have a negative relationship with investment performance.

Kengatharan and Kengatharan (2014) analysed the behavioural factors influencing the investment decisions of individuals at the Colombo stock exchange and their influence on investment performance. Herding, prospect, heuristics and market factors were found to be the factors affecting investment decisions. Choice of trading from the herding factor and overconfidence from the heuristics factor had a negative significant influence on investment performance, while anchoring from the heuristics factor had a positive influence on investment performance.

Ranjbar, Abedini, and Jamali (2014) examined the relationship between heuristic factors, prosepct theory and herding behaviour on the investment performance of investors in the Tehran stock exchange. Structural equation modelling has been used for analysis. The results revealed that heuristics and herding behaviour influence the investment performance of investors positively, whereas prospect variables influence investment performance negatively.

Park et al. (2010) explored whether psychological factors influence investors' information processing from virtual communities and whether it influences their investment performance. The data were collected from 502 investors in South Korea. The results imply that there exists a significant confirmation bias among investors in Korea. Furthermore, confirmation bias among investors leads to higher levels of overconfidence, which adversely affect investment performance.

Oh, Parwada, and Walter (2008) made a comparative study of the trading behaviour and performance of online equity investors with that of non-online investors in Korea. The trading activity of individual traders, local institutions and foreign investors has been studied. The findings indicate that the performance of non-online investors was better than that of online investors. The best returns were made by the foreign investors compared to the other investor types.

Grinblatt and Keloharju (2000) attempted to study the behaviour and performance of different types of investors in Finland. They examined the influence of past returns on the propensity to buy and sell. A binomial parametric test has been used for analysing the data. The results indicate that foreign investors pursue momentum strategies, whereas domestic investors pursue contrarian strategies when making investments.

2.3 Research Gap

The extensive literature review and the researchers' experience brought a sharp focus on the research gap, which is identified as follows:

1. At present, there are limited studies undertaken to analyse the relationship between equity mutual funds and the stock market in India.

2. Many studies have been conducted in the field of mutual fund performance evaluation. But only a few studies have focused on forecasting the future performance of equity mutual funds.
3. Only a limited number of studies were conducted to assess the behavioural bias of equity mutual fund investors.
4. No studies have been found to examine the impact of investors' behavioural biases on the investment performance of equity mutual fund investors.
5. So far, there is rarely any study of this area in India, particularly in Kerala.

Thus, the findings of this study would certainly contribute to filling the existing gap in the concerned research area.

Chapter 3

RESEARCH METHODOLOGY

Contents

3.1 Introduction

The present study pertains to examining the influence of behavioural bias on the investment performance of equity mutual fund investors in Kerala. The first two objectives are to examine the long-run relationship between the stock market and equity mutual funds in India and to analyse the trend of the performance of equity mutual funds in India. The third objective of the study is to analyse the nature and extent of behavioural bias among equity mutual fund investors in Kerala with regard to different socio-economic variables and the fourth objective is to analyse the influence of behavioural bias among equity mutual fund investors on their investment performance. To fulfil the first and second objectives, the researcher has used secondary data obtained from the websites of AMFI, BSE and different asset management companies in India. Primary data was collected from equity mutual fund investors in Kerala for the third and fourth objectives, which was then analysed using various statistical tools. The following methodologies were used in the study:

3.2 Research Design

The study is both descriptive and analytical in nature. The study is descriptive in nature, as it describes the characteristics of the investors. The study is analytical because it developed the hypotheses and used various statistical tools to test them.The study is based on both secondary and primary data.

3.2.1 Source of Data

3.2.1.1 Secondary Data

The secondary data source for the study include journals, books, publications and websites of various mutual fund companies, websites of AMFI, NSE, BSE, SEBI, World Bank, IMF and government publications.The reports of CRISIL, RBI, MOSPI and various other wealth management organizations have also been considered.

3.2.1.2 Primary Data

Primary data for the study have been collected from individual equity mutual fund investors. The equity mutual fund investors in Kerala constitute the target population. Since the population is infinite, census survey is not possible. Hence, sample survey is used.

3.2.2 Sampling Design

Two sets of samples are required to fulfill the objectives of the study: sample equity mutual funds and sample equity mutual fund investors.

3.2.2.1 Selection of Equity Mutual Funds

As per SEBI guidelines, equity mutual funds are classified into various types based on their market capitalisation and investment strategy. In this study, equity mutual funds classified based on market capitalisation are considered.

The classification of equity mutual funds as per market capitalisation is as follows:

i. Large-cap fund: At least 80% of its assets are invested in large-cap stocks.
ii. Large and Mid-cap fund: At least 35% of its assets are invested in large-cap stocks and 35% in mid-cap stocks.
iii. Mid-cap fund: At least 65% of its assets are invested in mid-cap stocks.
iv. Small-cap fund: At least 65% of its assets are invested in small-cap stocks.
v. Multi-cap fund: At least 65% of its assets are invested in equity and equity-related instruments.

Since the multi-cap funds invest in stocks of varying market capitalisation, only the first four categories of equity mutual funds are considered for the study.

The funds that have outperformed the benchmark for most of the years out of the past 11 years (2011-2021) have been taken as samples for the study. The following funds have been selected from each of these categories:

Large-cap fund: Canara Robeco Bluechip equity fund
Large and Mid-cap fund: Mirae Asset Emerging Bluechip fund
Mid-cap fund: UTI Mid-cap fund
Small-cap fund: Nippon India Small-cap fund

The daily net asset values of these funds and the Sensex for the period 1st January 2011 to 31st December 2021 have been considered for the study.

3.2.2.2 Selection of Equity Mutual Fund Investors

a. Population of Investors

The target population consists of individual equity mutual fund investors in Kerala. Due to the lack of an official database regarding mutual fund investors and their geographical distribution, the assistance of various banks and stock broking companies engaged in mutual fund investment, such as Geojit BNP Paribas, Motilal Oswal Financial Services, Tata Mutual Fund, Canara Bank and SBI has been sought. Furthermore, many investors are investing in direct funds using applications such as Upstox, Zerodha, Growapp and so on. Hence, it becomes difficult to identify the number of investors in Kerala. However, with the help of the banks and stock broking companies, the details regarding equity mutual fund investors were accumulated.

b. Determination of Sample size of Investors

The data relating to the number of investors and their geographical distribution is unavailable. Hence, the sample size of investors is calculated using the following statistical equation. The highest standard deviation obtained from the pilot study was used in the equation.

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

n = number of sample size

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

S = sample standard deviation (1.2903)

E = acceptable magnitude of error (assumed as 0.129)

$$n_0 = \left(\frac{1.96*1.2903}{0.129}\right)^2 = 19.60456^2 = 384.3387$$

Thus, the sample size of investors has been rounded off to 390.

c. Sampling Method

Multi-stage sampling method has been adopted for collecting primary data from investors in Kerala. In the first stage, the districts in Kerala have been classified into three groups based on the number of branches of mutual fund AMCs present. Mutual fund AMCs have their presence in 11 districts in Kerala, which are Thiruvananthapuram, Kollam, Alappuzha, Pathanamthitta, Kottayam, Ernakulam, Thrissur, Palakkad, Malappuram, Kozhikode and Kannur. The districts with the most number of branches of AMCs are Ernakulam, Thiruvananthapuram, Kozhikode and Thrissur. The districts with moderate number of branches are Kottayam, Kannur and Palakkad. The districts with the least number of branches are Pathanamthitta, Kollam, Malappuram and Alappuzha.

In the second stage, one district has been selected from each of these groups as sample districts using simple random sampling method. Kozhikode was selected from the group of districts with the highest number of branches, Kollam from the group with the least number of branches and Kannur from the group with moderate number of branches.

In the third stage, 130 investors were selected from each of these districts. For identifying investors in these regions, the assistance of various banks and stock broking firms engaged in mutual fund investment such as Geojit BNP Paribas, Motilal Oswal Financial Services, Tata mutual fund, Canara Bank and SBI has been sought.

3.2.3 Research Instrument

The researcher has used structured questionnaire as the instrument for collecting the primary data from the sample investors. Initially, a pilot study was conducted among 50 equity mutual fund investors in the Ernakulam district. Several experts in the fields of finance, behavioural finance and research have been consulted and their suggestions were incorporated while preparing the questionnaire to ensure the content validity of the instrument.Based on the pilot study, some of the questions were refined and the questionnaire was finalized.The researcher personally met some of the investors and gave them the questionnaires and mailed them to the rest of them to get the questionnaires filled. The period of the actual survey was from August 2020 to December 2021.

The questionnaire consisted of three parts which are as follows:
Part 1: Questions related to the socio-economic profile of the respondents
Part 2: Questions for collecting the responses related to behavioural bias
Part 3: Questions for collecting the responses related to investment performance

3.2.4 Variables used for the study

The present study examines the nature and extent of behavioural bias with regard to different socio-economic factors and the influence of behavioural bias on the investment performance of equity mutual fund investors in Kerala. For this purpose, the following variables are used.

Table 3.1

Variables Used for the Study

Sl. No.	Nature of the Variable	Name of the Variables
1	Socio-economic Variables	1. Gender 2. Age 3. Education level 4. Occupation 5. Marital status 6. Annual Income 7. Investment Experience
2.	Behavioural bias	A. Belief Perseverance Bias 1. Representativeness Bias 2. Confirmation Bias 3. Cognitive Dissonance bias 4. Illusion of Control Bias
		B. Information Processing Bias 5. Anchoring bias 6. Availability bias 7. Self Attribution bias 8. Mental Accounting bias
		C. Emotional Bias 9. Overconfidence bias 10. Loss Aversion bias 11. Regret Aversion bias 12. Herding bias
3.	Investment Performance	Investment Performance

3.2.5 Reliability Analysis

In the present study, reliability of the measurement scales is tested by using Cronbach's Alpha Reliability Co-efficient. The results of the reliability analysis are presented in table 3.2.

Table 3.2

Reliability Analysis

Sl. No.	Variables	Number of Items	Alpha Value
Behavioural Bias			
1	Representativeness Bias	4	0.807
2	Confirmation Bias	4	0.843
3	Cognitive Dissonance Bias	2	0.810
4	Illusion of Control Bias	3	0.754
5	Anchoring Bias	5	0.844
6	Availability Bias	5	0.786
7	Self Attribution Bias	3	0.787
8	Mental Accounting Bias	2	0.756
9	Overconfidence Bias	6	0.892
10	Loss Aversion Bias	4	0.777
11	Regret Aversion Bias	3	0.778
12	Herding Bias	5	0.851
Investment Performance		3	0.863

Source: Survey Data

Since all the values of Cronbach's alpha are above 0.7, it can be inferred that the scale is reliable in terms of internal consistency (Nunnally, 1967).

3.2.6 Normality Analysis

Normality test determines whether the data set is well-modeled by a normal distribution or not. One sample K-S test is commonly used to examine the normality of data.

Table 3.3

Kolmogorov-Smirnov Test of Normality

Sl. No.	Variables	N	Mean	Std. Deviation	p-value
Behavioural Bias					
1	Representativeness Bias	390	14.37	3.31	.000
2	Confirmation Bias	390	14.56	3.29	.000
3	Cognitive Dissonance Bias	390	7.04	1.80	.000
4	Illusion of Control Bias	390	10.27	2.41	.000
5	Anchoring Bias	390	16.00	4.06	.005
6	Availability Bias	390	17.67	3.67	.000
7	Self Attribution Bias	390	9.92	2.01	.000
8	Mental Accounting Bias	390	7.55	1.55	.000
9	Overconfidence Bias	390	21.21	4.67	.000
10	Loss Aversion Bias	390	13.75	2.86	.008
11	Regret Aversion Bias	390	9.84	2.40	.000
12	Herding Bias	390	16.07	4.12	.001
Investment Performance		390	11.68	2.43	.000

Source: Survey Data

The results in table 3.3 revealed that none of the data set is normally distributed. Hence, the researcher has employed Skewness and Kurtosis tests for checking the normality of the data. Skewness relates to the symmetry or asymmetry of a distribution while kurtosis relates to the peakedness of the distribution. Chou & Bentler (1995) suggested that the data will be normalwhen thevalues of skewness fall between-3and +3 and the values of kurtosis fall between -10 and +10.The studies by Black, Hiar, Babin and Anderson (2006) suggested that the data become normal when the values of skewness and kurtosis are in the range of ± 2.58 and ± 1.98.The results of skewness and kurtosis tests are presented in table 3.4.

Table 3.4

Skewness and Kurtosis Results

Sl. No.	Variables	Skewness		Kurtosis	
		Statistic	Std. Error	Statistic	Std. Error
Behavioural Bias					
1	Representativeness Bias	-.448	.124	-.476	.247
2	Confirmation Bias	.071	.124	-.733	.247
3	Cognitive Dissonance Bias	.155	.124	-.010	.247
4	Illusion of Control Bias	-.003	.124	-.180	.247
5	Anchoring Bias	-.422	.124	.125	.247
6	Availability Bias	.151	.124	.822	.247
7	Self Attribution Bias	-.133	.124	-.949	.247
8	Mental Accounting Bias	.147	.124	-.408	.247
9	Overconfidence Bias	.246	.124	-.451	.247
10	Loss Aversion Bias	-.280	.124	-.059	.247
11	Regret Aversion Bias	-.111	.124	-.473	.247
12	Herding Bias	-.492	.124	.315	.247
Investment Performance		-.661	.124	.171	.247

Source: Survey Data

The results of table 3.4 implied that the skewness and kurtosis values of all the variables fall within the acceptable ranges. Hence, normality can be assumed and parametric tests can be used for analysis in the study.

3.3 Data Analysis

3.3.1 Secondary Data Analysis

1. **Unit Root Tests**

In statistics, unit root tests are used to check the stationarity of the time series data. In the present study, the Augmented Dickey Fuller testis employed to examine whether the data are non-stationary and possess a unit root. Data are said to be stationary when their statistical properties such as mean, variance, etc. are constant over time.

2. **Vector Auto Regression (VAR)**

   VAR is a widely accepted method adopted to determine the optimum lag length of each variable. Various criteria which are used for the selection of optimum lag length are the Likelihood Ratio, Akaike Information Criteria, Final Prediction Error, Hannan- Quinn Information Criteria and Schwarz Information Criteria.

3. **Co-Integration tests**

   Co-integration is a statistical method used to find a possible correlation between time series processes in the long run. Johansen Co-integration test is used to determine the number of co-integrating equations among the variables.

4. **Vector Error Correction Models (VECM)**

   VECM is a co-integrated VAR model. It is used to examine the short-run dynamics and long-run equilibrium of the model.

5. **Causality tests**

   If there is co-integration among the variables, the exogeneity tests are applied based on VECM. Causality refers to the ability of one variable to predict and influence the value of another variable. It reveals which variable is endogenous and which one is exogenous. Engle & Granger (1987) found that a causal relationship exists among variables in one direction if they are co-integrated. In this study, the Granger causality test is applied to examine the causality between the variables.

6. **Variance Decomposition Analysis**

   Variance decomposition is used to assess the proportion of the movement of dependent variables due to their own shock and due to the shock of other independent variables. In this study, Cholesky decomposition is used to obtain variance decomposition.

7. **Impulse Response Function**

   The impulse response function is used to determine the direction, magnitude and duration of the variables in the system which is affected by an external variable's shock. Cholesky decomposition is used to obtain the impulse response of linkages.

8. **Auto Regressive Integrated Moving Average (ARIMA)**

   ARIMA is a statistical analysis model in which time series data have been used to understand the data and to predict the future trends. ARIMA forecasts future values based on past values assuming that the future will resemble the past.

3.3.2 Primary Data Analysis

1. **Mean**

   Mean is a measure which represents the entire data by a single value. It is the average value of the given set of data.

2. **Standard Deviation**

   Standard deviation measures the deviation of values from the mean value. It is the degree of dispersion relative to its mean.

3. **Independent Sample t Test**

   The Independent Sample t-test is used for comparing the means of two independent groups to examine whether significant difference exists between them. Levene's test is used to assess the equality of variances of the group of variables. It tests the null hypothesis that the variance of the group is homogeneous. If the p-value of Levene's test is less than 0.05, the variance is said to be heterogeneous (Garson, 2012). In such cases, the second set of analysis which is 'equal variance not assumed' has to be considered.

4. One-way Analysis of Variance/ Welch F

The One-way ANOVA is used to examine whether significant difference exists among the means of three or more independent groups. The assumption of homogeneity of variance is tested using Levene's test. The null hypothesis is that the variance of the group is homogeneous. If the p-value of Levene's test is less than 0.05, the variance is said to be heterogeneous (Garson, 2012). In such cases, the values of the Welch F test are considered instead of ANOVA.

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

When there existsa significant difference among the independent groups using ANOVA, post hoc tests are employed to examine the exact difference between the groups. Post hoc tests such as the Tukey HSD test and Tamhane's T2 test are widely used. The Tukey HSD test is used when equal variances are assumed and Tamhane's T2 is used when equal variances are not assumed.

6. Multiple Regression Analysis

Multiple regression is a statistical test employed to analyse the relationship between a single dependent variable and many independent variables (Hair, Black, & Anderson, 2015).

Chapter 4

RELATIONSHIP BETWEEN EQUITY MUTUAL FUNDS AND THE STOCK MARKET IN INDIA

Contents

4.1 Introduction

Indian capital market exhibits rapid growth by attracting foreign investments. Many financial innovations have taken place in the past decade, highly contributing to its growth. A bi-directional causal relationship exists between the Indian economy and stock market (Deb & Mukherjee, 2008).The mutual fund industry plays a significant role in the development of financial markets in India. The industry has registered significant growth in terms of its assets under management. The overall size of the Indian mutual fund industry has increased to 38.04 trillion as of April 30, 2022, from 6.80 trillion as of April 30, 2012, a more than 5-and-a-half-fold increase in a decade (AMFI, 2022).

According to the portfolio theory, varying degrees of price co-movements exist between securities in the gains obtained from a diversified portfolio. People can participate in the economic growth of the nation by investing in equity shares. By analysing the history, it is clear that equity shares have been providing huge returns to its investors. But due to lack of knowledge regarding the financial market, common people refrain from making such investments. Also, fixed income-bearing instruments do not have the ability to meet inflation in the economy. However, selecting stocks thatdeliver great returns would be a difficult task that requires adequate knowledge regarding financial markets. Diversification of investment is made possible with the expertise of professional fund managers. Hence, equity mutual funds have been considered as an alternative mode of investment to direct investment in the stock market. However, investors are reluctant to make huge investments in mutual funds due to volatility in the market.

Analysing the degree and direction in which the fund prices move in relation to the stock market index is significant. Alexakis, et al. (2005) examined the relationship of mutual fund flows with stock market returns in Greece and concluded that the cash inflows and outflows in equity funds facilitated higher and lower returns in the stock market, respectively. A strong long-run relationship has been found between equity mutual funds and stock market indices (Gupta, Mathur, & Singh, 2021). Both stock market indices and mutual fund returns seem to be affected by global phenomena. Hence, it becomes imperative to study whether there exists a relationship between equity mutual funds and the stock market in India, which would aid the investors in selecting mutual funds that can be considered as an alternative to shares and facilitate financial experts in formulating policy decisions.

4.2 Data and Methodology

Large-cap funds, large and mid-cap funds, mid-cap funds, small-cap funds and BSE Sensex have been considered for the study. The funds which have outperformed the benchmark for most of the years out of the past 11 years (2011-2021) have been taken as sample for the study. The following funds have been selected from each of these categories:

Large-cap fund: Canara Robeco Bluechip Equity Fund
Large and Mid-cap fund: Mirae Asset Emerging Bluechip Fund
Mid-cap fund: UTI Mid Cap Fund
Small-cap fund: Nippon India Small Cap Fund

The daily net asset values of these funds and the Sensex for the period 1 January 2011 to 31 December 2021 have been considered for the study. Unit root tests are used to determine the order of integration. Vector Autoregression (VAR) has been used for selecting the optimum lag length for the models. The Johansen's cointegration test within a VECM framework has been used to identify the long-run relationships between equity mutual funds and Sensex. The Granger-causality test examines the short-run causality and exogeneity between equity mutual funds and the Sensex. The results of variance decomposition and the impulse response function indicate long-run exogeneity.

4.3 Analysis, Results and Discussion

In this section, the relationship between equity mutual funds and the stock market in India is analysed. Furtherrmore, the empirical results are arrived at and discussed.

4.3.1 Unit Root Test

The research done by Granger and Newbold (1974) indicated the presence of spurious regressions in regressions with non-stationary variables. Stationarity means the statistical properties of a time series do not change over time. If a time series has a unit root, it shows a systematic pattern that is unpredictable. The VAR model is designed for use with non-stationary series that are known to be cointegrated (Chu, 2011).

According to the efficient market hypothesis theory, all publicly available information is reflected in stock prices (Fama, 1970). Then, testing the presence or absence of a unit root among variables can be interpreted as testing the weak-form market efficiency (Groenewold & Kang, 1993). As a result, it is imperative to test the stationarity of variables prior to performing the VAR model analysis. Augmented Dickey Fuller test (Dickey & Fuller, 1981) is used in this study for checking the stationarity of the data. The results of ADF tests are given in Table 4.1.

Table 4.1

ADF Test Results of Sensex and Equity Mutual Funds in India

Variables	Level						1ST Difference						Integration Order
	Intercept		Trend and Intercept		None		Intercept		Trend and Intercept		None		
	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value	
SENSEX	0.85	1.00	-1.88	0.67	2.26	1.00	-12.67	0.00	-14.57	0.00	-12.50	0.00	I (1)
Large-cap funds	1.35	1.00	-1.11	0.93	2.96	1.00	-14.29	0.00	-14.41	0.00	-14.03	0.00	I (1)
Large and Mid-cap funds	1.77	1.00	-0.76	0.97	3.55	1.00	-11.95	0.00	-12.14	0.00	-11.53	0.00	I (1)
Mid-cap funds	1.28	1.00	-0.74	0.97	2.91	1.00	-10.97	0.00	-11.11	0.00	-10.64	0.00	I(1)
Small cap funds	2.44	1.00	0.36	0.99	3.74	1.00	-12.56	0.00	-12.82	0.00	-10.14	0.00	I(1)

Source: EViews Output

Table 4.1 indicates the presence of unit root in their levels as their *p*-values are greater than 0.05. Hence, first differencing of the variables is done and the results imply that the variables become stationary at I (1). So, the integration order of all the variables is I (1).

4.3.2 Selection of Optimal Lag Length

Since all the variables are integrated in the same order i.e., I (1), Johansen's co-integration test can be used to check whether a long-run relationship exists between the variables. Selection of optimum lag length is inevitable in time series analysis in order to bring valid results. Vector autoregressive model (VAR) is used for identifying the optimum lag length for the models. Likelihood Ratio, Final Prediction Error, Akaike Information Criterion, Schwarz Information Criterion and Hannan-Quinn Information Criterion are the commonly used criteria to identify the optimal lag length for the models. In this study, Akaike Information Criterion is used to select the appropriate lag length.

Table 4.2

Optimal Lag Selection of Large-cap Funds and Sensex

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-33264.65	NA	1.76e+08	24.66023	24.66460	24.66181
1	-19040.05	28417.58	4641.936	14.11864	14.13176*	14.12339
2	-19039.75	0.594538	4654.692	14.12139	14.14325	14.12929
3	-19033.70	12.06556	4647.630	14.11987	14.15048	14.13094
4	-19030.18	7.022401	4649.274	14.12022	14.15958	14.13446
5	-19026.66	7.011583	4650.928	14.12058	14.16869	14.13798
6	-19005.41	42.28925	4591.844	14.10779	14.16465	14.12835
7	-18982.11	46.34904	4526.604	14.09348	14.15909	14.11721
8	-18963.79	36.40279*	4478.818*	14.08287*	14.15722	14.10976*

Source: EViews Output
**indicates lag order selected by the criterion*
LR: Sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 4.2 indicates that all the criteria except the Schwarz information criteria select 8 as the optimum lag length for the model. As a result, 8 is regarded as the optimal lag length for further investigation of the relationship between large-cap equity mutual funds and the Sensex.

Table 4.3

Optimal Lag Selection of Large and Mid-cap Funds and Sensex

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-36531.64	NA	1.94e+09	27.06196	27.06633	27.06354
1	-21196.26	30636.68	22688.79	15.70538	15.71849*	15.71012
2	-21188.37	15.75106	22623.50	15.70250	15.72435	15.71040
3	-21187.08	2.582358	22668.89	15.70450	15.73510	15.71557
4	-21184.45	5.232976	22691.98	15.70552	15.74486	15.71975
5	-21173.75	21.30980	22579.67	15.70056	15.74864	15.71795
6	-21147.44	52.37243	22209.54	15.68403	15.74086	15.70458
7	-21126.77	41.11316	21936.96	15.67168	15.73725	15.69539
8	-21112.06	29.22792*	21763.67*	15.66375*	15.73806	15.69062*

Source: EViews Output
** indicates lag order selected by the criterion*
LR: Sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 4.3 shows that, except for the Schwarz information criteria, all the criteria choose 8 as the optimum lag length for the model. So, 8 is considered the optimal lag length for analysing the relationship between large and mid-cap funds and the Sensex.

Table 4.4

Optimal Lag Selection of Mid-cap Funds and Sensex

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-39211.07	NA	1.43e+10	29.05748	29.06185	29.05906
1	-23126.02	32134.35	95360.95	17.14118	17.15430	17.14592
2	-23109.30	33.37233	94466.53	17.13175	17.15362*	17.13966
3	-23107.71	3.178475	94635.15	17.13354	17.16415	17.14461
4	-23105.93	3.541160	94791.20	17.13519	17.17454	17.14942
5	-23104.67	2.521904	94983.44	17.13721	17.18531	17.15461
6	-23084.02	41.08776	93819.21	17.12488	17.18172	17.14544
7	-23069.53	28.83420	93092.23	17.11710	17.18269	17.14082
8	-23057.29	24.30941*	92526.12*	17.11100*	17.18533	17.13788*

Source: EViews Output
** indicates lag order selected by the criterion*
LR: Sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 4.4 implies that all the criteria except Schwarz information criterion select 8 as the optimum lag length for the model. Therefore, 8 is considered as the optimal lag length for the further analysis of the relationship between mid-cap equity funds and the Sensex.

Table 4.5

Optimal Lag Selection of Small-cap Funds and Sensex

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-36860.52	NA	2.48e+09	27.30557	27.30994	27.30715
1	-20730.20	32224.79	16064.94	15.36015	15.37326	15.36489
2	-20686.99	86.26811	15605.01	15.33110	15.35296*	15.33900
3	-20686.44	1.085832	15645.00	15.33366	15.36426	15.34473
4	-20684.55	3.770718	15669.46	15.33522	15.37456	15.34945
5	-20674.77	19.48859	15602.46	15.33094	15.37902	15.34833
6	-20654.18	40.98346	15411.89	15.31865	15.37547	15.33920
7	-20637.01	34.13202	15262.37	15.30890	15.37447	15.33261
8	-20626.91	20.09065*	15193.46*	15.30437*	15.37868	15.33125*

Source: EViews Output
** indicates lag order selected by the criterion*
LR: Sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table 4.5 implies that as per all the criteria except Schwarz information criteria, 8 is the optimum lag length for the model. Therefore, 8 is considered as the optimal lag length for analysing the relationship between small-cap equity mutual funds and the Sensex.

4.3.3 Johansen's Co-Integration Test

In order to identify the nature of long-run relationship between the variables, Johansen's maximum likelihood method of co-integration, developed by Johansen (1988) is applied. Johansens cointegration was employed to examine the dynamic linkage between stock market and equity funds in Australia (Pojanavatee, 2014). The long term relationship between investment fund flows and stock returns in Turkey was also explored using Johansens cointegration (Burucu & Contuk, 2011). In this study, Johansens' co-integration was employed to examine whether long-run relationship exists between stock mareket and equity mutual funds in India.

The long-run relationship between the variables is dependent upon the number of co-integrating equations. For estimating the number of co-integrating equations,Trace test and Max-Eigen value statistics are used at a 5 percent level of significance. These tests are based on five alternative assumptions, which are:

1) The model does not allow for any deterministic components in the data.

2) The model does not allow for any linear trends in the data, but allows for constants in the co-integrating equations.

3) The model allows for linear trends in the data, but no trends in the co-integrating equations.

4) The model allows both constants and linear trends in the co-integrating equations.

5) The model allows for non-linear trends and this is the least restrictive model on deterministic components.

Table 4.6

Johansen's Co-integration Test - Large-cap Funds and Sensex

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.046597	129.8136	15.49471	0.0001
At most 1	0.000415	1.119766	3.841466	0.2900
Trace test indicates 1 cointegrating eqn(s) at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.046597	128.6939	14.26460	0.0001
At most 1	0.000415	1.119766	3.841466	0.2900
Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				

Source: EViews Output

Table 4.6 indicates the presence of one co-integrating equation at a 1% level of significance. Hence, it can be inferred that there exists a long-run relationship between large-cap equity mutual funds and the Sensex.

Table 4.7

Johansen's Co-integration Test-Large and Mid-cap Funds and Sensex

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.022716	64.37409	15.49471	0.0000
At most 1	0.000873	2.357073	3.841466	0.1247
Trace test indicates 1 cointegrating eqn(s) at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.022716	62.01702	14.26460	0.0000
At most 1	0.000873	2.357073	3.841466	0.1247
Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				

Source: EViews Output

The results indicated in Table 4.7 suggest that there exists one co-integrating equation at a 1% level of significance. Thus, there exists a long-run relationship between large and mid-cap equity mutual funds and the Sensex.

Table 4.8

Johansen's Co-integration Test - Mid-cap Funds and Sensex

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.007514	22.90895	15.49471	0.0032
At most 1	0.000948	2.559334	3.841466	0.1096
Trace test indicates 1 cointegrating eqn(s) at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.007514	20.34961	14.26460	0.0048
At most 1	0.000948	2.559334	3.841466	0.1096
Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				

Source: EViews Output

Table 4.8 implies that there exists one co-integrating equation at a 1% level of significance. Therefore, the results indicate the existence of a long-run relationship between mid-cap equity mutual funds and the Sensex.

Table 4.9

Johansen's Co-integration Test - Small-cap Funds and Sensex

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.008179	29.03494	15.49471	0.0003
At most 1	0.002542	6.869487	3.841466	0.0088
Trace test indicates 2 cointegrating eqn(s) at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.008179	22.16546	14.26460	0.0023
At most 1	0.002542	6.869487	3.841466	0.0088
Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level				
* denotes rejection of the hypothesis at the 0.05 level				
**MacKinnon-Haug-Michelis (1999) p-values				

Source: EViews Output

Table 4.9 implies that two co-integrating equations exist at 1% levels of significance. Hence, it can be inferred that there is a long-run relationship between small-cap equity mutual funds and the Sensex.

The results of the present research is consistent with the studies of Alexakis, Dasilas, and Grose, (2013) in which they found that the Japanese mutual funds and stock prices were cointegrated. Furthermore, co-integration was found to exist between mutual funds' return and the stock market index in Dhaka (Hossain, Rahman, & Rajib, 2009).

4.3.4 Vector Error Correction Model

Since Co-integration test confirms the existence of long run relationship between the variables, VECM is used to examine the long run causality of Sensex and equity mutual funds in India. The normalised co-integrating coefficients of Sensex and large-cap funds are given in the table 4.10.

Table 4.10

Normalised Co-integrating Coefficients of Sensex and Large-cap Funds

Sensex	Large-cap Funds
1.000000	-1312.062
	(15.2123)
**(standard error in parentheses)*	

The signs of the normalized co-integrating coefficients are reversed to enable their proper interpretation.

Estimated Equation

Sensex = 1312.062Large-cap Funds

The results reveal that, in the long-run, large-cap equity mutual funds exert positive influence on the stock market, which implies that the Sensex will rise with the increase in the net asset values of large-cap equity mutual funds and fall with the decrease in the net asset values.

The Error Correction Term (ECT) indicates the speed of adjustment of the model or the time taken by the system in order to rectify the temporary disequilibrium.

Table 4.11

Estimates of Error Correction Term *c*(1) - Large-cap Funds and Sensex

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.049884	0.004429	-11.26184**	0.0000
C(2)	0.030808	0.018912	1.628987	0.1034
C(3)	0.005941	0.018892	0.314454	0.7532
C(4)	-0.035001	0.018802	-1.861598	0.0627
C(5)	0.022484	0.018744	1.199566	0.2304
C(6)	0.089482	0.018743	4.774129**	0.0000
C(7)	-0.077827	0.018774	-4.145518**	0.0000
C(8)	0.062754	0.018938	3.313652**	0.0009
C(9)	0.003418	0.018962	0.180281	0.8569
C(10)	-28.81830	30.55820	-0.943063	0.3457
C(11)	-95.48335	30.57515	-3.122907**	0.0018
C(12)	19.33537	30.35226	0.637032	0.5241
C(13)	-81.10883	30.35674	-2.671856	0.0076
C(14)	-74.86008	30.39319	-2.463054	0.0138
C(15)	25.66714	30.40726	0.844112	0.3986
C(16)	-100.5869	30.47051	-3.301122	0.0010
C(17)	-54.97775	30.63657	-1.794514	0.0728
C(18)	16.89629	6.300953	2.681545	0.0074

Source: EViews Output

**Significant at 1% level of Significance

C(1) denotes the co-efficient of the speed of adjustment to the long-run in a VECM. For the ECT to be consistent, the coefficient should be negative and statistically significant. Table 4.11 indicates that the coefficient is negative and statistically significant at a 1% level of significance. Hence, the results imply that any disturbance caused to the temporary equilibrium of the variables in the model will be automatically corrected in the long run.

The normalised co-integrating coefficients of Sensex and large and mid-cap funds are given in table 4.12.

Table 4.12

Normalised Co-integrating Coefficients of Sensex and Large and Mid-cap Funds

Sensex	Large and Mid-cap Funds
1.000000	**-474.0625**
	(10.3653)
***(standard error in parentheses)**	

The signs of the normalized co-integrating coefficients are reversed to enable their proper interpretation.

Estimated Equation

Sensex = 474.0625Large and Mid-cap Funds

The results reveal that, in the long-run, large and mid-cap equity mutual funds exert positive influence on the stock market, which indicates that the Sensex will rise with the increase in the net asset values of large and mid-cap equity mutual funds and fall with the decrease in their net asset values.

Table 4.13

Estimates of Error Correction Term *c*(1) - Large and Mid-cap Funds and Sensex

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.026114	0.003386	-7.711672	0.0000
C(2)	0.032218	0.019122	1.684882	0.0921
C(3)	0.000168	0.019135	0.008790	0.9930
C(4)	-0.032338	0.019101	-1.693008	0.0905
C(5)	0.033265	0.019047	1.746464	0.0808
C(6)	0.088915	0.018994	4.681326	0.0000
C(7)	-0.073009	0.019066	-3.829246	0.0001
C(8)	0.062444	0.019124	3.265281	0.0011
C(9)	0.002043	0.019127	0.106828	0.9149
C(10)	24.07000	14.01425	1.717538	0.0859
C(11)	-15.75122	14.04098	-1.121804	0.2620
C(12)	-19.15655	13.94345	-1.373875	0.1695
C(13)	52.68541	13.91928	3.785067	0.0002
C(14)	-42.69434	13.96295	-3.057688	0.0022
C(15)	-7.257915	14.02218	-0.517602	0.6048
C(16)	-14.63593	14.09778	-1.038173	0.2992
C(17)	-24.16858	14.11888	-1.711791	0.0870
C(18)	14.46034	6.396480	2.260672	0.0238

Source: EViews Output

**Significant at 1% level

Table 4.13, makes it clear that the coefficient is negative and statistically significant at a 1% level of significance. Hence, the results indicate that any disturbance caused to the temporary equilibrium of the variables in the model will be automatically corrected in the long run.

The normalised co-integrating coefficients of the Sensex and mid-cap funds are given in the table 4.14.

Table 4.14

Normalised Co-integrating Coefficients of Sensex and Mid-cap Funds

Sensex	Mid-cap Funds
1.000000	-282.2175
	(17.7377)
**(standard error in parenthese)*	

The signs of the normalized co-integrating coefficients are reversed to enable their proper interpretation.

Estimated Equation

Sensex = 282.2175 Mid-cap Funds

The results reveal that, in the long-run, mid-cap equity mutual funds exert positive influence on the stock market, which implies that the Sensex will rise with the increase in the net asset values of mid-cap equity mutual funds and fall with the decrease in their net asset values.

Table 4.15

Estimates of Error Correction Term *c*(1) - Mid-cap Funds and Sensex

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.009086	0.002006	-4.529791	0.0000
C(2)	0.020847	0.019301	1.080090	0.2802
C(3)	-0.000674	0.019304	-0.034926	0.9721
C(4)	-0.032329	0.019249	-1.679555	0.0931
C(5)	0.021424	0.019166	1.117828	0.2637
C(6)	0.087031	0.019166	4.540997	0.0000
C(7)	-0.078219	0.019237	-4.066101	0.0000
C(8)	0.056748	0.019283	2.942915	0.0033
C(9)	0.007469	0.019421	0.384587	0.7006
C(10)	0.806252	6.873977	0.117291	0.9066
C(11)	10.73228	6.915211	1.551982	0.1207
C(12)	-1.874086	6.898118	-0.271681	0.7859
C(13)	-1.114219	6.884601	-0.161842	0.8714
C(14)	20.85031	6.890220	3.026073	0.0025
C(15)	-5.293837	6.916046	-0.765443	0.4440
C(16)	3.217694	6.935988	0.463913	0.6427
C(17)	-6.201473	6.915763	-0.896716	0.3699
C(18)	11.91701	6.418738	1.856597	0.0634

Source: EViews Output

**Significant at 1% level

The results in table 4.15 indicate that the coefficient is negative and statistically significant at a 1% level of significance. Hence, any disturbance caused to the temporary equilibrium of the variables in the model will be automatically corrected in the long run.

The normalised co-integrating co-efficients of Sensex and small-cap funds is given in table 4.16.

Table 4.16

Normalised Co-integrating Coefficients of Sensex and Small-cap Funds

Sensex	Small-cap Funds
1.000000	**-626.9283**
	(34.8875)
(standard error in parenthese)	

The signs of the normalized co-integrating coefficients are reversed to enable their proper interpretation.

Estimated Equation

Sensex = 626.9283Small-cap Funds

The results reveal that, in the long-run, small-cap equity mutual funds exert positive influence on the stock market, which indicates that the Sensex will rise with the increase in the net asset values of small-cap equity mutual funds and fall with the decrease in the net asset values.

Table 4.17

Estimates of Error Correction Term *c*(1)-Small-cap Funds and Sensex

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.010259	0.002162	-4.745270	0.0000
C(2)	0.025800	0.019247	1.340467	0.1802
C(3)	-0.001927	0.019254	-0.100095	0.9203
C(4)	-0.033674	0.019220	-1.752057	0.0798
C(5)	0.026748	0.019167	1.395534	0.1629
C(6)	0.090950	0.019127	4.754963	0.0000
C(7)	-0.080147	0.019204	-4.173380	0.0000
C(8)	0.060653	0.019255	3.149897	0.0016
C(9)	0.000738	0.019287	0.038289	0.9695
C(10)	4.810044	16.94737	0.283822	0.7766
C(11)	19.99500	17.22368	1.160902	0.2457
C(12)	-12.97499	17.15482	-0.756347	0.4495
C(13)	70.17205	17.09812	4.104080	0.0000
C(14)	-24.53337	17.18613	-1.427510	0.1535
C(15)	-10.89412	17.26023	-0.631169	0.5280
C(16)	-3.736188	17.32861	-0.215608	0.8293
C(17)	-13.75350	17.09552	-0.804509	0.4211
C(18)	12.46862	6.430928	1.938852	0.0526

Source: EViews Output

**Significant at 1% level

Table 4.17 makes it evident that the coefficient is negative and statistically significant at a 1% level of significance. Hence, it can be concluded that any disturbance caused to the temporary equilibrium of the variables in the model will be automatically corrected in the long run.

4.3.5 Granger-Causality Test

After establishing that the variables are cointegrated, it is imperative to analyse the nature of the short-run relationship between equity mutual funds and the stock market. Hence, the VECM-based Granger causality test, along with variance decomposition analysis and impulse response analysis, is employed. Chu (2010) used the Granger causality test to analyse the short-run relationship between the equity funds of the Hong Kong Mandatory Provident Fund (MPF) and the indices of the Hong Kong Investment Fund Association. The relationship between mutual funds and the stock index in Jordan has also been examined using the Granger causality test (Al-Jafari, Salameh, & Asil, 2013).

Table 4.18

Granger Causality Test Results

Direction of Causality	F-Statistic	Probability value	Outcome
Large-cap funds > Sensex	18.79	1.E-27	Large-cap funds cause Sensex
Sensex > Large-cap funds	1.07	0.38	Sensex does not cause Large-cap funds
Large and Mid-cap funds > Sensex	11.31	7.E-16	Large and Mid-cap funds cause Sensex
SENSEX > Large and Mid-cap funds	1.19	0.30	Sensex does not cause Large and Mid-cap funds
Mid-cap funds > Sensex	4.49	2.E-05	Mid-cap funds cause Sensex
SENSEX > Mid-cap funds	0.60	0.78	Sensex does not cause Mid-cap funds
Small-cap funds > Sensex	5.45	8.E-07	Small-cap funds cause Sensex
SENSEX > Small-cap funds	1.08	0.38	Sensex does not cause Small-cap funds

Source: EViews Output

The Granger causality test indicates that the Sensex is granger caused by the net asset values of equity mutual funds. One way causal relation runs from equity mutual funds to Sensex, which denotes that a change in the net asset values of equity mutual funds causes Sensex to change accordingly. Hence, it can be implied that equity mutual funds tend to influence the stock market in India.

4.3.6 Variance Decomposition Analysis

Variance decomposition analysis is applied to determine the relative quantitative importance of shocks given to the variables in the VECM system. It examines the contribution of each innovation using a 120-day forecast error variance of the variables. To obtain the variance decomposition of price linkages, Cholesky decomposition is used.

The variance decomposition results of large-cap equity mutual funds and the Sensex are shown in table 4.19.

Table 4.19

Variance Decomposition Analysis of Large-cap Funds and Sensex

Period (in days)	Variance Decomposition of Sensex		Variance Decomposition of Large-cap Funds	
	SENSEX	Large-cap Funds	SENSEX	Large-cap Funds
1	100.000	0.000	0.022	99.978
30	69.477	30.521	1.467	98.533
60	28.664	71.335	2.396	97.604
90	16.964	83.036	2.846	97.154
120	12.572	87.428	3.088	96.912

Source: EViews Output

The results indicate that on the first day, the variance in the Sensex is explained by its own shocks. As the days progress, the variance in the Sensex is due to the influence exerted by large-cap equity mutual funds. After 120 days, 87% of the change in the Sensex is explained by the shock exerted on large-cap equity mutual funds. However, only 3% of the variance in large-cap equity mutual funds is explained by the shocks on the Sensex after 120 days.

Table 4.20

Variance Decomposition Analysis of Large and Mid-cap Funds and Sensex

Period (in days)	Variance Decomposition- Sensex		Variance Decomposition- Large and Mid-cap Funds	
	Sensex	Large and Mid-cap Funds	Sensex	Large and Mid-cap Funds
1	100.000	0.0000	0.017	99.983
30	91.984	8.0156	0.668	99.332
60	65.364	34.637	1.426	98.574
90	43.463	56.537	1.966	98.037
120	31.007	68.993	2.328	97.672

Source: EViews Output

From the empirical evidence, it is implied that on the first day, the variance in the Sensex is explained by its own shocks. Further, large and mid-cap equity mutual funds begin to exert an influence on the Sensex, which results in its variance. After 120 days, 69% of the change in the Sensex is explained by the shocks to large and mid-cap equity mutual funds. Moreover, movements in the Sensex explain only 2% of the forecast error variance in large-cap equity mutual funds after 120 days.

Table 4.21

Variance Decomposition Analysis of Mid-cap Funds and Sensex

Period (in days)	Variance Decomposition of Sensex		Variance Decomposition of Large-cap Funds	
	Sensex	Mid-cap Funds	Sensex	Mid-cap Funds
1	100.000	0.000	0.316	99.684
30	96.173	3.827	0.0473	99.953
60	88.655	11.344	0.0265	99.976
90	88.655	11.345	0.0215	99.978
120	68.091	31.909	0.0205	99.979

Source: EViews Output

Table 4.21 presents the variance decomposition of the Sensex and mid-cap equity mutual funds. It is obvious that on the first day, the variance in the Sensex is explained by its own shocks. After 120 days, the shocks on mid-cap equity mutual funds cause 32% of forecast error variance in the Sensex. Furthermore, the variance in mid-cap equity mutual funds is almost completely explained by its own shocks after 120 days. It implies that the Sensex has no role in influencing the values of mid-cap equity mutual funds.

Table 4.22

Variance Decomposition Analysis of Small-cap Funds and Sensex

Period (in days)	Variance Decomposition of Sensex		Variance Decomposition of Small-cap Funds	
	Sensex	Small-cap Funds	Sensex	Small-cap Funds
1	100.000	0.000	0.316	99.684
30	96.314	3.6864	0.037	99.963
60	87.563	12.437	0.087	99.913
90	75.558	24.442	0.158	99.842
120	63.105	36.895	0.234	99.766

Source: EViews Output

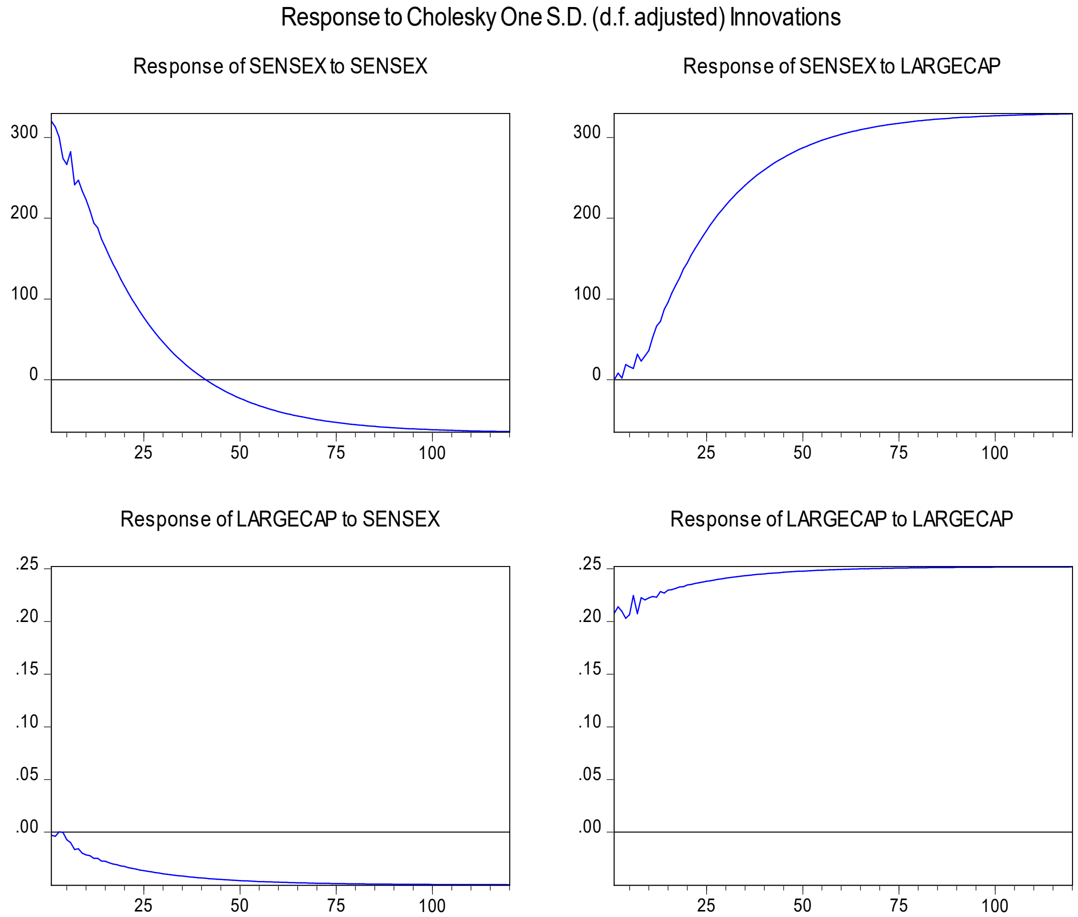
The results in table 4.22 suggest that on the 1st day the variance in Sensex is wholly explained by its own shocks. However, the forecast error variance in it increases due to movements in small-cap equity mutual funds day by day. After 120 days, 37% of the variance in the Sensex is explained by the movements in small-cap equity mutual funds. But the variance in small-cap equity mutual funds is almost completely explained by its own shocks after 120 days which indicates that the Sensex exerts no role in influencing the values of small-cap equity mutual funds.

4.3.7 Impulse Response Analysis

The impulse response function is applied in order to analyse the transmission mechanism between equity mutual funds and stock market in India. It reveals the direction of change in the dependent variable due to shocks imposed by external variables. The persistence of shock indicates the speed by which the price system returns to equilibrium. Cholesky decomposition is considered to obtain the impulse response function of the price linkages. The impulse response function is reported for 120 days and is followed by the significance and magnitude of VAR lag order selection criteria. Figure 4.1 indicates the response of Sensex to its own shock and shocks in large-cap equity mutual funds and the response of large-cap equity mutual funds to shocks in Sensex and its own shocks.

Figure 4.1

Impulse Response Analysis - Large-cap Funds and Sensex

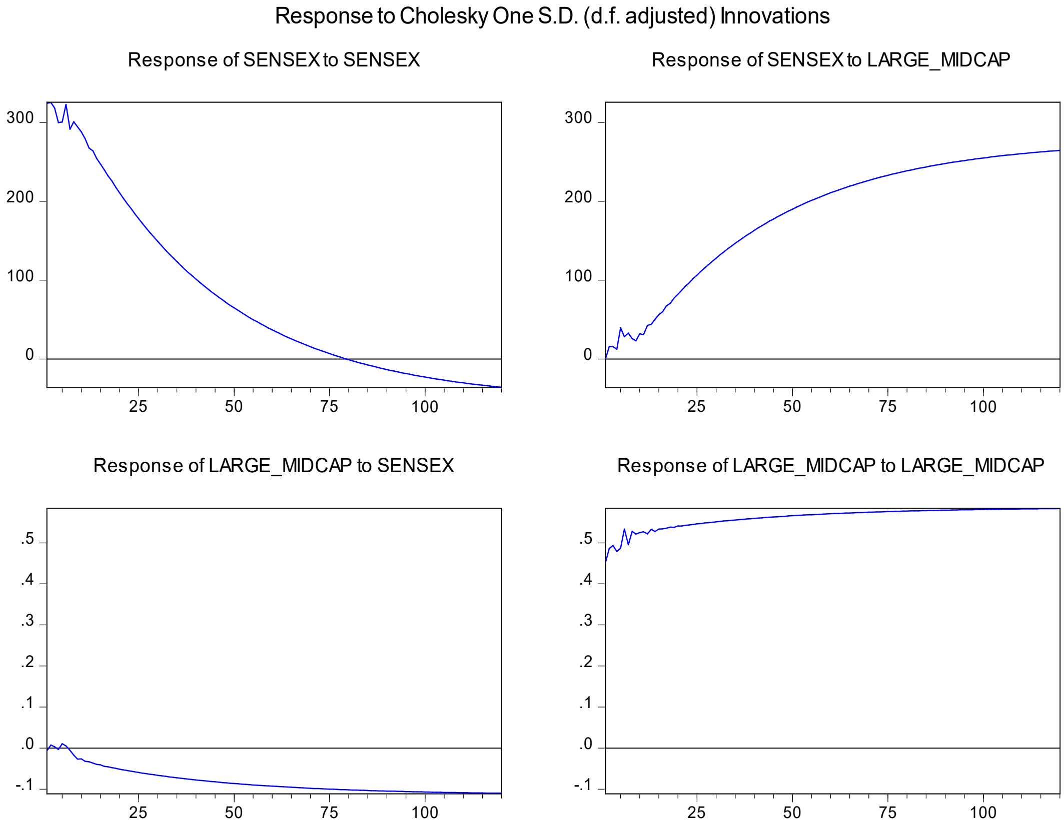


Source: EViews Output

The results imply that the Sensex exhibits a negative response to its own shocks, whereas, it shows a positive response towards shocks in large-cap equity mutual funds. While, large-cap equity mutual funds have a negative response to shocks in the Sensex, it responds positively to its own shocks.

Figure 4.2

Impulse Response Analysis - Large and Mid-cap Funds and Sensex

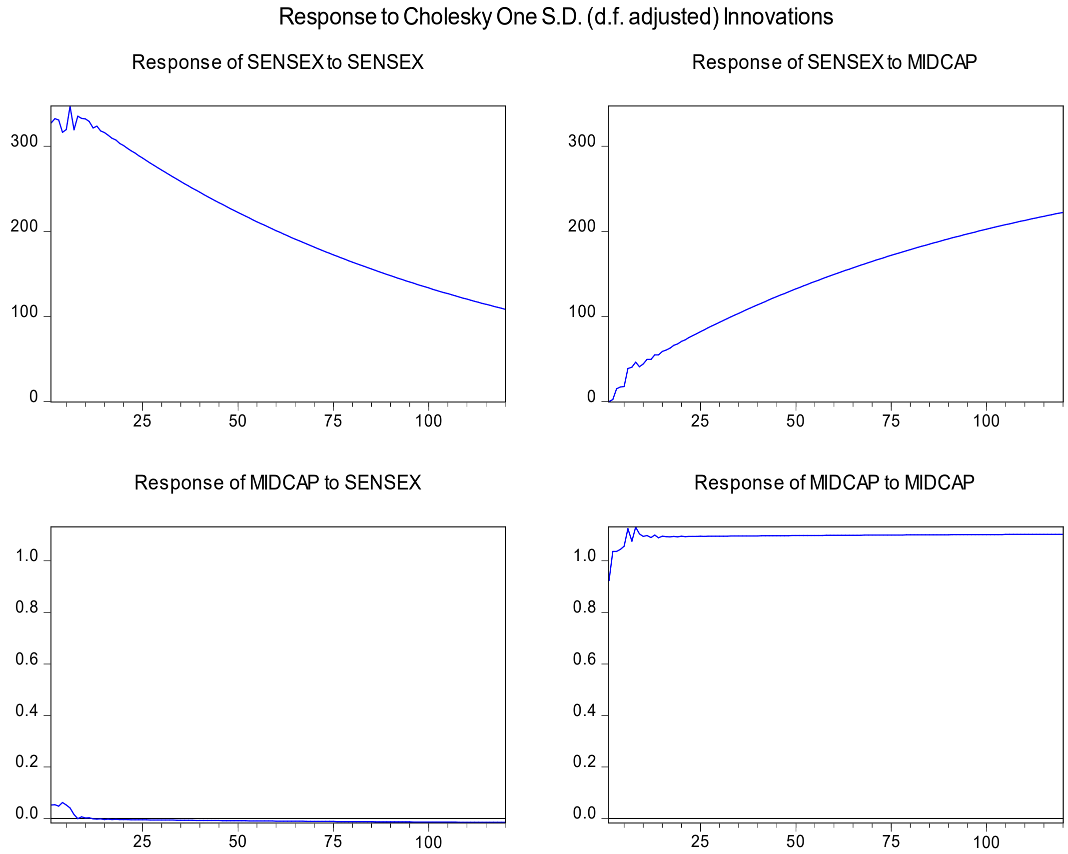


Source: EViews Output

The empirical evidence suggests that the Sensex shows a negative response to its own shocks, while it shows a positive response towards shocks in large and mid-cap equity mutual funds. On the other hand, large and mid-cap equity mutual funds show a negative response to shocks in the Sensex. However, it exhibits a slightly positive response to its own shocks.

Figure 4.3

Impulse Response Analysis - Mid-cap Funds and Sensex

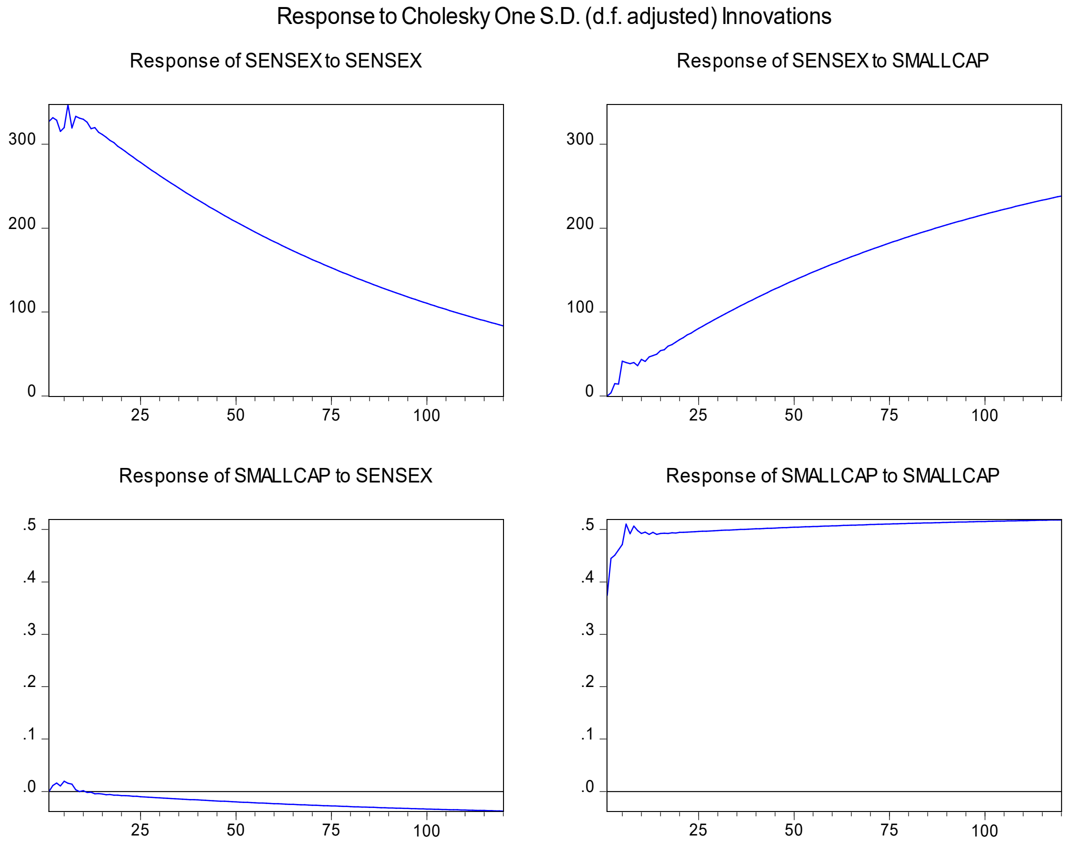


Source: EViews Output

The results in table 4.3 imply that the Sensex shows a negative response to its own shocks and a positive response to shocks in mid-cap equity mutual funds. The results also indicate that the mid-cap equity mutual funds show a slightly negative response to shocks in the Sensex, whereas they exhibit a slightly positive response to their own shocks.

Figure 4.4

Impulse Response Analysis - Small-cap Funds and Sensex



Source: EViews Output

Figure 4.4 makes it clear that the Sensex shows a negative response to its own shocks and a positive response to shocks in small-cap equity mutual funds. The results also imply that the small-cap equity mutual funds have a slightly negative response to shocks in the Sensex and a slightly positive response to their own shocks.

From the impulse response function results, it can be concluded that the findings are consistent with the results of Johansen's cointegration tests, which indicate the cointegrated nature of the stock market index and equity mutual funds. The results of the impulse response function confirm the findings of the Granger causality tests, indicating the causal relationship that runs from equity mutual funds to the Sensex. The results are also consistent with those of the variance decomposition analysis, which implies that the Sensex is strongly endogenous.

4.4 Conclusion

The study examined the dynamic relationship between equity mutual funds and the stock market in India. The time series data employed in this study become stationary at the first difference. Johansen's cointegration test results imply that a long-run relationship exists between equity mutual funds and the stock market in India. Additionally, according to VECM results, equity mutual funds have a positive long-term influence on the stock market. Furthermore, it is discovered that for the Sensex and equity mutual funds, the rate of price adjustment to long-run equilibrium is significant.

Granger-causality test results indicate that equity mutual funds granger cause Sensex, indicating that a movement in the net asset values of equity mutual funds could cause Sensex to change. As per the variance decomposition analysis, the Sensex has less exogeneity. The impulse response function suggests the existence of a close relationship between the net asset values of equity mutual funds and the stock market index for future periods, which indicates that, in India, movements in equity mutual fund values cause the stock market index to change. Hence, equity mutual funds can be considered as an alternative to direct investment in the stock market. Moreover, equity mutual funds provide diversification and professional expertise, making them a more suitable option for investors to reap huge benefits from the market.

Chapter 5

TREND OF THE PERFORMANCE OF EQUITY MUTUAL FUNDS IN INDIA

Contents

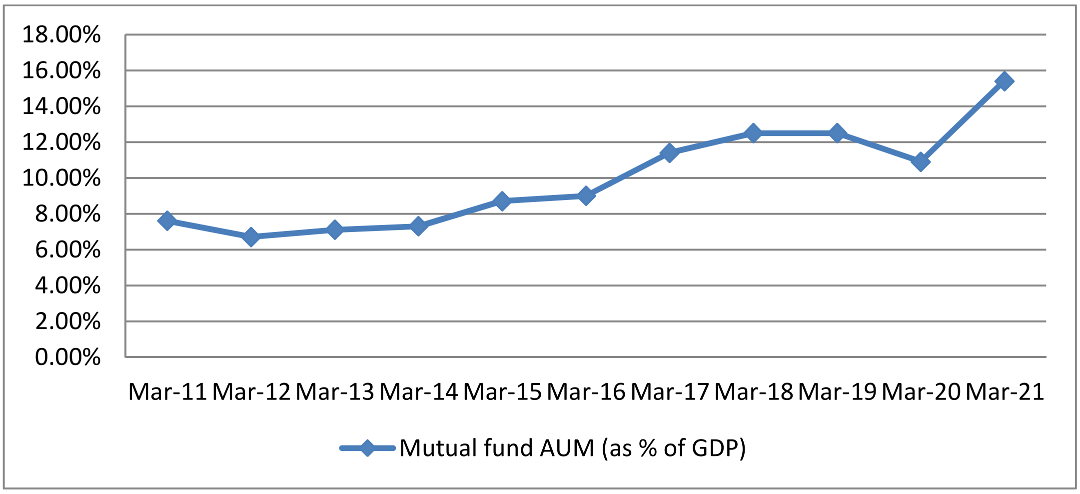
5.1 Introduction

Mutual funds have emerged as an attractive investment option for investors seeking huge returns. Capital market growth and financial system orientation are the major factors driving the growth of mutual funds all over the world (Klapper, Sulla, & Vittas, 2004). Despite being subjected to market risks, mutual funds are the most suitable investment avenue for cautious investors, as they offer an opportunity to invest in diversified and professionally managed securities. Mutual funds offer a variety of investment products at a reasonable cost, enabling households to participate in the long-term growth prospects of our country. The Indian mutual fund industry has witnessed dramatic improvements in quantity as well as quality of product and service offerings in recent years. Furthermore, technological advancement, professional expertise and investors' participation over time enhanced the growth of the mutual fund industry in India. The Indian mutual fund industry's AUM stood at Rs. 37.72 trillion as of December 31, 2021 (AMFI, 2021).

The value of assets held by individual investors in mutual funds increased to Rs. 20.86 trillion in December 2021 from Rs. 16.17 trillion in December 2020, marking a growth of 29.04 percent. The value of assets held by institutions increased by 15.28%, from Rs. 14.80 trillion to Rs. 17.06 trillion in December 2021 (AMFI, 2021). Fig. 5.1 represents mutual fund AUM as a percentage of the nation's GDP from 2010–11 to 2020–21.

Figure 5.1

Mutual fund AUM (as % of GDP)

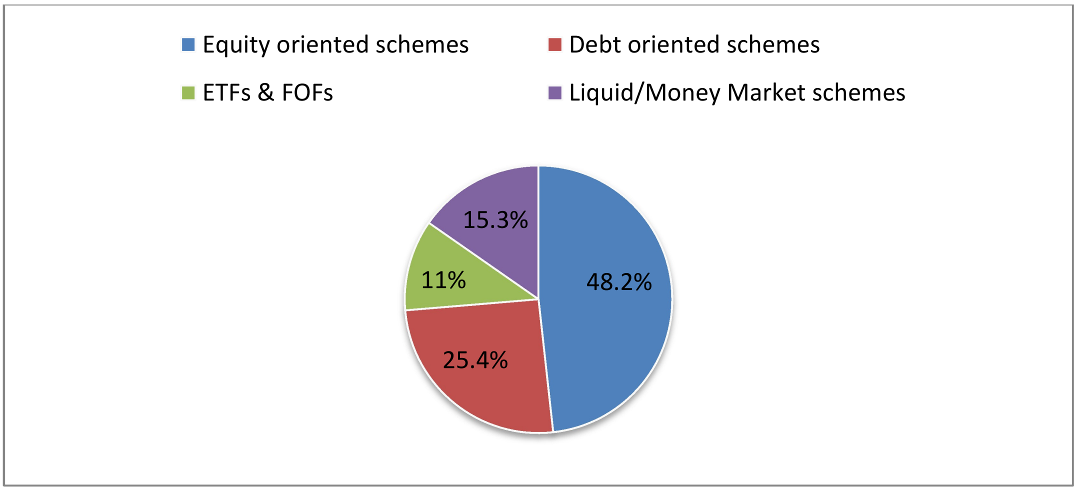


Source: AMFI

The mutual fund AUM as a percentage of GDP rises to 15.40% in the F.Y. 2020-21 (Fig. 5.1).

Fig 5.2

Scheme-wise composition of Assets



Source: AMFI

Equity-oriented schemes constitute the highest percentage (48.2%) among the different schemes offered by mutual funds (Fig. 5.2). The AUM held by equity-oriented schemes alone stood at Rs. 13.06 trillion as of December 31, 2021 (SEBI, 2021). The increased percentage of investment in equity-oriented schemes would be due to the high rate of return offered by such schemes.

Equity shares have offered higher returns when compared to other investment avenues in the long run. Selecting the right shares to invest in would be a difficult task for a common man who lacks knowledge regarding the financial market. Equity mutual funds are managed by fund managers who make asset allocations and continuously monitor the portfolio in order to make better returns. Being handled by professional experts, it becomes a safe haven, thus enabling the common people to participate in economic growth.

The role of mutual funds in transforming the Indian economy makes it imperative to understand the trend and pattern of the performance of mutual funds in India. High returns offered by equity mutual funds make them the most attractive investment option for investors who lack professional knowledge and are interested to participate in the stock market in order to earn better returns.

5.2 Data and Methodology

Equity mutual funds are classified into different categories as per SEBI guidelines (AMFI, 2021). On the basis of market cap mix, Equity mutual funds are classified into the following categories:

i. Large-cap funds – The funds which make at least 80% investment in large-cap stocks.
ii. Large and Mid-cap funds - The funds which make at least 35% investment in large-cap stocks and 35% in mid-cap stocks.
iii. Mid-cap funds - The funds which make at least 65% investment in mid-cap stocks.
iv. Small-cap funds - The funds which make at least 65% investment in small-cap stocks.
v. Multi-cap funds - The funds which make 65% investment in equity and equity-related instruments.

As the multi-cap funds invest in stocks across market capitalization, only the first four categories of equity mutual funds are considered for the study.

Trend analysis and the Box-Jenkins ARIMA model have been used to analyse the trend and pattern of equity funds in India.

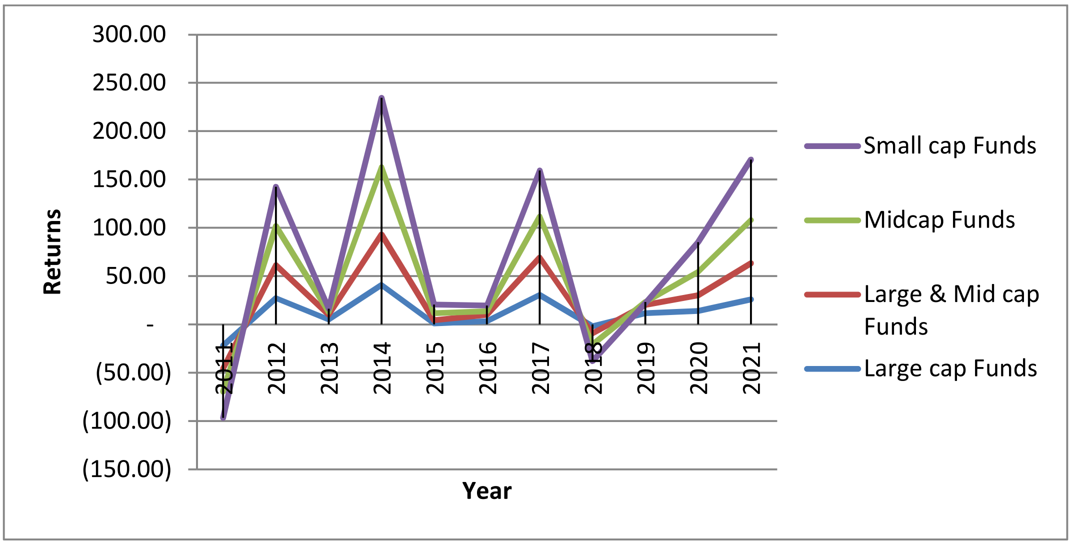
5.3 Analysis, Results and Discussion

5.3.1 Trend Analysis

Trend analysis was done to explore the performance of equity mutual funds in India. The average annual returns of large-cap funds, large and mid-cap funds, mid-cap funds and small-cap funds for the period 2011–2021 have been taken for the study. Data were gathered from the Association of Mutual Funds in India (AMFI) and Morningstar websites. The annual returns of all the funds in these categories are taken into account while calculating the average annual return.

Figure 5.3

Performance of Equity Mutual Funds during 2011-2021



Source: AMFI

The performance of large-cap funds, large and mid-cap funds, mid-cap funds and small-cap funds for the years 2011–2021 are depicted in Figure 5.3. Mutual fund NAVs move in tandem with the prices of the securities in which they are invested. As the study examines the trend of equity fund performance, the reasons for their performance can be related to the stock market movements in the corresponding years.

Figure 5.3 implies that all the fund categories delivered negative returns in 2011, of which the returns of the small-cap funds were the lowest. The economic downturn in the year was mainly due to the downfall of the Indian currency. A weak rupee would have a negative impact on FII inflows.

In 2012, the returns of all the funds increased, and the small-cap funds performed the best while the large-cap funds provided the least returns.

In 2013, all the funds provided slightly positive returns, while the average return of all the categories was 4.05%, with large-cap funds providing the highest returns (5%) and small-cap funds providing the lowest returns (3.07%).

All the funds exhibited their highest performance in 2014, giving an average return of 58.69% due to the rise of the National Democratic Alliance (NDA) government. The small-cap funds provided exceptionally good returns (71.98%). The lowest returns were provided by large-cap funds (40.96%).

In 2015, the market went down, providing considerably lower returns. Large-cap funds provided the lowest returns (1.01%), whereas small-cap funds provided the highest returns (8.89%). The major cause of the year's economic downturn was the depreciation of the Chinese Yuan, which caused currency rates in other countries to fall.

In 2016, the returns of large-cap funds and large and mid-cap funds went up slightly, while mid-cap funds and small-cap funds provided lower returns compared to the previous year. The increase in non-performing assets (NPAs) and the government's "demonetization drive" caused the stock market to crash.

2017 was another great year for mutual funds, showing remarkable returns after 2014. Small-cap funds provided the highest returns (47.52%) and large-cap funds provided the lowest returns (30.63%). The funds went down considerably, providing negative returns in 2018. The introduction of a 10% long-term capital gain tax on equity shares was a major reason for the downtrend of the economy. Small-cap funds performed the least, providing -17.27% returns, while large-cap funds provided slightly negative returns (-1.91%).

In 2019, the industry witnessed an optimistic sentiment as the majority of the funds bounced back and all the fund categories except small-cap funds provided positive returns. It is evident from figure 5.3 that the equity funds went through a slowdown during the first half of 2020, which eventually advanced, giving higher returns in the second half. The COVID-19 outbreak was an unprecedented shock to the Indian economy. The lockdown declared on March 24th had a negative impact on the economy, particularly on the stock market. However, equity funds provided positive returns during the year. Small-cap funds have shown the best performance providing (30.66%) returns, whereas, the lowest returns were provided by the large-cap funds (14%).

The equity funds continued to provide high returns in 2021. Small-cap funds delivered the highest returns (62.8%), while large-cap funds provided the lowest returns (25.9%). Figure 5.3 makes it evident that small-cap funds are the most volatile category, as they were the best performers during the ups and worst performers during the downs in the market.

5.3.2 Application of Auto Regressive Integrated Moving Average (ARIMA) Modelling in the Performance of Equity Mutual Funds in India

The Box-Jenkins method, also known as Auto-Regressive Integrated Moving Average (ARIMA) is a statistical model for analysing and forecasting time series data. The method was first introduced by the famous mathematicians George Box and Gwilym Jenkins. The 'AR' portion of ARIMA stands for Auto-Regressive, 'I' for Integrated and 'MA' stands for Moving Average. Auto-regression refers to the number of lag orders included in the model. Integration refers to the number of times the observations are differenced. The moving average indicates that the forecast error is a linear combination of the respective past errors.

Guha and Bandyopadhyay (2016) have used the ARIMA model to forecast the future value of gold prices in India. The ARMA methodology was used to model the Fund of Mutual Funds in India (Gowri & Deo, 2015). In this study, the trend and pattern of large-cap funds, large and mid-cap funds, mid-cap funds and small-cap funds are studied for the period from January 1, 2011, to December 31, 2021. The funds which have provided higher returns in the most number of years out of 11 years have been taken as a sample from each of these categories.

The following funds are taken as samples:

Large-cap fund	- Canara Robeco Bluechip Equity Fund
Large and Mid-cap fund	- Mirae Asset Emerging Bluechip Fund
Mid-cap fund	- UTI Mid Cap Fund
Small-cap fund	- Nippon India Small Cap Fund

The Net Asset Value (NAV) of a fund represents its price and is used to compute the returns generated from them. The return from a fund is calculated by deducting the NAV on the date of purchase from the NAV on the date of sale and then converting it into percentage.

The net asset values of these funds for the period 1 January 2011 to 31 December 2021 have been taken from the website of AMFI and ARIMA modelling is applied to forecast their NAVs for the period 1 January 2022 to 31 December 2023.The results of ARIMA modeling are as follows:

5.3.2.1 Unit Root Test

Stationarity means that the statistical properties of a process generating a time series do not change over time. Checking stationarity is imperative for time series analysis. Unit root test helps to check whether a time series data is non-stationary and possesses a unit root. Unit root tests help to avoid spurious results (Havi, Enu, Gyimah, Obeng, & Opoku, 2013). The commonly used test to examine the presence of unit roots is the Augmented Dickey Fuller test (Dickey & Fuller, 1981). In this study, the ADF test is used to check whether the data taken for the study is stationary or not.

Table 5.1

ADF Test Results of Performance of Equity Mutual Funds in India

Variables	Level						1ST DIFFERENCE						INTEGRATION ORDER
	Intercept		Trend and Intercept		None		Intercept		Trend and Intercept		None		
	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value	t-stat	p-value	
Large-cap funds	1.35	1.00	-1.11	0.93	2.96	1.00	-14.29	0.00	-14.41	0.00	-14.03	0.00	I (1)
Large and Mid- cap funds	1.77	1.00	-0.76	0.97	3.55	1.00	-11.95	0.00	-12.14	0.00	-11.53	0.00	I (1)
Mid-cap funds	1.28	1.00	-0.74	0.97	2.92	1.00	-10.97	0.00	-11.11	0.00	-10.64	0.00	I(1)
Small-cap funds	2.44	1.00	0.36	1.00	3.74	1.00	-12.56	0.00	-12.82	0.00	-10.14	0.00	I(1)

Source: EViews Output

Table 5.1 shows the ADF test results of the performance of equity mutual funds. The results indicated the presence of unit root in their levels. Hence, the first differencing of the variables is done. As the p-values surpass its expected values at a 95% level of confidence, the data becomes stationary after the 1st difference. The null hypothesis that the data is not stationary, gets rejected since the probability values of the four variables are less than 5% level of significance. Hence, the test reveals that the order of integration of all four variables is 1.

5.3.2.2 ARMA Model Specification

As all the variables became stationery at the first difference, the order of integration is found to be I(1). The next step is to find out the values of AR and MA in ARIMA, for which the following steps are to be followed.

Large-cap funds

The ARMA modelling of large-cap funds is discussed in this section. Table 5.2 presents the ARMA models of the large-cap funds and their corresponding values of the selection criteria. Many criteria can be used for ARMA model selection, such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (AIC) and Hannan-Quinn Information Criterion (HQ). Hurvich and Tsai (1989) inferred AIC as the best model selection criterion. Akaike Information Criterion (AIC) is used to estimate the amount of information lost by a given model. The quality of the model increases when information lost by the model decreases. In this study, AIC has been used for the selection of the ARMA model. The model corresponding to the lowest value of AIC is chosen as the ARMA model.

Table 5.2

ARMA Model Selection Criteria of Performance of Large-cap funds

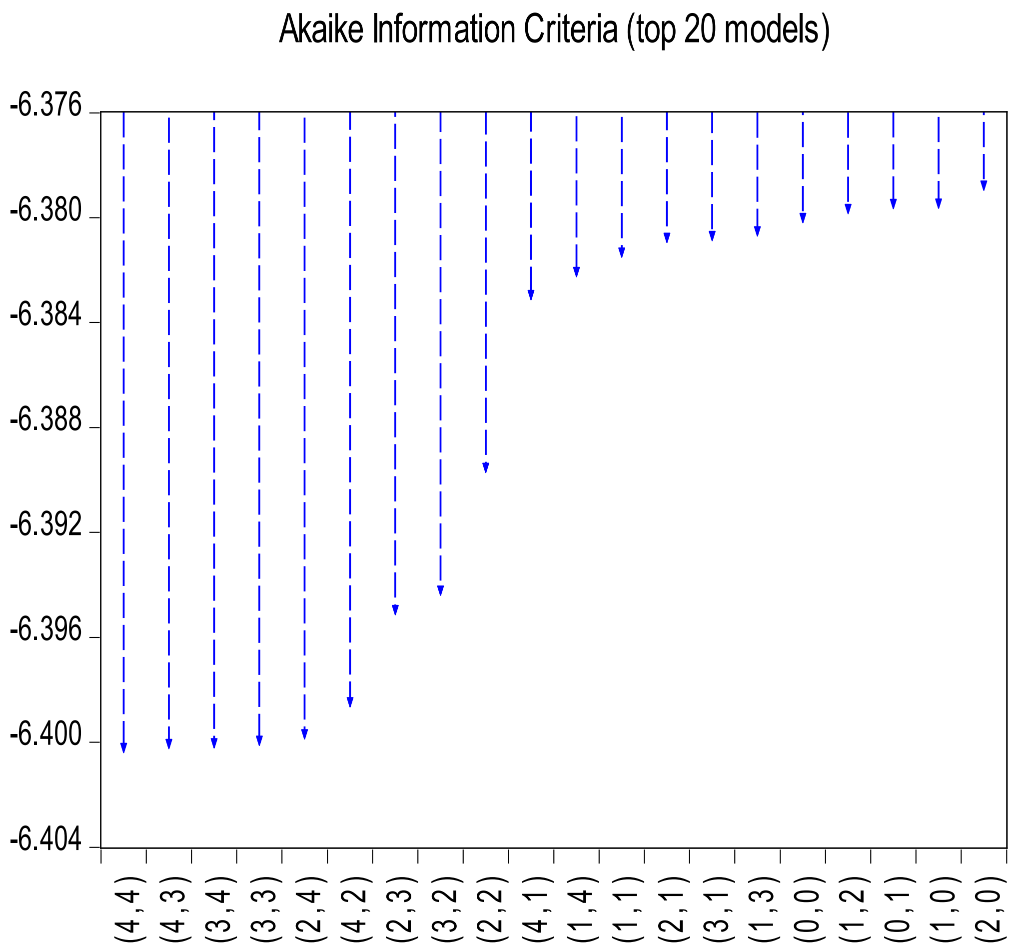
Model	LogL	AIC*	BIC	HQ
(4,4)	8666.264054	-6.400195	-6.378373	-6.392304
(4,3)	8665.055757	-6.400041	-6.380401	-6.392940
(3,4)	8665.022429	-6.400017	-6.380377	-6.392915
(3,3)	8663.885025	-6.399915	-6.382457	-6.393602
(2,4)	8663.547753	-6.399666	-6.382208	-6.393353
(4,2)	8661.900692	-6.398448	-6.380990	-6.392135
(2,3)	8656.143331	-6.394930	-6.379655	-6.389407
(3,2)	8655.146644	-6.394193	-6.378918	-6.388670
(2,2)	8647.813482	-6.389511	-6.376418	-6.384776
(4,1)	8639.905314	-6.382924	-6.367649	-6.377401
(1,4)	8638.713916	-6.382044	-6.366768	-6.376520
(1,1)	8634.707158	-6.381299	-6.372570	-6.378143
(2,1)	8634.962820	-6.380749	-6.369838	-6.376803
(3,1)	8635.863861	-6.380676	-6.367582	-6.375941
(1,3)	8635.620123	-6.380495	-6.367402	-6.375761
(0,0)	8630.925331	-6.379982	-6.375617	-6.378404
(1,2)	8633.476661	-6.379650	-6.368739	-6.375705
(0,1)	8631.202685	-6.379447	-6.372901	-6.377080
(1,0)	8631.198961	-6.379445	-6.372898	-6.377077
(2,0)	8631.263223	-6.378753	-6.370024	-6.375597
(0,2)	8631.262487	-6.378752	-6.370023	-6.375596
(3,0)	8631.304458	-6.378044	-6.367133	-6.374099
(0,3)	8631.293716	-6.378036	-6.367125	-6.374091
(0,4)	8631.652051	-6.377562	-6.364468	-6.372827
(4,0)	8631.548857	-6.377485	-6.364392	-6.372751

Source: EViews Output

Table 5.2 shows the ARMA models of the performance of the large-cap funds, which indicates that the ARMA (4,4) is the best model that can be used to forecast the future values of the large-cap funds.

Figure 5.4

ARMA Model of Performance of Large-cap funds

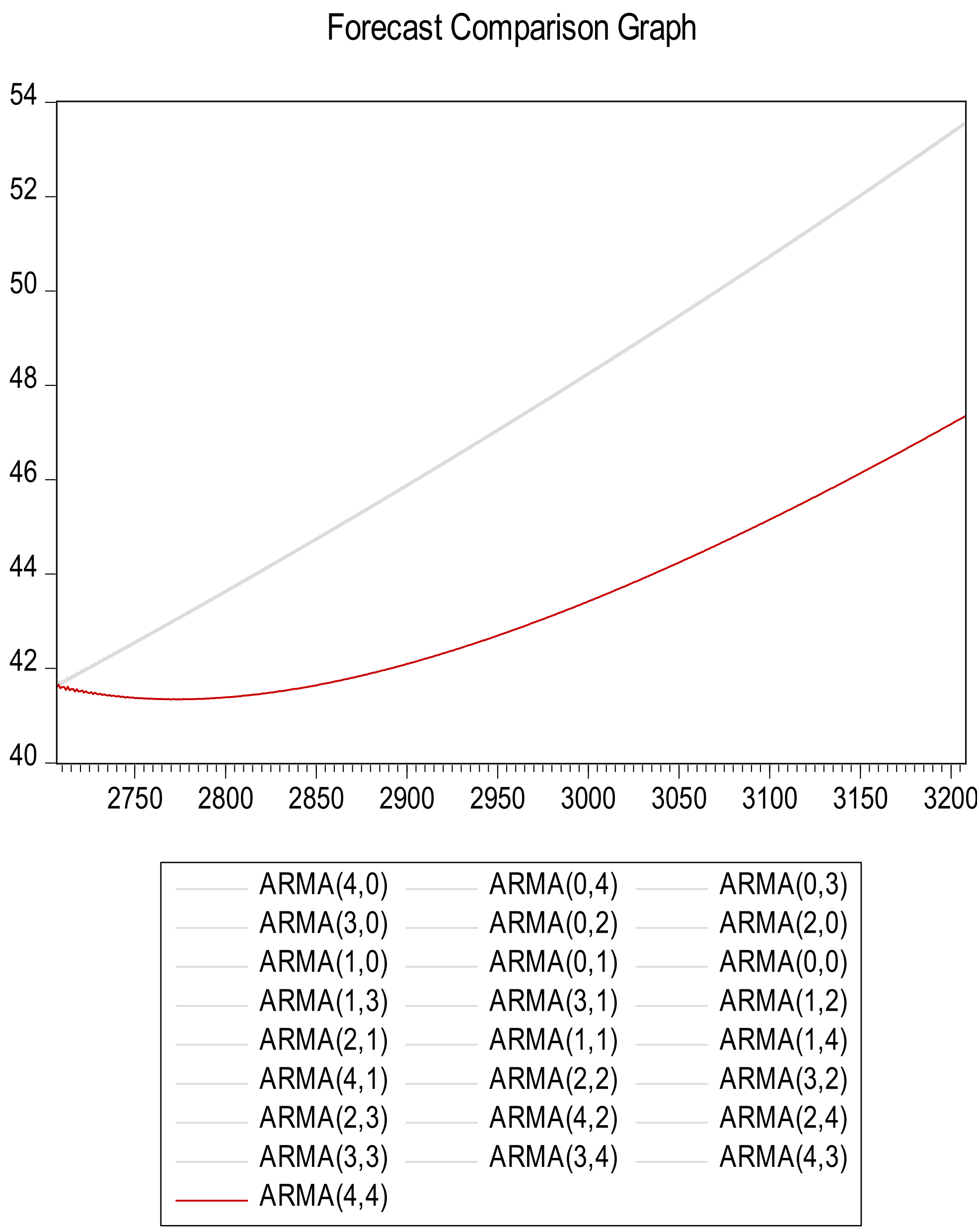


Source: EViews Output

Figure 5.4 represents the top 20 models generated by ARMA forecasting with their respective AIC values. The model with the lowest AIC should be selected as the best model. The model corresponding to the lowest AIC value, i.e., -6.40, is (4,4). Hence, ARMA (4,4) is selected as the best model.

Figure 5.5

Forecast Comparison Graph of Performance of Large-cap funds



Source: EViews Output

Figure 5.5 shows the forecast comparison graph of performance of large-cap funds using AIC criteria. It can be confirmed that, ARMA (4,4) is the best model.

Table 5.3

ARMA Maximum Likelihood Estimation of Performance of Large-cap funds

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000503	7.12E-05	7.071821	0.0000
AR(1)	-1.079506	0.073091	-14.76937	0.0000
AR(2)	0.292951	0.048054	6.096293	0.0000
AR(3)	1.234819	0.047713	25.88016	0.0000
AR(4)	0.522459	0.072050	7.251371	0.0000
MA(1)	1.120226	0.254150	4.407745	0.0000
MA(2)	-0.246892	0.059124	-4.175848	0.0000
MA(3)	-1.262082	0.509017	-2.479450	0.0132
MA(4)	-0.611249	0.371286	-1.646304	0.0998
SIGMASQ	9.65E-05	5.93E-06	16.27578	0.0000
R-squared	0.026646	Mean dependent var		0.000502
Adjusted R-squared	0.023396	S.D. dependent var		0.009957
S.E. of regression	0.009840	Akaike info criterion		-6.400195
Sum squared resid	0.260934	Schwarz criterion		-6.378373
Log likelihood	8666.264	Hannan-Quinn criter.		-6.392304
F-statistic	8.197455	Durbin-Watson stat		2.017731
Prob(F-statistic)	0.000000			
Inverted AR Roots	.99	-.58	-.75+.59i	-.75-.59i
Inverted MA Roots	1.00	-.69	-.72+.61i	-.72-.61i

Source: EViews Output

Table 5.3 shows the maximum likelihood estimation of performance of large-cap funds. From the table, it is evident that the model has met all the necessary criteria. Hence, ARMA (4,4) can be selected as the best model indicating the performance of large-cap funds in India. As the integration order is found to be 1, the ARIMA model can be represented as ARIMA (4,1,4).

Large and Mid-cap funds

Table 5.4 shows the ARMA models of Large and Mid-cap funds and their corresponding values of the selection criteria. The model corresponding to the lowest value of AIC is chosen as the ARMA model.

Table 5.4

ARMA Model Selection Criteria of Performance of Large and Mid-cap funds

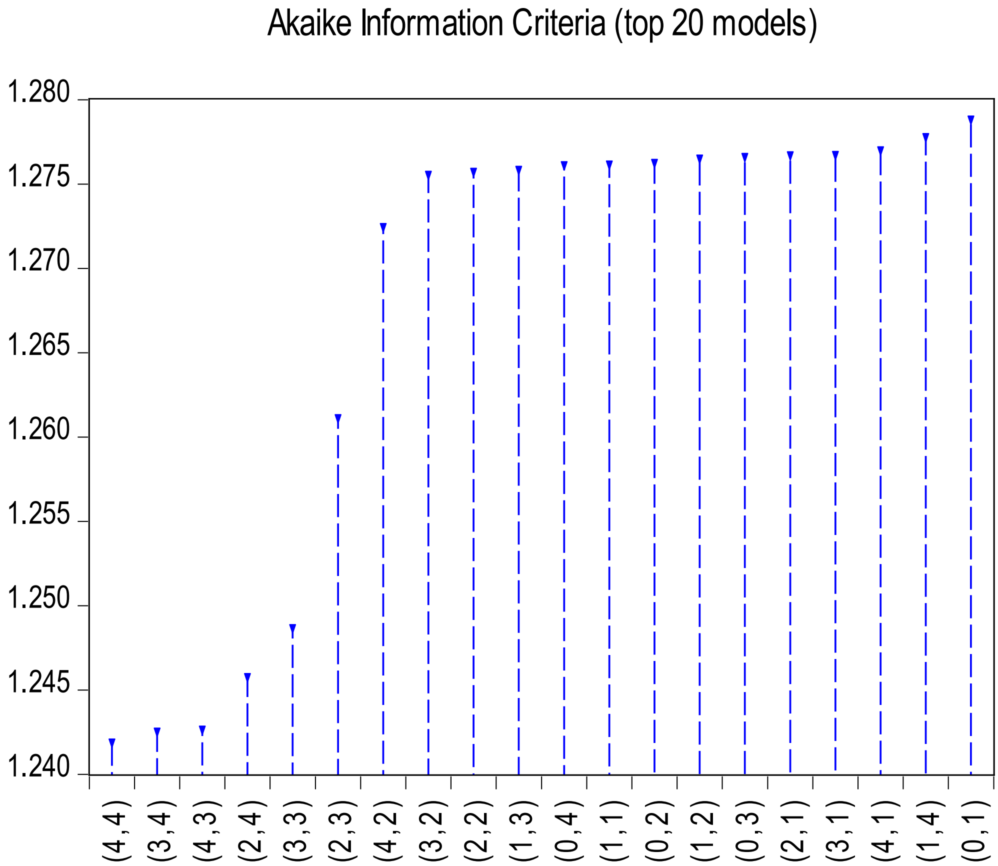
Model	LogL	AIC*	BIC	HQ
(4,4)	-1669.003915	1.241867	1.263696	1.249760
(3,4)	-1670.887852	1.242521	1.262166	1.249625
(4,3)	-1671.047689	1.242639	1.262285	1.249743
(2,4)	-1676.265526	1.245759	1.263222	1.252073
(3,3)	-1680.193534	1.248664	1.266127	1.254979
(2,3)	-1698.005730	1.261099	1.276379	1.266624
(4,2)	-1712.353044	1.272450	1.289913	1.278765
(3,2)	-1717.516266	1.275530	1.290810	1.281055
(2,2)	-1718.768338	1.275716	1.288813	1.280452
(1,3)	-1718.914016	1.275824	1.288921	1.280560
(0,4)	-1719.287050	1.276100	1.289197	1.280836
(1,1)	-1721.344818	1.276143	1.284874	1.279300
(0,2)	-1721.492420	1.276252	1.284983	1.279409
(1,2)	-1720.822687	1.276496	1.287410	1.280443
(0,3)	-1720.964926	1.276601	1.287516	1.280548
(2,1)	-1721.103680	1.276704	1.287618	1.280651
(3,1)	-1720.111132	1.276709	1.289807	1.281445
(4,1)	-1719.478836	1.276981	1.292261	1.282507
(1,4)	-1720.558750	1.277780	1.293060	1.283305
(0,1)	-1725.946100	1.278806	1.285355	1.281174
(4,0)	-1902.287832	1.411455	1.424553	1.416191
(3,0)	-2005.095446	1.486757	1.497671	1.490704
(2,0)	-2103.966642	1.559147	1.567878	1.562304
(1,0)	-2227.451584	1.649742	1.656291	1.652110
(0,0)	-2577.587761	1.907979	1.912345	1.909558

Source: EViews Output

Table 5.4 indicates that the ARMA (4,4) is the best model of the performance of large and mid-cap funds, which can be used to forecast the future values of the large and mid-cap funds.

Figure 5.6

ARMA Model of Performance of Large and Mid-cap funds

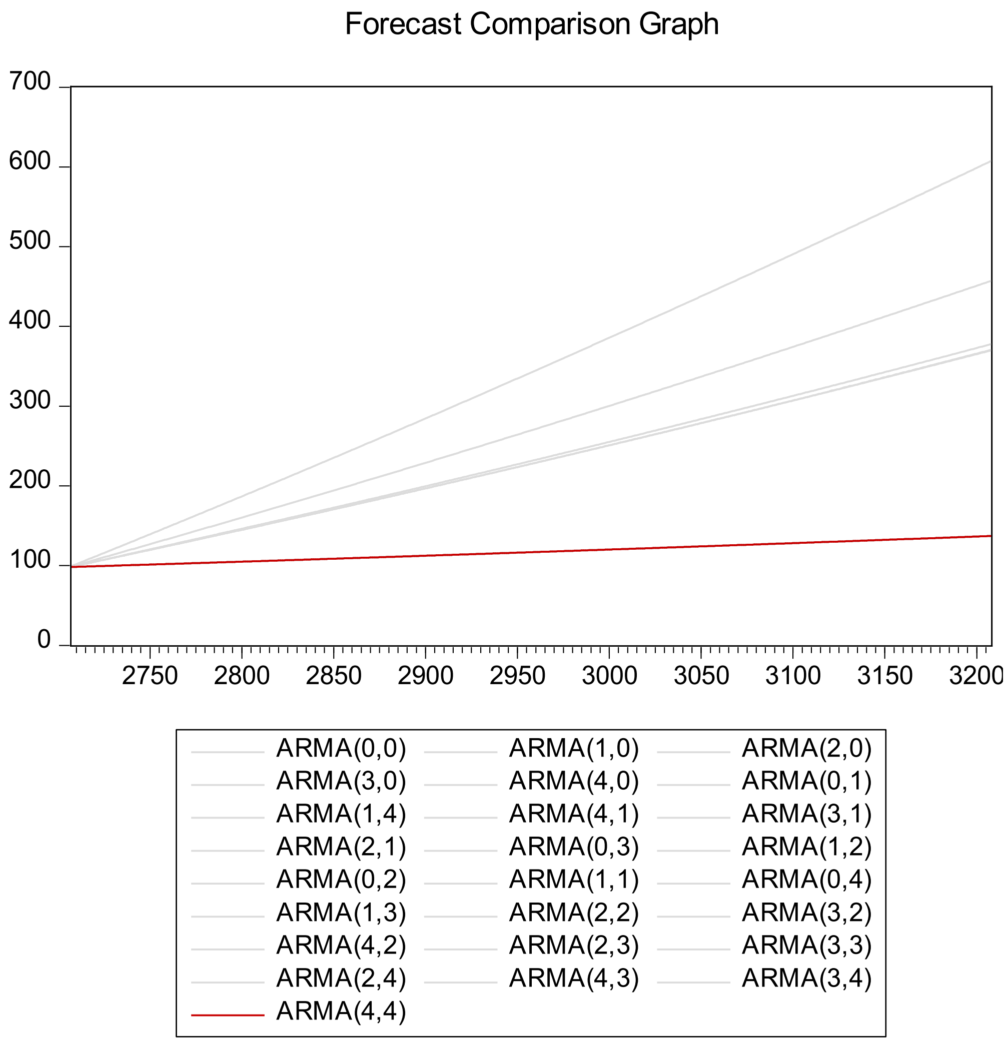


Source: E Views Output

The model corresponding to the lowest AIC value i.e.,1.241867 is (4,4). Hence, ARMA (4,4) is selected as the best model.

Figure 5.7

Forecast Comparison Graph of Performance of Large and Mid-cap funds



Source: EViews Output

Fig 5.7 shows the forecast comparison graph of performance of large and mid-cap funds. The graph confirms ARMA (4,4) as the best model.

Table 5.5

ARMA Maximum Likelihood Estimation of Performance of Large and Mid-cap funds

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.84E-05	1.12E-05	2.533732	0.0113
AR(1)	-1.583119	0.103542	-15.28968	0.0000
AR(2)	-1.101532	0.143897	-7.654981	0.0000
AR(3)	-0.213363	0.072729	-2.933660	0.0034
AR(4)	-0.066472	0.019946	-3.332619	0.0009
MA(1)	0.668458	0.101211	6.604590	0.0000
MA(2)	-0.417853	0.070702	-5.910061	0.0000
MA(3)	-0.982457	0.298807	-3.287930	0.0010
MA(4)	-0.268104	0.159986	-1.675794	0.0939
SIGMASQ	0.200609	0.008238	24.35021	0.0000
R-squared	0.490854	Mean dependent var		0.000354
Adjusted R-squared	0.489153	S.D. dependent var		0.627819
S.E. of regression	0.448724	Akaike info criterion		1.241866
Sum squared resid	542.4463	Schwarz criterion		1.263695
Log likelihood	-1669.003	Hannan-Quinn criter.		1.249760
F-statistic	288.5796			
Prob (F-statistic)	0.000000	Durbin-Watson stat		1.997560
Inverted AR Roots	-.06+.27i	-.06-.27i	-.73+.56i	-.73-.56i
Inverted MA Roots	1.00	-.33	-.67+.60i	-.67-.60i

Source: EViews Output

From table 5.5, it is evident that the model has met all the necessary criteria. Hence, ARMA (4,4) can be selected as the best model indicating the performance of large and mid-cap funds in India. As the integration order is found to be 1, the ARIMA model can be represented as ARIMA (4,1,4).

Mid-cap funds

Table 5.6 shows the ARMA models of mid-cap funds and their corresponding values of the selection criteria. The model corresponding to the lowest value of AIC is chosen as the ARMA model.

Table 5.6

ARMA Model Selection Criteria of Performance of Mid-cap funds

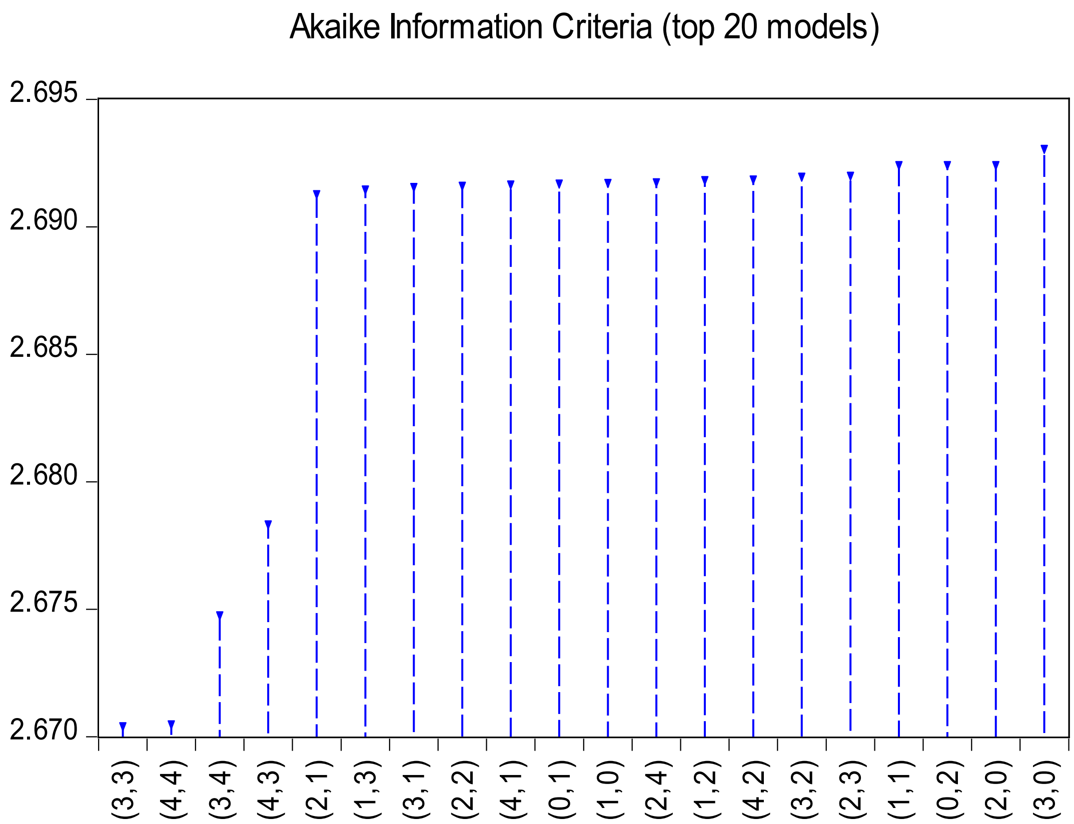
Model	LogL	AIC*	BIC	HQ
(3,3)	-3603.730108	2.670410	2.687868	2.676723
(4,4)	-3601.829100	2.670484	2.692306	2.678374
(3,4)	-3608.606662	2.674755	2.694395	2.681857
(4,3)	-3613.434945	2.678325	2.697965	2.685427
(2,1)	-3634.961265	2.691284	2.702195	2.695229
(1,3)	-3634.197853	2.691459	2.704552	2.696193
(3,1)	-3634.331984	2.691558	2.704651	2.696292
(2,2)	-3634.412430	2.691617	2.704711	2.696352
(4,1)	-3633.466444	2.691657	2.706933	2.697181
(0,1)	-3637.522929	2.691699	2.698246	2.694066
(1,0)	-3637.558673	2.691725	2.698272	2.694093
(2,4)	-3632.584419	2.691744	2.709202	2.698057
(1,2)	-3635.694771	2.691826	2.702737	2.695771
(4,2)	-3632.744181	2.691863	2.709320	2.698175
(3,2)	-3633.890691	2.691971	2.707246	2.697494
(2,3)	-3633.930003	2.692000	2.707275	2.697524
(1,1)	-3637.492555	2.692416	2.701145	2.695572
(0,2)	-3637.496785	2.692419	2.701148	2.695575
(2,0)	-3637.503084	2.692424	2.701153	2.695580
(3,0)	-3637.365787	2.693062	2.703973	2.697007
(0,3)	-3637.404489	2.693090	2.704001	2.697036
(4,0)	-3636.929572	2.693478	2.706572	2.698213
(1,4)	-3636.104360	2.693608	2.708883	2.699131
(0,4)	-3637.397393	2.693824	2.706918	2.698559
(0,0)	-3654.620907	2.703601	2.707966	2.705180

Source: EViews Output

Table 5.6 shows that the ARMA (3,3) is the best model of the performance of mid-cap funds.

Figure 5.8

ARMA Model of Performance of Mid-cap funds

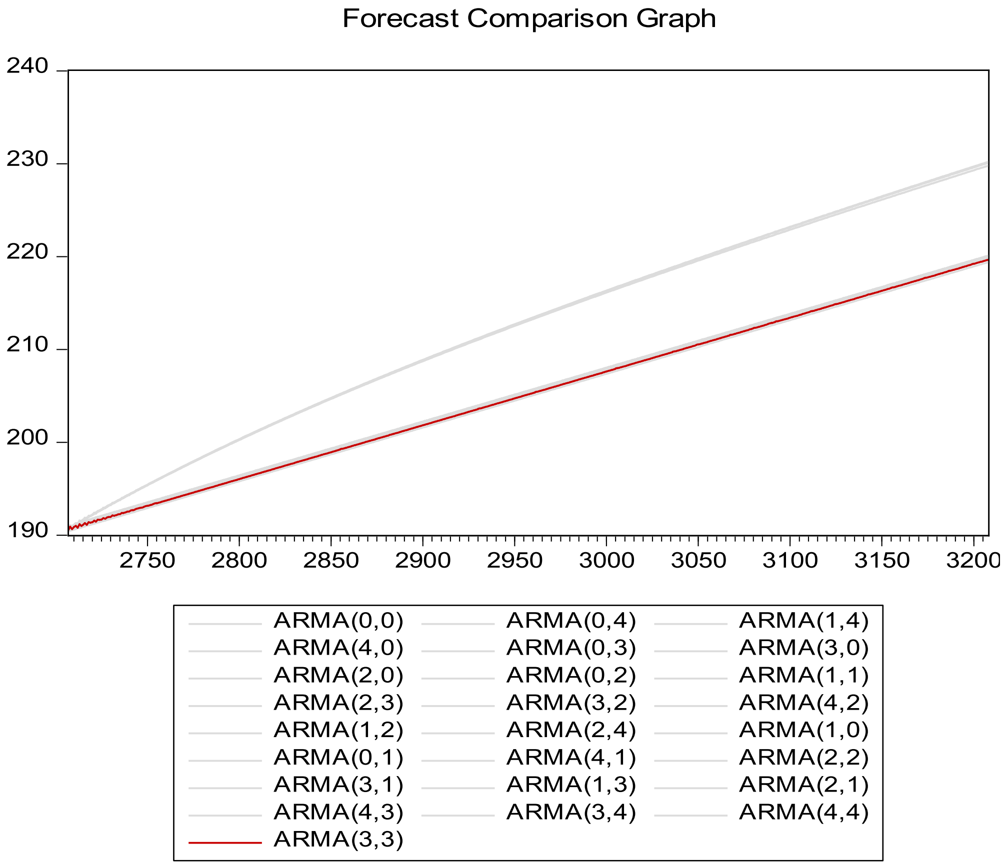


Source: EViews Output

The model corresponding to the lowest AIC value i.e., 2.670410 is (3,3). Hence, ARMA (3,3) is selected as the best model.

Figure 5.9

Forecast Comparison Graph of Performance of Mid-cap funds



Source: EViews Output

Figure 5.9 shows the forecast comparison graph of performance of mid-cap funds. The graph confirms ARMA (3,3) as the best model.

Table 5.7

ARMA Maximum Likelihood Estimation of Performance of Mid-cap funds

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.057932	0.021581	2.684447	0.0073
AR(1)	-1.829314	0.052146	-35.08046	0.0000
AR(2)	-1.417846	0.084589	-16.76168	0.0000
AR(3)	-0.320311	0.054642	-5.862016	0.0000
MA(1)	1.962988	0.048831	40.19925	0.0000
MA(2)	1.664976	0.077651	21.44184	0.0000
MA(3)	0.492376	0.049827	9.881772	0.0000
SIGMASQ	0.840728	0.011240	74.79468	0.0000
R-squared	0.037029	Mean dependent var		0.057848
Adjusted R-squared	0.034530	S.D. dependent var		0.934548
S.E. of regression	0.918271	Akaike info criterion		2.670410
Sum squared resid	2274.170	Schwarz criterion		2.687868
Log likelihood	-3603.730	Hannan-Quinn criter.		2.676723
F-statistic	14.81554			
Prob(F-statistic)	0.000000	Durbin-Watson stat		2.000344
Inverted AR Roots	-.36	-.73+.59i	-.73-.59i	
Inverted MA Roots	-.56	-.70-.62i	-.70+.62i	

Source: EViews Output

From table 5.7, it is evident that the model has met all the necessary criteria. Hence, ARMA (3,3) can be selected as the best model indicating the performance of mid-cap funds in India. As the integration order is found to be 1, the ARIMA model can be represented as ARIMA (3,1,3).

Small-cap funds

Table 5.8 shows the ARMA models of small-cap funds and their corresponding values of the selection criteria. The model corresponding to the lowest value of AIC is chosen as the ARMA model.

Table 5.8

ARMA Model Selection Criteria of Performance of Small-cap funds

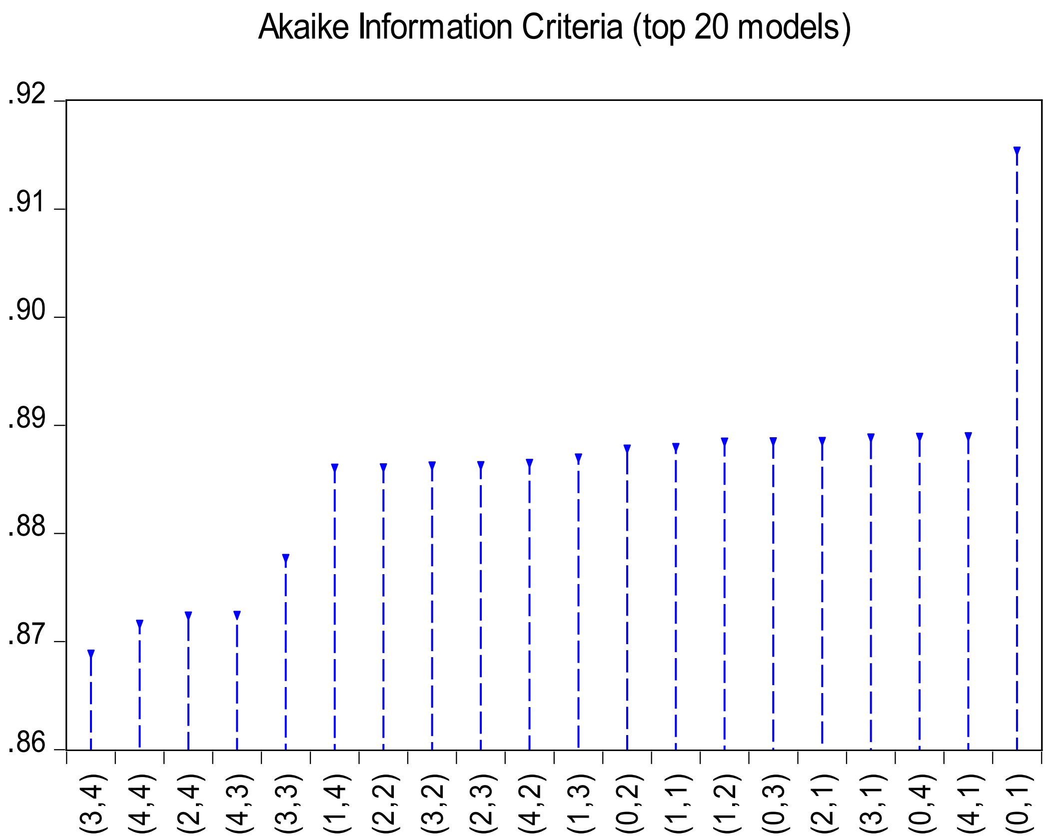
Model	LogL	AIC*	BIC	HQ
(3,4)	-1165.704244	0.868864	0.888510	0.875968
(4,4)	-1168.436290	0.871624	0.893453	0.879518
(2,4)	-1171.495748	0.872408	0.889871	0.878723
(4,3)	-1170.570374	0.872463	0.892109	0.879567
(3,3)	-1178.663916	0.877710	0.895173	0.884025
(1,4)	-1190.959800	0.886065	0.901345	0.891590
(2,2)	-1191.996510	0.886092	0.899189	0.890828
(3,2)	-1191.241285	0.886273	0.901553	0.891798
(2,3)	-1191.295713	0.886313	0.901594	0.891839
(4,2)	-1190.568305	0.886515	0.903978	0.892830
(1,3)	-1193.231616	0.887006	0.900103	0.891742
(0,2)	-1196.371885	0.887849	0.896581	0.891006
(1,1)	-1196.563250	0.887991	0.896722	0.891148
(1,2)	-1196.234932	0.888487	0.899402	0.892434
(0,3)	-1196.261523	0.888507	0.899421	0.892454
(2,1)	-1196.304688	0.888539	0.899453	0.892486
(3,1)	-1195.746900	0.888866	0.901963	0.893602
(0,4)	-1195.845752	0.888939	0.902036	0.893675
(4,1)	-1194.906434	0.888984	0.904264	0.894509
(0,1)	-1234.615578	0.915396	0.921945	0.917764
(4,0)	-1367.800801	1.016125	1.029222	1.020861
(3,0)	-1445.828536	1.073098	1.084012	1.077045
(2,0)	-1528.341528	1.133389	1.142120	1.136546
(1,0)	-1668.349835	1.236205	1.242754	1.238573
(0,0)	-1914.117137	1.417246	1.421612	1.418825

Source: EViews Output

According to Table 5.8, the ARMA (3,4) is the best model of small-cap funds' performance that can be used to predict the future values of the small-cap funds.

Figure 5.10

ARMA Model of Performance of Small-cap funds

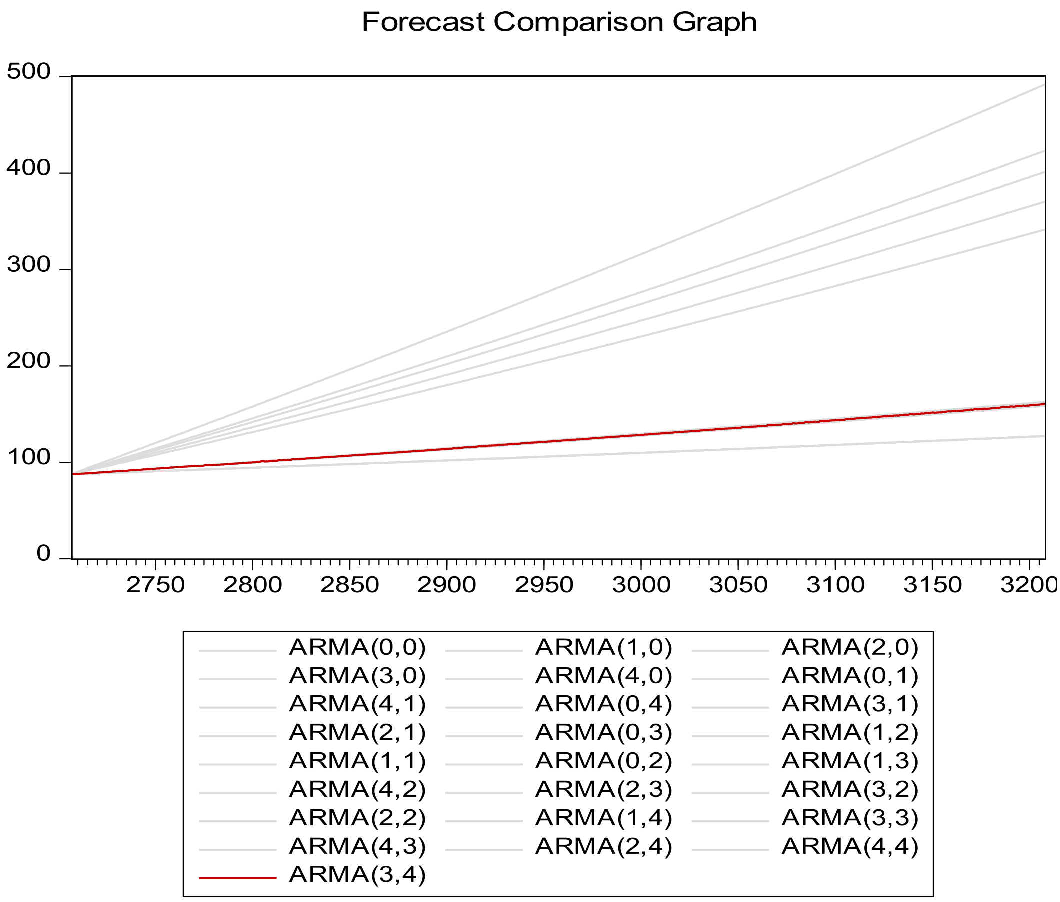


Source: EViews Output

The model corresponding to the lowest AIC value i.e.,0.868864 is (3,4). Hence, ARMA (3,4) is selected as the best model.

Figure 5.11

Forecast Comparison Graph of Performance of Small-cap funds



Source: EViews Output

Figure 5.11 shows the forecast comparison graph of performance of small-cap funds. The graph confirms ARMA (3,4) as the best model.

Table 5.12

ARMA Maximum Likelihood Estimation of Performance of Small-cap funds

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.38E-05	5.66E-05	0.950591	0.3419
AR(1)	-1.724588	0.041109	-41.95147	0.0000
AR(2)	-1.223432	0.070222	-17.42222	0.0000
AR(3)	-0.213628	0.044473	-4.803586	0.0000
MA(1)	0.919257	0.038253	24.03092	0.0000
MA(2)	-0.348705	0.031483	-11.07612	0.0000
MA(3)	-1.107559	0.028588	-38.74273	0.0000
MA(4)	-0.434001	0.040712	-10.66035	0.0000
SIGMASQ	0.138446	0.001712	80.86730	0.0000
R-squared	0.426022	Mean dependent var		0.000277
Adjusted R-squared	0.424318	S.D. dependent var		0.491217
S.E. of regression	0.372704	Akaike info criterion		0.868864
Sum squared resid	374.3583	Schwarz criterion		0.888510
Log likelihood	-1165.704	Hannan-Quinn criter.		0.875968
F-statistic	250.0377			
Prob(F-statistic)	0.000000	Durbin-Watson stat		1.999106
Inverted AR Roots	-.25	-.74+.56i	-.74-.56i	
Inverted MA Roots	.99	-.54	-.69+.58i	-.69-.58i

Source: EViews Output

Table 5.12, makes it evident that the model has met all the necessary criteria. Hence, ARMA (3,4) can be selected as the best model indicating the performance of small-cap funds in India. As the integration order is found to be 1, the ARIMA model can be represented as ARIMA (3,1,4).

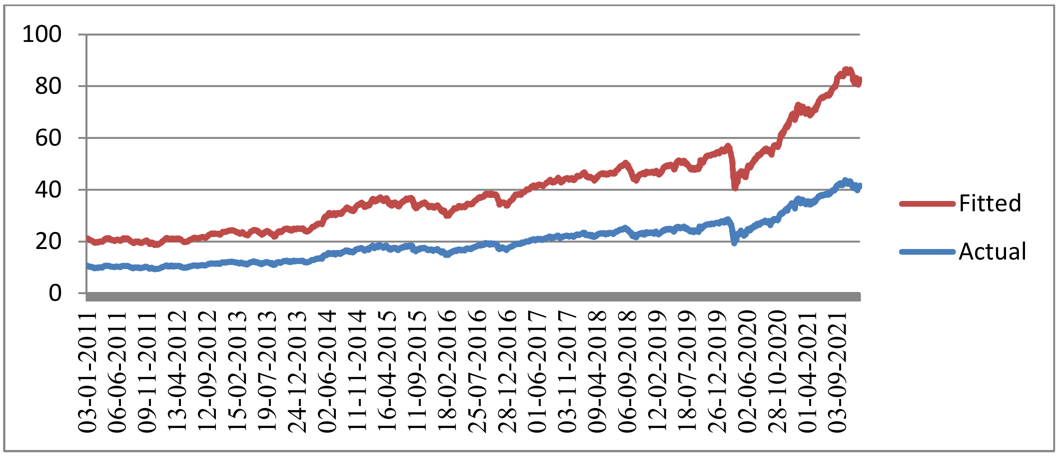
5.3.2.3 Analysis of Actual, Fitted and Residual Values of ARIMA Models

The nature of the performance of equity funds can be identified by analysing the actual, fitted and residual values of the variables using ARIMA modelling. Actual values are those that are already available in the dataset, whereas fitted values are those generated by the system by applying ARIMA modeling. Residual values are the deviation of actual values from the fitted ones.

Large-cap funds

Figure 5.12

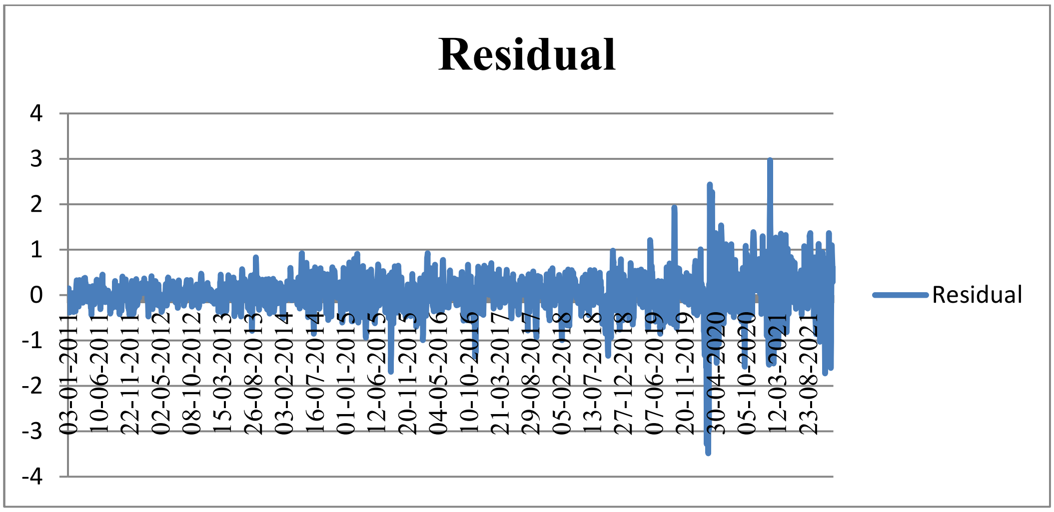
Actual and Fitted Comparison graph of Large-cap funds



Source: EViews Output

Figure 5.13

Residual Plot of Large-cap funds



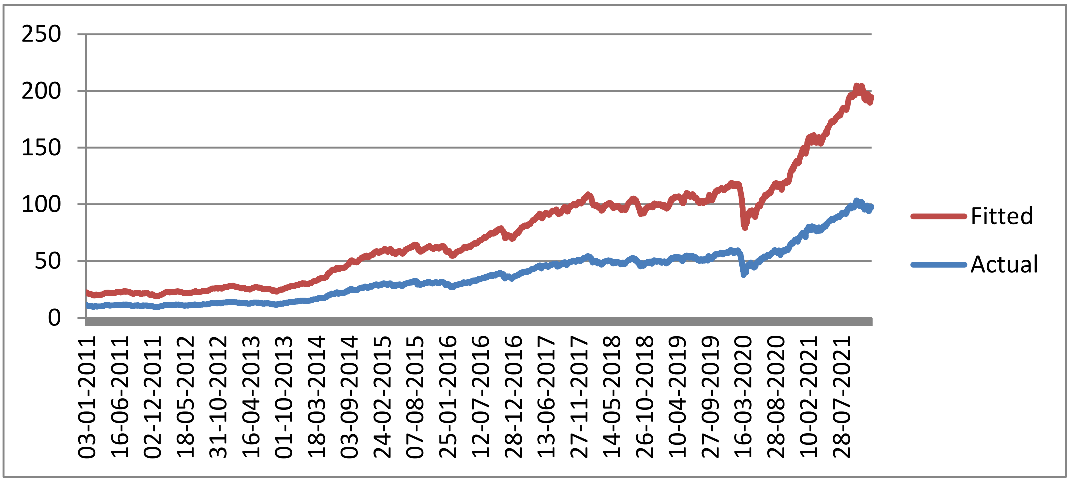
Source: EViews Output

Figure 5.12 presents the actual and fitted comparison graph of large-cap funds for the period 2011-2021 and figure 5.13 presents the residual plot of large-cap funds for the same period.

Large and Mid-cap funds

Figure 5.14

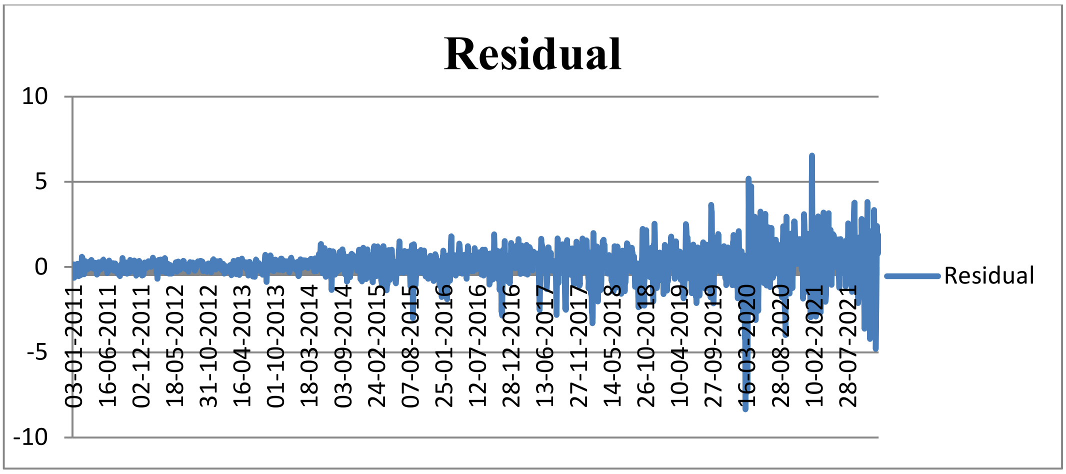
Actual and Fitted Comparison graph of Large and Mid-cap funds



Source: EViews Output

Figure 5.15

Residual Plot of Large and Mid-cap funds



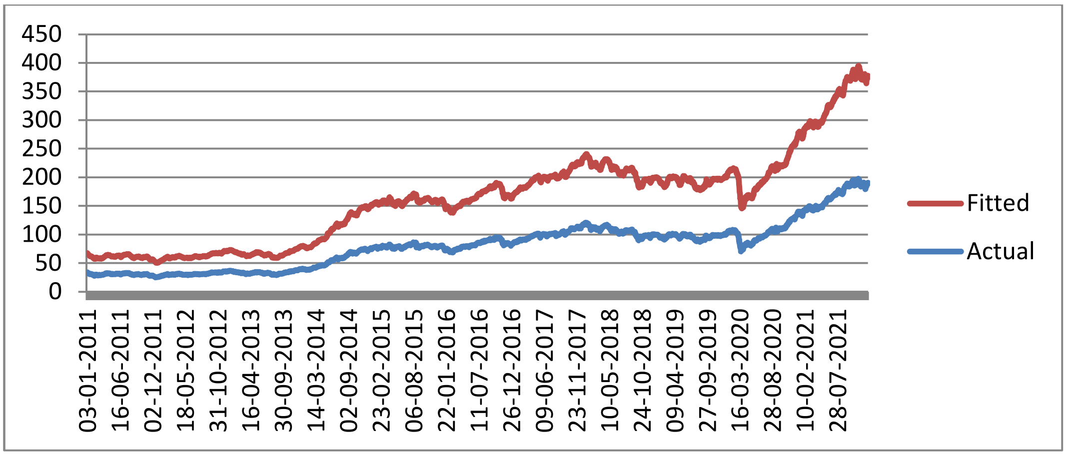
Source: EViews Output

Figure 5.14 demonstrates the actual and fitted comparison graph of large and mid-cap funds and figure 5.15 shows the residual plot of large and mid-cap funds in India for the period 2011–2021.

Mid-cap funds

Figure 5.16

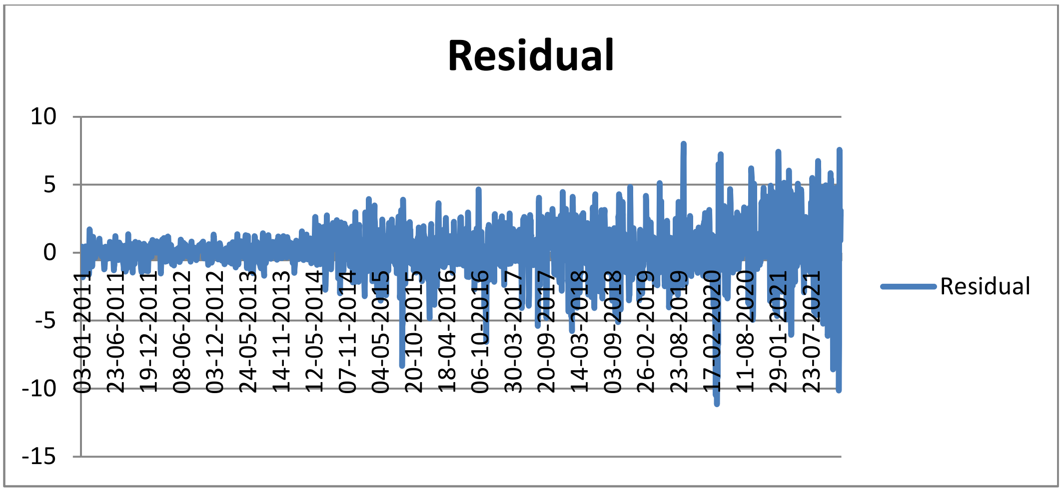
Actual and Fitted Comparison graph of Mid-cap funds



Source: EViews Output

Figure 5.17

Residual Plot of Mid-cap funds



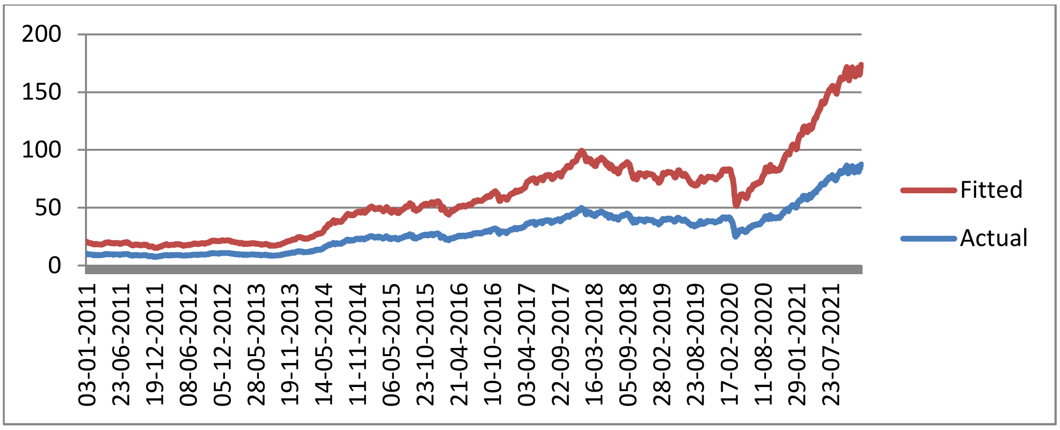
Source: EViews Output

Figure 5.16 shows the actual and fitted comparison graph of mid-cap funds and figure 5.17 shows the residual plot of mid-cap funds in India for the period 2011-2021.

Small-cap funds

Figure 5.18

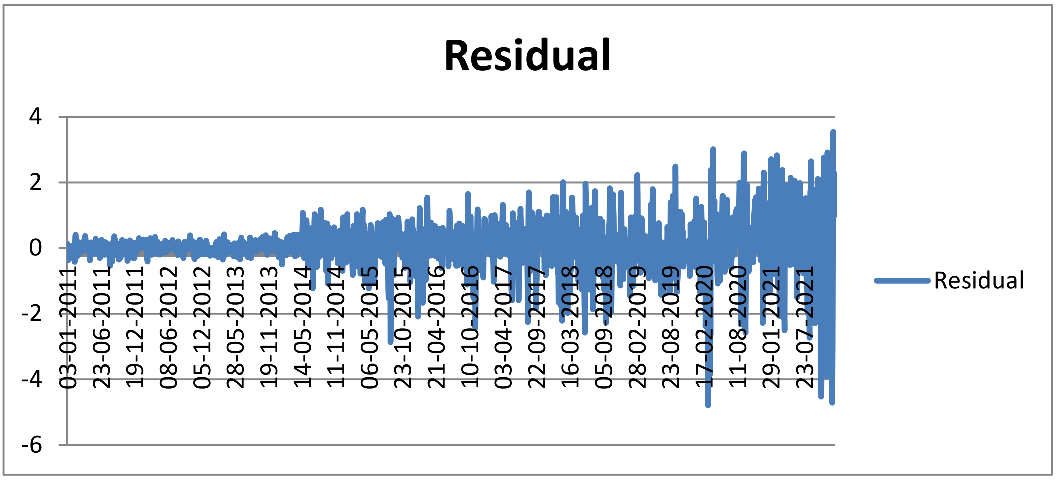
Actual and Fitted Comparison graph of Small-cap funds



Source: EViews Output

Figure 5.19

Residual Plot of Small-cap funds



Source: EViews Output

Figure 5.18 displays the actual and fitted comparison graph of small-cap funds and figure 5.19 presents the residual plot of small-cap funds in India for the period 2011-2021.

While analysing the actual, fitted and residual values, it is obvious that all the categories of funds exhibit negative deviations from their fitted values. Negative deviation occurs when the actual values fall below the fitted values. In the initial years (2011–2013), large-cap funds showed more variations from the fitted values compared to other categories of funds, whereas the actual values of large and mid-cap funds showed slighter variations from their fitted values in those years.

In 2014-15, mid-cap funds experienced a wider range of deviations, followed by large-cap funds, while a narrow range was exhibited by large and mid-cap funds. In 2016, the deviations between actual and fitted values of all the funds have been showing an increasing trend. In 2017, the actual and fitted values of large and mid-cap funds exhibited tremendous variation compared to their performance in the previous years. Also, a sharp rise can be seen in the performance of all the funds in the same year.

Large-cap funds and large and mid-cap funds continue to grow, whereas mid-cap funds and small-cap funds began to show negative returns in 2018 and 2019. The range of residuals of small-cap funds seems to be wider compared to others. A steep decline occurs in the performance of all the funds in the 1st half of 2020, making the residuals wider. By the second half of the year, all of the funds had grown dramatically, with the deviations between actual and fitted values becoming nearly identical. By the end of 2021, the residuals of mid-cap funds and small-cap funds had again increased. While analysing the residuals, the small-cap funds have shown more fluctuations, making them the most volatile category of funds, whereas large-cap funds are the least volatile funds. Small-cap funds are those that invest at least 65% of their assets in small-cap companies. Small-cap companies are in their nascent stages of growth and they have a long way to go before they deliver growth consistently. Small-cap stocks are riskier investments. However, these funds have a high potential for long-term outperformance. While analysing the trend of yearly returns as well, it is clear that, in peak times, small-cap funds are the ones that provide the highest returns. But if the market is going through a bearish phase, these funds deliver the lowest returns. Large-cap funds invest a large portion of their corpus in companies with large market capitalisations. Hence, these funds offer stability and sustainable returns.

5.3.2.4 Forecasting of NAVs of Equity Mutual Funds using ARIMA Model

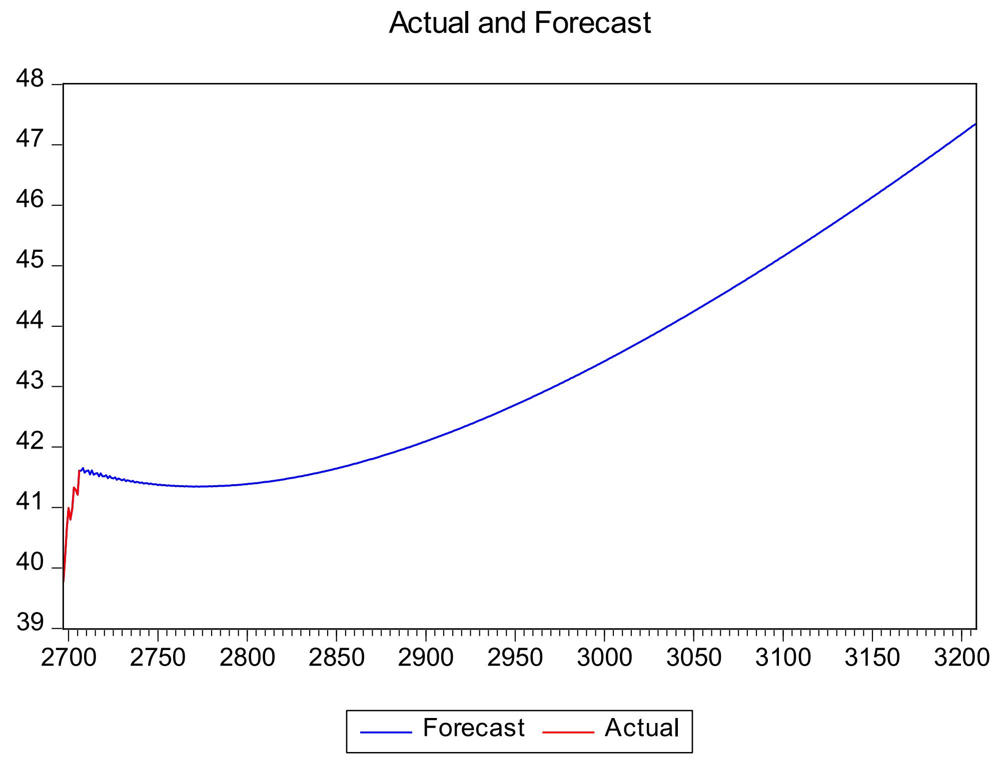
Application of the ARIMA model facilitates forecasting the future NAVs of equity mutual funds, enabling investors to know the growth of the funds. The NAVs of the funds for the years 2011–2021 were taken as samples for the study, and forecasts were made for the years 2022 and 2023.

Large-cap funds

The actual and forecast graph of large-cap funds is presented in figure 5.20.

Figure 5.20

Actual and Forecast graph of Large-cap funds



Source: EViews Output

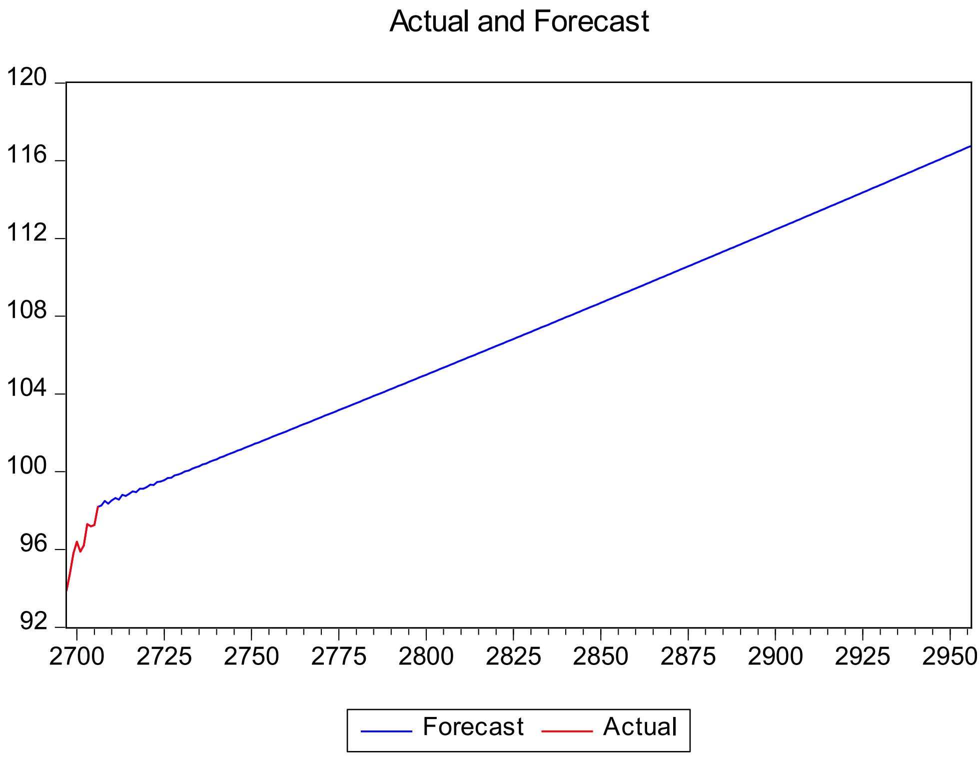
Figure 5.20 makes it evident that the NAVs of the large-cap funds would decline during the first half of 2022 and further rise at a slow pace in the second half. It would be due to the corrections that would take place in the stock market, leading to a fall in the share prices of large-cap companies. Moreover, the returns are expected to grow considerably in 2023.

Large and Mid-cap funds

The actual and forecast graph of large and mid-cap funds is presented in figure 5.21.

Figure 5.21

Actual and Forecast graph of Large and Mid-cap funds



Source: EViews Output

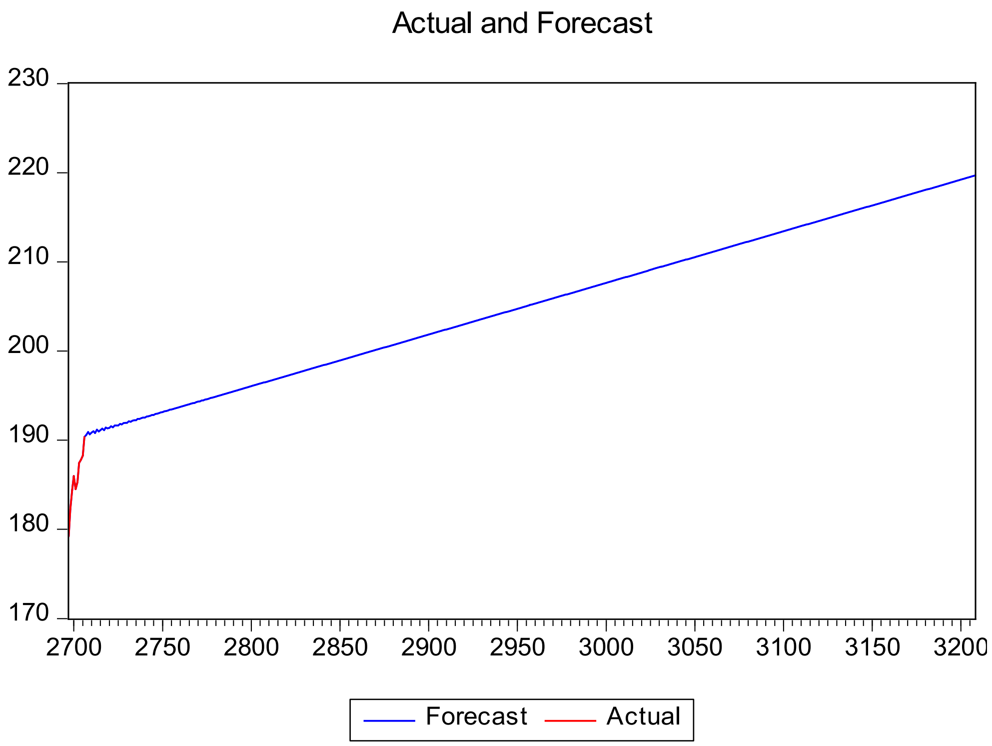
By analysing Fig. 5.21, it is evident that the performance of large and mid-cap funds would increase constantly during the years 2022 and 2023.

Mid-cap funds

The actual and forecast graph of mid-cap funds is presented in figure 5.22.

Figure 5.22

Actual and Forecast graph of Mid-cap funds



Source: EViews Output

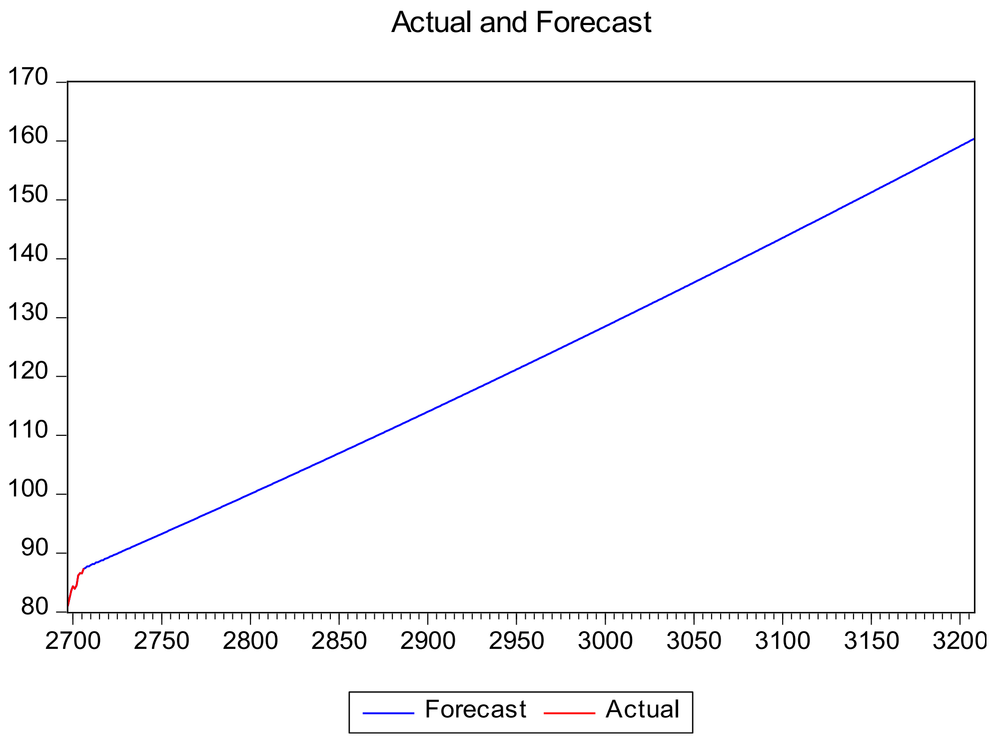
Figure 5.22 indicates the actual and forecast graph of mid-cap funds. The forecasts imply that the mid-cap funds would perform positively during 2022 and 2023.

Small cap funds

The actual and forecast graph of small-cap funds is presented in figure 5.23.

Figure 5.23

Actual and Forecast graph of Small-cap funds



Source: EViews Output

By analysing Figure 5.23, it is obvious that the small-cap funds would continue to prosper during 2022 and 2023 by providing higher returns.

Small-cap funds would outperform the other categories of equity mutual funds in terms of returns in 2022. The NAVs of large-cap funds would decline during the initial phase of 2022 and bounce back further, providing continuous growth during the subsequent phase. Even with a slow rate of growth, large and mid-cap funds and mid-cap funds would perform well in 2022. However, as per the forecasts, 2023 would be a positive year for all the categories of mutual funds.

5.4 Conclusion

The findings imply that equity mutual funds have gone through hikes and dips in the past. Despite the high returns provided by small-cap funds during the booms in the economy, it has been the most volatile category compared to others. Since large-cap funds invest in companies that have a good track record in the market, investing in those funds makes the investment less risky. Large-cap funds proved to be less volatile followed by large and mid-cap funds and mid-cap funds. Small-cap funds are found to be the most volatile category of equity mutual funds, which invest at least 65% of their assets in small-cap companies with high risk and huge growth potential.

According to the forecasts, all of the funds would provide positive returns in 2022 and 2023. However, the forecasts indicate that small-cap funds would be the best performers in 2022. The performance of large-cap funds would decline in the initial phase but increase eventually. The large and mid-cap funds and mid-cap funds would continue to grow in 2022, albeit at a slow pace. Furthermore, all of the funds are expected to deliver positive returns in 2023. Due to the highly volatile nature of small-cap funds, it would be suitable for aggressive investors to invest in them. Large-cap funds would be advisable for conservative investors since the risk is low.

Chapter 6

NATURE AND EXTENT OF BEHAVIOURAL BIAS AMONG EQUITY MUTUAL FUND INVESTORS

Contents

6.1 Introduction

Standard finance theory relies upon two basic assumptions, namely, rationality and market efficiency. As per the assumptions of traditional economists, humans are rational beings who always try to maximise their utility. They believe that all known information has already been priced into an investment. The assumptions of traditional finance have been criticised on the grounds that human beings make decisions based on their emotions and behaviour and not merely on objective factors. These criticisms led to the evolution of behavioural finance.

Behavioural finance is an emerging field that integrates behavioural and cognitive psychology with financial decision-making processes (Parikh, 2009). It explores the "how and why" aspect of the thoughts and feelings of investors. Further, it explores the impact biases have on investors' decisions (Sulphey, 2014).

Behavioural biases can be classified into Cognitive biases and Emotional biases (Fernandes, Pena, & Tabak, 2010). Cognitive biases occur due to faulty reasoning or lack of understanding in the processing of information. Cognitive biases can be further classified into belief perseverance bias and information processing bias. Belief perseverance bias refers to the tendency of an individual to hold on to a set of beliefs even though they come across evidence that proves otherwise. Belief perseverance bias can be further classified into several biases in which the researcher considers representativeness, confirmation, cognitive dissonance and illusion of control for the study. Information processing bias occurs when people make errors in thinking when processing information related to a financial decision. In information processing bias, anchoring, availability, self-attribution and mental accounting are considered for the study. Emotional biases occur spontaneously based on feelings, perceptions or beliefs that distort cognition and decision-making. Emotional biases include overconfidence, loss aversion, regret aversion and herd behaviour.

For analysing the extent of behavioural bias, data were collected from 390 equity mutual fund investors in Kerala. The present chapter and the following chapter involve primary data analysis regarding behavioural bias and investment performance. The researcher selected gender, age, marital status, educational qualification, occupation and experience in equity mutual fund investment as the socio-economic variables and checked their responses regarding different behavioural biases and investment performance. In the case of gender and marital status, the Independent sample 't-test is used for analysis as these variables have only two levels. As all other socio-economic variables possess more than two levels, ANOVA has been used to test the significant difference among the levels of variables.

The present chapter is divided into two sections, namely Section A and Section B. Section A deals with the profile of sample investors to understand their socio-economic characteristics and Section B deals with the primary data analysis.

SECTION A

6.2 Profile of Sample Investors

It is imperative to analyse the profile of sample investors before conducting the primary data analysis. It is presented below:

6.2.1 Gender-wise Classification of Sample Investors

Kerala has the highest sex ratio in India, which means that females outnumber males. The gender-wise classification of the sample investors is presented in table 6.1.

Table 6.1

Gender-wise Classification of Sample Investors

Gender	Frequency	Percent
Male	281	72.1
Female	109	27.9
Total	**390**	**100**

Source: Survey Data

Table 6.1 makes it clear that 281 (72.1%) of the sample investors are male and the remaining 109 (27.9%) are female. Despite the fact that females outnumber males in Kerala, female participation in equity mutual fund investment is very low.

6.2.2 Age-wise Classification of Sample Investors

Investors belonging to different age group exhibit different behavioural biases. Hence, analysing investors according to their age is inevitable. The age-wise classification of the sample investors is shown in table 6.2.

Table 6.2

Age-wise Classification of Sample Investors

Age (in years)	Frequency	Percent
Below 25	16	4.1
26 - 40	290	74.4
41 - 60	70	17.9
Above 60	14	3.6
Total	**390**	**100**

Source: Survey Data

From table 6.2, it can be inferred that out of 390 investors, 16 (4.1%) belong to the age group "below 25 years," 290 (74.4%) belong to the "26–40 years" category, 70 (17.9%) belong to the "41–60 years" category and 14 (3.6%) belong to “above 60 years” category. This makes it evident that the youth are more involved in equity mutual fund investments in Kerala.

6.2.3 Place of Domicile-wise Classification of the Sample Investors

The researcher categorised the place of domicile of investors as Municipal Corporations, Municipalities and Grama Panchayaths. Presently, there are 6 Municipal Corporations, 87 Municipalities and 941 Grama Panchayaths in Kerala. The investors are classified according to their place of domicile, which is presented in table 6.3.

Table 6.3

Place of Domicile-wise Classification of the Sample Investors

Place of Domicile	Frequency	Percent
Corporation	79	20.3
Municipality	116	29.7
Panchayath	195	50
Total	**390**	**100**

Source: Survey Data

Table 6.3 indicates that 79 (20.3%) of the sample investors reside in Municipal Corporations, 116 (29.7%) reside in Municipalities and 195 (50%) reside in Panchayaths.

6.2.4 Marital Status-wise Classification of Sample Investors

Married people are assumed to be more cautious in making investment decisions compared to the unmarried ones. In order to test this assumption, marital status-wise classification of sample investors is done and is presented in table 6.4.

Table 6.4

Marital Status-wise Classification of Sample Investors

Marital Status	Frequency	Percent
Married	270	69.2
Unmarried	120	30.8
Total	**390**	**100**

Source: Survey Data

The results imply that 270 (69.2%) of the sample investors are married and the remaining are unmarried. It makes it obvious that married individuals are more involved in equity mutual fund investment in Kerala.

6.2.5 Education-wise Classification of Sample Investors

Kerala is the most literate state in India. Education-wise classification of sample investors is presented in table 6.5.

Table 6.5

Education-wise Classification of Sample Investors

Educational Qualification	Frequency	Percent
Higher Secondary and Below	24	6.2
Graduate	118	30.3
Post Graduate	155	39.7
Professional	66	16.9
Vocational/Technical	27	6.9
Total	**390**	**100**

Source: Survey Data

The results indicate that 24 (6.2%) of the sample investors are undergraduates, 118 (30.3%) are graduates, 155 (39.7%) are post graduates, 66 (16.9%) are professionally qualified and 27 (6.9%) are technically qualified. From this, it is obvious that the majority of the sample investors are reasonably educated.

6.2.6 Occupation-wise Classification of Sample Investors

The occupation-wise classification of sample investors is given in table 6.6.

Table 6.6

Occupation-wise Classification of Sample Investors

Occupation	Frequency	Percent
Employed	263	67.4
Professional	70	17.9
Businessman	10	2.6
Retired	19	4.9
Others	28	7.2
Total	**390**	**100**

Source: Survey Data

The results indicate that 263 (67.4%) of the respondents are employed on a salaried basis, 70 (17.9%) are professionals, 10 (2.6%) are businessmen, 19 (4.9%) are retired and the rest 28 (7.2%) belong to other occupations.

6.2.7 Income-wise Classification of Sample Investors

It is imperative to examine the influence of investors' annual income on their investment decisions. To examine whether annual income of investors influence their investment decisions, the respondents are classified on the basis of their annual income which is shown in table 6.7.

Table 6.7

Income-wise Classification of Sample Investors

Annual income (Rs.)	Frequency	Percent
Less than 5,00,000	190	48.7
5,00,000 - 10,00,000	151	38.7
10,00,000 - 15,00,000	19	4.9
More than 15,00,000	30	7.7
Total	**390**	**100**

Source: Survey Data

The results indicate that 190 (48.7%) of the sample investors belong to the 'less than Rs. 5,00,000' category, 151 (38.7%) belong to the 'Rs. 5,00,000-10,00,0000' category, 19 (4.9%) belong to the 'Rs. 10,00,000-15,00,000' category and 30 (7.7%) belong to the 'more than Rs. 15,00,000' category. This indicates that the majority of equity fund investors in Kerala belong to lower-income groups.

6.2.8 Mutual fund Investment-wise Classification of Sample Investors

The amount of savings made by investors in mutual funds varies across individuals. Table 6.8 presents the annual mutual fund investment-wise classification of informants.

Table 6.8
Mutual fund Investment-wise Classification of Sample Investors

Annual Mutual fund Investment (Rs.)	Frequency	Percent
Less than 25,000	193	49.5
25,001 - 50,000	63	16.2
50,001 - 1,00,000	55	14.1
More than 1,00,000	79	20.3
Total	**390**	**100**

Source: Survey Data

It can be inferred from table 6.8, that 193 (49.5%) of the sample investors belong to the 'less than Rs. 25,000' category, 63 (16.2%) belong to the 'Rs. 25,001-50.000' category, 55 (14.1%) belong to the 'Rs. 50,001-1,00,000' category and 79 (20.3%) belong to the 'more than Rs. 1,00,000' category. The majority of investors tend to invest less than Rs. 25,000 in equity mutual funds on an annual basis.

6.2.9 Mutual Fund Investment Mode-wise Classification of Sample Investors

The different modes of investing in equity mutual funds are lumpsum and systematic investment plans. Lumpsum mode of investment refers to investing entire money in one-time. Systematic investment plans refer to investing a fixed amount of money at pre-defined intervals in the selected mutual fund scheme. Investors are classified according to their mode of mutual fund investment and the results are presented in Table 6.9.

Table 6.9

Mutual Fund Investment Mode-wise Classification of Sample Investors

Investment Mode	Frequency	Percent
Lumpsum	69	17.7
SIP	229	58.7
Lump sum and SIP	92	23.6
Total	**390**	**100**

Source: Survey Data

The results indicate that 69 (17.7%) of the sample investors resort to the lumpsum mode of investment, 229 (58.7%) invest through SIPs and 92 (23.6%) invest through both modes of investment. The majority of investors were found to invest through the SIP mode of investment.

6.2.10 Investment Experience-wise Classification of Sample Investors

More experienced investors are assumed to outperform less experienced investors. In order to check this assumption, investors are classified according to their experience in mutual fund investment. The results are presented in table 6.10.

Table 6.10

Investment Experience-wise Classification of Sample Investors

Investment Experience (in years)	Frequency	Percent
Less than 1	82	21.0
1-3	128	32.8
3-5	46	11.8
Above 5	134	34.4
Total	**390**	**100**

Source: Survey Data

It can be inferred that 82 (21%) sample investors have experience of less than 1 year, 128 (32.8%) have experience of 1-3 years, 46 (11.8%) have experience of 3-5 years and 134 (34.4%) have experience of more than 5 years.

SECTION B

In order to analyse the extent of behavioural biases, a five-point Likert scale is developed and the respondents are asked to rate the statements on a scale ranging from strongly agree (5) to strongly disagree (1). Statements B1 to B4 are used to explore representativeness bias, statements B21 to B22 are used to study cognitive dissonance, statements B26 to B29 are used to examine confirmation bias and statements B42 to B44 are used to check illusion of control bias. All these statements collectively represent belief perseverance bias.

Statements B11 to B15 are used to explore anchoring bias, statements B16 to B20 to examine availability bias, statements B23 to B25 to analyse self-attribution bias, and statements B45 and B46 are used to check mental accounting bias. All these statements together constitute information processing bias.

Statements B5 to B10 are used to study overconfidence bias, statements B30 to B33 are used to examine loss aversion bias, statements B34 to B36 are used to analyse regret aversion bias and statements B37 to B41 are used to check herding bias. All these statements collectively constitute emotional bias. The mean values and standard deviations of the statements are given in Table 6.11.

Table 6.11
Statements of Behavioural Bias

Statement code	Statements	Mean	Standard Deviation
B1	I make investment decisions by monitoring the performance of a few samples.	3.62	1.02
B2	I invest in funds that have performed better recently.	3.51	.98
B3	I avoid investing in funds that have performed poorly in the recent past.	3.67	1.06
B4	I prefer to buy hot stocks instead of poorly performed stocks.	3.61	1.04
B5	I have sufficient knowledge about the Indian mutual fund industry.	3.66	.89
B6	My experience in trading with funds helps me choose funds that outperform the market.	3.57	1.00
B7	I have confidence in my ability to pick better funds.	3.64	.91
B8	I never commit mistakes while making investment decisions.	3.28	1.02
B9	I believe that I can master the future trend of my investment.	3.56	.96
B10	I think that market trends are often consistent with my perspectives.	3.50	1.00
B11	I rely heavily on one piece of information in making investment decision.	3.02	1.02
B12	I forecast the changes in net asset value of funds in the future based on the recent net asset values.	3.23	.95
B13	I invest in a fund because I heard good news about it when I decided to make an investment.	3.17	1.19
B14	I become more optimistic when the market rises.	3.47	1.01
B15	I become more pessimistic when the market falls.	3.10	1.00
B16	I make investment decisions based on available information.	3.67	.91
B17	I give more importance to current information when I make investment decisions.	3.47	1.02
B18	I select the funds of companies which I already know.	3.73	.89
B19	I consider the information from friends and relatives as a reliable reference for my investment decisions.	3.17	1.23
B20	I prefer to invest in already known funds.	3.63	.91
B21	I hold the funds when the price decreases, even if it increases the loss.	3.58	1.00
B22	I invest in funds that I already own, even if their NAV goes down, to justify my investment decision.	3.46	.97
B23	I believe that I get profit on investment due to my skill.	3.37	.89
B24	The NAV of funds, which I selected by studying myself, increases.	3.47	.78
B25	The NAV of funds, which I selected due to others' recommendations, falls.	3.07	.73
B26	I collect maximum information from experts about funds, to confirm my investment decisions.	3.53	1.00
B27	I study the nature of funds and search for information while making investments.	3.78	.90
B28	I seek market news that confirms my investment decision as correct.	3.65	.99
B29	When an investment is not going well, I usually seek information that confirms I made the right decision about it.	3.60	1.09

(Contd.)

Statement code	Statements	Mean	Standard Deviation
B30	I seek more risk after a prior gain.	3.30	.94
B31	I become more risk averse after a prior loss.	3.20	.95
B32	The pain of financial loss is greater than the pleasure of financial gain.	3.55	.94
B33	I prefer to invest in high-performing funds.	3.70	.87
B34	I tend to hold onto losing funds too long, hoping for a reversal.	3.39	.90
B35	I used to sell winning funds too soon.	3.19	.934
B36	I feel more sorrow about holding onto losing funds too long than about selling winning funds too soon.	3.26	1.05
B37	I buy funds in times of bullish trends.	3.00	1.09
B38	I sell funds in times of bearish trends.	3.09	1.03
B39	I invest in funds in which my friends invest.	3.15	1.11
B40	My investment decisions are influenced by the investment behaviour of the majority.	3.18	1.06
B41	I would follow the market information to trade.	3.65	.91
B42	I believe I have greater control over my investment.	3.57	.87
B43	I can predict the market in a more logical manner.	3.21	1.05
B44	I tend to invest more when I am successful in my previous investment.	3.49	1.01
B45	I tend to treat each element of my investment portfolio separately.	3.62	.85
B46	I save a part of my income for investing in the stock market.	3.93	.89

Source: Survey Data

Table 6.11 implies that the statement 'I save a part of my income for investing in the stock market' have the highest mean score of 3.93 (SD 0.89) followed by the statement 'I study the nature of funds and search for information while making investments' with mean score of 3.78 (SD 0.90). The statement 'I buy funds in times of bullish trends' has the lowest mean score of 3.00 (SD 1.09).

Table 6.12

Descriptive Statistics of Different Types of Behavioural Bias

Types of Bias	Mean	Standard Deviation
Belief Perseverance Bias	3.56	0.68
Information Processing Bias	3.41	0.63
Emotional Bias	3.38	0.63

Source: Survey Data

The results indicate that the mean scores of all the types of behavioural bias are higher than 3.3 (65%), which implies that the equity mutual fund investors in Kerala possess an above-average level of behavioural bias while making investment decisions. Belief perseverance bias has the highest mean score of 3.56 (SD 0.68) indicating that it has 71% influence among investors in Kerala. The lowest mean score is in the case of emotional bias which is 3.38 (SD 0.63) which has an average influence of 68% among investors in Kerala.

6.3 Influence of Socio-Economic factors on different types of Behavioural Bias

Behavioural biases may vary across individuals based on their socio-economic characteristics. In this section, socio-economic variables such as gender, age, marital status, education, occupation, annual income and experience in mutual fund investment have been used to examine the variability of behavioural bias among different categories of equity mutual fund investors.

6.3.1 Gender-wise Analysis of Behavioural Bias

Male and female investors may have different levels of behavioural biases. Descriptive analysis has been done to determine the mean score of males and females with regard to behavioural bias. Then, the 't test' was applied to analyse the significance of difference between the means of male and female investors.The homogeneity of variance has been tested using Levene's test. Table 6.13 presents the results of the t-test.

Table 6.13

Gender-wise Analysis of Behavioural Bias

Gender	N	Mean	SD	t value	Max Score	*p*-value	Remarks
Male	281	163.81	28.36	7.475^{**}	230	0.000	Equal variances not assumed
Female	109	143.95	21.41				
Total	**390**	**158.26**	**28.03**				

Source: Survey Data

** Statistically significant at 1% significant level

From table 6.13, it can be seen that out of a maximum score of 230, the mean score of male and female investors combined is 158.26 (SD 28.03), which indicates that on an average the investors are affected 69% by behavioural bias while making investment decisions. The behavioural bias among male investors has a mean score of 163.81 (SD 28.36). The mean score of behavioural bias among female investors is 143.95 (SD 21.41). Independent sample t-test is used to check whether significant difference exists among the mean scores of male and female investors in respect of behavioural bias. Since the equal variance assumption is rejected, the researcher considers the results that assume unequal variance.

Table 6.13 makes it clear that there is significant difference between male and female investors with regard to behavioural bias, as the *p*-value is significant at 1% level. The results indicate that male investors are more affected by behavioural bias, as the mean score of male investors is higher compared to female investors.

The researcher also tests whether significant difference exists between male and female investors with respect to different types of behavioural bias. In the case of information processing bias and emotional bias, the equal variance assumption is rejected and the results which assume unequal variance have been considered for the study. The results are presented in table 6.14.

Table 6.14
Gender-wise Analysis of Types of Behavioural Bias

Types of Behavioural Bias	Gender	N	Mean	SD	t value	Max Score	*p*-value	Remarks
Belief Perseverance Bias	Male	281	47.78	8.55	5.715**	65	0.000	Equal variances assumed
	Female	109	42.33	8.15				
	Total	**390**	**46.25**	**8.77**				
Information Processing Bias	Male	281	52.65	9.94	6.146**	75	0.000	Equal variances not assumed
	Female	109	47.25	6.77				
	Total	**390**	**51.14**	**9.47**				
Emotional Bias	Male	281	63.40	11.45	8.712**	90	0.000	Equal variances not assumed
	Female	109	54.37	8.14				
	Total	**390**	**60.87**	**11.37**				

Source: Survey Data
** Statistically significant at 1% significant level

From table 6.14, it is clear that all three types of behavioural bias have a significant difference between male and female investors as their *p*-values are less than .05.

The mean score of the belief perseverance bias of the male investors, 47.78, with a standard deviation of 8.55, is higher than that of the female investors, with a mean of 42.33 and a standard deviation of 8.15. This implies that male investors are more prone to the belief perseverance bias than female investors. Similarly, in the case of information processing bias and emotional bias, the mean score of male investors is higher compared to their female counterparts, making it evident that male investors are more affected by belief perseverance bias.

6.3.2 Age-wise Analysis of Behavioural Bias

Investors' levels of behavioural bias may differ across age groups. In order to know the mean score of the behavioural bias of investors among different age categories, a descriptive analysis has been done. Then, ANOVA is applied to check whether there is a significant difference among different age categories of investors with respect to behavioural bias.

Table 6.15 presents the age-wise test of homogeneity of variances of behavioral bias among investors.

Table 6.15

Age-wise Test of Homogeneity of Variances of Behavioural Bias

Variable	Levens's Statistic	*p*-value
Behavioural Bias	15.295**	0.000

Source: Survey Data
** Statistically significant at 1% significant level

Since the *p*-value of the test is less than 0.05, the assumption of equal variance is rejected. Hence, instead of ANOVA, Welch's F value is considered in the study. The results are shown in table 6.16.

Table 6.16

Age-wise Analysis of Behavioural Bias

Age (Years)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Below 25	16	177.31	41.66	230	3.048*	0.040	Welch
26 – 40	290	158.87	28.47				
41 – 60	70	152.60	22.26				
Above 60	14	152.14	13.96				
Total	**390**	**158.26**	**28.03**				

Source: Survey Data
* Statistically significant at 5% significant level

The results indicate that there exists a significant difference among the age group of investors with regard to behavioural bias, as the *p*-value is significant at the 5% level. Investors belonging to the age group below 25 years possess the highest mean score of 177.31 (SD 41.66) and investors who are above 60 years of age have the lowest mean score of 152.14 (SD 13.96). From this, it is obvious that young investors are more influenced by behavioural bias, whereas older investors are least affected by behavioural bias while making investment decisions.

For a more specific analysis, a descriptive analysis of the types of behavioural bias with respect to the age category of investors is performed. ANOVA is applied to determine the significant difference among the age group of investors with regard to different types of behavioural bias. Table 6.17 presents the age-wise test of homogeneity of variances for different types of behavioural bias among investors.

Table 6.17

Age-wise Test of Homogeneity of Variances of Types of Behavioural Bias

Variables	Levens's Statistic	*p*-value
Belief Perseverance Bias	11.995**	0.000
Information Processing Bias	12.058**	0.000
Emotional Bias	14.042**	0.000

Source: Survey Data

** Statistically significant at 1% significant level

Since the *p*-value of the test is less than 0.05 for all the types, the assumption of equal variance is rejected. Hence, instead of ANOVA, Welch's F value is considered in the study. The results are presented in table 6.18.

Table 6.18

Age-wise Analysis of Types of Behavioural Bias

Types of Behavioural Bias	Age (Years)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Belief Perseverance Bias	Below 25	16	50.63	12.34	65	1.525	0.225	Welch
	26 – 40	290	46.36	9.07				
	41 – 60	70	44.87	6.61				
	Above 60	14	45.93	5.84				
	Total	**390**	**46.25**	**8.77**				
Information Processing Bias	Below 25	16	57.00	15.19	75	3.106*	0.038	Welch
	26 – 40	290	51.44	9.32				
	41 – 60	70	49.04	8.55				
	Above 60	14	48.64	4.92				
	Total	**390**	**51.14**	**9.47**				
Emotional Bias	Below 25	16	69.69	15.40	90	4.958**	0.005	Welch
	26 – 40	290	61.07	11.68				
	41 – 60	70	58.69	8.74				
	Above 60	14	57.57	4.05				
	Total	**390**	**60.87**	**11.37**				

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Table 6.18 shows the significant difference among different age groups of investors with respect to the different types of behavioural bias. The results indicate that there is no significant difference among the age group of investors with regard to belief perseverance bias, as the *p*-value is greater than 0.05. The *p*-values of information processing bias and emotional bias are 0.038 and 0.005, respectively. This makes it evident that a significant difference exists among investors' age categories with regard to information processing bias and emotional bias.

6.3.3 Education-wise Analysis of Behavioural Bias

Investors with different educational qualifications may possess different levels of behavioural bias. In order to know the mean score of different education levels with regard to behavioural bias, descriptive analysis has been done. Further, to test the significant difference among education levels, ANOVA is applied. The homogeneity of variances has been tested using Levene's test, which is presented in Table 6.19.

Table 6.19

Education-wise Test of Homogeneity of Variances of Behavioural Bias

Variable	Levens's Statistic	*p*-value
Behavioural Bias	8.001**	.000

Source: Survey Data
** Statistically significant at 1% significant level

Since the *p*-value of the test is less than 0.05, the assumption of equal variance is rejected. Hence, instead of ANOVA, Welch's F value is considered in the study. The results are presented in table 6.20.

Table 6.20

Education-wise Analysis of Behavioural Bias

Education	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Higher Secondary and Below	24	174.88	33.56	230	19.025**	.000	Welch
Graduate	118	159.45	30.04				
Post Graduate	155	162.28	25.20				
Professional	66	138.41	19.93				
Vocational/Technical	27	163.78	25.53				
Total	**390**	**158.26**	**28.03**				

Source: Survey Data

** Statistically significant at 1% significant level

The *p*-value is less than .05 indicating that there is a significant difference among different education levels of investors. While analysing the mean score, it is understood that undergraduates possess the highest mean score of 174.88 (SD 33.56), followed by investors who are technically qualified. Professionally qualified investors have the lowest mean score of 138.41 (SD 19.93). This indicates that investors with the lowest qualifications are more affected by behavioural bias while making investment decisions, whereas professionally qualified investors are least affected by behavioural bias. Post hoc analysis is done for multiple comparisons to find out the exact difference among the groups. Since equal variances are not assumed, Tamhane's T2 test has been used to determine the pair-wise differences among the groups. The results are depicted in table 6.21.

Table 6.21

Education-wise Post Hoc Test – Behavioural Bias

Education (I)	Education (J)	Mean Difference (I-J)	Std. Error	*p*-value
Higher Secondary and Below	Graduate	15.42585	7.38822	.370
	Post Graduate	12.59758	7.14400	.607
	Professional	36.46591**	7.23670	.000
	Vocational/Technical	11.09722	8.43056	.886
Graduate	Higher Secondary and Below	-15.42585	7.38822	.370
	Post Graduate	-2.82827	3.42688	.995
	Professional	21.04006**	3.61616	.000
	Vocational/Technical	-4.32863	5.63748	.997
Post Graduate	Higher Secondary and Below	-12.59758	7.14400	.607
	Graduate	2.82827	3.42688	.995
	Professional	23.86833**	3.08666	.000
	Vocational/Technical	-1.50036	5.31338	1.000
Professional	Higher Secondary and Below	-36.46591**	7.23670	.000
	Graduate	-21.04006**	3.61616	.000
	Post Graduate	-23.86833**	3.08666	.000
	Vocational/Technical	-25.36869**	5.43738	.000
Vocational/Technical	Higher Secondary and Below	-11.09722	8.43056	.886
	Graduate	4.32863	5.63748	.997
	Post Graduate	1.50036	5.31338	1.000
	Professional	25.36869**	5.43738	.000

Source: Survey Data

** Statistically significant at 1% significant level

The results imply that there exists a significant difference in the education of investors between professionally qualified investors with all other categories of investors with regard to behavioural bias. The investors who belong to the 'higher secondary and below' category have the highest mean score, followed by technically qualified investors. Hence, it can be concluded that investors with the lowest educational qualifications are more prone to behavioural bias.

For a more specific analysis, a descriptive analysis of the types of behavioural bias with respect to the educational qualifications of investors is done. Further, ANOVA is used to check whether a significant difference exists among investors belonging to different educational backgrounds with regard to different types of behavioural bias. Levene's test is used to examine the homogeneity of variances in investors' education with regard to various types of behavioural bias.

Table 6.22

Education-wise Test of Homogeneity of Variances of Types of Behavioural Bias

Variables	Levens's Statistic	*p*-value
Belief Perseverance Bias	3.932**	.004
Information Processing Bias	10.874**	.000
Emotional Bias	2.514*	.041

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Table 6.22 reveals that the *p*-value of the test is less than 0.05 for all the types of behavioural bias and hence, the assumption of equal variance is rejected. So, instead of ANOVA, Welch's F value is considered in the study. The results are presented in table 6.23.

Table 6.23

Education-wise Analysis of Types of Behavioural Bias

Types of Behavioural Bias	Education	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Belief Perseverance Bias	Higher Secondary and Below	24	48.63	10.24	65	9.456	0.000	Welch
	Graduate	118	46.32	9.28				
	Post Graduate	155	47.80	7.98				
	Professional	66	41.05	7.63				
	Vocational/ Technical	27	47.67	7.69				
	Total	**390**	**46.25**	**8.78**				
Information Processing Bias	Higher Secondary and Below	24	56.92	11.46	75	14.588	0.000	Welch
	Graduate	118	51.63	10.69				
	Post Graduate	155	52	8.48				
	Professional	66	45.61	5.81				
	Vocational/ Technical	27	52.44	9.27				
	Total	**390**	**51.14**	**9.47**				
Emotional Bias	Higher Secondary and Below	24	69.33	12.71	90	22.626	0.000	Welch
	Graduate	118	61.50	11.30				
	Post Graduate	155	62.48	10.56				
	Professional	66	51.76	8.35				
	Vocational/ Technical	27	63.67	8.87				
	Total	**390**	**60.87**	**11.37**				

Source: Survey Data

** Statistically significant at 1% significant level

The results indicate that there is a significant difference among investors' levels of education, as the *p*-values of all the biases are less than 0.05. Hence it can be concluded that there exists a significant difference among investors' levels of education with regard to the types of behavioural bias.

To find out the exact difference among the categories of education level, multiple comparisons have been done using post hoc analysis.

Education-wise Multiple Comparisons: Types of Behavioural Bias

Welch's F tests show that there exists a significant difference among the educational qualifications of investors with regard to all the types of behavioural bias. Post hoc test is done to explore the exact difference among the educational qualification of investors.

1. Belief Perseverance Bias

Tamhane's T2 test is done to know the exact significant difference among the educational qualification of investors with regard to belief perseverance bias. The results are given in table 6.24.

Table 6.24

Education-wise Post Hoc Test – Belief Perseverance Bias

Education (I)	Education (J)	Mean Difference (I-J)	Std. Error	*p*-value
Higher Secondary and Below	Graduate	2.30297	2.25726	.977
	Post Graduate	.82500	2.18532	1.000
	Professional	7.57955*	2.29064	.023
	Vocational/Technical	.95833	2.55994	1.000
Graduate	Higher Secondary and Below	-2.30297	2.25726	.977
	Post Graduate	-1.47797	1.06785	.840
	Professional	5.27658**	1.26954	.001
	Vocational/Technical	-1.34463	1.70821	.997
Post Graduate	Higher Secondary and Below	-.82500	2.18532	1.000
	Graduate	1.47797	1.06785	.840
	Professional	6.75455**	1.13672	.000
	Vocational/Technical	.13333	1.61195	1.000
Professional	Higher Secondary and Below	-7.57955*	2.29064	.023
	Graduate	-5.27658**	1.26954	.001
	Post Graduate	-6.75455**	1.13672	.000
	Vocational/Technical	-6.62121**	1.75209	.004

(Contd.)

Education (I)	Education (J)	Mean Difference (I-J)	Std. Error	*p*-value
Vocational/Technical	Higher Secondary and Below	-.95833	2.55994	1.000
	Graduate	1.34463	1.70821	.997
	Post Graduate	-.13333	1.61195	1.000
	Professional	6.62121**	1.75209	.004

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

The results in table 6.24 indicate that there exists a significant difference between professionally qualified investors with all other categories. The investors who belong to the 'higher secondary and below' category have the highest mean score. Hence, it can be concluded that undergraduates are more prone to belief perseverance bias.

2. Information Processing Bias

As the equal variance assumption is rejected, Tamhane's T2 test is done to explore the exact significant difference among the educational levels of investors with regard to information processing bias. The results are given in Table 6.25.

Table 6.25

Education-wise Post Hoc Test – Information Processing Bias

Education (I)	Education (J)	Mean Difference (I-J)	Std. Error	*p*-value
Higher Secondary and Below	Graduate	5.28955	2.53831	.371
	Post Graduate	4.91667	2.43696	.424
	Professional	11.31061**	2.44657	.001
	Vocational/Technical	4.47222	2.94190	.767
Graduate	Higher Secondary and Below	-5.28955	2.53831	.371
	Post Graduate	-.37288	1.19713	1.000
	Professional	6.02106**	1.21657	.000
	Vocational/Technical	-.81733	2.03694	1.000
Post Graduate	Higher Secondary and Below	-4.91667	2.43696	.424
	Graduate	.37288	1.19713	1.000
	Professional	6.39394**	.98782	.000
	Vocational/Technical	-.44444	1.90915	1.000
Professional	Higher Secondary and Below	-11.31061**	2.44657	.001
	Graduate	-6.02106**	1.21657	.000
	Post Graduate	-6.39394**	.98782	.000
	Vocational/Technical	-6.83838**	1.92141	.011

(Contd.)

Education (I)	Education (J)	Mean Difference (I-J)	Std. Error	*p*-value
Vocational/Technical	Higher Secondary and Below	-4.47222	2.94190	.767
	Graduate	.81733	2.03694	1.000
	Post Graduate	.44444	1.90915	1.000
	Professional	6.83838*	1.92141	.011

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

The post hoc test results of information processing bias imply that significant differences exist between professionally qualified investors with all other categories. The mean score is highest for investors with 'higher secondary and below' educational qualification, indicating that investors with the lowest educational qualification are more prone to information processing bias.

3. Emotional Bias

Since the assumption of equal variance is rejected, Tamhane's T2 test is done to explore the exact significant difference among the educational qualification of investors with regard to emotional bias. The results are given in table 6.26.

Table 6.26

Education-wise Post Hoc Test – Emotional Bias

Education (I)	Education(J)	Mean Difference (I-J)	Std. Error	*p*-value
Higher Secondary and Below	Graduate	7.83333	2.79576	.084
	Post Graduate	6.85591	2.73017	.167
	Professional	17.57576**	2.79102	.000
	Vocational/Technical	5.66667	3.10626	.544
Graduate	Higher Secondary and Below	-7.83333	2.79576	.084
	Post Graduate	-.97742	1.34219	.998
	Professional	9.74242**	1.46201	.000
	Vocational/Technical	-2.16667	1.99912	.965
Post Graduate	Higher Secondary and Below	-6.85591	2.73017	.167
	Graduate	.97742	1.34219	.998
	Professional	10.71984**	1.33230	.000
	Vocational/Technical	-1.18925	1.90632	1.000
Professional	Higher Secondary and Below	-17.57576**	2.79102	.000
	Graduate	-9.74242**	1.46201	.000
	Post Graduate	-10.71984**	1.33230	.000
	Vocational/Technical	11.90909**	1.99249	.000

(Contd.)

Education (I)	Education(J)	Mean Difference (I-J)	Std. Error	*p*-value
Vocational/Technical	Higher Secondary and Below	-5.66667	3.10626	.544
	Graduate	2.16667	1.99912	.965
	Post Graduate	1.18925	1.90632	1.000
	Professional	11.90909**	1.99249	.000

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

In the case of emotional bias, there exists a significant difference between professionally qualified investors with all the other categories of investors. The mean score indicates that undergraduates possess the highest mean score. This implies that investors who have the lowest educational qualifications are more prone to emotional bias.

6.3.4 Occupation-wise Analysis of Behavioural Bias

The level of behavioural bias may vary according to investors' occupations. In order to know the mean score of investors with different occupations, descriptive analysis has been done. Levene's test is used to check the homogeneity of variances. Further, ANOVA is applied to test the significant difference among investors' occupations with regard to behavioural bias.

The results of occupation-wise test of homogeneity of variance of behavioural bias among investors are depicted in Table 6.27.

Table 6.27

Occupation-wise Test of Homogeneity of Variances of Behavioural Bias

Variable	Levens's Statistic	*p*-value
Behavioural Bias	5.747**	.000

Source: Survey Data

** Statistically significant at 1% significant level

Since the *p*-value of the test is less than 0.05, the assumption of equal variance is rejected. Hence, instead of ANOVA, Welch's F value is considered in the study. The results are presented in table 6.28.

Table 6.28

Occupation-wise Analysis of Behavioural Bias

Occupation	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Employed	263	160.54	29.79	230	6.073^{**}	.001	Welch
Professional	70	159.56	23.76				
Businessman	10	139.40	15.86				
Retired	19	147.84	21.45				
Others	28	147.43	22.17				
Total	**390**	**158.26**	**28.03**				

Source: Survey Data

** Statistically significant at 1% significant level

The results indicate that there exists a significant difference among investors' occupations with regard to behavioural bias, as the *p*-value is less than 0.05. The employed investors have the highest mean score of 160.54 (SD 29.79) and businessmen have the lowest mean score of 139.40 (SD 15.86). The results imply that investors who are employed are more prone to behavioural bias, whereas businessmen are the least affected category. To find out the significant difference among the groups, post hoc analysis has been done. Since there is no equality of variance, Tamhane's T2 test has been used to determine the pair-wise differences among the groups.

Table 6.29

Occupation-wise Post Hoc Test – Behavioural Bias

Occupation (I)	Occupation (J)	Mean Difference (I-J)	Std. Error	*p*-value
Employed	Professional	.98278	3.38229	1.000
	Businessman	21.13992^{*}	5.34170	.020
	Retired	12.69782	5.25223	.214
	Others	13.11135	4.57441	.065
Professional	Employed	-.98278	3.38229	1.000
	Businessman	20.15714^{*}	5.76421	.031
	Retired	11.71504	5.68139	.386
	Others	12.12857	5.06137	.184
Businessman	Employed	-21.13992^{*}	5.34170	.020
	Professional	-20.15714^{*}	5.76421	.031
	Retired	-8.44211	7.02653	.937
	Others	-8.02857	6.53540	.929

(Contd.)

Occupation (I)	Occupation (J)	Mean Difference (I-J)	Std. Error	*p*-value
Retired	Employed	-12.69782	5.25223	.214
	Professional	-11.71504	5.68139	.386
	Businessman	8.44211	7.02653	.937
	Others	.41353	6.46247	1.000
Others	Employed	-13.11135	4.57441	.065
	Professional	-12.12857	5.06137	.184
	Businessman	8.02857	6.53540	.929
	Retired	-.41353	6.46247	1.000

Source: Survey Data

** Statistically significant at 1% significant level

The results in table 6.29 imply that there exists a significant difference in the occupation of investors between businessmen with investors who are employed on a regular basis and professionals. The mean score is highest for employed investors, making it evident that employed investors are more affected by behavioural bias.

For a more specific analysis, a descriptive analysis of different types of behavioural bias with respect to the occupation of investors is done. Further, ANOVA is used to check whether a significant difference exists among investors having different occupations with regard to the types of behavioural bias. Levene's test is used to examine investors' occupation-wise homogeneity of variances with regard to different types of behavioural bias.

Table 6.30

Occupation-wise Test of Homogeneity of Variances of Types of Behavioural Bias

Variables	Levens's Statistic	*p*-value
Belief Perseverance Bias	2.819*	0.025
Information Processing Bias	2.146	0.074
Emotional Bias	7.272**	0.000

Source: Survey Data

*, ** Statistically significant at 5% and 1% significant level

The equality of variance assumption is accepted in the case of information processing bias as the *p*-value is greater than 0.05. So, ANOVA is applied to test the significance of differences among different occupations of investors with regard to information processing bias. Since the *p*-value of the test is less than 0.05 for belief perseverance bias and emotional bias, the assumption of the equality of variance is rejected. Hence, instead of ANOVA, Welch's F value is considered in the study. The results are presented in table 6.31.

Table 6.31

Occupation-wise Analysis of Types of Behavioural Bias

Types of Behavioural Bias	Occupation	N	Mean	SD	Max Score	Welch F/ F Value	*p*-value	Remarks
Belief Perseverance Bias	Employed	263	46.58	9.25	65	1.422	.243	Welch
	Professional	70	46.77	7.25				
	Businessman	10	42.40	7.20				
	Retired	19	44.26	7.06				
	Others	28	44.61	9.01				
	Total	**390**	**46.25**	**8.77**				
Information Processing Bias	Employed	263	52.12	9.73	75	3.829	.005	ANOVA
	Professional	70	50.81	8.92				
	Businessman	10	44.40	5.87				
	Retired	19	46.68	8.80				
	Others	28	48.18	7.72				
	Total	**390**	**51.14**	**9.47**				
Emotional Bias	Employed	263	61.84	12.14	90	11.041	.000	Welch
	Professional	70	61.97	9.54				
	Businessman	10	52.60	4.93				
	Retired	19	56.89	6.31				
	Others	28	54.64	8.71				
	Total	**390**	**60.87**	**11.37**				

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Table 6.31 shows the significant difference among different occupations of investors with regard to the types of behavioural bias. The results indicate that there is no significant difference among occupations of investors with regard to belief perseverance bias as the *p*-value is greater than 0.05. Whereas, the *p*-values of the ANOVA and Welch F tests of the information processing bias and emotional bias are 0.005 and 0.000, respectively. This shows that there exists a significant difference among investors' occupations with regard to information processing bias and emotional bias. A post hoc test is used to examine the exact difference among the occupations of investors.

Occupation-wise Multiple Comparisons: Types of Behavioural Bias

As the significant difference among investors' occupations with regard to information processing bias and emotional bias is figured out, a post hoc test is done to explore the exact difference among the occupations of investors.

1. Information processing bias

Since equal variances are assumed, the Tukey HSD test is used to check the pair-wise differences among the occupations of investors with regard to information processing bias.

Table 6.32

Occupation-wise Post Hoc Test – Information Processing Bias

Occupation (I)	Occupation (J)	Mean Difference (I-J)	Std. Error	*p*-value
Employed	Professional	1.30359	1.25609	.838
	Businessman	7.71787*	1.95154	.022
	Retired	5.43366	2.21869	.105
	Others	3.93930	1.85659	.213
Professional	Employed	-1.30359	1.25609	.838
	Businessman	6.41429	3.15735	.253
	Retired	4.13008	2.41599	.429
	Others	2.63571	2.08839	.715
Businessman	Employed	-7.71787*	1.95154	.022
	Professional	-6.41429	3.15735	.253
	Retired	-2.28421	3.64879	.971
	Others	-3.77857	3.44064	.807
Retired	Employed	-5.43366	2.21869	.105
	Professional	-4.13008	2.41599	.429
	Businessman	2.28421	3.64879	.971
	Others	-1.49436	2.77600	.983
Others	Employed	-3.93930	1.85659	.213
	Professional	-2.63571	2.08839	.715
	Businessman	3.77857	3.44064	.807
	Retired	1.49436	2.77600	.983

Source: Survey Data

* Statistically significant at 5% significant level

Table 6.32 reveals that there exists significant difference between the investors who are employed and the businessmen with regard to information processing bias, as the *p*-values is less than 0.05.

2. Emotional bias

Since equal variances are not assumed, Tamhane'sT2 test is used to check the pair-wise differences among the occupations of investors with regard to emotional bias.

Table 6.33

Occupation-wise Post Hoc Test – Emotional Bias

Occupation (I)	Occupation (J)	Mean Difference (I-J)	Std. Error	*p*-value
Employed	Professional	-.12732	1.36406	1.000
	Businessman	9.24411**	1.72821	.001
	Retired	4.94937*	1.63060	.049
	Others	7.20125**	1.80821	.003
Professional	Employed	.12732	1.36406	1.000
	Businessman	9.37143**	1.93062	.001
	Retired	5.07669	1.84375	.083
	Others	7.32857**	2.00254	.006
Businessman	Employed	-9.24411**	1.72821	.001
	Professional	-9.37143**	1.93062	.001
	Retired	-4.29474	2.12731	.435
	Others	-2.04286	2.26632	.991
Retired	Employed	-4.94937*	1.63060	.049
	Professional	-5.07669	1.84375	.083
	Businessman	4.29474	2.12731	.435
	Others	2.25188	2.19280	.976
Others	Employed	-7.20125**	1.80821	.003
	Professional	-7.32857**	2.00254	.006
	Businessman	2.04286	2.26632	.991
	Retired	-2.25188	2.19280	.976

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Table 6.33 reveals that in the case of emotional bias, there exists a significant difference between employed investors with all other categories of occupations except professionals. Furthermore, a significant difference exists between professionals with businessmen and investors who resort to other occupations. While analysing the mean difference, it is understood that professionals are highly affected by emotional bias and businessmen are the least affected.

6.3.5 Marital Status-wise Analysis of Behavioural Bias

The level of behavioural bias may vary according to the marital status of investors. Descriptive analysis has been done to find out the mean score of behavioural bias of married and unmarried investors. In order to explore the significant difference between married and unmarried investors, 't' test has been applied. The results are presented in table 6.34.

Table 6.34

Marital Status-wise Analysis of Behavioural Bias

Marital Status	N	Mean	SD	t value	Max Score	*p*-value	Remarks
Married	270	154.16	25.98	-4.193^{**}	230	0.000	Equal variances not assumed
Unmarried	120	167.51	30.30				
Total	**390**	**158.26**	**28.03**				

Source: Survey Data

** Statistically significant at 1% significant level

From table 6.34, it is understood that the *p*-value of the t-test is less than 0.05. Hence, there exists a significant difference between married and unmarried investors. The mean score of married investors is 154.16 (SD 25.98), whereas, the mean score of unmarried investors is 167.51 (30.30). This indicates that unmarried investors are highly affected by behavioural bias.

Since the *p*-value of the t-test is less than 0.05, a significant difference is found to exist between married and unmarried investors with respect to behavioural bias. Furthermore, unmarried investors are more affected by behavioural bias than married investors.

The researcher also tests whether a significant difference exists between married and unmarried investors with respect to different types of behavioural bias. In the case of information processing bias and emotional bias, the equal variance assumption is rejected and the results that assume unequal variance have been considered for the study. The results are presented in table 6.35.

Table 6.35

Marital Status-wise Analysis of Types of Behavioural Bias

Types of Behavioural Bias	Marital Status	N	Mean	SD	t value	Max Score	*p*-value	Remarks
Belief Perseverance Bias	Married	270	45.16	8.46	-3.748**	65	0.000	Equal variances assumed
	Unmarried	120	48.71	9.02				
	Total	**390**	**46.25**	**8.77**				
Information Processing Bias	Married	270	49.86	8.64	-3.771**	75	0.000	Equal variances not assumed
	Unmarried	120	54.02	10.61				
	Total	**390**	**51.14**	**9.47**				
Emotional Bias	Married	270	59.13	10.71	-4.471**	90	0.000	Equal variances not assumed
	Unmarried	120	64.78	11.86				
	Total	**390**	**60.87**	**11.37**				

Source: Survey Data

** Statistically significant at 1% significant level

The results make it evident that all three types of behavioural bias show a significant difference between married and unmarried investors since the *p*-values are less than 0.05. The results imply that the mean score of unmarried investors is higher than that of the married investors. Hence, it can be concluded that unmarried investors are more prone to behavioural bias.

6.3.6 Income-wise Analysis of Behavioural Bias

Investors with different income levels may possess different levels of behavioural bias. To know the mean score of the behavioural bias of investors among different income levels, a descriptive analysis has been done. Then ANOVA is applied to check whether there is a significant difference among the annual income categories of investors with respect to behavioural bias. Levene's test is used to check the homogeneity of variances.

Table 6.36

Income-wise Test of Homogeneity of Variances of Behavioural Bias

Variable	Levens's Statistic	*p*-value
Behavioural Bias	3.607*	0.014

Source: Survey Data

*Statistically significant at 5% significant level

Since the *p*-value of Levene'stest is less than 0.05, the assumption of equal variance is rejected. Hence, instead of ANOVA, Welch's F value is considered in the study. The results are presented in table 6.37.

Table 6.37

Income-wise Analysis of Behavioural Bias

Annual Income(Rs.)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Less than 5,00,000	190	163.06	27.91	230	3.863*	0.013	Welch
5,00,000 - 10,00,000	151	153.89	28.40				
10,00,000- 15,00,000	19	154.16	14.45				
More than 15,00,000	30	152.43	29.39				
Total	**390**	**158.26**	**28.03**				

Source: Survey Data

* Statistically significant at 5% significant level

The results indicate that there exists a significant difference among the annual income categories of investors with regard to behavioural bias, as the *p*-value is significant at a 5% level. The mean score is maximum for investors having an annual income of 'less than Rs. 5,00,000,' which is 163.06 (SD 27.91), whereas the mean score is minimum for investors having an annual income of 'more than Rs. 15,00,000,' which is 152.43 (SD 29.39). This indicates that investors with lower incomes are more affected by behavioural bias. Multiple comparisons through post hoc analysis are done in order to examine the exact significance between the annual income categories of investors. Since equal variances are not assumed, Tamhane's T2 test is used to examine the pair-wise differences among investors with regard to behavioural bias. The results are presented in table 6.38.

Table 6.38

Income-wise Post Hoc Test – Behavioural Bias

Annual Income (Rs.) (I)	Annual Income (Rs.) (J)	Mean Difference (I-J)	Std. Error	*p*-value
Less than 5,00,000	5,00,000 - 10,00,000	9.16912*	3.07284	.018
	10,00,000- 15,00,000	8.90526	3.88370	.158
	More than 15,00,000	10.62982	5.73591	.360
5,00,000 - 10,00,000	Less than 5,00,000	-9.16912*	3.07284	.018
	10,00,000- 15,00,000	-.26386	4.04070	1.000
	More than 15,00,000	1.46071	5.84336	1.000

(Contd.)

Annual Income (Rs.) (I)	Annual Income (Rs.) (J)	Mean Difference (I-J)	Std. Error	*p*-value
10,00,000- 15,00,000	Less than 5,00,000	-8.90526	3.88370	.158
	5,00,000 - 10,00,000	.26386	4.04070	1.000
	More than 15,00,000	1.72456	6.30758	1.000
More than 15,00,000	Less than 5,00,000	-10.62982	5.73591	.360
	5,00,000 - 10,00,000	-1.46071	5.84336	1.000
	10,00,000- 15,00,000	-1.72456	6.30758	1.000

Source: Survey Data

* Statistically significant at 5% significant level

The results indicate that there exists a significant difference between the 'less than 5,00,000' and '5,00,000-10,00,000' annual income categories, as the *p*-values are less than 0.05. While analysing the mean difference, it is understood that investors with less than Rs. 5,00,000 of annual income are more prone to behavioural bias. Hence, we can arrive at the conclusion that as the income level decreases, behavioural bias among investors increases.

For a more specific analysis, a descriptive analysis of the types of behavioural bias with respect to the annual income of investors is done. ANOVA is applied to determine the significant difference among income of investors with regard to different types of behavioural bias. Table 6.39 presents the income-wise test of homogeneity of variances for different types of behavioural bias among investors.

Table 6.39

Income-wise Test of Homogeneity of Variances -Types of Behavioural Bias

Variables	Levenes's Statistic	*p*-value
Belief Perseverance Bias	2.909*	0.034
Information Processing Bias	2.796*	0.040
Emotional Bias	6.467**	0.000

Source: Survey Data

*, ** Statistically significant at 5% and 1% significant level

Since the *p*-value of the test is less than 0.05 for all the biases, the assumption of equal variance is rejected. Hence, instead of ANOVA, Welch's F value is considered in the study. The results are presented in table 6.40.

Table 6.40

Income-wise Analysis of Types of Behavioural Bias

Types of Behavioural Bias	Annual Income (Rs.)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Belief Perseverance Bias	Less than 5,00,000	190	47.39	8.82	65	2.151	.102	Welch
	5,00,000 - 10,00,000	151	45.01	8.99				
	10,00,000-15,00,000	19	46.42	5.12				
	More than 15,00,000	30	45.17	8.56				
	Total	**390**	**46.25**	**8.78**				
Information Processing Bias	Less than 5,00,000	190	52.94	9.76	75	4.626**	.006	Welch
	5,00,000 - 10,00,000	151	49.67	8.87				
	10,00,000-15,00,000	19	49.63	7.40				
	More than 15,00,000	30	48.07	9.97				
	Total	**390**	**51.13**	**9.48**				
Emotional Bias	Less than 5,00,000	190	62.73	10.97	90	4.600**	.005	Welch
	5,00,000 - 10,00,000	151	59.21	11.87				
	10,00,000-15,00,000	19	58.11	5.12				
	More than 15,00,000	30	59.20	12.69				
	Total	**390**	**60.87**	**11.37**				

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Table 6.40 shows the significant difference among investors with different levels of annual income with regard to the types of behavioural bias. The results indicate that there is no significant difference among the annual income of investors with regard to belief perseverance bias, as the *p*-value is greater than 0.05. Whereas, the *p*-values of the Welch F tests for the information processing bias and emotional bias of 0.006 and 0.005, respectively, indicate the existence of a significant difference among investors' annual income with regard to the information processing bias and emotional bias. To examine the exact difference among the annual income of investors, a post hoc test is used for multiple comparisons.

Income-wise Multiple Comparisons: Types of Behavioural Bias

Because there is a significant difference in investors' income in terms of information processing bias and emotional bias, a post hoc test is performed to investigate the exact difference in investors' annual income.

1. Information processing bias

Since equal variances are not assumed, Tamhane's T2 test is used to check the pair-wise differences among the annual income levels of investors with regard to information processing bias.

Table 6.41

Income-wise Post Hoc Test – Information Processing Bias

Annual Income (Rs.) (I)	Annual Income (Rs.) (J)	Mean Difference (I-J)	Std. Error	*p*-value
Less than 5,00,000	5,00,000 - 10,00,000	3.27323*	1.01070	.008
	10,00,000 - 15,00,000	3.31053	1.83989	.410
	More than 15,00,000	4.87544	1.95280	.098
5,00,000 - 10,00,000	Less than 5,00,000	-3.27323*	1.01070	.008
	10,00,000 - 15,00,000	.03730	1.84523	1.000
	More than 15,00,000	1.60221	1.95783	.961
10,00,000- 15,00,000	Less than 5,00,000	-3.31053	1.83989	.410
	5,00,000 - 10,00,000	-.03730	1.84523	1.000
	More than 15,00,000	1.56491	2.48933	.990
More than 15,00,000	Less than 5,00,000	-4.87544	1.95280	.098
	5,00,000 - 10,00,000	-1.60221	1.95783	.961
	10,00,000 - 15,00,000	-1.56491	2.48933	.990

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

The results indicate that there is a significant difference between investors belonging to the 'less than 5,00,000' and investors belonging to the '5,00,000 - 10,00,000' annual income categories, as the *p*-values are less than 0.05. While analysing the mean difference, it is understood that investors with less than Rs. 5,00,000 of annual income are more prone to behavioural bias.

2. Emotional bias

Tamhane's T2 test is used to check the pair-wise differences among the annual income levels of investors with regard to emotional bias as the equal variance assumptions are rejected.

Table 6.42

Income-wise Post Hoc Test – Emotional Bias

Annual Income (Rs.) (I)	Annual Income (Rs.) (J)	Mean Difference (I-J)	Std. Error	*p*-value
Less than 5,00,000	5,00,000 - 10,00,000	3.50777*	1.25073	.032
	10,00,000 - 15,00,000	4.62105*	1.41852	.014
	More than 15,00,000	3.52632	2.45025	.645
5,00,000 - 10,00,000	Less than 5,00,000	-3.50777*	1.25073	.032
	10,00,000 - 15,00,000	1.11328	1.52025	.977
	More than 15,00,000	.01854	2.51051	1.000
10,00,000- 15,00,000	Less than 5,00,000	-4.62105*	1.41852	.014
	5,00,000 - 10,00,000	-1.11328	1.52025	.977
	More than 15,00,000	-1.09474	2.59818	.999
More than 15,00,000	Less than 5,00,000	-3.52632	2.45025	.645
	5,00,000 - 10,00,000	-.01854	2.51051	1.000
	10,00,000 - 15,00,000	1.09474	2.59818	.999

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

The results indicate that there is a significant difference between investors having income 'less than 5,00,000' and investors belonging to '5,00,000 - 10,00,000' and '10,00,000 – 15,00,000' annual income categories, as the *p*-values are less than 0.05. The mean difference reveals that investors with less than Rs. 5,00,000 of annual income are more affected by behavioural bias.

6.3.7 Investment Experience-wise Analysis of Behavioural Bias

Investors' behavioural biases may differ depending on their mutual fund investment experience. In order to know the mean score of the behavioural bias of investors among different levels of experience in mutual fund investment, a descriptive analysis has been done. Then ANOVA is applied to check whether there exists a significant difference among investors' experiences in mutual fund investment with respect to behavioural bias. Table 6.43 presents the mutual fund investment experience-wise test of homogeneity of variances of behavioural bias among investors.

Table 6.43

Investment Experience-wise Test of Homogeneity of Variances of Behavioural Bias

Variable	Levens's Statistic	*p*-value
Behavioural Bias	2.546*	0.056

Source: Survey Data

* Statistically significant at 5% significant level

Since the *p*-value of Levene's test is greater than 0.05, the assumption of equal variance is not rejected. Hence, ANOVA can be used to examine the significance of differences among investors' experiences in mutual fund investment with regard to behavioural bias. The results of the ANOVA are presented in table 6.44.

Table 6.44

Investment Experience-wise Analysis of Behavioural Bias

Investment Experience (Years)	N	Mean	SD	Max Score	F Value	*p*-value	Remarks
Less than 1	82	164.37	26.86	230	3.292*	0.021	ANOVA
1-3	128	152.63	30.42				
3-5	46	161.48	30.64				
Above 5	134	158.80	24.50				
Total	**390**	**158.26**	**28.03**				

Source: Survey Data

* Statistically significant at 5% significant level

Table 6.44 indicates that the *p*-value of the test is less than 0.05. This indicates that there exists a significant difference among the investors' experience regarding mutual fund investment with regard to behavioural bias. The mean score is maximum for the investors having investment experience of 'less than 1 year' 164.37 (SD 26.86). Investors with experience of '1 – 3 years' possess the lowest mean score of 152.63 (SD 30.42). This indicates that investors with the least experience in mutual fund investment are more prone to behavioural bias. Multiple comparisons through post hoc analysis are done in order to examine the exact significance of the investors' experience in mutual fund investment. Since equal variances are assumed, the Tukey HSD test is used to examine the pair-wise differences among investors' experiences with regard to behavioural bias. The results are presented in table 6.45.

Table 6.45

Investment Experience-wise Post Hoc Test – Behavioural Bias

Investment Experience (Years) (I)	Investment Experience (Years)(J)	Mean Difference (I-J)	Std. Error	*p*-value
Less than 1	1-3	11.73304*	3.93026	.016
	3-5	2.88759	5.11849	.943
	Above 5	5.56735	3.89575	.482
1-3	Less than 1	-11.73304*	3.93026	.016
	3-5	-8.84545	4.77654	.251
	Above 5	-6.16569	3.43413	.277
3-5	Less than 1	-2.88759	5.11849	.943
	1-3	8.84545	4.77654	.251
	Above 5	2.67975	4.74819	.943
Above 5	Less than 1	-5.56735	3.89575	.482
	1-3	6.16569	3.43413	.277
	3-5	-2.67975	4.74819	.943

Source: Survey Data

* Statistically significant at 5% significant level

From table 6.45, it is clear that there exists a significant difference between investors with investment experience of 'less than 1 year' and '1-3 years' as the *p*-values are less than 0.05. While analysing the mean difference, it is understood that investors with 'less than 1 year' experience are more prone to behavioural bias.

A descriptive analysis of the types of behavioural bias with regard to investment experience is performed for a more specific analysis. ANOVA is applied to determine the significant difference among the investment experiences of investors with regard to different types of behavioural bias. Table 6.46 presents the investors' experience-wise test of homogeneity of variances for different types of behavioural bias among themselves.

Table 6.46

Investment Experience-wise Test of Homogeneity of Variances of Types of Behavioural Bias

Variables	Levens's Statistic	*p*-value
Belief Perseverance Bias	4.291**	.005
Information Processing Bias	0.950	.416
Emotional Bias	3.475*	.016

Source: Survey Data

*, ** Statistically significant at 5% and 1% significant level

Since the *p*-value of the test is less than 0.05 for belief perseverance bias and emotional bias, the assumption of equal variance is rejected. Hence, instead of ANOVA, Welch's F value can be used for analysis. In the case of information processing bias, ANOVA can be applied to test the significant differences among investment experiences, as the *p*-value is greater than 0.05. The results are presented in table 6.47.

Table 6.47

Investment Experience-wise Analysis of Types of Behavioural Bias

Types of Behavioural Bias	Investment Experience (Years)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Belief Perseverance Bias	Less than 1	82	48.00	8.30	65	5.663	.001	Welch
	1-3	128	43.56	9.45				
	3-5	46	47.87	9.489				
	Above 5	134	47.19	7.539				
	Total	**390**	**46.25**	**8.77**				
Information Processing Bias	Less than 1	82	53.29	9.48	75	2.675*	.047	ANOVA
	1-3	128	49.55	9.82				
	3-5	46	51.48	10.65				
	Above 5	134	51.22	8.484				
	Total	**390**	**51.13**	**9.474**				
Emotional Bias	Less than 1	82	63.07	10.65	90	1.907	.131	Welch
	1-3	128	59.52	12.50				
	3-5	46	62.13	12.32				
	Above 5	134	60.38	10.13				
	Total	**390**	**60.87**	**11.37**				

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

The findings show a significant difference in investors' experiences with mutual fund investment with regard to the types of behavioural bias. The results reveal that, with *p*-values of 0.001 and 0.047, there is a significant difference among the investors' experiences in the cases of belief perseverance bias and information processing bias. The results indicate that there is no significant difference among investment experiences with regard to emotional bias, as the *p*-value is greater than 0.05. To examine the exact difference among the investment experiences of investors, a post hoc test is used for multiple comparisons.

Investment Experience Multiple Comparisons: Types of Behavioural Bias

Since a significant difference in investors' experiences with regard to belief perseverance bias and information processing bias has been discovered, a post hoc test is performed to investigate the exact difference in investors' investment experiences.

1. Belief Perseverance Bias

Since equal variances are not assumed, Tamhane'sT2 test is used to check the pair-wise differences among the experiences of investors with regard to belief perseverance bias.

Table 6.48

Investment Experience-wise Post Hoc Test – Belief Perseverance Bias

Investment Experience (Years) (I)	Investment Experience (Years) (J)	Mean Difference (I-J)	Std. Error	*p*-value
Less than 1	1-3	4.43750*	1.24032	.003
	3-5	.13043	1.67267	1.000
	Above 5	.80597	1.12465	.979
1-3	Less than 1	-4.43750*	1.24032	.003
	3-5	-4.30707	1.62935	.058
	Above 5	-3.63153*	1.05916	.004
3-5	Less than 1	-.13043	1.67267	1.000
	1-3	4.30707	1.62935	.058
	Above 5	.67554	1.54313	.999
Above 5	Less than 1	-.80597	1.12465	.979
	1-3	3.63153*	1.05916	.004
	3-5	-.67554	1.54313	.999

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

The results indicate that there exists a significant difference between investors with investment experience of '1-3 years' and investors with experience of 'less than 1 year' and 'above 5 years', since the *p*-values are less than 0.05. While analysing the mean difference, it is understood that investors with experience below 1 year are more prone to behavioural bias.

2. Information Processing Bias

The Tukey HSD test is used to check the pair-wise differences among the experiences of investors with regard to information processing bias, as there is equality of variances. The results are presented in table 6.49.

Table 6.49

Investment Experience-wise Post Hoc Test – Information Processing Bias

Investment Experience (Years) (I)	Investment Experience (Years) (J)	Mean Difference (I-J)	Std. Error	*p*-value
Less than 1	1-3	3.74581*	1.33157	.026
	3-5	1.81442	1.73415	.722
	Above 5	2.06880	1.31988	.399
1-3	Less than 1	-3.74581*	1.33157	.026
	3-5	-1.93139	1.61829	.631
	Above 5	-1.67701	1.16348	.474
3-5	Less than 1	-1.81442	1.73415	.722
	1-3	1.93139	1.61829	.631
	Above 5	.25438	1.60869	.999
Above 5	Less than 1	-2.06880	1.31988	.399
	1-3	1.67701	1.16348	.474
	3-5	-.25438	1.60869	.999

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

The results indicate that there exists a significant difference between investors with investment experience of 'less than 1 year' and investors with investment experience of '1-3 years' as the *p*-values are less than 0.05. While analysing the mean difference, it is understood that investors with investment experience below 1 year are more affected by behavioural bias.

6.4 Influence of Socio-Economic factors on different sub-types of Behavioural Bias

In this section, the relation between socio-economic variables and different sub-types of behavioural bias is examined. These types of behavioural biases are components of previously studied types. The components of belief perseverance bias are representativeness, confirmation, cognitive dissonance and illusion of control. Information processing bias consists of anchoring, availability, self-attribution and mental accounting. Emotional biases include overconfidence, loss aversion, regret aversion and herd behaviour. The different types of behavioural bias and their sub-types are as follows:

Cognitive Bias

Cognitive bias is a systematic error in thinking that occurs when individuals process and interpret information around them and affects the decisions and judgments made by them. Cognitive biases are classified into belief perseverance bias and information processing bias.

I. Belief Perseverance Bias

Belief perseverance bias refers to the tendency of people to hold their beliefs as true even though there is sufficient evidence to discredit the belief. Here, representativeness, confirmation, cognitive dissonance and illusion of control are considered for the study.

1. Representativeness

Representativeness refers to the tendency of investors to view events as representative of some specific class, that is, to see patterns where none exist. It is a judgement on the basis of stereotypes (Shefrin, 2000). An important consequence of representative bias is that investors tend to assume that recent events will continue in the near future, and therefore they try to buy "hot" stocks and avoid stocks that have performed poorly in the recent past.

2. Confirmation

Confirmation bias occurs when people selectively acquire information that allows them to continue believing what they initially believe (Nickerson, 1998). Here, investors tend to consider what confirms their beliefs and ignore what contradictsthem.

3. Cognitive Dissonance

Cognitive dissonance refers to the mental conflict that occurs when an individual's behaviour and beliefs contradict each other (Festinger, 1957). It occurs when a person voluntarily engages in some unpleasant activities to achieve a goal.

4. Illusion of Control

Illusion of control bias occurs due to the belief of people that they have sufficient control over the outcome of uncontrollable events (Langer, 1975). This is common among online traders.

II. Information Processing Bias

Information processing bias arises when information is processed and used irrationally or illogically. In studying information processing biases, the researcher considers anchoring, availability, self-attribution and mental accounting for the study.

1. Anchoring

People often have the tendency to make judgements starting with a certain initial reference point called an "anchor" and then making further adjustments to arrive at the final decision. This is called "anchoring bias" (Kahneman & Tversky, 1974).

2. Availability

Individuals tend to make judgements on the basis of pieces of information that are readily available or that they can recall easily. This is termed availability bias. Investors often rely on availability when judging the frequency of events (Kahneman & Tversky, 1973).

3. Self-Attribution

Self-attribution bias refers to the tendency of people to attribute their success in some activity to their own talents and blame their failures on bad luck rather than their personal incompetence (Heider, 2013).

4. Mental Accounting

Mental accounting bias is the tendency of individuals to place events into mental accounts on the basis of their superficial attributes (Shiller, 1998). It is a process by which the brain maintains separate goals and proceeds towards those goals independently of each other (Thaler, 1999).

Emotional Bias

Emotional biases occur spontaneously based on the personal feelings of an individual at the time of making decisions. It is a distortion in cognition and decision-making due to emotional factors. In analysing emotional biases, overconfidence, loss aversion, regret aversion and herd behaviour are taken into account.

1. Overconfidence

Overconfidence is an emotional bias in which people possess unwarranted faith in their intuitive thinking, cognitive abilities and judgements (Pompain & Wood, 2006). Overconfident investors become too confident about their skills and underestimate the risks associated with the investment.

2. Loss Aversion

Loss aversion is the tendency of individuals to avoid losses over achieving equivalent gains. It is the thought that the pain of loss is greater than the pleasure from an equal amount of gain (Barberis & Thaler, 2003).

3. Regret Aversion

Regret aversion refers to the tendency of investors to avoid actions that have the potential to create discomfort over faulty investment decisions. Furthermore, investors tend to regret holding losing stocks for too long rather than selling winning stocks too soon (Lehenkari & Perttunen, 2004).

4. Herd Behaviour

Herd behaviour is the tendency of people to do what others do instead of using their own information or making independent decisions (Shiller, 1995). It simply refers to how individual decisions are influenced by the decisions of groups.

A descriptive analysis of the different sub-types of behavioural bias has been done and the results are presented in Table 6.50.

Table 6.50

Descriptive Statistics of Sub-Types of Behavioural Bias

Types of Behavioural Bias	Sub-Types of Behavioural Bias	Mean	Standard Deviation
Belief Perseverance Bias	Representativeness	3.59	0.82
	Confirmation	3.53	0.70
	Cognitive Dissonance	3.20	0.81
	Illusion of Control	3.53	0.73
Information Processing Bias	Anchoring	3.52	0.90
	Availability	3.31	0.67
	Self-Attribution	3.64	0.82
	Mental Accounting	3.44	0.71
Emotional Bias	Overconfidence	3.28	0.80
	Loss Aversion	3.21	0.82
	Regret Aversion	3.42	0.80
	Herding	3.78	0.78

Source: Survey Data

According to table 6.50, all sub-types of behavioural bias have mean scores greater than 3, indicating that all behavioural biases have an above-average level of influence on investors in Kerala. Herding bias has the highest mean score of 3.78 (SD 0.78) and cognitive dissonance bias has the lowest mean score of 3.20 (SD

0.81). This makes it obvious that herding bias has the most influence among the investors, whereas cognitive dissonance bias has the least influence among the investors in Kerala.

6.4.1 Gender-wise Analysis of Different Sub-Types of Behavioural Bias

Different sub-types of behavioural bias may have a different level of influence on investors based on their gender. Descriptive analysis has been done to determine the mean score of males and females with regard to behavioural bias. To check whether significant difference exists between male and female investors in Kerala, the 't' test is applied. Table 6.51 presents the results of t-test.

Table 6.51

Gender-wise Analysis - Sub-Types of Behavioural Bias

Sub-Types of Behavioural Bias	Gender	N	Mean	SD	Max Score	t value	*p*-value	Remarks
Representativeness	Male	281	14.99	3.28	20	6.162**	.000	Equal Variances Assumed
	Female	109	12.79	2.85				
	Total	**390**	**14.37**	**3.31**				
Confirmation	Male	281	15.03	3.14	20	4.590**	.000	Equal Variances Assumed
	Female	109	13.37	3.38				
	Total	**390**	**14.56**	**3.29**				
Cognitive Dissonance	Male	281	7.15	1.88	10	1.823	.069	Equal Variances Assumed
	Female	109	6.7	1.55				
	Total	**390**	**7.05**	**1.80**				
Illusion of Control	Male	281	10.61	2.40	15	4.560**	.000	Equal Variances Assumed
	Female	109	9.39	2.21				
	Total	**390**	**10.27**	**2.41**				
Anchoring	Male	281	16.44	4.39	25	4.272**	.000	Equal Variances not Assumed
	Female	109	14.85	2.78				
	Total	**390**	**16.00**	**4.06**				
Availability	Male	281	18.21	3.74	25	5.297**	.000	Equal Variances not Assumed
	Female	109	16.26	3.07				
	Total	**390**	**17.67**	**3.67**				
Self Attribution	Male	281	10.14	2.19	15	4.427**	.000	Equal Variances not Assumed
	Female	109	9.34	1.31				
	Total	**390**	**9.92**	**2.01**				
Mental Accounting	Male	281	7.84	1.55	10	6.241**	.000	Equal Variances Assumed
	Female	109	6.79	1.30				
	Total	**390**	**7.55**	**1.55**				

(Contd.)

Sub-Types of Behavioural Bias	Gender	N	Mean	SD	Max Score	t value	*p*-value	Remarks
Overconfidence	Male	281	22.17	4.79	30	8.193**	.000	Equal Variances not Assumed
	Female	109	18.71	3.24				
	Total	**390**	**21.20**	**4.67**				
Loss Aversion	Male	281	14.33	2.84	20	6.790**	.000	Equal Variances Assumed
	Female	109	12.26	2.33				
	Total	**390**	**13.75**	**2.86**				
Regret Aversion	Male	281	10.17	2.53	15	5.225**	.000	Equal Variances not Assumed
	Female	109	8.99	1.76				
	Total	**390**	**9.84**	**2.40**				
Herding	Male	281	16.72	4.26	25	5.792**	.000	Equal Variances not Assumed
	Female	109	14.40	3.22				
	Total	**390**	**16.07**	**4.12**				

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

From table 6.51, it is understood that all the sub-types of behavioural bias except cognitive dissonance have a significant difference between male and female investors, as the *p*-values are less than 0.05.

Representativeness bias shows a significant difference between male and female investors. While analysing the mean score, it is understood that male investors are more affected by representativeness bias. This makes it clear that male investors give more importance to their recent experience when taking decisions regarding equity mutual fund investments.

In the case of confirmation bias, the *p*-value is less than 0.05, which means that there is a significant difference between male and female investors. The mean score of male investors is 15.03 (SD 3.14), which is higher than that of female investors, at 13.37 (SD 3.38). This means that male investors are more prone to confirmation bias.

Illusion of control bias shows a significant difference between male and female investors, as the *p*-value is less than 0.05. The mean score of male investors is high, making it evident that the illusion of control bias is higher among male investors than their female counterparts.

Since the *p*-value of anchoring bias is less than 0.05, there is a significant difference between male and female investors. Male investors show a higher degree of anchoring bias than female investors.

In the case of availability bias, there is a significant difference between male and female investors. Male investors seem to be more affected by anchoring bias since their mean score is higher compared to female investors.

Self-attribution bias shows a significant difference between male and female investors. The mean scores indicate that male investors are more prone to self-attribution bias than their female counterparts. They tend to attribute their success in investment decisions to their own talents while blaming their failures on outside influences more than female investors.

In mental accounting bias, a significant difference exists between male and female investors. The results imply that male investors are more prone to mental accounting bias than female investors.

Overconfidence bias shows a significant difference between male and female investors. Male investors are found to be more overconfident than female investors. This is on par with many studies in this field. Barber and Odean (2001) and Mishra and Metilda (2015) found that men are more overconfident than women and trade more.

Since the *p*-value of loss aversion bias is less than 0.05, there exists a significant difference between male and female investors. Male investors are more prone to loss aversion bias than female investors.

Regret aversion bias also shows a significant difference between male and female investors. The mean score of male investors being higher than female investors indicate that male investors are more prone to regret aversion bias.

Herding bias shows a significant difference between male and female investors. The mean score of male investors is higher than that of female investors, which means male investors are more affected by herding bias. It makes it evident that male investors are more likely to follow the market trend when making investment decisions than female investors. Kumar and Goyal (2016) found that male investors are more prone to herding bias.

6.4.2 Age-wise Analysis of Different Sub-Types of Behavioural Biases

Investors belonging to different age groups may have different types of behavioural biases while making investment decisions. Descriptive analysis has been done to determine the mean score of sub-types of behavioural bias among investors belonging to different age categories. ANOVA was applied to check whether a significant difference exists among investors of different age groups with regard to different behavioural biases. Levene's test is done to examine the homogeneity of variances. The results are shown in Table 6.52.

Table 6.52

Age-wise Test of Homogeneity of Variances - Sub-Types of Behavioural Bias

Sub-Types of Behavioural Bias	Levene's Statistic	*p*-value
Representativeness	6.085	.000
Confirmation	6.957	.000
Cognitive Dissonance	3.405	.018
Illusion of Control	3.323	.020
Anchoring	8.685	.000
Availability	5.092	.002
Self Attribution	6.029	.001
Mental Accounting	2.932	.033
Overconfidence	3.084	.027
Loss Aversion	8.894	.000
Regret Aversion	4.084	.007
Herding	2.652	.048

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Table 6.52 shows that the *p*-valuesof the variables are less than 0.05 for all the sub-types of behavioural bias and the assumption of equal variance is rejected. Hence, instead of ANOVA, Welch's F value is considered in the study for all the biases. The results are presented in table 6.53.

Table 6.53

Age-wise Analysis - Sub-Types of Behavioural Bias

Sub-Types of Behavioural Bias	Age (Years)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Representativeness	Below 25	16	14.13	4.40	20	0.086	0.967	Welch
	26 – 40	290	14.42	3.37				
	41 – 60	70	14.24	3.01				
	Above 60	14	14.29	2.27				
	Total	**390**	**14.37**	**3.31**				
Confirmation	Below 25	16	16.88	4.18	20	1.773	0.169	Welch
	26 – 40	290	14.44	3.34				
	41 – 60	70	14.50	2.91				
	Above 60	14	14.79	1.85				
	Total	**390**	**14.5**	**3.29**				
Cognitive Dissonance	Below 25	16	7.88	2.22	10	2.382	0.086	Welch
	26 – 40	290	7.13	1.70				
	41 – 60	70	6.56	2.09				
	Above 60	14	6.79	1.25				
	Total	**390**	**7.05**	**1.80**				
Illusion of Control	Below 25	16	11.75	2.46	15	4.508*	0.009	Welch
	26 – 40	290	10.36	2.47				
	41 – 60	70	9.57	2.09				
	Above 60	14	10.07	1.49				
	Total	**390**	**10.27**	**2.41**				
Anchoring	Below 25	16	18.13	6.33	25	3.773*	0.019	Welch
	26 – 40	290	16.21	3.96				
	41 – 60	70	14.98	3.72				
	Above 60	14	14.29	3.12				
	Total	**390**	**16.00**	**4.06**				
Availability	Below 25	16	19.25	4.81	25	1.665	0.191	Welch
	26 – 40	290	17.72	3.55				
	41 – 60	70	17.21	4.11				
	Above 60	14	16.93	1.64				
	Total	**390**	**17.67**	**3.67**				
Self Attribution	Below 25	16	11.38	2.78	15	4.157*	0.012	Welch
	26 – 40	290	9.97	1.94				
	41 – 60	70	9.47	2.14				
	Above 60	14	9.36	.84				
	Total	**390**	**9.92**	**2.01**				
Mental Accounting	Below 25	16	8.25	1.84	10	2.463	0.078	Welch
	26 – 40	290	7.53	1.55				
	41 – 60	70	7.37	1.57				
	Above 60	14	8.07	.92				
	Total	**390**	**7.55**	**1.55**				

(Contd.)

Sub-Types of Behavioural Bias	Age (Years)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Overconfidence	Below 25	16	23.19	6.10	30	2.756	0.057	Welch
	26 – 40	290	21.40	4.61				
	41 – 60	70	20.41	4.52				
	Above 60	14	19.00	3.96				
	Total	**390**	**21.21**	**4.67**				
Loss Aversion	Below 25	16	15.13	4.11	20	2.221	0.102	Welch
	26 – 40	290	13.83	2.84				
	41 – 60	70	13.21	2.72				
	Above 60	14	13.14	1.41				
	Total	**390**	**13.75**	**2.86**				
Regret Aversion	Below 25	16	11.75	2.57	15	3.787*	0.018	Welch
	26 – 40	290	9.84	2.40				
	41 – 60	70	9.37	2.37				
	Above 60	14	10.00	1.36				
	Total	**390**	**9.84**	**2.40**				
Herding	Below 25	16	19.63	4.50	25	3.878*	0.016	Welch
	26 – 40	290	16.00	4.21				
	41 – 60	70	15.69	3.63				
	Above 60	14	15.43	1.99				
	Total	**390**	**16.07**	**4.12**				

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Table 6.53 shows the significant difference among age categories of investors with regard to different behavioural biases. The results indicate that illusion of control bias, anchoring bias, self-attribution bias, regret aversion bias and herding bias have significant differences among age categories of investors.

Illusion of control bias shows a significant difference among different age categories of investors, as the *p*-value is less than 0.05. The age category 'below 25 years' has the highest mean score of 11.75 (SD 2.46). This indicates that younger investors are more prone to illusion of control bias.

The *p*-value of anchoring bias is less than 0.05, which indicates the presence of a significant difference among different age categories of investors. The age category 'below 25 years' has the highest mean score of 18.13 (SD 6.33), whereas the lowest mean score of 14.29 (SD 3.12) belongs to the age category ‘above 60 years’. This implies that anchoring bias decreases among investors with an increase in their age.

In the case of self-attribution bias, there is a significant difference among the different age categories of investors. The age category ‘below 25 years’ has the highest mean score of 11.38 (SD 2.78). This suggests that younger investors are more affected by self-attribution bias.

Regret aversion bias shows significant differences among different age categories of investors. The highest mean score belongs to the age category ‘below 25 years’ 11.75 (SD 2.57). This means that younger investors are more prone to regret aversion bias.

In the case of herding bias, a significant difference exists among different age categories of investors. The mean score is highest in the case of investors belonging to the ‘below 25 years’ age category and lowest in the case of ‘above 60 years’ age category. From this, it is understood that younger investors are more affected by herding bias. Moreover, herding bias decreases with an increase in their age.

6.4.3 Education-wise Analysis of Different Sub-Types of Behavioural Bias

Investors with different educational qualifications may be affected by different behavioural biases while making investment decisions. A descriptive analysis was performed to determine the mean score of behavioural bias among investors with varying educational qualifications. ANOVA was applied to examine whether a significant difference exists among investors belonging to different levels of education with regard to different behavioural biases.

The results of Levene’s test of homogeneity of variances are shown in table 6.54.

Table 6.54

Education-wise Test of Homogeneity of Variances - Sub-Types of Behavioural Bias

Sub-Types of Behavioural Bias	Levene's Statistic	*p*-value
Representativeness	3.212*	.013
Confirmation	3.436**	.009
Cognitive Dissonance	5.954**	.000
Illusion of Control	1.463	.213
Anchoring	2.032	.089
Availability	10.172**	.000
Self Attribution	1.425	.225
Mental Accounting	8.840**	.000
Overconfidence	5.389**	.000
Loss Aversion	2.470*	.044
Regret Aversion	3.071*	.016
Herding	4.089**	.003

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Illusion of control bias, anchoring bias and self-attribution bias show the homogeneity of variances. Therefore, ANOVA can be applied in the case of these biases and for the rest of them, the Welch F value can be considered as there is no equality of variances. The results are presented in table 6.55.

Table 6.55

Education-wise Analysis - Sub-Types of Behavioural Bias

Sub-Types of Behavioural Bias	Education Level	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Representativeness	Higher Secondary and Below	24	14.70	4.15	20	8.933**	.000	Welch
	Graduate	118	14.47	3.24				
	Post Graduate	155	15.12	3.02				
	Professional	66	12.39	3.11				
	Vocational/ Technical	27	14.22	3.14				
	Total	**390**	**14.37**	**3.31**				
Confirmation	Higher Secondary and Below	24	14.79	2.77	20	11.697**	.000	Welch
	Graduate	118	14.80	3.49				
	Post Graduate	155	15.34	2.86				
	Professional	66	12.17	3.26				
	Vocational/ Technical	27	14.67	2.59				
	Total	**390**	**14.56**	**3.29**				

(Contd.)

Sub-Types of Behavioural Bias	Education Level	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Cognitive Dissonance	Higher Secondary and Below	24	7.63	1.41	10	4.913**	.001	Welch
	Graduate	118	6.63	2.02				
	Post Graduate	155	6.98	1.86				
	Professional	66	7.65	1.42				
	Vocational/ Technical	27	7.22	.93				
	Total	**390**	**7.05**	**1.80**				
Illusion of Control	Higher Secondary and Below	24	11.50	2.83	15	10.399**	.000	ANOVA
	Graduate	118	10.42	2.30				
	Post Graduate	155	10.35	2.31				
	Professional	66	8.83	2.23				
	Vocational/ Technical	27	11.56	1.93				
	Total	**390**	**10.27**	**2.41**				
Anchoring	Higher Secondary and Below	24	18.88	3.27	25	16.038**	.000	ANOVA
	Graduate	118	16.42	4.17				
	Post Graduate	155	16.42	3.78				
	Professional	66	12.86	3.29				
	Vocational/ Technical	27	16.89	3.54				
	Total	**390**	**16.00**	**4.06**				
Availability	Higher Secondary and Below	24	18.92	5.12	25	6.420**	.000	Welch
	Graduate	118	17.75	4.10				
	Post Graduate	155	18.08	3.30				
	Professional	66	16.14	2.51				
	Vocational/ Technical	27	17.56	3.72				
	Total	**390**	**17.67**	**3.67**				
Self-Attribution	Higher Secondary and Below	24	11.67	2.12	15	8.410**	.000	ANOVA
	Graduate	118	10.11	2.08				
	Post Graduate	155	9.72	1.86				
	Professional	66	9.18	1.86				
	Vocational/ Technical	27	10.44	1.80				
	Total	**390**	**9.92**	**2.01**				
Mental Accounting	Higher Secondary and Below	24	7.46	2.15	10	1.547	.195	Welch
	Graduate	118	7.34	1.83				
	Post Graduate	155	7.78	1.38				
	Professional	66	7.42	1.33				
	Vocational/ Technical	27	7.56	.85				
	Total	**390**	**7.55**	**1.55**				

(Contd.)

Sub-Types of Behavioural Bias	Education Level	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Overconfidence	Higher Secondary and Below	24	23.25	5.15	30	3.347*	.013	Welch
	Graduate	118	21.53	4.64				
	Post Graduate	155	21.23	4.90				
	Professional	66	20.32	4.54				
	Vocational/ Technical	27	20.00	2.15				
	Total	**390**	**21.21**	**4.67**				
Loss Aversion	Higher Secondary and Below	24	15.33	3.37	20	10.344**	.000	Welch
	Graduate	118	13.59	2.83				
	Post Graduate	155	14.32	2.77				
	Professional	66	12.06	2.50				
	Vocational/ Technical	27	13.89	1.89				
	Total	**390**	**13.75**	**2.86**				
Regret Aversion	Higher Secondary and Below	24	11.67	2.39	15	31.687**	.000	Welch
	Graduate	118	9.78	2.29				
	Post Graduate	155	10.27	2.15				
	Professional	66	7.68	1.79				
	Vocational/ Technical	27	11.33	1.98				
	Total	**390**	**9.84**	**2.40**				
Herding	Higher Secondary and Below	24	19.08	2.83	25	28.764**	.000	Welch
	Graduate	118	16.60	3.56				
	Post Graduate	155	16.65	3.44				
	Professional	66	11.70	4.17				
	Vocational/ Technical	27	18.44	3.26				
	Total	**390**	**16.07**	**4.12**				

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

The *p*-values of all the sub-types of behavioural bias except mental accounting bias are less than 0.05. From this, it is obvious that all the behavioural biases except the mental accounting bias have significant differences among different educational qualifications.

In The case of representativeness bias, there exists a significant difference among various educational levels of equity mutual fund investors. The 'post graduate' category of investors has the highest mean score of 15.12 (SD 3.02) while the ‘professional’ category of investors has the lowest mean score of 12.39 (SD 3.11).

As the *p*-value of confirmation bias is less than 0.05, there is a significant difference among various educational levels of investors. The ‘post graduate’ category possesses the highest mean score of 15.34 (SD 2.86), whereas the ‘professional’ education possesses the lowest mean score of 12.17 (SD 3.26). This implies that post graduates are more prone to confirmation bias.

In the case of cognitive dissonance bias, there is a significant difference among various educational levels of investors. The mean scores indicate that professionally qualified investors are more affected by cognitive dissonance bias, whereas, graduate investors are less prone to cognitive dissonance bias.

Illusion of control bias shows a significant difference among various educational levels of investors. By analysing the mean scores of different educational categories, it is evident that technically qualified investors are more affected by illusion of control bias, while professionally qualified investors are less affected by illusion of control bias.

As the *p*-value of the test is less than 0.05, anchoring bias shows a significant difference among various educational levels of investors. The ‘higher secondary and below’ category has the highest mean score of 18.88 (SD 3.27), whereas, the ‘professional’ category has the lowest mean score of 12.86 (SD 3.29). This implies that investors with lower educational qualifications are more susceptible to anchoring bias than highly qualified investors.

The availability bias demonstrates the existence of a significant difference in investor education levels. The investors who belong to the ‘higher secondary and below’ category possess the highest mean score of 18.92 (SD 5.12), while the ‘professional’ category possesses the lowest mean score of 16.14 (SD 2.51). This indicates that investors with low education are more prone to availability bias.

Since the *p*-value of self-attribution bias is less than 0.05, this bias shows a significant difference among various educational levels of investors. In this case, investors who belong to lower education levels are more affected by self-attribution bias than highly qualified investors.

Overconfidence bias shows a significant difference among different educational levels of investors. Investors belonging to ‘higher secondary and below’ category has the highest mean score of 23.25 (SD 5.15). This indicates that investors with lowest educational qualification are more overconfident than others.

In the case of loss aversion bias, there exists a significant difference among various educational levels of investors. The mean scores indicate that the undergraduates are more affected by loss aversion bias, whereas, professionally qualified investors are less prone to loss aversion bias.

Since the *p*-value of the regret aversion bias is less than 0.05, this bias shows a significant difference among various educational levels of investors. Investors who belong to the ‘higher secondary and below’ category have the highest mean score of 11.67 (SD 2.39), whereas investors with ‘professional’ education have the lowest mean score of 7.68 (SD 1.79). This demonstrates that investors with the least education are more susceptible to regret aversion bias than others.

Herding bias reveals a significant difference in investor education levels. According to the mean scores, investors with higher secondary and below-qualification levels are more vulnerable to herding bias, whereas professionally qualified investors are less vulnerable.

6.4.4 Occupation-wise Analysis of Different Sub-Types of Behavioural Bias

Behavioural bias may vary across investors according to their occupation. The researcher has done descriptive analysis to know the mean score of sub-types of behavioural bias among investors with different occupations. Further, ANOVA was applied to examine whether there exists a significant difference among investors belonging to different occupations with regard to different behavioural biases.

The results of Levene's test of homogeneity of variances are shown in Table 6.56.

Table 6.56

Occupation-wise Test of Homogeneity of Variances - Sub-Types of Behavioural Bias

Sub-Types of Behavioural Bias	Levene's Statistic	*p*-value
Representativeness	2.184	.070
Confirmation	6.578**	.000
Cognitive Dissonance	2.453*	.046
Illusion of Control	2.036	.089
Anchoring	3.291*	.011
Availability	3.191*	.013
Self Attribution	.994	.411
Mental Accounting	2.796*	.026
Overconfidence	1.249	.290
Loss Aversion	2.705*	.030
Regret Aversion	5.334**	.000
Herding	3.870**	.004

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Representativeness, illusion of control, self-attribution and overconfidence show the homogeneity of variances. Hence, ANOVA can be applied in the case of these biases. As the *p*-values of other biases are less than 0.05, the assumption of equality of variances is rejected. So, Welch's F value can be considered to check the significance of difference among the variables. The results are presented in table 6.57.

Table 6.57

Occupation-wise Analysis - Sub-Types of Behavioural Bias

Sub-Types of Behavioural Bias	Occupation	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Representativeness	Employed	263	14.51	3.35	20	.751	.558	ANOVA
	Professional	70	14.27	3.25				
	Businessman	10	13.00	3.59				
	Retired	19	14.42	2.09				
	Others	28	13.82	3.68				
	Total	**390**	**14.37**	**3.31**				
Confirmation	Employed	263	14.41	3.50	20	1.881	.132	Welch
	Professional	70	15.24	2.40				
	Businessman	10	13.80	2.53				
	Retired	19	14.00	2.92				
	Others	28	15.00	3.55				
	Total	**390**	**14.56**	**3.29**				
Cognitive Dissonance	Employed	263	7.20	1.82	10	7.602	.000	Welch
	Professional	70	7.11	1.74				
	Businessman	10	6.00	.67				
	Retired	19	6.26	1.59				
	Others	28	6.36	1.87				
	Total	**390**	**7.05**	**1.80**				
Illusion of Control	Employed	263	10.46	2.46	15	1.927	.105	ANOVA
	Professional	70	10.14	2.43				
	Businessman	10	9.60	1.58				
	Retired	19	9.58	1.61				
	Others	28	9.43	2.36				
	Total	**390**	**10.27**	**2.41**				
Anchoring	Employed	263	16.25	4.26	25	4.449	.004	Welch
	Professional	70	16.11	3.57				
	Businessman	10	12.00	3.33				
	Retired	19	14.37	3.89				
	Others	28	15.93	2.68				
	Total	**390**	**16.00**	**4.06**				
Availability	Employed	263	17.97	3.53	25	3.986	.007	Welch
	Professional	70	17.87	3.89				
	Businessman	10	16.60	1.43				
	Retired	19	15.53	3.98				
	Others	28	16.18	4.05				
	Total	**390**	**17.67**	**3.67**				

(Contd.)

Sub-Types of Behavioural Bias	Occupation	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Self-Attribution	Employed	263	10.31	1.93	15	8.556	.000	ANOVA
	Professional	70	9.03	2.23				
	Businessman	10	8.80	1.81				
	Retired	19	9.11	1.33				
	Others	28	9.39	1.64				
	Total	**390**	**9.92**	**2.01**				
Mental Accounting	Employed	263	7.59	1.54	10	1.956	.120	Welch
	Professional	70	7.80	1.30				
	Businessman	10	7.00	2.11				
	Retired	19	7.68	1.06				
	Others	28	6.68	2.06				
	Total	**390**	**7.55**	**1.55**				
Overconfidence	Employed	263	21.84	4.52	30	4.401	.002	ANOVA
	Professional	70	20.17	4.82				
	Businessman	10	20.80	4.69				
	Retired	19	19.58	3.55				
	Others	28	19.00	5.24				
	Total	**390**	**21.21**	**4.67**				
Loss Aversion	Employed	263	13.95	2.95	20	6.069	.001	Welch
	Professional	70	14.23	2.28				
	Businessman	10	11.20	2.62				
	Retired	19	12.68	2.73				
	Others	28	12.32	2.55				
	Total	**390**	**13.75**	**2.86**				
Regret Aversion	Employed	263	9.89	2.38	15	9.282	.000	Welch
	Professional	70	10.59	2.57				
	Businessman	10	8.00	1.33				
	Retired	19	9.21	2.20				
	Others	28	8.61	1.69				
	Total	**390**	**9.84**	**2.40**				
Herding	Employed	263	16.15	4.49	25	7.416	.000	Welch
	Professional	70	16.99	3.26				
	Businessman	10	12.60	2.55				
	Retired	19	15.42	1.98				
	Others	28	14.71	2.95				
	Total	**390**	**16.07**	**4.12**				

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Since the *p*-values of cognitive dissonance bias, anchoring bias, availability bias, self-attribution bias, overconfidence bias, loss aversion bias, regret aversion bias and herding bias are less than 0.05, these biases have significant differences among different occupations.

Cognitive dissonance bias shows a significant difference among different occupations. Investors who are employed have the highest mean score of 7.20 (SD 1.82), while investors who are engaged in business have the lowest mean score of 6 (SD 0.67). This indicates that salaried investors are more prone to cognitive dissonance bias.

Since the *p*-value of anchoring bias is less than 0.05, it shows a significant difference among different occupations. The highest mean score of 16.25 (SD 4.26) belongs to the 'employed' category, whereas the lowest mean score of 12 (SD 3.33) belongs to the 'businessman' category. This means that investors who are employed on a regular basis are more affected by the anchoring bias.

In the case of availability bias, there exists a significant difference among different occupations. The 'employed' category possesses the highest mean score of 17.97 (SD 3.53), while the 'retired' category possesses the lowest mean score of 15.53 (SD 3.98). This indicates that employed investors are the most affected by availability bias, whereas, retired investors are the least affected.

There is a significant difference among different occupations of investors with regard to self-attribution bias. Investors who are employed have the highest mean score of 10.31 (SD 1.93), while investors who are engaged in business have the lowest mean score of 8.80 (SD 1.81). This indicates that employed investors are more affected by self-attribution bias.

Overconfidence bias shows a significant difference among different occupations. In this case, the highest mean score of 21.85 (SD 4.52) belongs to the 'employed' category, whereas, the lowest mean score of 19 (SD 5.24) belongs to the 'others' category. From this, it is obvious that employed investors are more overconfident when making investment decisions.

Since the *p*-value of loss aversion bias is less than 0.05, it shows a significant difference among different occupations. In this case, the 'professional' category of investors has the highest mean score of 14.23 (SD 2.28), while the lowest mean score of 11.20 (SD 2.62) belongs to the 'businessman' category. This clearly shows that professionals are more prone to loss aversion bias.

There exists a significant difference in regret aversion bias among different investor occupations. Investors belonging to the 'professional' category possess the highest mean score of 10.59 (SD 2.57). This implies that professionally occupied investors are more affected by the regret aversion bias.

There exists a significant difference among different occupations of investors with regard to herding bias, as the *p*-value is less than a 5% level of significance. The highest mean score of 16.99 (SD 3.26) belongs to the 'professional' category and the lowest mean score of 12.60 (SD 2.55) belongs to the 'businessman' category of occupation. This indicates that professionally occupied investors are more prone to herding bias.

6.4.5 Marital Status-wise Analysis of Different Sub-Types of Behavioural Bias

Behavioural bias may have a different level of influence on the investors based on their marital status. Descriptive analysis has been done to determine the mean score of married and unmarried investors with regard to different sub-types of behavioural bias. To check whether a significant difference exists between married and unmarried investors in Kerala, Independent Sample 't' test was applied. Table 6.58 presents the results of the t-test.

Table 6.58

Marital Status-wise Analysis - Sub-Types of Behavioural Bias

Sub-Types of Behavioural Bias	Marital Status	N	Mean	SD	Max Score	t value	*p*-value	Remarks
Representativeness	Married	270	14.13	3.22	20	-2.200*	.028	Equal Variances Assumed
	Unmarried	120	14.93	3.47				
	Total	**390**	**14.37**	**3.31**				
Confirmation	Married	270	14.38	3.25	20	-1.630	.104	Equal Variances not Assumed
	Unmarried	120	14.98	3.35				
	Total	**390**	**14.56**	**3.29**				
Cognitive Dissonance	Married	270	6.83	1.87	10	-3.967**	.000	Equal Variances not Assumed
	Unmarried	120	7.54	1.53				
	Total	**390**	**7.05**	**1.80**				
Illusion of Control	Married	270	9.82	2.30	15	-5.619**	.000	Equal Variances Assumed
	Unmarried	120	11.27	2.36				
	Total	**390**	**10.27**	**2.41**				
Anchoring	Married	270	15.53	3.79	25	-3.256**	.001	Equal Variances not Assumed
	Unmarried	120	17.06	4.47				
	Total	**390**	**16.00**	**4.06**				
Availability	Married	270	17.39	3.59	25	-2.283*	.023	Equal Variances Assumed
	Unmarried	120	18.30	3.80				
	Total	**390**	**17.67**	**3.67**				
Self Attribution	Married	270	9.62	1.91	15	-4.451**	.000	Equal Variances Assumed
	Unmarried	120	10.58	2.09				
	Total	**390**	**9.92**	**2.01**				
Mental Accounting	Married	270	7.32	1.57	10	-4.760**	.000	Equal Variances not Assumed
	Unmarried	120	8.08	1.39				
	Total	**390**	**7.55**	**1.55**				
Overconfidence	Married	270	20.60	4.64	30	-3.905**	.000	Equal Variances Assumed
	Unmarried	120	22.57	4.48				
	Total	**390**	**21.20**	**4.67**				
Loss Aversion	Married	270	13.33	2.80	20	-4.432**	.000	Equal Variances Assumed
	Unmarried	120	14.69	2.78				
	Total	**390**	**13.75**	**2.86**				
Regret Aversion	Married	270	9.59	2.32	15	-3.049**	.003	Equal Variances not Assumed
	Unmarried	120	10.41	2.49				
	Total	**390**	**9.84**	**2.40**				
Herding	Married	270	15.61	3.77	25	-3.114**	.002	Equal Variances not Assumed
	Unmarried	120	17.12	4.68				
	Total	**390**	**16.07**	**4.12**				

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Table 6.58 represents the t-test results among different behavioural biases. The results indicate that all the behavioural biases except confirmation bias have a significant difference between married and unmarried investors, as their *p*-values are less than 0.05.

In representativeness bias, there exists a significant difference between married and unmarried investors. The mean score of married investors is 14.13 (SD 3.22), whereas the mean score of unmarried investors is 14.93 (SD 3.47). This implies that unmarried investors are more prone to representativeness bias.

Cognitive dissonance bias shows a significant difference between married and unmarried investors. Married investors have a mean score of 6.83 (SD 1.87), while the mean score of unmarried investors is 7.54 (SD 1.53). This means that unmarried investors are more dissonant than married investors.

In the case of illusion of control bias, a significant difference exists between married and unmarried investors. The mean score is higher among unmarried investors, 11.27 (SD 2.36), whereas it is lower among married investors, 9.82 (SD 2.30). From this, it is clear that unmarried investors are more affected by the illusion of control bias.

Since the *p*-value of anchoring bias is less than 0.05, there exists a significant difference between married and unmarried investors. The mean score of married investors is 15.53 (SD 3.79), whereas, the mean score of unmarried investors is 17.06 (SD 4.47). This implies that unmarried investors are more prone to anchoring bias.

Availability bias shows a significant difference between married and unmarried investors. Married investors have a mean score of 17.39 (SD 3.59), while the mean score of unmarried investors is 18.30 (SD 3.80). This means that unmarried investors are more affected by the availability bias.

In self-attribution bias, a significant difference exists between married and unmarried investors. The mean score of married investors is 9.62 (SD 1.91), whereas, the mean score of unmarried investors is 10.58 (SD 2.09). This implies that unmarried investors are more prone to self-attribution bias.

Since the *p*-value of mental accounting bias is less than 0.05, there exists a significant difference between married and unmarried investors. The mean score of married investors is 7.32 (SD 1.57), whereas the mean score of unmarried investors is 8.08 (SD 1.39). This implies that mental accounting bias is higher in the case of unmarried investors than in married investors.

Overconfidence bias shows a significant difference between married and unmarried investors. Unmarried investors possess a higher mean value of 20.60 (SD 4.64), whereas, married investors have a lower mean value of 22.57 (SD 4.48). From this, it is understood that unmarried investors are more overconfident than married investors while making investment decisions.

In the case of loss aversion bias, a significant difference exists between married and unmarried investors. The mean score of married investors is 13.33 (SD 2.80), whereas the mean score of unmarried investors is 14.69 (SD 2.78). This implies that unmarried investors are more prone to loss aversion bias.

Since the *p*-value of regret aversion bias is less than 0.05, there exists a significant difference between married and unmarried investors. Married investors have a mean score of 9.59 (SD 2.32), while the mean score of unmarried investors is 10.41 (SD 2.49). This means that unmarried investors are more affected by the regret aversion bias.

Herding bias shows a significant difference between married and unmarried investors. The mean score is higher in the case of unmarried investors, 17.12 (SD 4.68), while the mean score is lower in the case of married investors, 15.61 (SD 3.77). This implies that unmarried investors tend to follow the crowd more than married investors when making investment decisions.

6.4.6 Income-wise Analysis of Different Sub-Types of Behavioural Bias

Behavioural bias may vary across individuals according to the annual income they have. In order to find out the mean score of each annual income category, descriptive analysis has been done. ANOVA was applied to determine whether a significant difference exists among these categories of annual income. The homogeneity of variance has been examined using Levene's test and the results are given in Table 6.59.

Table 6.59

Income-wise Test of Homogeneity of Variances - Sub-Types of Behavioural Bias

Sub-Types of Behavioural Bias	Levene's Statistic	*p*-value
Representativeness	2.688*	.046
Confirmation	5.659**	.001
Cognitive Dissonance	.439	.725
Illusion of Control	2.192	.089
Anchoring	1.946	.122
Availability	5.347**	.001
Self Attribution	7.216**	.000
Mental Accounting	3.812*	.010
Overconfidence	.376	.770
Loss Aversion	4.240**	.006
Regret Aversion	1.518	.209
Herding	4.522**	.004

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Cognitive dissonance bias, illusion of control bias, anchoring bias, overconfidence bias, and regret aversion bias show the homogeneity of variances. Hence, ANOVA can be applied in the case of these biases. As the assumption of equality of variances is rejected, Welch's F value can be considered to check the significance of differences among them. Table 6.60 presents the results.

Table 6.60

Income-wise Analysis - Sub-Types of Behavioural Bias

Sub-Types of Behavioural Bias	Annual Income (Rs.)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Representativeness	Less than 5,00,000	190	14.44	3.29	20	1.913	.136	Welch
	5,00,000 - 10,00,000	151	14.03	3.41				
	10,00,000-15,00,000	19	15.21	2.18				
	More than 15,00,000	30	15.17	3.45				
	Total	**390**	**14.37**	**3.31**				
Confirmation	Less than 5,00,000	190	15.11	3.13	20	3.709*	.016	Welch
	5,00,000 - 10,00,000	151	13.97	3.54				
	10,00,000-15,00,000	19	14.68	3.32				
	More than 15,00,000	30	14.03	2.40				
	Total	**390**	**14.56**	**3.29**				
Cognitive Dissonance	Less than 5,00,000	190	7.16	1.72	10	2.130	.096	ANOVA
	5,00,000 - 10,00,000	151	7.09	1.90				
	10,00,000-15,00,000	19	6.68	1.49				
	More than 15,00,000	30	6.33	1.84				
	Total	**390**	**7.05**	**1.80**				
Illusion of Control	Less than 5,00,000	190	10.69	2.46	15	4.000**	.008	ANOVA
	5,00,000 - 10,00,000	151	9.91	2.36				
	10,00,000-15,00,000	19	9.84	1.46				
	More than 15,00,000	30	9.63	2.43				
	Total	**390**	**10.27**	**2.41**				
Anchoring	Less than 5,00,000	190	17.07	3.53	25	10.168**	.000	ANOVA
	5,00,000 - 10,00,000	151	15.03	4.25				
	10,00,000-15,00,000	19	16.10	3.36				
	More than 15,00,000	30	14.07	4.87				
	Total	**390**	**16.00**	**4.06**				
Availability	Less than 5,00,000	190	18.16	3.89	25	2.452	.071	Welch
	5,00,000 - 10,00,000	151	17.22	3.51				
	10,00,000-15,00,000	19	16.84	2.69				
	More than 15,00,000	30	17.27	3.26				
	Total	**390**	**17.67**	**3.67**				

(Contd.)

Sub-Types of Behavioural Bias	Annual Income (Rs.)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Self-Attribution	Less than 5,00,000	190	10.28	2.21	15	4.847**	.004	Welch
	5,00,000 - 10,00,000	151	9.74	1.59				
	10,00,000- 15,00,000	19	9.16	1.71				
	More than 15,00,000	30	9.00	2.36				
	Total	**390**	**9.92**	**2.01**				
Mental Accounting	Less than 5,00,000	190	7.43	1.72	10	.801	.498	Welch
	5,00,000 - 10,00,000	151	7.67	1.30				
	10,00,000- 15,00,000	19	7.53	1.81				
	More than 15,00,000	30	7.73	1.48				
	Total	**390**	**7.55**	**1.55**				
Overconfidence	Less than 5,00,000	190	21.26	4.63	30	.977	.403	ANOVA
	5,00,000 - 10,00,000	151	21.33	4.60				
	10,00,000- 15,00,000	19	19.42	4.71				
	More than 15,00,000	30	21.30	5.27				
	Total	**390**	**21.21**	**4.67**				
Loss Aversion	Less than 5,00,000	190	13.84	2.73	20	.327	.806	Welch
	5,00,000 - 10,00,000	151	13.64	3.07				
	10,00,000- 15,00,000	19	14.05	1.84				
	More than 15,00,000	30	13.53	3.15				
	Total	**390**	**13.75**	**2.86**				
Regret Aversion	Less than 5,00,000	190	10.25	2.28	15	4.894**	.002	ANOVA
	5,00,000 - 10,00,000	151	9.64	2.47				
	10,00,000- 15,00,000	19	8.95	1.78				
	More than 15,00,000	30	8.87	2.65				
	Total	**390**	**9.84**	**2.40**				
Herding	Less than 5,00,000	190	17.37	3.48	25	13.753**	.000	Welch
	5,00,000 - 10,00,000	151	14.60	4.55				
	10,00,000- 15,00,000	19	15.68	1.89				
	More than 15,00,000	30	15.50	4.15				
	Total	**390**	**16.07**	**4.12**				

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Table 6.60 shows the significant difference among the annual income categories of investors with regard to different sub-types of behavioural bias. The results indicate that confirmation bias, illusion of control bias, anchoring bias, self-attribution bias, regret aversion bias and herding bias have significant differences among different annual income categories of investors.

Confirmation bias shows a significant difference among investors with different annual incomes. The mean score of the annual income category ‘less than Rs. 5,00,000’ is 15.11 (SD 3.13) and the mean score of the annual income category ‘5,00,000-10,00,000’ is 13.97 (SD 3.54). This implies that investors belonging to the lowest income category are more prone to confirmation bias.

Illusion of control bias reveals a significant difference among different annual income categories. The mean score of the annual income category ‘less than Rs. 5,00,000’ is 10.69 (SD 2.46) while the mean score of the annual income category ‘more than Rs. 15,00,000’ is 9.63 (SD 2.43). This implies that illusion of control bias increases with a decrease in the annual income of investors.

Anchoring bias shows a significant difference among different annual income categories. The annual income category ‘less than Rs. 5,00,000’ possesses the highest mean score of 17.07 (SD 3.53), whereas the category ‘more than Rs. 15,00,000’ possesses the lowest mean score of 14.07 (SD 4.87). This indicates that investors with lower annual income are highly affected by anchoring bias.

Self-attribution bias shows a significant difference among different annual income categories of investors. The mean score of the annual income category ‘less than Rs. 5,00,000’ is 10.28 (SD 2.21), while the mean score of the annual income category ‘more than Rs. 15,00,000’ is 9 (SD 2.36). This makes it evident that self-attribution bias increase with a decrease in the annual income of investors.

In regret aversion bias, a significant difference exists among different annual income categories of investors. The annual income category ‘less than Rs. 5,00,000’ has the highest mean score of 10.25 (SD 2.28), whereas the category ‘more than Rs. 15,00,000’ has the lowest mean score of 8.87 (SD 2.65). This implies that investors with lower annual income are more affected by regret aversion bias.

Herding bias shows a significant difference among different annual income categories of investors. In this case, the highest mean score of 17.37 (SD 3.48) belongs to the annual income category 'less than Rs. 5,00,000', while the lowest mean score of 14.60 (SD 4.55) belongs to the annual income category 'Rs. 5,00,000 – 10,00,000'. This indicates that investors with lower annual income are highly prone to herding bias.

6.4.7 Investment Experience-wise Analysis of Different Sub-Types of Behavioural Bias

Behavioural bias may vary across individuals according to the experience they have in equity mutual fund investment. Descriptive analysis has been done to find out the mean score of mutual fund investment experience of investors. ANOVA was applied to know whether a significant difference exists among investors having different levels of experience. Homogeneity of variance has been examined using Levene's test and the results are given in Table 6.61.

Table 6.61

Investment Experience-wise Test of Homogeneity of Variances - Sub-Types of Behavioural Bias

Sub-Types of Behavioural Bias	Levene's Statistic	*p*-value
Representativeness	4.288**	.005
Confirmation	5.198**	.002
Cognitive Dissonance	1.577	.194
Illusion of Control	5.090**	.002
Anchoring	.549	.649
Availability	5.897**	.001
Self Attribution	1.775	.151
Mental Accounting	2.297	.077
Overconfidence	15.426**	.000
Loss Aversion	6.045**	.000
Regret Aversion	3.010*	.030
Herding	3.221*	.023

Source: Survey Data
*, ** Statistically significant at 5%, and 1% significant level

Cognitive dissonance bias, anchoring bias, self-attribution bias and mental accounting bias show the homogeneity of variances. Hence, ANOVA can be applied in the case of these biases. As the *p*-values of other biases are less than 0.05, the assumption of equality of variances is rejected. So, the Welch's F value can be considered to check the significance of differences among them. Table 6.62 presents the significance of differences in various behavioural biases among different levels of investment experience in mutual funds.

Table 6.62

Investment Experience-wise Analysis - Sub-Types of Behavioural Bias

Types of Behavioural Bias	Investment Experience (Years)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Representativeness	Less than 1	82	14.30	2.97	20	4.370**	.006	Welch
	1-3	128	13.56	3.61				
	3-5	46	15.17	3.38				
	Above 5	134	14.92	3.04				
	Total	**390**	**14.37**	**3.31**				
Confirmation	Less than 1	82	15.16	3.48	20	9.059**	.000	Welch
	1-3	128	13.34	3.39				
	3-5	46	15.54	3.10				
	Above 5	134	15.04	2.80				
	Total	**390**	**14.56**	**3.29**				
Cognitive Dissonance	Less than 1	82	7.45	1.53	10	1.823	.142	ANOVA
	1-3	128	6.91	1.87				
	3-5	46	7.04	2.04				
	Above 5	134	6.93	1.79				
	Total	**390**	**7.05**	**1.80**				
Illusion of Control	Less than 1	82	11.09	2.15	15	5.564**	.001	Welch
	1-3	128	9.75	2.58				
	3-5	46	10.11	2.93				
	Above 5	134	10.31	2.06				
	Total	**390**	**10.27**	**2.41**				
Anchoring	Less than 1	82	17.29	3.82	25	5.243**	.001	ANOVA
	1-3	128	15.16	3.95				
	3-5	46	16.63	4.48				
	Above 5	134	15.81	3.98				
	Total	**390**	**16.00**	**4.06**				

(Contd.)

Types of Behavioural Bias	Investment Experience (Years)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Availability	Less than 1	82	18.07	3.63	25	.979	.405	Welch
	1-3	128	17.20	4.13				
	3-5	46	17.76	4.16				
	Above 5	134	17.83	2.99				
	Total	**390**	**17.67**	**3.67**				
Self-Attribution	Less than 1	82	10.44	1.93	15	3.686*	.012	ANOVA
	1-3	128	9.88	1.77				
	3-5	46	9.24	2.32				
	Above 5	134	9.87	2.11				
	Total	**390**	**9.92**	**2.01**				
Mental Accounting	Less than 1	82	7.49	1.33	10	2.248	.082	ANOVA
	1-3	128	7.30	1.52				
	3-5	46	7.85	1.63				
	Above 5	134	7.72	1.66				
	Total	**390**	**7.55**	**1.55**				
Overconfidence	Less than 1	82	21.22	3.74	30	.213	.887	Welch
	1-3	128	20.99	4.58				
	3-5	46	21.09	6.50				
	Above 5	134	21.44	4.57				
	Total	**390**	**21.21**	**4.67**				
Loss Aversion Bias	Less than 1	82	13.83	2.56	20	.316	.814	Welch
	1-3	128	13.77	3.35				
	3-5	46	14.00	2.66				
	Above 5	134	13.60	2.60				
	Total	**390**	**13.75**	**2.86**				
Regret Aversion	Less than 1	82	10.56	2.13	15	4.780**	.003	Welch
	1-3	128	9.67	2.62				
	3-5	46	10.15	2.48				
	Above 5	134	9.46	2.23				
	Total	**390**	**9.84**	**2.40**				
Herding	Less than 1	82	17.46	4.01	25	6.149**	.001	Welch
	1-3	128	15.09	4.58				
	3-5	46	16.89	3.41				
	Above 5	134	15.88	3.69				
	Total	**390**	**16.07**	**4.12**				

Source: Survey Data

*, ** Statistically significant at 5%, and 1% significant level

Table 6.62 shows the significant difference in the investment experience of mutual fund investors with regard to different behavioural biases. The results indicate that representativeness bias, confirmation bias, illusion of control bias, anchoring bias, self-attribution bias, regret aversion bias and herding bias have significant differences among investors with different levels of investment experience.

Representativeness bias shows a significant difference among investors' experiences in mutual fund investment. Investors with experience levels of 3-5 years have the highest mean score of 15.17 (SD 3.38), while investors belonging to '1-3 years' experience category have the lowest mean score of 13.56 (SD 3.61). This indicates that investors with 3–5 years of experience are more prone to representativeness bias.

In confirmation bias, a significant difference exists among investors' experiences in mutual fund investment. The mean score of the mutual fund investment experience category of '3-5 years' is 15.54 (SD 3.10), while the mean score of the category '1-3 years' is 13.34 (SD 3.39). This implies that investors with 3-5 years of experience are more affected by confirmation bias.

Since the *p*-value of illusion of control bias is less than 0.05, there is a significant difference in investors' experience in mutual fund investment. The mean score of the mutual fund investment experience category 'less than 1 year' is 11.09 (SD 2.15), while the mean score of the category '1-3 years' is 9.75 (SD 2.58). This makes it clear that investors with the lowest experience level in investment are more prone to illusion of control bias.

Anchoring bias shows a significant difference among investors' experiences in mutual fund investment. The mean score of mutual fund investment experience category 'less than 1 year' is 17.29 (SD 3.82), while the mean score of the category '1-3 years' is 15.16 (SD 3.95). From this, it is understood that investors with the lowest experience level in investment are more affected by anchoring bias.

In the case of self-attribution bias, a significant difference exists among investors' experiences in mutual fund investment. The mean score is the highest for the experience level category 'less than 1 year' 10.44 (SD 1.93), whereas the mean score is the lowest for the category '3-5 years' 9.24 (SD 2.32). This indicates that investors with less than one year of experience are more prone to self-attribution bias.

Since the *p*-value of regret aversion bias is less than 0.05, there is a significant difference among investors' experiences in mutual fund investment. Investors with an experience level of 'less than 1 year' have the highest mean score of 10.56 (SD 2.13), while investors belonging to the 'above 5 years' experience category have the lowest mean score of 9.46 (SD 2.23). This implies that regret aversion bias decreases with increase in mutual fund investment experience.

Herding bias shows a significant difference among investors' experiences in mutual fund investment. The mean score of mutual fund investment experience category 'less than 1 year' is 17.46 (SD 4.01), while the mean score of the category '1-3 years' is 15.09 (SD 4.58). This makes it clear that investors with less experience in investment are more prone to herding bias.

6.5 Conclusion

Based on the above analysis, it can be concluded that, on an average, investors are 65% affected by behavioural bias when making investment decisions. It is found that investors are most affected by belief perseverance bias (71%), whereas investors are least affected by emotional bias (68%).

Significant difference exists between male and female investors with regard to behavioural bias. The results imply that male investors are more affected by behavioural bias than female investors. While analysing the types of behavioural bias, there exists significant difference between male and female investors with regard to various behavioural biases. In this case, male investors tend to be more prone to belief perseverance bias, information processing bias and emotional bias compared to their female counterparts.

In age-wise analysis, a significant difference exists among investors belonging to different age categories with regard to behavioural bias. The results indicate that young investors are more prone to behavioural bias. In the case of different types of behavioural biases, young investors are more affected by belief perseverance bias, information processing bias and emotional bias compared to older investors.

While analysing the education of investors, it is understood that there exists a significant difference among investors belonging to different educational levels with regard to behavioural bias. Investors with lowest educational qualification are the most affected by behavioural bias whereas, the professionally qualified investors are the least affected by behavioural bias. Belief perseverance bias, information processing bias and emotional bias show significant differences among investors belonging to various educational qualifications.

In occupation-wise analysis, significant difference exists among investors having different occupations with regard to behavioural bias. Behavioural bias is highest among employed investors while it is lowest in the case of businessmen. Regarding the types of behavioural bias, information processing bias and emotional bias show significant differences among different occupations. Information processing bias is highest among employed investors, whereas, emotional bias is highest in the case of professionals.

Regarding marital status, there is a significant difference between married and unmarried investors with regard to behavioural bias. All three types of behavioural bias show a significant difference between married and unmarried investors and these biases are higher among unmarried investors.

In the income-wise analysis, a significant difference exists among investors belonging to different annual income categories. Investors with lower incomes are found to be more affected by behavioural bias. Analysing the types of behavioural bias, information processing bias and emotional bias shows significant differences among different annual income categories. Investors belonging to the lowest income level are more prone to these biases.

In the case of mutual fund investment experience, there is a significant difference among investors with regard to behavioural bias. Further, the investors with the least experience in mutual fund investment are more prone to behavioural bias. Analysing the types of behavioural bias, belief perseverance bias and emotional bias show significant differences among investors' experiences. Investors with the least experience in mutual fund investment are more affected by these biases.

It can be concluded that all the types of behavioural biases have an above-average level of influence among investors, as their mean values are higher than 3. Herding bias has the most influence among the equity mutual fund investors in Kerala, whereas cognitive dissonance bias has the least influence.

It is found that all the sub-types of behavioural bias except cognitive dissonance have a significant difference between male and female investors.

Representativeness bias shows a significant difference between male and female investors. Since the mean score is higher for male investors, they are more affected by representativeness bias.

In confirmation bias, there is a significant difference between male and female investors. The results indicate that male investors are more prone to confirmation bias.

In the case of illusion of control bias, there exists a significant difference between male and female investors. The mean score is higher among male investors, making it clear that the illusion of control bias is higher among male investors than their female counterparts.

Anchoring bias shows a significant difference between male and female investors. The mean score indicates that male investors show a higher degree of anchoring bias than female investors.

In availability bias, there exists a significant difference between male and female investors. Male investors are more affected by anchoring bias since their mean score is higher compared to female investors.

In the case of self-attribution bias, there exists a significant difference between male and female investors. Male investors are more prone to self-attribution bias than their female counterparts.

Mental accounting bias shows a significant difference between male and female investors. The results imply that male investors are more affected by mental accounting bias than female investors.

Overconfidence bias shows a significant difference between male and female investors. Male investors are found to be more overconfident than female investors.

In loss aversion bias, there exists a significant difference between male and female investors. Male investors are more prone to loss aversion bias than female investors.

Regret aversion bias shows a significant difference between male and female investors. The results indicate that male investors are more prone to regret aversion bias.

Herding bias shows a significant difference between male and female investors. The mean score of male investors is higher than that of female investors, indicating that male investors are more affected by herding bias.

It can be concluded that illusion of control bias, anchoring bias, self-attribution bias, regret aversion bias and herding bias have significant differences among age categories of investors.

Illusion of control bias shows a significant difference among different age categories of investors. The results indicate that younger investors are more prone to illusion of control bias.

In the case of anchoring bias, there exists a significant difference among the different age categories of investors. The results imply that anchoring bias decreases among investors according to an increase in their age.

In self-attribution bias, a significant difference exists among different age categories of investors. The results suggest that younger investors are more affected by self-attribution bias.

Regret aversion bias shows a significant difference among different age categories of investors. The findings show that younger investors are more prone to regret aversion bias.

In the case of herding bias, a significant difference exists among different age categories of investors. The results indicate that younger investors are more affected by herding bias and herding bias decreases among investors with an increase in their age.

From the results, it can be concluded that all the behavioural biases except the mental accounting bias have significant differences among different educational qualifications.

Representativeness bias shows a significant difference among various educational levels of investors. The results indicate that the post graduates are more prone to representative bias.

In the case of confirmation bias, there exists a significant difference among various educational levels of investors. The results exhibit that post graduates are more prone to confirmation bias.

In the case of cognitive dissonance bias, there exists a significant difference among various educational levels of investors. The results indicate that professionally qualified investors are more affected by cognitive dissonance bias, whereas graduates are less prone to cognitive dissonance bias.

In illusion of control bias, there exists a significant difference among various educational levels of investors. The results make it evident that technically qualified investors are more affected by the illusion of control bias, while professionally qualified investors are less affected by the illusion of control bias.

Anchoring bias shows a significant difference among investors with various educational qualifications. The results imply that investors with lower educational qualifications are more prone to anchoring bias than highly qualified investors.

In the case of availability bias, there exists a significant difference among different educational levels of investors. The results show that investors with lower educational levels are more prone to availability bias.

Self-attribution bias shows a significant difference among various educational levels of investors. In this case, investors with lower educational levels are more affected by self-attribution bias than highly qualified investors.

Overconfidence bias shows a significant difference among the different educational levels of investors. It is found that investors with the lowest educational qualifications are more overconfident than others.

In the case of loss aversion bias, there is a significant difference among various educational levels of investors. The results indicate that the investors with the lowest qualifications are more affected by loss aversion bias, whereas, professionally qualified investors are less prone to loss aversion bias.

Regret aversion bias shows a significant difference among various educational levels of investors. The results show that investors with the lowest educational qualification are more prone to regret aversion bias than others.

In the case of herding bias, there exists a significant difference among the different educational levels of investors. It is found that the investors with the lowest qualification are more prone to herding bias, whereas professionally qualified investors are less prone to herding bias.

The results imply that cognitive dissonance bias, anchoring bias, availability bias, self-attribution bias, overconfidence bias, loss aversion bias, regret aversion bias and herding bias show significant differences among investors with different occupations.

Cognitive dissonance bias shows a significant difference among different occupations. The results revealed that employed investors are more prone to cognitive dissonance bias than others.

In anchoring bias, there exists a significant difference among investors with different occupations. It is found that investors who are employed on a regular basis are more affected by anchoring bias.

In the case of availability bias, there exists a significant difference among different occupations. The results indicate that employed investors are the most affected by availability bias, whereas retired investors are the least affected.

Self-attribution bias shows a significant difference among different occupations. The results show that employed investors are more affected by self-attribution bias.

Overconfidence bias shows a significant difference among different occupations. The results imply that employed investors are more overconfident when making investment decisions.

In the case of loss aversion bias, there exists a significant difference among different occupations of investors. It is found that professionally occupied investors are more prone to loss aversion bias.

In regret aversion bias, there exists a significant difference among different occupations of investors. The results show that professionally occupied investors are more affected by regret aversion bias.

Herding bias shows a significant difference among different occupations of investors. Professionally occupied investors are found to be more prone to herding bias.

In marital status-wise analysis, all the behavioural biases except confirmation bias have significant differences between married and unmarried investors.

Representativeness bias shows a significant difference between married and unmarried investors. The results suggest that unmarried investors are more prone to representativeness bias.

In cognitive dissonance bias, there exists a significant difference between married and unmarried investors. It is found that unmarried investors are more prone to cognitive dissonance bias than married investors.

In the case of illusion of control bias, a significant difference exists between married and unmarried investors. The results show that unmarried investors are more affected by illusion of control bias.

Anchoring bias shows a significant difference between married and unmarried investors. The results indicate that unmarried investors are more prone to anchoring bias.

In availability bias, a significant difference exists between married and unmarried investors. The results make it evident that unmarried investors are more affected by availability bias.

In the case of self-attribution bias, a significant difference exists between married and unmarried investors. Unmarried investors are found to be more prone to self-attribution bias.

Mental accounting bias shows the existence of a significant difference between married and unmarried investors. The results suggest that mental accounting bias is higher in the case of unmarried investors than married investors.

Overconfidence bias shows a significant difference between married and unmarried investors. Unmarried investors are found to be more overconfident than married investors when making investment decisions.

In the case of loss aversion bias, a significant difference exists between married and unmarried investors. The results indicate that unmarried investors are more prone to loss aversion bias.

In regret aversion bias, there is a significant difference between married and unmarried investors. The results suggest that unmarried investors are more affected by the regret aversion bias.

Herding bias shows a significant difference between married and unmarried investors. The results indicate that unmarried investors are more prone to herding bias than married investors.

The results show that confirmation bias, illusion of control bias, anchoring bias, self-attribution bias, regret aversion bias and herding bias have significant differences among different annual income categories of investors.

Confirmation bias shows a significant difference among different annual income categories of equity mutual fund investors. The results indicate that investors belonging to the lowest income category are the most affected by confirmation bias.

In the case of illusion of control bias, there exists a significant difference among different annual income categories. The results make it evident that the illusion of control bias increases with a decrease in the annual income of investors.

In anchoring bias, a significant difference exists among different annual income categories. From the results, it is understood that investors with lower annual income are highly affected by anchoring bias.

Self-attribution bias shows a significant difference among different annual income categories. The results suggest that self-attribution bias increases with a decrease in the annual income of investors.

In regret aversion bias, a significant difference exists among different annual income categories of investors. It is found that investors with lower annual incomes are more affected by the regret aversion bias.

Herding bias shows a significant difference among different annual income categories of investors. The results indicate that investors with lower annual income are highly prone to herding bias.

The results indicate that representativeness bias, confirmation bias, illusion of control bias, anchoring bias, self-attribution bias, regret aversion bias and herding bias have significant differences among different investment experience levels of investors.

Representativeness bias shows a significant difference among investors' experiences in mutual fund investment. The results indicate that investors with 3-5 years of experience are more prone to representativeness bias.

In confirmation bias, a significant difference exists among investors' experiences in mutual fund investment. The results show that investors with 3-5 years of experience are more affected by confirmation bias.

In the case of illusion of control bias, there exists a significant difference among investors' experiences in mutual fund investment. The results suggest that investors with the lowest experience level in investment are the most affected by illusion of control bias.

Anchoring bias shows significant differences among investors' experiences in mutual fund investment. The results show that investors with the lowest experience level in investment are more affected by anchoring bias.

In the case of self-attribution bias, a significant difference exists among investors' experiences in mutual fund investment. The results indicate that investors with less than one year of experience are more prone to self-attribution bias.

In regret aversion bias, there exists a significant difference among investors’ experiences in mutual fund investment. It is found there exists a significant difference among investors’ experience in mutual fund investment.

Herding bias shows a significant difference among investors’ experiences in mutual fund investment. The findings imply that investors with little investment experience are more vulnerable to herding bias.

Chapter 7

BEHAVIOURAL BIAS AND INVESTMENT PERFORMANCE AMONG EQUITY MUTUAL FUND INVESTORS

Contents

7.1 Introduction

People invest in various asset classes in order to maximise their returns. Mutual fund returns are calculated by comparing the appreciation in the value of investments over time to the initial investment. A mutual fund’s Net Asset Value (NAV) represents the fund’s market value per share. The performance of a particular scheme of a mutual fund is denoted by its NAV. Mutual fund returns are computed as the difference between the NAV on the date of sale and the NAV on the date of purchase and converted into percentages by multiplying by 100. Any dividend or interest earned by the fund during the holding period is also added to the capital appreciation at the time of computing returns. An increase in the NAV of funds is reflected in their capital appreciation over time. The performance of the return on the mutual fund investment is termed "investment performance."

The influence of behavioural bias on the investment decisions of investors is studied in the previous chapter. In the present chapter, the researcher investigates the impact of behavioural bias on investment performance. For this, the respondents are asked to assess their own investment performance. The rate of return is assessed by demanding the respondents to compare their current rate of return to both the expected rate of return and the average rate of return. Investors’ satisfaction level is also considered as a criterion to measure investment performance.

The investment performance is considered good if the rate of return of the equity mutual funds is higher than the investors' expected rate of return. If the rate of return is less than the expected rate, the investment performance is considered as poor, resulting in the investors being unhappy. To examine the investment performance of investors, a five-point Likert scale is developed and the respondents are asked to rate the statements ranging from strongly agree (5) to strongly disagree (1). Table 7.1 presents the statements used to analyse investment performance, showing the respective means and standard deviations obtained.

Table 7.1

Statements of Investment Performance

Statement code	Statements	Mean	Standard Deviation
IP1	The rate of return on my recent investment meets my expectations.	2.07	1.45
IP2	My rate of return is equal to or higher than the average rate of return in the market.	2.03	1.31
IP3	I feel satisfied with my investment decisions over the last year.	2.61	1.29
IP	Overall Investment Performance	6.72	3.91

Source: Survey Data

The mean score of overall investment performance is 6.72 (SD 3.91) out of 15, which indicates that investors' satisfaction level regarding the investment performance of mutual funds is 45%. The statement "I feel satisfied with my investment decisions over the last year"has the highest mean score of 2.61 (SD 1.29), which implies that more than 52% of investors are satisfied with their investment decisions made in the previous year. The statement "my rate of return is equal to or higher than the average rate of return in the market" has the lowest mean score of 2.03 (SD 1.31). This indicates that only 40% of the investors receive more than average return in the market. From the results presented in table 7.1, it can be inferred that most of the investors are not very satisfied with their equity mutual fund investment.

7.2 Influence of Socio-Economic Factors on Investment Performance

The socio-economic variables like gender, age, educational qualification, occupation, marital status, annual income and experience in mutual fund investment are used for analysing investors' performance towards their investment in equity mutual funds. The results of descriptive and inferential statistics of the socio-economic variables with regard to investment performance are presented below.

7.2.1 Gender-wise Analysis of Investment Performance

In order to analyse the investment performance between male and female investors, the researcher has classified the data according to gender. To find out whether significant difference exists between male and female investors, 't' test is applied. Levene's test is used to check the homogeneity of variances.

Table 7.2

Gender-wise Analysis of Investment Performance

Gender	N	Mean	SD	t value	Max Score	*p*-value	Remarks
Male	281	5.99	3.49	-5.629**	15	.000	Equal variances not assumed
Female	109	8.60	4.31				
Total	**390**	**6.72**	**3.91**				

Source: Survey Data

** Statistically significant at 1% significant level

From the table 7.2, it is clear that there is significant difference between male and female investors with regard to investment performance as the p-value is significant at 1% level. The mean score of investment performance among male investors is 5.99 (SD 3.49), while the mean score of investment performance among female investors is 8.60 (SD 4.31). This implies that female investors have better performed than their male counterparts while making equity mutual fund investment.

7.2.2 Age-wise Analysis of Investment Performance

The investment performance of mutual funds may vary across individuals according to the age group they belong to. In order to know the mean score of investment performance of investors among different age categories, descriptive analysis has been done. Then ANOVA is applied to check whether there is significant difference among age category of investors with respect to investment performance. Table 7.3 presents the age-wise test of homogeneity of variances of investment performance among investors.

Table 7.3

Age-wise Test of Homogeneity of Variances of Investment Performance

Variable	Levens's Statistic	*p*-value
Investment Performance	5.909**	0.001

Source: Survey Data

**, * Statistically significant at 5% and 1% significant level

Since the p-value of the test is less than 0.05, the assumption of equal variance is rejected. Hence, instead of ANOVA, Welch's F value is considered in the study. The results are presented in table 7.4.

Table 7.4

Age-wise Analysis of Investment Performance

Age (Years)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Below 25	16	5.75	3.36	15	1.930	0.143	Welch
26 – 40	290	6.86	3.99				
41 – 60	70	6.04	3.41				
Above 60	14	8.29	4.53				
Total	**390**	**6.72**	**3.91**				

Source: Survey Data

Since the *p*-value of the test is more than 0.05, significant difference does not exist among different age category of investors with regard to investment performance.

7.2.3 Education-wise Analysis of Investment Performance

Investment performance may be different for investors having different educational qualifications. Descriptive analysis has been done to know the mean score of different education levels with regard to investment performance. Further, to test the significant difference among education levels, ANOVA is applied.

Table 7.5 presents the education -wise test of homogeneity of variances of investment performance among investors.

Table 7.5

Education-wise Test of Homogeneity of Variances of Investment Performance

Variable	Levens's Statistic	*p*-value
Investment Performance	3.472**	.008

Source: Survey Data

** Statistically significant at 1% significant level

Since the p-value of the test is less than 0.05, the assumption of equal variance is rejected. Hence, instead of ANOVA, Welch's F value is considered in the study. The results are presented in table 7.6.

Table 7.6

Education-wise Analysis of Investment Performance

Education Level	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Higher Secondary and Below	24	5.79	4.37	15	3.114*	.019	Welch
Graduate	118	6.51	4.04				
Post Graduate	155	6.28	3.52				
Professional	66	7.79	3.83				
Vocational/Technical	27	8.41	4.50				
Total	**390**	**6.72**	**3.91**				

Source: Survey Data

* Statistically significant at 5% significant level

Since the p-value is less than .05, there exists significant difference among different education levels of investors. While analysing the mean score, it is understood that investors who have technical qualifications possess the highest mean score of 8.41 (SD 4.5). Investors belonging to 'higher secondary & below' category possess the lowest mean score of 5.79 (4.37). This indicates that technically qualified investors have best investment performance, whereas, low qualified investors have weak performance.

7.2.4 Occupation-wise Analysis of Investment Performance

In order to examine the variability of investment performance among investors belonging to different occupations, descriptive analysis has been done. Levene's test is used to check the homogeneity of variances. Further, ANOVA is carried out to test the significant difference among investors' occupation with regard to investment performance.

The results of occupation wise test of homogeneity of variance of investment performance among investors are depicted in table 7.7.

Table 7.7

Occupation-wise Test of Homogeneity of Variances of Investment Performance

Variable	Levens's Statistic	*p*-value
Investment Performance	.901	.463

Source: Survey Data

Since the p-value of the test is more than 0.05, the assumption of equal variance is not rejected. Hence, the value of ANOVA is considered in the study. The results are presented in table 7.8.

Table 7.8

Occupation-wise Analysis of Investment Performance

Occupation	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Employed	263	6.50	3.87	15	.834	.504	ANOVA
Professional	70	7.11	3.96				
Businessman	10	6.30	3.09				
Retired	19	7.63	4.44				
Others	28	7.32	4.13				
Total	**390**	**6.72**	**3.91**				

Source: Survey Data

The results indicate that there is no significant difference among investors' occupation with regard to investment performance as the p value of the ANOVA is more than .05.

7.2.5 Marital Status-wise Analysis of Investment Performance

Descriptive analysis has been done to know the mean score of investment performance among married and unmarried investors. In order to explore the significant difference between married and unmarried investors, 't' test has been applied. The results are presented in table 7.9.

Table 7.9

Marital Status-wise Analysis of Investment Performance

Marital Status	N	Mean	SD	t value	Max Score	*p*-value	Remarks
Married	270	6.92	3.95	1.531	15	.127	Equal variances assumed
Unmarried	120	6.27	3.79				
Total	**390**	**6.72**	**3.91**				

Source: Survey Data

Since, the p value of the t-test is greater than 0.05, there is no significant difference between married and unmarried investors. Hence, it can be concluded that investment performance is not significantly different between married and unmarried investors.

7.2.6 Income-wise Analysis of Investment Performance

Investment performance may vary across investors with the annual income they have. In order to know the mean score of investment performance of investors among different income groups, descriptive analysis has been done. Then ANOVA is applied to check whether there is significant difference among annual income category of investors with respect to investment performance. Test of homogeneity of variances of investment performance among investors have been done and the results are presented in table 7.10.

Table 7.10

Income-wise Test of Homogeneity of Variances of Investment Performance

Variable	Levens's Statistic	*p*-value
Investment Performance	4.947**	.002

Source: Survey Data

** Statistically significant at 1% significant level

Since the p-value of the Levene's test is less than 0.05, the assumption of equal variance is rejected. Hence, instead of ANOVA, Welch's F value is considered in the study. The results are presented in table 7.11.

Table 7.11

Income-wise Analysis of Investment Performance

Annual Income (Rs.)	N	Mean	SD	Max Score	F Value/ Welch F	*p*-value	Remarks
Less than 5,00,000	190	6.78	4.01	15	1.117	.349	Welch
5,00,000 - 10,00,000	151	6.88	3.93				
10,00,000- 15,00,000	19	5.68	2.81				
More than 15,00,000	30	6.17	3.79				
Total	**390**	**6.72**	**3.91**				

Source: Survey Data

The results indicate that investment performance has no significant difference among the annual income categories of investors as the p-value is more than 0.05.

7.2.7 Investment Experience-wise Analysis of Investment Performance

Investment performance may vary across investors according to the experience they have in mutual fund investment. In order to know the mean score of investment experience, descriptive analysis has been done. Then ANOVA is applied to check whether there is significant difference among investors' experience in mutual funds investment with respect to investment experience. Table 7.12 presents the results of Levene's test of homogeneity of variances.

Table 7.12

Investment Experience-wise Test of Homogeneity of Variances of Investment Performance

Variable	Levens's Statistic	*p*-value
Investment Performance	2.353	.072

Source: Survey Data

* Statistically significant at 5% significant level

Since the p-value of the Levene's test is more than 0.05, the assumption of equal variance is not rejected. Hence, ANOVA can be used to examine the significance of difference among investors' experience in mutual funds investment with regard to investment performance. The results of ANOVA are presented in table 7.13.

Table 7.13

Investment Experience-wise Analysis of Investment Performance

Investment Experience (Years)	N	Mean	SD	Max Score	F Value	*p*-value	Remarks
Less than 1	82	7.27	3.87	15	1.178	.318	ANOVA
1-3	128	6.85	4.01				
3-5	46	6.07	3.44				
Above 5	134	6.49	3.98				
Total	**390**	**6.72**	**3.91**				

Source: Survey Data

* Statistically significant at 5% significant level

Table 7.14 indicates that the p value of the test is more than 0.05. This makes it evident that significant difference does not exist among the investors' experience regarding mutual fund investment with regard to investment performance.

7.3 Influence of Behavioural Bias on Investment Performance

One of the important objectives of the study is to analyse the impact of behavioural bias on investment performance. Multiple regression analysis has been done for analysing the same.

7.3.1 Influence of Behavioural Bias on Investment Performance

From the existing literature, it is evident that behavioural bias has a negative impact on investment performance. In this section, the impact of various factors of behavioural bias on investment performance is tested using multiple regression analysis. Here, investment performance is the dependent variable and the factors of behavioural bias are the independent variables.The results are presented in table 7.14.

Table 7.14

Multiple Regression Analysis showing Influence of Behavioural Bias on Investment Performance

Variable	Co-efficient	Standard error	t-statistic	Prob.
Intercept	17.219	.987	17.450**	.000
Belief Perseverance Bias	-.102	.043	-2.395*	.017
Information Processing Bias	.079	.044	1.791	.074
Emotional Bias	-.161	.029	-5.490**	.000
F-statistic	43.477**			
Prob (F-statistic)	.000			
R-squared	.253			
Adjusted R^2	.247			

Source: Survey Data

**, * Statistically significant at 1% and 5% significant level

Table 7.14 indicates that belief perseverance bias and emotional bias are significant at the 5% significant level with a negative co-efficient. This implies that belief perseverance bias and emotional bias exert a negative influence on the investment performance of equity mutual fund investors. Information processing bias is not significant as the p-value is greater than 0.05. Hence, it can be concluded that investors who are affected by belief perseverance bias and emotional bias have experienced weak investment performance, while the information processing bias does not affect the investment performance of investors.

The overall significance of the estimated model given by the F statistic is 43.477 and the p-value is less than 0.05. It means that all of the independent variables taken together are significant in explaining the dependent variable. R^2 of the model is 0.253, which means that all the independent variables (belief perseverance bias, information processing bias and emotional bias) taken together explain 25.3% of the total variation of the dependent variable (investment performance). The adjusted R^2 of the model is 24.7%.

7.4 Conclusion

The present chapter reveals that the investment performance of equity mutual fund investors in Kerala is low. The investors' satisfaction level regarding the investment performance of mutual funds is 45%.

In gender-wise analysis, there exists significant difference between male and female investors with regard to investment performance. The results indicate that female investors have performed better than their male counterparts while making mutual fund investment.

In the case of age-wise analysis, significant difference does not exist among different age categories of investors with regard to investment performance.

In the education level, there is significant difference among different education levels of investors. According to the findings, technically qualified investors outperform other categories of investors in terms of investment performance.

Analysing the occupation of investors, the results show that there is no significant difference among investors' occupations with regard to investment performance.

In the case of marital status-wise analysis, there is no significant difference between married and unmarried investors with regard to investment performance.

In the case of annual income-wise analysis, significant difference does not exist among different annual income categories of investors with regard to investment performance.

In investment experience-wise analysis, significant difference does not exist among the investors' experiences regarding mutual fund investment with regard to investment performance.

While analysing the influence of behavioural bias on investment performance, the results show that the coefficients of belief perseverance bias and emotional bias are significant at a 5% significant level, and the coefficients are negative. This implies that belief perseverance bias and emotional bias exert a negative influence on the investment performance of equity mutual fund investors.

Chapter 8

FINDINGS AND CONCLUSION

Contents

8.1 Introduction

The present study is intended to examine the relationship between the stock market and equity mutual funds in India, analyse the trend of the performance of equity mutual funds, assess the nature and extent of behavioural bias among equity mutual fund investors with regard to different socio-economic factors and examine the influence of behavioural bias of equity mutual fund investors in Kerala on their investment performance. The major findings and conclusion of the study are presented in the chapter.

8.2 Findings of the study

8.2.1Relationship between the stock market and equity mutual funds in India

- The results of the Johansen's cointegration test indicate the existence of long-run relationship between equity mutual funds and the stock market in India and the speed of price adjustment to long-run equilibrium is found to be significant for the Sensex and equity mutual funds as per the results of VECM.
- Granger-causality test results imply that a movement in equity mutual funds causes the Sensex to change.
- The results of Variance decomposition analysis and impulse response function proved that Sensex had less strength of exogeneity when

compared to the equity mutual fund categories and the movements in the values of equity mutual funds would cause the stock market index to change.

8.2.2 Trend of the Performance of Equity Mutual funds in India

- Among the equity mutual fund categories, small-cap funds were the most volatile mutual funds, as they make at least 65% of their investment in small-cap companies, which are highly risky and has huge growth potential.
- Large-cap funds were the least volatile mutual funds, proving them to be the least risky equity mutual fund category.
- Small-cap funds would offer the best returns in 2022 and 2023, per the ARIMA forecast results. The performance of large-cap funds would initially decline in 2022 before gradually improving.
- The large and mid-cap funds and the mid-cap funds would continue to grow in 2022 and 2023.

8.2.3 Descriptive Statistics of the Respondents

- The descriptive statistics of the sample investors indicate that 281 (72.1%) of the sample investors are male and the remaining 109 (27.9%) are female. Despite the fact that females outnumber males in Kerala, female participation in equity mutual fund investments appears to be very low.
- It is found that 16 (4.1%) of the investors belong to the age group ‘below 25 years’, 290 (74.4%) belong to ‘26 – 40 years’ category, 70 (17.9%) belong to ‘41-60 years’ category and 14 (3.6%) belong to ‘above 60 years’ category. Subsequently, it can be inferred that the majority of the investors involved in the equity mutual fund investment in Kerala are youngsters.
- The study shows that 79 (20.3%) of the sample investors reside in municipal corporations, 116 (29.7%) reside in municipalities and 195

(50%) reside in panchayaths, which indicate that half of the sample investors reside in the rural areas of Kerala.

- The study reveals that 270 (69.2%) of the sample investors are married and the remaining are unmarried.

- The study implies that 24 (6.2%) of the sample investors are undergraduates, 118 (30.3%) are graduates, 155 (39.7%) are post graduates, 66 (16.9%) are professionally qualified and 27 (6.9%) are technically qualified. This shows that majority of the sample investors are reasonably educated.

- It can be inferred from the study that 263 (67.4%) of the respondents are employed on a salaried basis, 70 (17.9%) are professionals, 10 (2.6%) are businessmen, 19 (4.9%) are retired and the rest, 28 (7.2%) belong to other occupations. Therefore, the majority of the investors belong to a fixed income group.

- It can be observed that 190 (48.7%) of the sample investors belong to the 'less than Rs. 5,00,000' annual income category, 151 (38.7%) belong to 'Rs. 5,00,000-10,00,0000' category, 19 (4.9%) belong to 'Rs. 10,00,000-15,00,000' category and 30 (7.7%) belong to the 'more than Rs. 15,00,000' category. This indicates that the majority of the sample investors fall into the lower income bracket.

- The study indicates that 193 (49.5%) of the sample investors invest 'less than Rs. 25,000' annually, 63 (16.2%) invest 'Rs. 25,001-50.000', 55 (14.1%) invest 'Rs. 50,001-1,00,000' and 79 (20.3%) invest 'more than Rs. 1,00,000' in equity mutual funds. It can be inferred that the majority of the investors tend to invest less than Rs. 25,000 in equity mutual funds on an annual basis.
- The analysis regarding the investment mode preferred by the sample investors suggests that 69 (17.7%) resort to the lump sum mode of investment, 229 (58.7%) invest through SIPs and 92 (23.6%) invest

through both modes of investment. The majority of investors were found to invest systematically in equity mutual funds.

- Investment experience-wise analysis shows that 82 (21%) sample investors have experience of less than 1 year, 128 (32.8 %) have experience of 1-3 years, 46 (11.8%) have experience of 3-5 years and 134 (34.4%) have experience of more than 5 years. The majority of the investors have at least five years of investment experience.

8.2.4 Influence of Socio-Economic factors on different Behavioural Biases

Behavioural biases can be classified into Cognitive biases and Emotional biases. Cognitive biases can be further classified into belief perseverance bias and information processing bias. Hence, belief perseverance bias, information processing bias and emotional bias are considered as the types of behavioural bias. Belief perseverance bias consists of representativeness, confirmation bias, cognitive dissonance and illusion of control bias. In information processing bias, anchoring, availability, self-attribution and mental accounting biases are considered for the study. Emotional biases include overconfidence bias, loss aversion, regret aversion and herd behaviour.

- The aggregate mean score of all the types of behavioural bias is more than 3.3 (65%), which implies that the equity mutual fund investors in Kerala possess an above-average level of behavioural bias while making investment decisions. Belief perseverance bias has the highest mean score of 3.56 (SD 0.68), indicating that it has 71% influence among investors in Kerala. Emotional bias possesses the lowest mean score of 3.38 (SD 0.63), which has 68% of influence among investors in Kerala.

- In gender-wise analysis, the mean score of behavioural bias among male investors is 163.81 (SD 28.36), whereas in the case of female investors, the mean score is 143.95 (SD 21.41). The mean scores indicate that male investors are more affected by behavioural bias. A significant difference exists between male and female investors with regard to behavioural bias.

The analysis of the types of behavioural bias implies that belief perseverance bias, information processing bias and emotional bias have a significant difference between male and female investors. Furthermore, male investors are found to be more affected by these biases when compared to their female counterparts.

- In age-wise analysis, investors belonging to the age group below 25 years have the highest mean score of 177.31 (SD 41.66), whereas investors who are above 60 years of age have the lowest mean score of 152.14 (SD 13.96). This implies that young investors are more influenced by behavioral bias. A significant difference is found to exist among the age categories of investors with regard to behavioural bias.

Analysing the types of behavioural bias makes it evident that significant difference does not exist among age category of investors with regard to belief perseverance bias. However, in the case of information processing bias and emotional bias, significant differences exist among different age group of investors.

- In educational level-wise analysis, investors who are undergraduates possess the highest mean score of 174.88 (SD 33.56), whereas professionally qualified investors have the least mean score of 138.41 (SD 19.93). This suggests that investors with the lowest qualifications are the most affected by behavioural bias when making investment decisions. Moreover, there exists a significant difference among different education levels of investors with regard to behavioural bias.

In the case of types of behavioural bias, a significant difference exists among investors' level of education with regard to all three types of behavioural bias.

- Occupation-wise analysis reveals that employed investors have the highest mean score of 160.54 (SD 29.79) and businessmen have the lowest mean score of 139.40 (SD 15.86). The empirical evidence suggests that investors who are employed on a regular basis are more prone to behavioural bias, whereas businessmen are the least affected category. As the p-value is less than 0.05, there exists a significant difference among investors' occupations with regard to behavioural bias.

While analysing the types of behavioural bias, it is evident that a significant difference does not exist among different occupations of investors with regard to belief perseverance bias. However, a significant difference is found to exist among investors' occupations with regard to information processing bias and emotional bias.

- While analysing the marital status of employees, the mean score of married investors is 154.16 (SD 25.98), whereas the mean score of unmarried investors is 167.51 (30.30), which implies that unmarried investors are more prone to behavioural bias. Furthermore, a significant difference exists between married and unmarried investors with regard to behavioural bias.

The analysis of the types of behavioural bias indicates that belief perseverance bias, information processing bias and emotional bias have a significant difference between married and unmarried investors. However, unmarried investors are found to be more affected by these biases when compared to the married investors.

- In income-wise analysis, the mean score is maximum for the investors having an annual income of 'less than Rs. 5,00,000' which is 163.06 (SD 27.91), whereas the mean score is minimum for the investors having an annual income of 'more than Rs. 15,00,000' which is 152.43 (SD 29.39). This suggests that investors with lower incomes are more affected by behavioural bias. Moreover, a significant difference exists among the annual income categories of investors with regard to behavioural bias.

Analysing the types of behavioural bias implies that there exists no significant difference among the annual income categories of investors with regard to belief perseverance bias. However, information processing bias and emotional bias have significant differences among investors belonging to different annual income categories. Investors with lower incomes are found to be more prone to these biases.

- In investment experience-wise analysis, the investors with investment experience of ‘less than 1 year’ possess the highest mean score of 164.37 (SD 26.86), while, the investors with investment experience of ‘1 – 3 years’ possess the lowest mean score of 152.63 (SD 30.42). Hence, it can be inferred that investors with the least experience in equity mutual fund investment are more prone to behavioural bias. Also, it is found that a significant difference exists among the investors’ experiences regarding equity mutual fund investment with regard to behavioural bias.

In the case of types of behavioural bias, there exists a significant difference among the investors' experience in the case of belief perseverance bias and information processing bias. However, no significant difference exists among investment experiences with regard to emotional bias. Investors with lower income are more prone to the belief perseverance bias and information processing bias.

The researcher analysed the influence of different sub-types of behavioural bias on the investment decisions of investors and found out that all the behavioural biases influence the equity mutual fund investors in Kerala on an above-average level. Herding bias possesses the highest mean score of 3.78 (SD 0.78) while cognitive dissonance bias possesses the lowest mean score of 3.20 (SD 0.81). From this, it is evident that herding bias exerts the greatest influence on the investors, whereas cognitive dissonance bias has the least influence among the investors in Kerala.

- Gender-wise analysis implies that all the sub-types of behavioural bias except cognitive dissonance have significant differences between male and female investors. While analysing the mean scores among the male and female investors, it is evident that male investors are more prone to all the biases such as representativeness, confirmation, illusion of control, anchoring, availability, self-attribution, mental accounting, overconfidence, loss aversion, regret aversion and herding while making investment decisions than female investors.

- In age-wise analysis, illusion of control bias, anchoring bias, self-attribution bias, regret aversion bias and herding bias have significant differences among the age categories of investors.

While analysing the mean score among different age groups of investors, it is evident that younger investors are more prone to these biases when compared to older investors while taking investment decisions.

- Education-wise analysis shows that all the behavioural biases except mental accounting bias have significant differences among different educational qualifications of investors.

In the case of representativeness and confirmation bias, post graduates are the most affected category, whereas professionally qualified investors are the least affected ones. Professionally qualified investors are the most affected by cognitive dissonance bias, whereas graduates are the least affected. Investors who resorted to vocational education are highly affected by illusion of control bias, while professionally qualified investors are least affected by it. Anchoring bias, availability bias, self-attribution bias, loss aversion bias, regret aversion bias and herding bias show that undergraduates are highly prone to it, whereas professionally qualified investors are the least affected category. Overconfidence bias is highest among the undergraduates and lowest among the technically qualified investors.

- Occupation-wise analysis suggests that cognitive dissonance bias, anchoring bias, availability bias, self-attribution bias, mental accounting bias, overconfidence bias, loss aversion bias, regret aversion bias and herding bias show significant differences among different occupations of investors.

Cognitive dissonance bias, anchoring bias, availability bias, self-attribution bias and overconfidence bias are highest among the investors who are employed on a regular basis. Mental accounting bias, loss aversion bias, regret aversion bias and herding bias are highest among professionals. Businessmen are least affected by cognitive dissonance, anchoring, self-attribution, loss aversion, regret aversion and herding bias. Retired employees are the least prone to availability bias, whereas investors belonging to other occupations are least affected by mental accounting bias and overconfidence.

- Marital status-wise analysis shows that all the biases except confirmation bias show a significant difference between married and unmarried investors.

While analysing the mean scores of the married and unmarried investors, it is evident that unmarried investors are more affected by all the biases such as representativeness, cognitive dissonance, illusion of control, anchoring, availability, self-attribution, mental accounting, overconfidence, loss aversion, regret aversion and herding while making investment decisions.

- Annual income-wise analysis shows that confirmation bias, illusion of control bias, anchoring bias, self-attribution bias, regret aversion bias and herding bias show significant differences among different annual income categories of investors.

The mean scores indicate that investors belonging to the lowest annual income group are more prone to these biases while making investment decisions.

- Investment experience-wise analysis implies that representativeness, confirmation, illusion of control, anchoring, self-attribution, regret aversion and herding bias show significant differences among investors with different levels of investment experience.

The study further indicates that representativeness bias and confirmation bias are highest among investors with ‘3-5 years’ of experience, whereas they are lowest among investors with ‘1-3 years’ of experience. However, the least experienced investors are more affected by confirmation, illusion of control, anchoring, self-attribution, regret aversion and herding bias.

8.2.5 Influence of behavioural bias of Equity Mutual Fund Investors on their Investment Performance

Overall investment performance possesses a mean score of 6.72 (SD 3.91), which indicates that investors’ satisfaction level regarding the investment performance of mutual funds is 45%. The statement ‘I feel satisfied with my investment decisions in the last year’ has the highest mean score of 2.61 (SD 1.29), which implies that more than 52% of investors are satisfied with their investment decisions made in the previous year. The statement ‘my rate of return is equal to or higher than the average rate of return in the market’ has the lowest mean score of 2.03 (SD 1.31). This indicates that only 40% of the investors receive more than the average return in the market. Hence, it can be concluded that most investors are not satisfied with their equity mutual fund investments.

- Gender-wise analysis shows that there exists a significant difference between male and female investors with regard to investment performance. Male investors possess a mean score of 5.99 (SD 3.49), while female investors have a mean score of 8.60 (SD 4.31). This implies that female investors have performed better than their male counterparts when making mutual fund investments.
- In the case of age-wise analysis, significant difference does not exist among different age categories of investors with regard to investment performance.
- Education level-wise analysis shows that there exists a significant difference among different education levels of investors. The results suggest that technically qualified investors have exhibited the best investment performance, whereas, investors with the lowest educational qualifications have exhibited weak performance.

- Occupation-wise analysis suggests that there exists no significant difference among investors' occupations with regard to investment performance.
- Marital status-wise analysis shows that there exists no significant difference between married and unmarried investors with regard to investment performance.
- In the case of annual income category-wise analysis, significant differences do not exist among different annual income categories of investors with regard to investment performance.
- In investment experience-wise analysis, there exists no significant difference among the investors' experiences regarding mutual fund investment with regard to investment performance.
- While analysing the influence of the types of behavioural bias on investment performance, the results show that the coefficients of belief perseverance bias and emotional bias are significant at a 5% significance level, and the coefficients are negative. This indicates that the investors who are affected by belief perseverance bias and emotional bias have weak investment performance.

8.3 Conclusion

The present study on the analysis of behavioural bias and investment performance among equity mutual fund investors in Kerala indicates that a long-run relationship exists between equity mutual funds and the stock market in India. A long-run equilibrium relationship is found to exist between the Sensex and equity mutual funds in India. Furthermore, equity mutual funds exert a significant influence on Sensex, suggesting that changes in the values of equity mutual funds cause Sensex to vary. Moreover, the Sensex has less strength of exogeneity when compared to equity mutual funds.

Equity mutual funds have provided good returns for most of the years in the past decade. Large-cap equity mutual funds provided consistent returns most of the time, making it the least volatile category since these funds invest a major portion of their assets in equity shares of highly reputed Indian companies. Small-cap equity mutual funds are the most volatile category among equity mutual funds, as they invest at least 65% of their assets in equity shares of small-cap companies. The high risk taken by the investors provides them with a high return. As per the forecasts, all the equity mutual fund categories would provide better returns in 2022 and 2023. Moreover, the forecasts indicate that small-cap funds would be the best performers in these years. The findings also suggest that the performance of large-cap funds would decline in the initial phase of 2022 and then rise at a slow pace. However, they would deliver good returns in 2023. The large and mid-cap funds and mid-cap funds would continue to grow in 2022 and 2023. Due to the highly volatile nature of small-cap funds, it would be suitable for aggressive investors to invest in them. Large-cap funds would be advisable for conservative investors due to the low level of risk.

On average, the investors in Kerala are 65% affected by behavioural bias when making investment decisions. Investors are most affected by belief perseverance bias (71%), whereas, investors are least affected by emotional bias (68%). All types of behavioural biases exert an above average level of influence among investors. Moreover, herding bias exerts the most influence among the equity mutual fund investors in Kerala, whereas, cognitive dissonance bias has the least influence on them.

The level of investment performance is low (44.8%) among equity mutual fund investors in Kerala, which indicates that the investors are not satisfied with their returns. Belief perseverance bias and emotional bias exert a negative influence on investment performance, which implies that investors who are prone to these biases have experienced weak investment performance.

Chapter 9

RECOMMENDATIONS, IMPLICATIONS AND SCOPE FOR FURTHER RESEARCH

Contents

9.1 Introduction

Mutual funds are ideal investment vehicles for the modern financial scenario as it offers investors an opportunity to invest in a diversified and professionally managed basket of securities at a relatively low cost. The present study discusses the relationship between stock market and equity funds in India, trend of the performance of equity funds, influence of socio-economic factors on different behavioural biases and the influence of behavioural bias of equity mutual fund investors on their investment performance. The recommendations, implications of the study and scope for the further research are discussed in the present chapter.

9.2 Recommendations of the study

Based on the findings of the study, the researcher put forward the following recommendations to enhance the investment performance among investors in Kerala.

9.2.1 To the Investors

The findings of the study would be useful for the investors as it examines the relationship between stock market and equity mutual funds and provides the forecasts of performance of equity mutual funds thereby facilitating them to take investment decisions. It also provides insights into the behavioural biases existing among investors in Kerala and its impact on their investment performance. Based on the findings, the researcher proposes the following recommendations to the investors:

1. There exists co-integration between stock market and equity mutual funds in India and causality runs from equity mutual funds to Sensex indicating that movements in equity mutual funds could cause Sensex to vary. Hence, the investors can invest in equity mutual funds as an alternative to direct investment in stock market. Furthermore, it provides diversification and professional expertise for the investors.

2. Despite the high volatile nature of equity mutual funds, they have performed greatly in the long run. Hence, the investors should try to make investment in equity mutual funds for a long term in order to reap the benefits.

3. Investors are advised to constantly review their decision making process to observe, identify and control the behavioural biases, if any.

4. Investors are suggested to consult financial advisors before making investment to make better investment decisions.

9.2.2 To the Asset Management Companies

1. Small-cap funds are the most volatile category in providing returns. The AMCs are recommended to select the shares of those companies having strong financial position.

2. Investors in Kerala are highly prone to various behavioural biases. The mutual fund companies should try to educate individuals by conducting more awareness programmes in the state, which would lead to increased penetration of mutual funds in Kerala.

3. The present study suggests that behavioural biases vary among investors based on investors' gender, age, education, occupation, marital status, annual income and investment experience. Hence, it is imperative for the

asset management companies to assess the needs of investors and launch schemes accordingly.

4. Mutual funds have least penetration in Kerala. People prefer to invest in Bank deposits and Post office savings as they found them as credible sources. The AMCs should increase the credibility of mutual funds and develop a sense of trust among investors.

5. AMCs should provide proper training to financial advisors about every scheme as they are the main source of influence to the people. By gaining proper knowledge about the schemes one could identify the right scheme catering to their needs.

9.3 Research Implications

Since, the empirical evidence indicates that equity mutual funds exert a positive influence on the performance of stock market in India, investors could consider equity mutual funds as an alternative to direct investment in the stock market. Furthermore, diversification and professional expertise would make the mutual funds a safe investment avenue for the investors. Although there have been various hikes and dips in the performance, equity funds have provided good returns in the long run. Hence, investing in equity funds for a longer period would be advisable.

As the investors in Kerala are significantly prone to various behavioural biases, they are advised to make investment only after receiving proper training or by consulting financial advisors. It would be better if mutual fund AMCs to take proper measures to increase the financial literacy among people by conducting awareness programmes. Investors' needs vary according to their socio-economic profile. So, mutual fund AMCs may come up with new schemes catering to their needs. Moreover, behavioural bias exerts a negative influence on the investment performance. Hence, it is imperative for the investors to constantly review their decision making process to identify and control the behavioural biases.

9.4 Scope for Further Research

The results and limitations of the present study observed several worthy topics. These topics would foster further research, expanding the findings of the present study.

1. The present study is restricted itself to one stock market index and four types of equity mutual funds. The future research could be extended to incorporate more types of equity mutual funds.

2. The researcher further recommends that studies could also be conducted to analyse the effect of various macro-economic variables such as exchange rate, gold price, crude oil price, money supply, interest rate and foreign exchange reserves on the performance of equity mutual funds.

3. The researcher recommends that a comparative analysis of the performance of Indian equity mutual funds with that of the other developing economies can also be carried out.

4. Empirical analysis on the volatility of equity mutual fund performance has not been done in the present research; hence, this area remains to be further investigated.

5. Studies could also be conducted to examine the relationship between different behavioural biases to know whether one bias could lead to other.

6. There is further scope to explore the impact of financial literacy on behavioural bias among equity mutual fund investors in Kerala.

7. Moreover, a comparative analysis on the influence of behavioural biases on the investment performance of stock market investors and equity mutual fund investors can be carried out to understand whether the magnitude of these biases is more among the investors in stock market or the mutual fund investors.

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Appendix A

An Analysis of Behavioural Bias and Investment Performance among Equity Mutual Fund Investors in Kerala

QUESTIONNAIRE

Please ✓ for each question.

1. Gender: a. Male ☐ b. Female ☐
2. District: ……………………..
3. Residential Location:

   a. Corporation ☐ b. Municipality ☐ c. Panchayath ☐

4. Age:

a.	Below 20 years
b.	20 – 40 years
c.	40 – 60 years
d.	Above 60 years

5. Education level:

a.	Higher Secondary & Below
b.	Graduate
c.	Post Graduate
d.	Professional
e.	Vocational/Technical

6. Occupation:

a.	Employed
b.	Professional
c.	Businessman
d.	Retired
e.	Others

7. Marital status:

a. Married ☐ b. Unmarried ☐

8. Annual Income :

a.	Less than Rs. 5,00,000
b.	Rs. 5,00,000 - 10,00,000
c.	Rs. 10,00,000- 15,00,000
d.	More than Rs. 15,00,000

9. Annual mutual fund Investment:

a.	Less than Rs. 25,000
b.	Rs. 25,001 – 50,000
c.	Rs. 50,001 – Rs. 1,00,000
d.	More than Rs. 1,00,000

10. Mode of Investment:

a.	Lumpsum
b.	SIP
c.	SIP & Lumpsum

11. Years of experience in mutual fund investment :

a.	Less than 1 year
b.	1-3 years
c.	3-5 years
d.	Above 5 years

Behavioural Aspects

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 make investment decisions by monitoring the performance of a few samples.	**SA**	**A**	**N**	**D**	**SD**
2.	I invest in funds that have performed better recently.	**SA**	**A**	**N**	**D**	**SD**
3.	I avoid investing in funds that have performed poorly in the recent past.	**SA**	**A**	**N**	**D**	**SD**
4.	I prefer to buy hot stocks instead of poorly performed stocks.	**SA**	**A**	**N**	**D**	**SD**
5.	I have sufficient knowledge about the Indian mutual fund industry.	**SA**	**A**	**N**	**D**	**SD**
6.	My experience in trading with funds helps me choose funds that outperform the market.	**SA**	**A**	**N**	**D**	**SD**
7.	I have confidence in my ability to pick better funds.	**SA**	**A**	**N**	**D**	**SD**
8.	I never commit mistakes while making investment decisions.	**SA**	**A**	**N**	**D**	**SD**
9.	I believe that I can master the future trend of my investment.	**SA**	**A**	**N**	**D**	**SD**
10.	I think that market trends are often consistent with my perspectives.	**SA**	**A**	**N**	**D**	**SD**
11.	I rely heavily on one piece of information in making investment decision.	**SA**	**A**	**N**	**D**	**SD**
12.	I forecast the changes in net asset value of funds in the future based on the recent net asset values.	**SA**	**A**	**N**	**D**	**SD**
13.	I invest in a fund because I heard good news about it when I decided to make a investment.	**SA**	**A**	**N**	**D**	**SD**
14.	I become more optimistic when the market rises.	**SA**	**A**	**N**	**D**	**SD**
15.	I become more pessimistic when the market	**SA**	**A**	**N**	**D**	**SD**

	falls.					
16.	I make investment decisions based on available information.	**SA**	**A**	**N**	**D**	**SD**
17.	I give more importance to current information when I make investment decisions.	**SA**	**A**	**N**	**D**	**SD**
18.	I select the funds of companies which I already know.	**SA**	**A**	**N**	**D**	**SD**
19.	I consider the information from friends and relatives as a reliable reference for my investment decisions.	**SA**	**A**	**N**	**D**	**SD**
20.	I prefer to invest in already known funds.	**SA**	**A**	**N**	**D**	**SD**
21.	I hold the funds when the price decreases, even if it increases the loss.	**SA**	**A**	**N**	**D**	**SD**
22.	I invest in funds that I already own, even if their NAV goes down, to justify my investment decision.	**SA**	**A**	**N**	**D**	**SD**
23.	I believe that I get profit on investment due to my skill.	**SA**	**A**	**N**	**D**	**SD**
24.	The NAV of funds, which I selected by studying myself, increases.	**SA**	**A**	**N**	**D**	**SD**
25.	The NAV of funds, which I selected due to others' recommendations, falls.	**SA**	**A**	**N**	**D**	**SD**
26.	I collect maximum information from experts about funds, to confirm my investment decisions.	**SA**	**A**	**N**	**D**	**SD**
27.	I study the nature of funds and search for information while making investments.	**SA**	**A**	**N**	**D**	**SD**
28.	I seek market news that confirms my investment decision as correct.	**SA**	**A**	**N**	**D**	**SD**
29.	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**
30.	I seek more risk after a prior gain.	**SA**	**A**	**N**	**D**	**SD**
31.	I become more risk averse after a prior loss.	**SA**	**A**	**N**	**D**	**SD**

32.	The pain of financial loss is greater than the pleasure of financial gain.	**SA**	**A**	**N**	**D**	**SD**
33.	I prefer to invest in high-performing funds.	**SA**	**A**	**N**	**D**	**SD**
34.	I tend to hold onto losing funds too long, hoping for a reversal.	**SA**	**A**	**N**	**D**	**SD**
35.	I used to sell winning funds too soon.	**SA**	**A**	**N**	**D**	**SD**
36.	I feel more sorrow about holding onto losing funds too long than about selling winning funds too soon.	**SA**	**A**	**N**	**D**	**SD**
37.	I buy funds in times of bullish trends.	**SA**	**A**	**N**	**D**	**SD**
38.	I sell funds in times of bearish trends.	**SA**	**A**	**N**	**D**	**SD**
39.	I invest in funds in which my friends invest.	**SA**	**A**	**N**	**D**	**SD**
40.	My investment decisions are influenced by the investment behaviour of the majority.	**SA**	**A**	**N**	**D**	**SD**
41.	I would follow the market information to trade.	**SA**	**A**	**N**	**D**	**SD**
42.	I believe I have greater control over my investment.	**SA**	**A**	**N**	**D**	**SD**
43.	I can predict the market in a more logical manner.	**SA**	**A**	**N**	**D**	**SD**
44.	I tend to invest more when I am successful in my previous investment.	**SA**	**A**	**N**	**D**	**SD**
45.	I tend to treat each element of my investment portfolio separately.	**SA**	**A**	**N**	**D**	**SD**
46.	I save a part of my income for investing in the stock market.	**SA**	**A**	**N**	**D**	**SD**
47.	The rate of return on my recent investment meets my expectations.	**SA**	**A**	**N**	**D**	**SD**
48.	My rate of return is equal to or higher than the average rate of return in the market.	**SA**	**A**	**N**	**D**	**SD**
49.	I feel satisfied with my investment decisions over the last year.	**SA**	**A**	**N**	**D**	**SD**

Appendix B

DATABASE FOR THE STUDY

B.1 Database for the First Objective

Table B.1

Average Annual Returns of Equity Mutual Funds in India

Year	Large-cap Funds	Large and Mid-cap Funds	Mid-cap Funds	Small-cap Funds
2011	(21.76)	(23.88)	(23.74)	(27.31)
2012	27.31	34.01	40.52	40.79
2013	5	4.99	3.13	3.07
2014	40.96	52.08	69.73	71.98
2015	1.01	3.55	7.17	8.89
2016	3.30	6.62	3.91	5.82
2017	30.63	38.82	42.40	47.52
2018	(1.91)	(7.33)	(11.37)	(17.27)
2019	11.78	8.54	3.04	(1.51)
2020	14	16.20	24.30	30.66
2021	25.9	37.43	44.6	62.8

Source: Compiled from the Websites of Mutual Fund AMCs

Appendix C

TOOLS USED IN TIME SERIES DATA ANALYSIS

C.1 Augmented Dickey Fuller Test

A stationary time series is one whose statistical properties such as mean, variance, autocorrelation, etc. are all constant over time. Such statistics are useful as descriptors of future behaviour only if the series is stationary. In statistics, a unit root test tests whether a time series variable is non-stationary and possesses a unit root. In this study, ADF tests have been conducted to examine the stationarity properties of the variables. Before understanding ADF Test, one must know the basics of a Dickey Fuller test. Dickey and Fuller (1979) consider three different regression equations that can be used to test the presence of a unit root:

$$\Delta Y_t = \gamma Y_{t-1} + \varepsilon t \qquad \text{(C.1)}$$

$$\Delta Y_t = \alpha 0 + \gamma Y_{t-1} + \varepsilon t \qquad \text{(C.2)}$$

$$\Delta Y_t = \alpha 0 + \gamma Y_{t-1} + \alpha 2t + \varepsilon t \qquad \text{(C.3)}$$

In the above equations, the difference between the three regressions concerns the presence of the deterministic elements a0, a2t. While the first equation represents a pure random walk model, the second equation adds an intercept or drift term into the model and the third equation includes both an intercept and linear time trend. The test is used to identify the value of γ. If $\gamma = 0$, it implies that the Yt sequence contains a unit root. The test estimates the value of γ and associated standard error of the equations using OLS method. By analysing the value of t-statistic along with the probability value helps to determine whether to accept or reject the null hypothesis of $\gamma = 0$. Dickey Fuller test assumes that the error term εt is uncorrelated. In case when no such assumption regarding εt is taken into consideration, Dickey and Fuller have developed another unit root test which is known as the ADF test. In this test, the lagged difference terms of the variable are included in the model to make the error term serially independent. This test is conducted by‘augmenting’the preceding three equations such as Equation (C.1, C.2 and C.3) by adding the lagged values of the independent variable ΔYt. The ADF test can handle more complex models than the Dickey-Fuller test, and it is also more powerful. The ADF test may be specified as follows:

$$\Delta Yt = \alpha 0 + \alpha 1t + \gamma Yt-1 + X\, k\, i=1\, \beta iYt-i + \varepsilon t \qquad \text{(C.4)}$$

Where εt represents a pure white noise error term

Δ represents the difference operator

γ and β represents the parameters.

ADF test follows the same asymptotic distribution as the DF statistics, i.e whether $\gamma = 0$ so the same critical values can be used. It is important to note that the selection of statistic depends on the deterministic components included in the regression equation. When there is no intercept and trend, τ statistic is used; with only the intercept, τ statistic is used and with both intercept and trend, $\tau\tau$ statistic is used. The statistics labelled τ, τ and $\tau\tau$ are the appropriate statistics to be used in Equations (C.1, C.2 and C.3) respectively. For ADF test, the value of K is determined based on either AIC or SIC.

C.2 Vector Auto Regression (VAR)

VAR method is widely used in the estimation of appropriate lag length of each variable in the system. It is possible to use different lag length for each variable in the equation. Such type of VAR is called as NEAR VAR and can be estimated through Seemingly Unrelated Regression. But for the sake of simplicity the same lag length is used for all equations. Various lag selection criteria are used to select the optimum lag length of the model. These are Likelihood Ratio, Final Prediction Error, Akaike Information Criteria, Schwarz Information Criteria and Hannan-Quinn information criteria. After setting lag length, the next step is to estimate the model through OLS. However, it is difficult to interpret individual coefficients in

estimated VAR models directly. To overcome this problem, advanced techniques like impulse response function and variance decomposition are made use of.
Suppose a multivariate VAR is given as follows:

Xt = A0 + A1Xt−1 + A1Xt−2 + ... + ApXt−p + et (C.5)

Where, Xt = the (n × 1) vector containing each of the n variables included in the VAR
A0 = an (n × 1) vector of intercept terms.
Ai = an (n × n) matrix of coefficient. et = an (n × 1) vector of error terms.
In the above example, matrix A0 contains n intercept term and each matrix Ai contains n2 coefficients, hence n + pn2 terms need to be estimated. Unquestionably, a VAR will be over parameterized by which many of these coefficient estimates can be properly excluded.

C.3 Johansen's Co-integration Test

Johansen Co-integration test, named after Søren Johansen, is a procedure for testing cointegration of several, say *k*, I(1) time series. This test permits more than one cointegrating relationship so is more generally applicable than the Engle–Granger test which is based on the Dickey–Fuller (or the augmented) test for unit roots in the residuals from a single (estimated) cointegrating relationship. There are two types of Johansen test, either with trace or with eigenvalue, and the inferences might be a little bit different. The null hypothesis for the trace test is that the number of cointegration vectors is $r = r^* < k$, vs. the alternative that $r = k$. Testing proceeds sequentially for $r^* = 1,2$, etc. and the first non-rejection of the null is taken as an estimate of *r*. The null hypothesis for the "maximum eigenvalue" test is as for the trace test but the alternative is $r = r^* + 1$ and, again, testing proceeds sequentially for $r^* = 1, 2$ etc., with the first non-rejection used as an estimator for *r*.

The trace test and maximum eigen value test can be shown in equations

J_{trance}=-T Σ^N

i=r+1ln (1- λˆi) (C.6)

J_{tmax}=-T ln (1- λˆr+1) (C.7)

Where T is the sample size

λˆi is the i^{th} largest canonical correlation.

The trace test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of n cointegrating vectors. The maximum eigen value test, on the other hand, tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of r +1 cointegrating vectors.

C.4 Vector Error Correction Model

If a set of variables are found to have one or more cointegrating vectors, then a suitable estimation technique that can be used to adjust both short run changes in variables and deviations from equilibrium a VECM. Granger (1969) argued that VECM is more appropriate to examine the causality between the series at I (1). VECM is the restricted form of unrestricted VAR and restriction is levied on the presence of the long run relationship between the series. The system of ECM makes use of all series endogenously. This system allows the predicted values to explain itself both by its own lags and lags of forcing variables as well as the lags of the ECT and by residual term. The VECM equation is as follows:

$$\begin{pmatrix} \Delta x_{1t} \\ \Delta y_{1t} \\ \Delta y_{2t} \\ \Delta y_{3t} \\ \cdots \\ \Delta y_{nt} \end{pmatrix} = \begin{pmatrix} C_{1t} \\ C_{2t} \\ C_{3t} \\ C_{4t} \\ \cdots \\ C_{nt} \end{pmatrix} + \Sigma_{i=1}^{p} \begin{bmatrix} \beta_{11i} & \beta_{12i} & \beta_{13i} & \beta_{14i} & \cdots & \beta_{1ni} \\ \beta_{21i} & \beta_{22i} & \beta_{23i} & \beta_{24i} & \cdots & \beta_{2ni} \\ \beta_{31i} & \beta_{32i} & \beta_{33i} & \beta_{34i} & \cdots & \beta_{3ni} \\ \beta_{41i} & \beta_{42i} & \beta_{43i} & \beta_{44i} & \cdots & \beta_{4ni} \\ \vdots & \vdots & \vdots & \vdots & \cdots & \vdots \\ \beta_{n1i} & \beta_{n2i} & \beta_{n3i} & \beta_{n4i} & \cdots & \beta_{nni} \end{bmatrix} \begin{pmatrix} \Delta x_{1_{t-i}} \\ \Delta y_{1_{t-i}} \\ \Delta y_{2_{t-i}} \\ \Delta y_{3_{t-i}} \\ \cdots \\ \Delta y_{n_{t-i}} \end{pmatrix} + \begin{pmatrix} \gamma_{1t} \\ \gamma_{2t} \\ \gamma_{3t} \\ \gamma_{4t} \\ \cdots \\ \gamma_{nt} \end{pmatrix} ECM_{t-1} + \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \cdots \\ \varepsilon_{nt} \end{pmatrix} \quad (C.8)$$

Where C's, β's and γ's are the parameters to be estimated

ECM t−1 represents the one period lagged error-term derived from the co-integration vector

ε's are serially independent with mean zero and finite covariance matrix

All variables in the model are treated as endogenous variables. F test is applied to examine the direction of causal relationship between the variables. The coefficients on the ECM represent how fast deviations from the long-run equilibrium become stable.

C.5 Granger Causality Test

Causality refers to the ability of one variable containing useful information to predict and therefore influence the value of another variable based on linear least squares (Diebold 2007). To explain the causality test, the Granger (1969) definition of the proof of causality is that if variable X_t can be predicted with greater accuracy by using past values of the variable Y_t when all other terms or factors remain unchanged, it simply says Y_t that causes X_t. Therefore, the variables Y_t and X_t can affect each other with distributed lags (past period). Causality test reveals which variable is exogenous and which variables are endogenous.

Engle and Granger (1987), find that a causal relationship exists in at least one direction if two individual variables are cointegrated. The VAR model can be constructed in terms of time series at level form, (I(0)). It also can be constructed in terms of the first difference of the variable, (I(1)), with the addition of an ECT to capture the dynamic short-run response. However, if the data are not cointegrated (I(1)), the causality test can be derived from transforming the data into stationarity.

C.6 Variance Decomposition Analysis

Short run variations occurring in a variable are mostly due to its own shocks. However, there are chances of other variables to have an impact on the variable. Forecast Error Variance Decomposition (FEVD) helps to measure the impact of external variables on the selected variable. While Impulse Response Function (IMF) analyses the dynamic behaviour of the target variables due to unanticipated shocks within a VAR model, variance decomposition analysis determines the relative importance of each innovation on the variables in the system. Variance decompositions analysis can be considered as similar to R2 values associated with the dependent variables in different horizons of shocks. To calculate n-period forecast error Xt+n considering the vector moving average representation of VAR, the following equation is used.

X_t+n-EtX_{t+n} = μ + Σ𝑛−1 θ𝑖=0 iεt+n−1 (C.9)

Considering Yt, the first element of the Xt+n matrix in Equation (C.9), the variance

of the n-step-ahead forecast error can be calculated as:

Y_t + n-EtX_{t+n} = $\theta^{11}(0)\varepsilon_{yt+n}$ + $\theta_{11}(1)$ ε_{yt+n-1}+....+ θ11(n-1)ε_{yt+1}+θ12(0)ε_{zt+n} +θ12(1)ε_{zt+n-1} + ... + θ12(n-1) εzt+1 (C.10)

or

σy(n)^2 = σ^2y [θ11(0)^2 + θ11(1)^2 +....+θ11(n-1)^2] + σ2z [θ12(0)^2 + θ12(1)^2 +.... + θ12(n-1)^2] (C.11)

Where σy(n)^2 and σz(n)^2 denote the n-step-ahead forecast error variance of Y_{t+n} and Z_{t+n}, respectively. While the first part of the Equation (C.10) shows the proportion of variance due to the variables own shock i.e., Y_t, the second part of the Equation (C.11) shows the proportion of variance due to the other variables shock i.e., Z_t.

Theoretically, the first part decreases over time and the second part of the variance increases. However, it is typical for a variable to explain almost all of its forecast error variance at a short horizon and smaller proportions at longer horizons. From this standpoint, variance decomposition analysis is useful to assess how one variable explains a considerable portion of forecast error variance of another variable. That is, when a shock εz explains none of the forecast error variance of the sequence Y_t at all forecast horizons, i.e., $\delta\sigma^2 y/\sigma^2 z \approx 0$, we may say that Y_t evolves indecently of the Z_t shocks i.e, εz. In addition to that, when a shock given to the Z_t sequence i.e.,εz explains the entire forecast error variance of the sequence

Y_t at all forecast horizons, i.e., δσ2 y/σ2z≈ 100%, may say that Y_t sequence is totally endogenous.

C.7 Impulse Response Function

Impulse response function is the reaction of any dynamic system in response to some external change. It is a useful tool in determining the magnitude, direction, and the duration of the variables in the system which are affected by an external variable's shock. Its main purpose is to describe the evolution of a model's variables in reaction to a shock in one or more variables. For estimating impulse response function, VAR model is be transformed into Vector Moving Average (VMA) as it allows to identify the effects of various shocks on variables in the system. In a VAR model which includes two variables, the form of the impulse response function can be written as:

$$\left[\frac{Y_t}{Z_t}\right] = \left[\frac{\bar{Y}}{\bar{Z}}\right] + \sum_{i=0}^{\infty} \frac{A^i}{1 - b_{12}b_{21}} \begin{bmatrix} 1 & -b12 \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{Y_{t-i}} \\ \varepsilon_{Z_{t-i}} \end{bmatrix} \tag{C.12}$$

$$\left[\frac{Y_t}{Z_t}\right] = \left[\frac{\bar{Y}}{\bar{Z}}\right] + \sum_{i=0}^{\infty} \begin{bmatrix} \theta_{11}^i & \theta_{12}^i \\ \theta_{21}^i & \theta_{22}^i \end{bmatrix} \begin{bmatrix} \varepsilon_{Y_{t-i}} \\ \varepsilon_{Z_{t-i}} \end{bmatrix} \tag{C.13}$$

and

$$X_t = \mu + \sum_{i=0}^{\infty} \theta_i \varepsilon_{t-i} \tag{C.14}$$

Where θi is the impulse response function of disturbances.

Therefore, impulse response function is analysed by reading off the coefficients in the moving average representation of the process. If the innovations εtâĹŠi are contemporaneously uncorrelated, interpretation of the impulse response will be straightforward. For example, the i^{th} innovation of εt is simply a shock to the i^{th} endogenous variable in the system. However, the residuals generated by the VAR models are usually contemporaneously correlated. This is because in a VAR model only lagged endogenous variables are admitted on the right-hand side of each equation (in addition to a constant term), and hence all the contemporaneous shocks which impact on X_t are forced to feed through the residuals u_{it}. While this may not cause a problem in the estimation of the VAR model, the impulse responses and variance decompositions derived from the initial estimates of the VAR model can be affected because any adjustment made in the order of the variables entered in the system could produce different results. Thus, there is a need to impose some restrictions when estimating the VAR model to identify the impulse response function. In this regard, a common approach is the Cholesky decomposition, which was originally applied by Sims in 1980. The Cholesky decomposition overcomes the problem of contemporaneous relationships among the innovations error terms within the estimated VAR model by identifying structural shocks so that the covariance matrix of the estimated residuals is lower triangular. In fact, the Cholesky decomposition suggests that there is no contemporaneous pass-through from Y_t to the other variable, z_t. More formally, in the VAR, the matrix error structure becomes left triangular. In practice, this means that the Cholesky decomposition attributes all the effect to the variable that comes first to the target variable in the VAR system.

C.8 Auto Regressive Integrated Moving Average (ARIMA)

An Autoregressive Integrated Moving Average (ARIMA) model is a generalization of an autoregressive moving average (ARMA) model. Both of these models are fitted to time series data either to better understand the data or to predict future points in the series (forecasting). ARIMA models are applied in some cases where data show evidence of non-stationarity, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied one or more times to eliminate the non-stationarity. The AR part of ARIMA indicates that the evolving variable of interest is regressed on its own lagged (i.e., prior) values. The equation for the AR model is shown below:

$$Y_t = \beta_1 + \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \ldots + \Phi_p Y_{t-p} \qquad \text{(C.15)}$$

The respective weights ($\Phi 1$, $\Phi 2$ …Φp) of the corresponding lagged observations are decided by the correlation between that lagged observation and the current observation. If the correlation is more, the weight corresponding to that lagged observation is high (and vice-versa). This (p) is called the lag order. It represents the number of prior lag observations we include in the model i.e., the number of lags which have a significant correlation with the current observation. The MA part indicates that the regression error is actually a linear combination of error terms whose values occurred contemporaneously and at various times in the past.

$$Y_t = \beta_2 + \omega_1 \varepsilon_{t-1} + \omega_2 \varepsilon_{t-2} + \ldots + \omega_q \varepsilon_{t-q} + \varepsilon_t \quad \text{(C.16)}$$

The ε terms represent the errors observed at respective lags and the weights ($\omega 1$, $\omega 2$ …ωq) are calculated statistically depending on the correlations. (q) represents the size of the moving window i.e., the number of lag observation errors which have a significant impact on the current observation. It's similar to the lag order (p), but it considers errors instead of the observations themselves.

When we combine the AR and MA equations, we get

$$\begin{aligned} Y_t = {} & (\beta_1 + \beta_2) \\ & +(\Phi_1 Y_{t-1} + \ldots + \Phi_p Y_{t-p}) \\ & + (\omega_1 \varepsilon_{t-1} + \ldots + \omega_q \varepsilon_{t-q} + \varepsilon_t) \end{aligned} \quad \text{(C.17)}$$

The I (for "integrated") indicates that the data values have been replaced with the difference between their values and the previous values (and this differencing process may have been performed more than once). This is equivalent to performing a transformation of the form:

$$Z_t = Y_{t+1} - Y_t \quad \text{(C.18)}$$

So to revise, the final ARIMA model will take the following form, ARIMA (*p,d,q*).

Where *p* represents Auto Regressive (AR)

d represents order of differencing (I)

q represents moving average (MA)