Charles University in Prague

Faculty of Social Sciences

Institute of Economic Studies

MASTER THESIS

Role of Behavioral Finance in Portfolio Investment Decisions: Evidence from India

Author: **Rahul Subash**

Supervisor: **PhDr. Karel Báťa**

Academic Year: **2011/2012**

Declaration of Authorship

I hereby declare that the thesis titled '**Role of Behavioral Finance in Portfolio Investment Decisions: Evidence from India**' is a bona fide record of the dissertation work carried out by me and submitted to Charles University in partial fulfillment of the requirement for Degree of Master in Economics and Finance. I grant Charles university permission to reproduce and distribute copies of this thesis document completely or in part.

Prague, May 18, 2012 _______________________

Rahul Subash

Acknowledgments

Firstly, I express my deep sense of gratitude to PhDr. Karel Báťa for his inspiring guidance, scholarly interpretations and valuable criticisms throughout the course of my work.

I am gratefully obliged to the Business Associates at Trivandrum Investor Services, for helping me to collect data necessary for the study.

I extend my sincere thanks to prof. Ing. Michal Mejstřík CSc., PhDr. Tomáš Havránek, PhDr. Zuzana Havránková, PhDr. Ing. Petr Soukup and Mr. Michal Bauer for their help and support.

I also thank my family members and colleagues for all their support and encouragement throughout the completion of the work

Above all, I bow before and thank 'God Almighty' without whose blessings this work would have never been completed.

Rahul Subash

Abstract

Extreme volatility has plagued financial markets worldwide since the 2008 Global Crisis. Investor sentiment has been one of the key determinants of market movements. In this context, studying the role played by emotions like fear, greed and anticipation, in shaping up investment decisions seemed important. Behavioral Finance is an evolving field that studies how psychological factors affect decision making under uncertainty. This thesis seeks to find the influence of certain identified behavioral finance concepts (or biases), namely, Overconfidence, Representativeness, Herding, Anchoring, Cognitive Dissonance, Regret Aversion, Gamblers' Fallacy, Mental Accounting, and Hindsight Bias, on the decision making process of individual investors in the Indian Stock Market. Primary data for analysis was gathered by distributing a structured questionnaire among investors who were categorized as (i) young, and (ii) experienced. Results obtained by analyzing a sample of 92 respondents, out of which 53 admitted to having suffered a loss of at least 30% because of the crisis, revealed that the degree of exposure to the biases separated the behavioral pattern of young and experienced investors. Gamblers' Fallacy, Anchoring and Hindsight biases were seen to affect the young investors significantly more than experienced investors.

Keywords	Behavioral Finance, Discriminant Analysis, Gamblers' Fallacy, Anchoring, Hindsight Bias
Author's e-mail	rahul6@gmail.com
Supervisor's e-mail	karel.bata@seznam.cz

Abstrakt

Od počátku globální ekonomické krize v roce 2008 jsou finanční trhy po celém světě sužovány extrémní nestabilitou. Jedním z klíčových činitelů, které ovlivňují pohyby na trhu, je smýšlení investorů. V tomto kontextu se jeví jako velice důležité studium role emocí jako je strach nebo hrabivost při utváření investičních rozhodnutí. Behaviorální finančnictví je rozvíjející se obor, který se zabývá tím, jak psychologické činitele ovlivňují přijímaní rozhodnutí v nepředvídatelných podmínkách. Cílem této práce je zjistit vliv konkrétních identifikovaných konceptů (nebo tlaků) behaviorálního finančnictví, a to Overconfidence, Representativeness, Herding, Anchoring, Cognitive Dissonance, Regret Aversion, Gamblers' Fallacy, Mental Accounting, and Hindsight Bias, na proces přijímaní rozhodnutí jednotlivých investorů na indické burze. Primární data pro analýzu byly získány prostřednictvím strukturovaného dotazníku distribuovaného mezi investory, kteří byli podle míry zkušeností a věku rozděleni na (i) mladé a (ii) zkušené investory. Výsledky, získané analýzou dat od 92 respondentů, ze kterých 53 přiznalo alespoň třicetiprocentní ztráty v důsledku krize, odhalili, že chování mladých a zkušených investorů se liší mírou, do které je jednotlivé tlaky ovlivňují. Pozorovali jsme, že Gamblers' Fallacy, Anchoring and Hindsight ovlivňují mladé investory v signifikantně vyšší míře než zkušené investory.

Klíčová slova	Behaviorální finančnictví , diskriminační analýza, Gamblers' Fallacy, Anchoring, Hindsight Bias
E-mail autora	rahul6@gmail.com
E-mail vedoucího práce	karel.bata@seznam.cz

Contents

List of Tables

List of Figures

Acronyms

APT	Arbitrage Pricing Theory
CAC40	Cotation Assistée en Continu, French Stock Market Index
CAPM	Capital Asset Pricing Model
EMH	Efficient Market Hypothesis
MPT	Modern Portfolio Theory
SENSEX	Sensitive Index, Bombay Stock Exchange, India
SPSS	Statistical Package for Social Sciences, IBM
USA	United States of America
VIF	Variance Inflation Factors

Thesis Proposal

Institute of Economic Studies
Faculty of Social Sciences
Charles University in Prague

Author:	**Rahul Subash**	Supervisor:	PhDr. Karel Bata
E-mail:	rahul6@gmail.com	E-mail:	Karel.bata@seznam.cz
Phone:	774261663	Phone:	777654587
Specialization:	Economics & Finance	Defense Planned:	2012

Notes: The proposal should be 2-3 pages long. Save it as "yoursurname_proposal.doc" and send it to both mejstrik@fsv.cuni.cz and tomas.havranek@ies-prague.org. Subject of the e-mail must be: "JEM001: Thesis Proposal Yoursurname".

Proposed Topic:

Role of Behavioral Finance in Portfolio Investment Decisions: Evidence from India

Topic Characteristics:

Much of the economic and financial theories presume that individuals act rationally in the process of decision making, by taking into account all available information. But there is evidence to show repeated patterns of irrationality in the way humans arrive at decisions and choices when faced with uncertainty. Behavioral finance, a study of the market that draws on psychology, throws light on why people buy or sell stocks and why sometimes do not buy or sell at all. The most crucial challenge faced by the investor is in the area of investment decisions. The profit made, or losses incurred by an investor can be attributed mainly to his decision-making abilities. The fact that even the most prominent and well-educated investors were affected by the collapse of the speculative bubble in the 2008 subprime crisis proved that something was fundamentally missing in the traditional models of rational market behavior.

In this study, the aim is to establish the existence of such fundamental issues, driven by various psychological biases, in the investment decision-making process. Behavioral economists firmly believe that psychological factors influence investment decisions. They argue that today's investment decisions demand a better understanding of individual investors' behavioral biases. However, many economists believe completely in the application of traditional theories in the decision making process and hence do not consider the concept of irrational behavior. In this context, it seems relevant to check whether the behavioral factors have an influence on the decision making process of portfolio investors.

A questionnaire will be formulated and distributed among the clients of a brokerage firm in India and their investment decisions and effects of behavioral factors on it will be studied. The focus will be on individual investors as they are more likely to have limited knowledge about application of traditional theories in decision-making and hence are prone to making psychological mistakes. The primary analysis would be focused on determining whether behavioral factors affect the investors' decision to buy sell or hold stocks.

Hypotheses:

1) Behavioral factors have no influence on the investment decisions of private investors
2) Awareness regarding behavioral factors do not influence portfolio investment decisions
3) Young investors are more affected by behavioral factors than experienced investors (experienced investors are those aged above 35 with at least 5 years of experience)
4) Overconfidence bias is the behavioral pattern most commonly observed with investors
5) There is no visible herding behavior in the Indian stock market
6) Stocks from South Indian stocks comprise majority of portfolios maintained by South Indian investors (local bias)

Methodology:

The study will have a descriptive research design. Primary and secondary data will be used. Primary data will be gathered using a structured questionnaire which will be presented to individual portfolio investors. Secondary data will be gathered from journals like SSRN journals, the IUP Journal of Behavioral finance and so on. The data collected will be processed and analyzed using tools like weighted averages, percentages, scaling techniques and econometric analysis using linear or logit(probit) regression models. Hypotheses developed will be tested using GRETL software and inbuilt functionalities. Collected data will be analyzed using Microsoft Excel.

Outline:

1) Introduction and Literature Review
2) Behavioral Finance – A theoretical framework
    a. Background
    b. Evolution
    c. Behavioral Theories
    d. Behavioral Biases
    e. Decision Making
3) Behavioral Finance and Investment Decisions – An analysis of the decisions & behavioral patterns of Indian Investors
4) Summary of Findings and Recommendations

Core Bibliography:

1) Redhead, Keith(2008) ' Personal Finance and Investments: A Behavioural Finance Perspective' Taylor and Francis Group
2) M. Schindler(2007) 'Rumours in Financial Markets: Insights into Behavioural Finance' John Wiley and Sons
3) Pompian, Michael(2006) 'Behavioral Finance and Wealth Management – How to Build Optimal Portfolios That Account for Investor Biases' John Wiley and Sons
4) M. Elvin(2004) 'An Introduction to the Psychology of Trading and Behavioral Finance' John Wiley and Sons
5) Shleifer, Andrei(2000) ' Inefficient Markets – An introduction to Behavioral Finance', Oxford University Press
6) Grou, Tabak (2008) 'Ambiguity Aversion and illusion of Control: Experimental Evidence in an Emerging Market', The Journal of Behavioral Finance, Vol. 9, No.1 : pp 22-29
7) Vasiliou, Eriotis & Papathanasiou (2008) ' Incorporating Technical Analysis into Behavioral Finance : A Field Experiment in the Large Capitalization Firms of the Athens Stock Exchange', International Research Journal of Finance and Economics, Issue 14
8) Barker, Loughran(2007) 'The Geography of S&P 500 Stock Returns', The Journal of Behavioral Finance, Vol.8, No.4, pp 177-190
9) Massa, Simonov(2005)' Behavioral Biases and Investment', Review of finance, Vol.9, pp 483 - 507
10) Chandra, Abhijeet(2008) 'Decision Making in the Stock Market : Incorporating Psychology with Finance', Department of Commerce & Business Studies, New Delhi, 2008

Author

Supervisor

Chapter One

Introduction

"One of the funny things about the stock market is that every time one person buys, another sells, and both think they are astute." - **William Feather**

The traditional finance paradigm seeks to understand financial markets using models in which investors are "rational". Even though many traditional theories of varying complexities and explanatory power have existed and evolved over the past several decades, the rationality of investors is a central assumption all and sundry. According to Nofsinger (2001), the field of finance has evolved over the past few decades based on the assumption that people make rational decisions and that they are unbiased in their predictions about the future. Investors are thought of as a rational lot that take carefully weighted economically feasible decisions every single time. A rational investor can be defined as a one that always (i) updates his beliefs in a timely and appropriate manner on receiving new information; (ii) makes choices that are normatively acceptable (Thaler, 2005).

In what is very likely to be termed as an "anomaly" by most traditional economic theories, the foundations of the world economy were shaken by the Financial Crisis of 2008 that originated in the USA and global recession that resulted. A vast majority of economists, and economic forecasters occupying influential seats in governments and financial institutions were caught unawares by this and the follow up events like bankruptcies and defaults. Even after the crisis had begun, many of them were not able to analyze the magnitude or depth of it. Going a bit more into the past, the case of a hedge fund by the name of Long Term Capital Management (LCTM) deserves special mention owing to the fact that, despite being partnered by an ex-vice chairman of the Federal Reserve Board, two Nobel Prize winners in Economics, and having 24 employees with Ph.D.s., it plunged into failure (Nofsinger, 2001).

Failures of economists, and consequently the theories they swear by, on various occasions has put forward the question: Are people really rational? Or are they likely to be driven by bouts of emotions like fear and greed which could lead to bad decisions?

Bernstein(1998) says that the *"evidence reveals repeated patterns of irrationality, inconsistency, and incompetence in the ways human beings arrive at decisions and choices when faced with uncertainty"*. Nofsinger (2001) says that the assumptions of rationality and unbiasedness of people have been drubbed by psychologists for a long time.

Theoretical and Experimental works of two psychologists Daniel Kahneman and Amos Tversky which contributed to psychology literature in 1970s served as foundation and gave rise to a new paradigm in the 1980s called Behavioral Finance, which *"studies how people actually behave in a financial setting. Specifically, it is the study of how psychology affects financial decisions, corporations, and the financial markets."*(Nofsinger, 2001)

From an academic perspective, one of the key reasons for the emergence of Behavioral Finance is owing to various difficulties faced by traditional theories. The science argued that, if the assumption of full rationality was relaxed, various financial phenomena would be better understandable. Subsequently, different models came into being. While some of them assumed that people only failed to update their beliefs promptly, other models considered scenarios where they were updating their beliefs rationally, but making normatively questionable choices. It requires emphasis that the key objective of behavioral finance has not been to prove any of the exiting theories obsolete, because if those theories were not able to explain puzzling scenarios successfully to a good extent, they, in all possibility, would have ceased to exist. So, what behavioral finance essentially tries to achieve is to supplement the traditional finance theories by merging it with cognitive psychology in an attempt to create a more complete model of human behavior in the process of decision making. (Thaler, 2005).

From a practitioner's perspective, Behavioral finance identifies various concepts that makes a human being behave irrationally thus leading to suboptimal decisions. For a smart investor to capture the essence of behavioral finance, all he/she would have to do is reflect on his/her own investment decisions. Humans are susceptible to various behavioral anomalies, which can become the biggest obstacle in their attempt to maximize wealth. If "Anchoring" - a behavioral anomaly that occurs when an individual relies too much on a specific piece of information (called anchor) while making decisions- could cost the likes of Warren Buffet a staggering $8 billion while in the process of buying Wal-Mart shares, it could affect just about anyone. So, it is not that great investors do not have these flaws, it is just that they understand the importance of emotions in trading, and train their mind not to mix emotions with decisions by following a two step process (i) understand one's own emotional and psychological weaknesses by studying various identified anomalies or 'biases' and determine whether he/she has committed these mistakes in the past or if there is a tendency to commit this in future; and (ii) after achieving objectives in previous step, understand the irrational behavior of others and benefit from their mistakes (Parikh, 2011).

Moving focus to India in 2008, the SENSEX – India's oldest and among the most popular stock market index of the Bombay Stock Exchange representing the free-float market value of 30 component stocks representing the most well-established companies across key sectors – had touched an all time high closing high of 20,873 points in January 2008 although the sub-prime mortgage crisis had already originated in the USA. A year later, in March 2009, the index had tanked to 8,160 points, after the crisis had spread globally. Even before the impacts of the crisis has smoothed out completely, the SENSEX touched a new all time high in November 2010 and closed at 20,893 points. Then a new crisis in the form of a Sovereign debt crisis originated in Europe (Sinha, 2012) making the SENSEX tank again. One word that has dominated the world of financial markets since 2008 has been 'Volatility' and the markets in India have been no exception. Extreme movements in stock prices because of fear and anticipation have, as it is supposed to, made life tough for a rational investor. Market sentiments have been observed to sway wildly from positive to negative and back, in the shortest timeframes like weeks, days and hours. In this context, understanding irrational investor behavior deserves more importance that it has ever had. Various psychological biases can be arguably influencing the investment decisions of investors, and this is where the problem was identified.

The objective of this thesis is to check if the average individual investor participating in the Indian Stock Market is rational at all times. The work focuses on nine identified behavioral biases, namely: Overconfidence, Representativeness, Herding, Anchoring, Cognitive Dissonance, Regret Aversion, Gamblers' Fallacy, Mental Accounting and Hindsight Bias. Effects of these nine factors on the decision making process of portfolio investors in Kerala, India has been analyzed in this study. Individual investors were picked for the study since they were more likely to have limited knowledge about application of behavioral theories in decision making and hence prone to making psychological mistakes. The influence has primarily been analyzed in terms of whether behavioral factors affect the investors' decision to buy sell or hold stocks.

The thesis follows a descriptive research design. Primary data for analysis has been gathered using a questionnaire[1] survey. The questionnaire was distributed to investors trading at a brokerage floor and as an online survey to reach out to investors who prefer to trade via internet based platforms. The final sample consisted of 92 investors, selected by applying judgment sampling based on two criteria (i) age of the respondent, and (ii) years of investing experience. Two sub-samples were of 46 investors were created: (i) experienced investors – those aged above 30 with at least 7 years of investing experience; and (ii) Young investors – those aged 30 or below with less than 7 years of experience. The sample has been processed and analyzed using IBM SPSS Software and Microsoft Excel. Ten variables were coded into SPSS, 1 of them a dichotomous variable representing investor group, and the remaining nine, each representing a bias, were created by using scaling techniques like 3-point and 5-point Likert Scales, and arithmetic mean. An overall analysis of these variables was conducted by performing various Multicollinearity Checks and the Discriminant Analysis, which checks if the behavioral pattern of young investors is different from that of the experienced ones. Further, effect of each bias on the two groups was analyzed separately using the Weighted Scoring Method and hypotheses were tested using the Chi-squared test for Independence.

The remaining part of thesis is structured as follows: *Chapter Two* describes details about causes of the advent of the field of Behavioral Finance. The background and evolution of the field, popular behavioral theories, and the nine behavioral biases relevant to this study are discussed. Existing literature relevant to the overall study, as well as to each bias has been reviewed in context. *Chapter Three* provides details on the design of the research and techniques used for facilitating the study; follows it up with theoretical descriptions of analysis methods used after which the actual analysis and results are presented in detail. *Chapter Four* provides a summary of the results obtained and gives recommendations; followed up by the conclusion in *Chapter Five.*

---

[1] Refer Appendix A

Chapter Two

Theoretical Framework and Literature Overview

2.1 Overview

Finance can be broadly defined as the study of how scare resources are allocated by humans, and how these resources are managed, acquired and invested over time. There are two key paradigms within the traditional Theory of Finance :(i) Market agents are perfectly rational: perfect rational behavior implies that any new available information is interpreted correctly and uniformly but all market agents while updating their beliefs, and (ii) Markets are Efficient: The Efficient Market Hypothesis (EMH) states all relevant information are reflected in the prices instantaneously and completely. When the hypothesis holds, prices are right, and there is 'no free lunch'. i.e. there is no investment strategy which can earn excess risk-adjusted average returns consistently. Over the past fifty years, there has been a lot of focus on the development and testing of various sophisticated asset pricing models. Subrahmanyam (2007) classifies central paradigms of finance as (i) Portfolio allocation based on expected return and risk (ii) risk-based asset pricing models (e.g. Capital Asset Pricing Model) (iii) the pricing of contingent claims, and (iv) the Modigliani-miller theorem and its augmentation by the theory of agency. The presumption is that, since people value wealth, they behave rationally while making financial decisions. Even though these models revolutionized the study of finance, many gaps were left unanswered by the theories. Traditional finance plays a very limited role in explaining issues such as (i) why do individual investors trade? (ii) Why do returns vary across stocks for reasons other than risk?

While this was happening in the financial world, researchers in psychology were discovering that people often behave in odd ways while making decisions where money is involved. Psychologists have found that economic decisions are often made in a seemingly irrational manner. Cognitive errors and extreme emotions can cause investors to make bad investment decisions. Shiller (2002) provided theoretical and empirical evidence to support the fact that CAPM, EMH, and other traditional financial theories did a great job in predicting and explaining certain events. However academics also started to find anomalies and behaviors which these traditional theories could not explain. Two popular examples are (i) The January

Effect, an anomaly in the financial market where the prices of a security increase in the month of January without fundamental reasons (Rozeff and Kinney, 1976), (ii) The Winner's Curse where the winning big in an auction tends to exceed intrinsic value of the item purchased, mainly due to incomplete information, and emotions leading bidders to overestimating the item's value. (Thaler, 1988). Academics were prompted to look to cognitive psychology to account for irrational and illogical investor behavior (Phung, 2002).

Behavioral finance is a relatively new paradigm of finance, which seeks to supplement the standard theories of finance by introducing behavioral aspects to the decision making process. Early proponents of behavioral finance are considered by some to be visionaries. The awarding of the 2002 Nobel Prize in economics to psychologist Daniel Kahneman and experimental economist Vernon Smith vindicated the field. Kahneman studied human judgment and decision making under uncertainty while Smith studied alternative market mechanism through experimental research. This was the first time a psychologist was awarded the Nobel Prize and played a key role in convincing mainstream financial economists that investors can behave irrationally.

2.2 Efficient Market Hypothesis

"An 'efficient' market is defined as a market where there are large numbers of rational, profit-maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and on events which, as of now, the market expects to take place in the future. In other words, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value." (Fama, 1965)

The Efficient Market Hypothesis (EMH) has been a central finance paradigm for over 40 years, probably the most criticized too. Fama (1970) defined an efficient market as one in which security prices fully reflect all available information, and hypothesis states that real world financial markets are efficient. Fama goes on to say that it would be impossible for a trading system based on currently available information to have excess returns consistently. The EMH became sensational in the 1970s and a lot of research work -centered on why the hypothesis should hold- developed supported by immense theoretical and empirical success. The University of Chicago, home to the EMH, became the world's center of academic finance.

The theoretical foundation of EMH is based on three key arguments (i) investors are rational and value securities rationally (ii) in case some investors are irrational, their trades are random and cancel each other out without affecting prices (iii) rational arbitrageurs eliminate the influence of irrational investors on market. The fact that Efficient Market Hypothesis was not purely based on rationality alone but also predicted efficient markets in cases where rationality did not exist, gave the theory a lot of credibility. The empirical evidence from the 1970s, which only strengthened the cause, fell into two main categories (i) any fresh news about a security should be reflected in its price promptly and completely and (ii) prices should not move as long as there is no new information about the company, since it must be exactly equal to the value of the security. In other words, non-reaction to non-information (Shleifer, 2000).

2.2.1 Support and Criticism

Fama (1965) distinguishes between three forms of the EMH (i) the "weak" form efficiency where all past market prices, returns and other information are fully incorporated in prices, which makes it impossible to earn credible risk-adjusted profits based on historical data. This renders technical analysis useless (ii) the "semi-strong" form states that it is impossible for investors to earn superior returns using publicly available information since they would already be incorporated in the prices. This renders fundamental analysis useless (iii) the "Strong" form of EMH states that all information, public and private, are fully reflected in securities prices. This would mean that even insider information would not help an investor land superior returns. Much of the evaluations have been based on the weak and semi-strong form efficiency since it was difficult to accept the strong form, and there was also evidence that insiders did in fact earn abnormal returns even while trading legally (Seyhun 1998, Jeng et al, 1999). In support of weak form efficiency Fama (1965) found that stock prices followed a random walk pattern. The semi-strong efficiency was tested by *event studies* – studies where effect of various news 'events' on share prices were studied – pioneered by Fama et al (1969).

The EMH peaked when it was declared by Michael Jensen – one of the inventors of EMH – that *"there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Markets Hypothesis"* (Jensen 1978). Shortly after this the EMH was challenged both on both the empirical and theoretical front. Grossman and Stiglitz (1980) argued that it was impossible for efficient markets to exist since information has a cost associated with it, and prices will not perfectly reflect available information, since if it did, there would be no incentive for investors to spend resources to obtain it. Investors are likely to act based on what they perceive to be relevant information, while this may actually be irrelevant, thus deviating actual prices from its fair value. Kahneman and Riepe (1998) showed that people deviated from the standard decision making model in key fundamental areas for e.g. based on varying risk appetite levels. Kahneman and Tversky with their theories – to be discussed later - provided psychological evidence that people did not deviate from rationality in a random manner. They showed that investors were unlikely to randomly trade between each other, and more likely to buy or sell at the same time. Shiller (1984) and Summers (1986) provided empirical evidence to show that returns were predictable to some extent which contradicted the existing market model assumption of constant expected returns. This raised eyebrows about the credibility of the testing of EMH done until the 1980s based on this model.

2.3 Behavioral Finance

2.3.1 Introduction

Behavioral finance is a branch of finance that studies how the behavior of agents in the financial market and influenced by psychological factors and the resulting influence on decisions made while buying or selling the market, thus affecting the prices. The science aims to explain the reasons why it's reasonable to believe that markets are inefficient. Some of the key definitions of behavioral finance are discussed below.

According to Sewell (2007), *"Behavioral finance is the study of the influence of psychology on the behaviour of financial practitioners and the subsequent effect on markets."* The science deals with theories and experiments focused on what happens when investors make decisions based on hunches or emotions.

Shefrin (2000) defines Behavioral finance as *"a rapidly growing area that deals with the influence of psychology on the behavior of financial practitioners".*

Belsky and Gilovich(1999) prefer to call behavioral finance as 'behavioral economics' and says that *"Behavioral economics combines the twin disciplines of psychology and economics to explain why and how people make seemingly irrational or illogical decisions when they spend, invest, save, and borrow money."*

"Behavioral finance relaxes the traditional assumptions of financial economics by incorporating these observable, systematic, and very human departures from rationality into standard models of financial markets. The tendency for human beings to be overconfident causes the first bias in investors, and the human desire to avoid regret prompts the second" (Barber and Odean,1999).

Thus, Behavioral finance can be defined as a field of finance that proposes explanation of stock market anomalies using identified psychological biases, rather than dismissing them as *"chance results consistent with the market efficiency hypothesis."(*Fama, 1998). It is assumed that individual investors and market outcomes are influenced by information structure, and various characteristics of market participants (Banerjee, 2011).

2.3.2 Background and Evolution

The Modern Portfolio Theory (MPT), Capital Asset Pricing Model (CAPM) and Arbitrage Pricing Theory (APT) are the quantitative models that underpin the rational expectations based theories. Unfortunately, there is a large amount of research, which could not confirm this theory in the available investment data. For example, Fama and French, (1993, 1996) and others have shown that the basic facts about the aggregate stock market, the cross-section average returns and individual trading behaviour are not easily understood in this framework. The behavioral finance paradigm has emerged in the response to the difficulties faced by the traditional paradigm. In essence, it argues that investment choices are not always made on the basis of full rationality, and it attempts to understand the investment market phenomena by relaxing the two doctrines of the traditional paradigm, that is, (i) agents fail to update their beliefs correctly and (ii) there is a systematic deviation from the normative process in making investment choices. (Kishore, 2004)

Schindler (2007) lists three main cornerstones for research in Behavioral finance. (i) Limits to arbitrage- which argues that *"it can be difficult for rational traders to undo the dislocations caused by less rational traders"* (Barberis and Thaler, 2003). So arbitrage opportunities exist which allows investor irrationality to be substantial and have long-lived impact on prices.

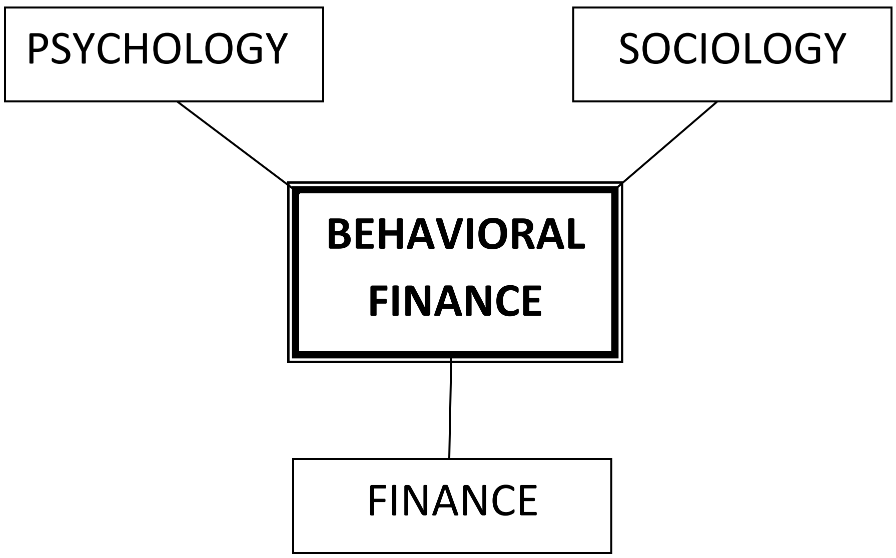

Figure 2.1 **Evolution of Behavioral Finance**, *Source:* ***Schindler (2007)***

To explain investor irrationality and their decision-making process, behavioral finance draws on the experimental evidence of the cognitive psychology and the biases that arise when people form beliefs, preferences and the way in which they make decisions, given their beliefs and preferences (Barberis and Thaler, 2003) thus bringing us to the second cornerstone (ii) Psychology – research in this area has shown that individuals exhibit certain biases systematically while formulating their beliefs and preferences thus affecting their decisions. (iii) Sociology – which emphasizes the fact that a considerably huge number of financial decisions are a result of social interaction rather than being made in isolation. This contradicts the implicit assumption that individuals reach decisions without external influences.

2.3.3 Fathers of Behavioral Finance

The aim of this section is to present some of the key literary works of Daniel Kahneman and Amos Tversky, recognized as the Fathers of Behavioral Finance. In the 1960s Kahneman and Tversky were focused on different lines of research and came together in the 1970s to create what were to be the benchmarks in the field. The initial step was to adapt psychological experiments in decision theory to real-world scenarios. They also started to differentiate normative solution to a problem from the real life subjective answers they gathered through experiments. Tversky's mathematical work on the normative theory and Kahneman's 'psychophysical emphasis on the difference between objective stimulus and subjective sensation' blended perfectly to serve the purpose (Heukelom, 2007).

- The first paper they authored together, "Belief in the Law of Small Numbers" was published in 1971, in which they report that *"People have erroneous intuitions about the laws of chance. In particular, they regard a sample randomly drawn from a population as highly representative"*(Kahneman and Tversky, 1971).
- In their 1972 publication titled "Subjective probability: A judgment of Representativeness", they study the Representativeness bias - which is explained later in this study – and followed it up with a 1973 publication titled "On the psychology of prediction" which says that Representativeness play a key role in intuitive predictions made by individuals (Kahneman and Tversky, 1972, 1973).
- In 1974 "Judgment under Uncertainty: Heuristics and Biases", one of their prominent works, was published. They described three heuristics – Representativeness, Availability and Anchoring. They said that *"a better understanding of these heuristics and of the biases to which they lead could improve judgment and decisions in situations of uncertainty".*
- In 1979 their most important work titled "Prospect Theory: An analysis of decision under risk" appeared in *Econometrica*, which was 'a critique of expected utility theory as a descriptive model of decision making under risk' and the alternative model developed was called Prospect Theory. Kahneman was awarded the Nobel Prize in Economics in 2002, for his work in Prospect Theory.
- In another important paper, Tversky and Kahneman (1981) introduced the effect famous as Framing. It was shown that when the same problem was framed in different ways, the psychological principles that governed the perception of decision problems and evaluation of probabilities and outcomes produced predicated shifts of preference.

2.4 Human Behavioral Theories

In order to explain the various irrational investor behaviors in financial markets, behavioral economists draw on the knowledge of human cognitive behavioral theories from psychology, sociology and anthropology. Two major theories are discussed: Prospect Theory and Heuristics

2.4.1 Prospect Theory

The Prospect theory was originally conceived by Kahneman and Tversky (1979) and later resulted in Daniel Kahneman being awarded the Nobel Prize for Economics. The theory distinguishes two phases in the choice process: the early phase of framing (or editing) and the subsequent phase of evaluation. Tversky and Kahneman, by developing the Prospect Theory, showed how people manage risk and uncertainty. In essence, the theory explains the apparent irregularity in human behavior when assessing risk under uncertainty. It says that human beings are not consistently risk-averse; rather they are risk-averse in gains but risk-takers in losses. People place much more weight on the outcomes that are perceived more certain than that are considered mere probable, a feature known as the *"certainty effect"*. (Kahneman and Tversky, 1979). People's choices are also affected by the 'Framing effect'. Framing refers to the way in which the same problem is worded in different ways and presented to decision makers and the effect deals with how framing can influence the decisions in a way that the classical axioms of rational choice do not hold. It was also demonstrated systematic reversals of preference when the same problem was presented in different ways (Tversky and Kahneman, 1981).

The value maximization function in the Prospect Theory is different from that in Modern Portfolio Theory. In the modern portfolio theory, the wealth maximization is based on the final wealth position whereas the prospect theory takes gains and losses into account. This is on the ground that people may make different choices in situations with identical final wealth levels. An important aspect of the framing process is that people tend to perceive outcomes as gains and losses, rather than as final states of wealth. Gains and losses are defined relative to some neutral reference point and changes are measured against it in relative terms, rather than in absolute terms (Kahneman and Tversky, 1979).

When it comes to investments in stocks, the natural reference point is the purchase price of stock. Indeed, most of the empirical studies motivated by the prospect theory find that the purchase price of stock appears to be one of the reference points used by an investor. However, it is possible that some additional reference points affect an investor. For example, the maximum stock prices in the recent return history are found to affect investors' trading decisions. In principle, framing can be broad or narrow. An investor applying a broad framing could analyze gains and losses in total wealth level. Intermediate and narrow framing, instead, refer to the process whereby an investor defines gains and losses with regard to isolated components of wealth. Intermediate framing may take place on the level of a stock portfolio, whereas the narrow framing is usually defined at level of individual securities. The vast majority of empirical studies implicitly assume narrow framing.

The most central element of the prospect theory is the S-shaped value function depicted in Figure below:

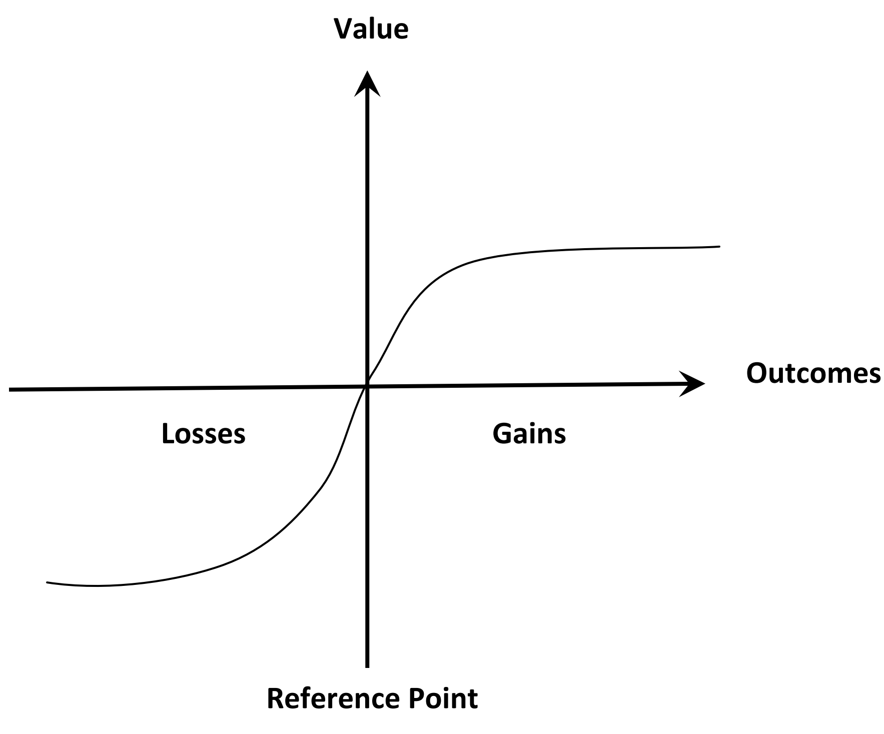

Figure 2.2 **Prospect Theory Value Function,** *Source:* ***Kahneman and Tversky (1979)***

The value function is defined in terms of changes in wealth rather than final states. The shape of the function is concave in the region of gains and convex in the loss region, reflecting risk aversion in the domain of gains and risk seeking in the domain of losses. An interesting property of the value function is that it is steepest at the reference point. This implies that a given change in gains or losses has a smaller effect on the value experienced by an investor when the distance to the reference point is large. Prospect theory argues that when choosing between gambles, people compute the gains and losses for each one and select the one with the highest prospective utility. In a financial context, this suggests that people may choose a portfolio allocation by computing, for each allocation, the potential gains and losses in the value of their holdings, and then taking the allocation with the highest prospective utility.

Another element of the prospect theory is the weighting function: The value of each outcome is multiplied by a decision weight. Decision weights measure the impact of events on the desirability of an investment. They are not probabilities and typically do not add up to unity. Kahneman and Tversky (1979) call this property sub-certainty. Decision weights are generally regressive with respect to true probabilities, implying that preferences are less sensitive to variations in probability than the rational benchmark would suggest. Prospect theory describes several states of mind that can be expected to influence an individual's decision-making processes.

2.4.2 Heuristics

"Heuristics are simple efficient rules of the thumb which have been proposed to explain how people make decisions, come to judgments and solve problems, typically when facing complex problems or incomplete information. These rules work well under most circumstances, but in certain cases lead to systematic cognitive biases" – Daniel Kahneman (Parikh, 2011).

Tversky and Kahneman identified the influence of human heuristics on the decision making process. Tversky defined heuristic as a strategy, which can be applied to a variety of problems, that usually–but not always–yields a correct solution. People often use heuristics (or shortcuts) that reduce complex problem solving to more simple judgmental operations (Tversky and Kahneman, 1981). Heuristic decision process is the process by which the investors find things out for themselves, usually by trial and error, lead to the development of rules of thumb.

In other words, it refers to rules of thumb, which humans use to made decisions in complex, uncertain environments (Brabazon, 2000).

Man is not capable to process all the information that one is presented with on a daily basis. While accumulating experience through the process of doing something, those experiences gives an impression of how something works. This process creates rules of thumb that can then be used when a similar situation is encountered. This phenomenon is called the use of heuristics. This is especially relevant in modern trading, when the number of instruments and the density of information have increased significantly. Using heuristics allows for speeding up of the decision-making compared to rationally processing the presented information. The most attractive aspect of this is the time that can be saved while the main drawback is the dependence on previous experience. Traditional financial models assume the exclusion of heuristics, and assume all decisions being based on rational statistical tools (Shefrin, 2000).

2.5 Behavioral Biases

Investors may be inclined toward various types of behavioral biases, which lead them to make cognitive errors. People may make predictable, non-optimal choices when faced with difficult and uncertain decisions because of heuristic simplification. Behavioral biases, abstractly, are defined in the same way as systematic errors are, in judgment (Chen et al, 2007).

Researchers distinguish a long list of specific biases, applying over fifty of these to individual investor behaviour in recent studies. When one considers the derivative and the undiscovered biases awaiting application in personal finance, the list of systematic investor errors seems very long indeed. Research that is more brilliant seeks to categorize the biases according to some kind of meaningful framework. Some authors refer to biases as heuristics (rules of thumb), while others call them beliefs, judgments, or preferences; still other scholars classify biases along cognitive or emotional lines. While "this sort of bias taxonomy is helpful—an underlying theory about why people operate under bias has not been produced. Instead of a universal theory of investment behaviour, behavioral finance research relies on a broad collection of evidence pointing to the ineffectiveness of human decision making in various economic decision-making circumstances" (Pompian, 2006).

2.5.1 Overconfidence Bias

"In this most basic form, Overconfidence can be summarized as unwarranted faith in one's intuitive reasoning, judgments, and cognitive abilities" (Pompian, 2006). Psychologists have determined that Overconfidence causes people to overestimate their knowledge, underestimate risks, and exaggerate their ability to control events. The concept of Overconfidence derives from a large body of cognitive psychological experiments and surveys in which subjects overestimate both their own predictive abilities and the precision of the information they have been given. People are poorly calibrated in estimating probabilities—events they think are certain to happen are often far less than 100 percent certain to occur. In short, people think they are smarter and have better information than they actually do (Pompian, 2006).

According to Shefrin (2000), Overconfidence *"pertains to how well people understand their own abilities and the limits of their knowledge"* Individuals who are overconfident about their abilities tends to think they are better than they actually are. The same applies to knowledge. Individuals who are overconfident about their level of knowledge tend to think they know more than they actually do. Overconfidence does not necessarily mean that individuals are ignorant or incompetent. Rather, it means that their view of themselves is better than is actually the case. A common trait among investors is a general overconfidence of their own ability when it comes to picking stocks, and to decide when to enter or exit a position. These tendencies were researched by Odean (1998) and it was found that traders that conducted the most trades tended, on average, to receive significantly lower yields than the market. Furthermore, psychologists have determined that overconfidence causes people to overestimate their knowledge, underestimate risks, and exaggerate their ability to control events. Specific security selection is a highly difficult undertaking. Interestingly this type of activity is precisely the task at which people exhibit the greatest overconfidence (Nofsinger, 2001).

Barber and Odean (2001) partitioned investors based on gender and, based on the previous psychological research fact that men are more overconfident than women, tested the theory that overconfident investors trade excessively. They document that men trade 45% more than women, and find that men's net returns were cut by 2.5% a year while it was 1.72% for women, in data gathered from 1991 through 1997.

Fagerström (2008) conducted a study to investigate overconfidence and over optimism in the market and factors that affect human beings in decision making when it comes to investing and analyzing. The scientific method of the research is a quantitative back-testing exercise method based on historic data taken from IBES, Institutional Brokers' Estimate System. The data taken is a summary of consensus expected growth of profits for the companies at S&P500 for the upcoming 12 months, compared with the realized outcome for the period February 1986 to April 2008. The results showed that analysts of the S&P 500 were exaggerated by the problems of over confidence and the over optimistic biases. It also confirms theory of Anchoring and Herding.

2.5.2 Representativeness Bias

Gilovich et al (1983) define Representativeness as *"an assessment of the degree of correspondence between a sample and a population, an instance and a category, an act and an actor or, more generally, between an outcome and a model."*

Representativeness is concerned with determining conditional probabilities. Using the heuristic the probability that an object or event A belongs to a class or process B is determined. Representativeness is said to be usually employed, while making judgments under uncertainty, when people are asked to judge the probability that A belongs to B (Tversky and Kahneman, 1983). In case A and B are described in the same terms, Representativeness can be reduced to 'similarity' (Tversky and Kahneman, 1981: in O'Hagan et al, 2006).

Representativeness is judgment based on overreliance stereotypes. The investors' recent success; tend to continue into the future also. The tendency of decisions of the investors to make based on experiences is known as stereotype (Shefrin, 2000). Ritter (1991) noted another interesting consequence of judgment by Representativeness bias where he attributes long run underperformance of IPOs to the investors' short term orientation. This has many implications to investment decision making. While making investments, individuals tend to attribute good characteristics of a company directly to good characteristic of its stock. These companies turn out to be poor investments more often than not (Lakonishok et al, 1994).

2.5.3 Herding Bias

Herding in financial markets can be defined as mutual imitation leading to a convergence of action (Hirshleifer and Teoh, 2003). This is the most common mistake where investors tend to follow the investment decisions taken by the majority. That is why, in financial markets, when the best time to buy or sell is at hand, even the person who thinks he should take action experiences a strong psychological pressure refraining him to do so. The main reason for this is pressure from or influence by peers. The Reliance Power IPO, 2008 is an example of an instance where many investors subscribed without having full information on the issue. Investors apply to "herd behavior" because they are concerned of what others think of their investment decisions (Scharfstein and Stein, 1990).

Private investors tend to be influenced by recommendations of popular analysts. Welch (2000) in his study found out analysts could be exhibiting Herding behavior too. It was not confirmed due to lack of micro level data. Whenever and analyst revised his recommendations, it had a positive correlation with the next two analyst's revisions. The revision was found to be heavily influenced by the prevailing market consensus, and to recent information updates (Welch, 2000).

Herd behavior is the tendency individuals have to mimic the actions of a large group irrespective of whether or not they would make the decision individually. One reason is that people are sociable and generally tend to seek acceptance from the group rather than being a standout. Another reason is that investors tend to think that it is unlikely that a large group could be wrong. This could make him follow the herd under the illusion that the herd may know something he does not.

Economou, Kostakis and Philippas (2010) examined herd behavior in extreme market conditions using daily data from the Greek, Italian, Portuguese and Spanish stock markets for the years 1998- 2008 i.e. the existence of asymmetric Herding behavior associated with market returns, trading volume, and return volatility. Along with this, they also investigated the presence of herd behavior during the global financial crisis of 2008. The results of the study showed that Herding is found to be stronger during periods of rising markets in these stock markets. Herding is present in the Portuguese stock market during periods of down returns and there is no evidence of Herding in the Spanish stock market. Finally, it is said that there is evidence of Herding during the global financial crisis of 2008 only for the Portuguese stock market and evidence of anti-Herding for the Spanish and the Italian stock markets. Investor behavior seems to have been rational for the Greek stock market during the global financial crisis.

2.5.4 Anchoring Bias

"In many situations, people make estimates by starting from an initial value that is adjusted to yield the final answer. The initial value, or starting point, may be suggested by the formulation of the problem, or it may be the result of a partial computation. In either case, adjustments are typically insufficient (Slovic and Lichtenstein, 1971). That is, different starting points yield different estimates, which are biased toward the initial values. We call this phenomenon Anchoring." (Tversky and Kahneman, 1974).

Anchoring is a psychological heuristic which can be said to occur when investors give unnecessary importance to statistically random and psychologically determined 'anchors' which leads them to investment decisions that are not essentially 'rational'. When required to estimate a good buy price for a share and investor is likely to start by using an initial value – called the "anchor" – without much analysis, say for e.g. the 52-week low of the stock. Then they adjust this anchor up or down to reflect their analysis or new information, but studies have shown that this adjustment is insufficient and ends producing results that are biased. Investors exhibiting this bias are likely to be influenced by these anchors while answering key questions like 'Is this a good time to buy or sell the stock?' or 'is the stock fairly priced?' The concept of Anchoring can thus be explained by the tendency of investors to "anchor" their thoughts to a logically irrelevant reference point while making an investment decision (Pompian, 2006).

Kristensen and Gaerling (1997) tested the hypothesis that "in negotiations counteroffers are generated through an Anchoring-and-adjustment process leading to an effect of the anchor point, and those counteroffers are influenced by changes in reference point which in turn determine whether the anchor point is perceived as a gain or a loss." The negotiation process was simulated with the help of business administration undergraduate students and results showed that the participants treated the proposed selling price as an anchor.

Andersen (2010) shows the involvement of Anchoring in decision making of market participants by using an existing trading algorithm. The algorithm was applied to real market data of the Dow Jones Industrial average and CAC40 stock index to look for arbitrage possibilities. The model returned out-of-sample profit even while considering transaction costs on the CAC40 and thus provide evidence that Anchoring had a role to play in the weekly price fixing of the Dow and CAC40.

2.5.5 Cognitive Dissonance Bias

"Cognitive Dissonance is the mental conflict that people experience when they are presented with evidence that their beliefs or assumptions are wrong." (Montier, 2002)

When an investor faces a situation where he has to choose between two alternatives, it is likely that some conflict will follow after a decision has been reached. The negative aspects of the alternative he chose are likely to be prominently visible while the positives of the discarded alternative will add to the conflict. This ends up challenging the investor's confidence in the decision he has just made. *"Psychologists conclude that people often perform far-reaching rationalizations in order to synchronize their cognitions and maintain psychological stability"* (Pompian, 2006).

According to Pompian (2006), there are two identified aspects of Cognitive Dissonance that is related to decision making. (i) Selective perception: where investors only register information, which affirms their beliefs thus creating an incomplete view of the real picture. (ii) Selective decision-making: Investors are likely to reinforce commitments previously made even though it might be visible that it is the wrong thing to do. This occurs because of commitment to the original decision forcing the investor to rationalize actions, which would allow him to stick to it, even though these actions are sub-optimal.

2.5.6 Regret Aversion Bias

"I should have computed the historical covariance of the asset classes and drawn an efficient frontier. Instead, I visualized my grief if the stock market went way up and I wasn't in it-or if it went way down and I was completely in it. My intention was to minimize my future regret, so I split my [pension scheme] contributions 50/50 between bonds and equities."- Harry Markowitz, Founder of Modern Portfolio Theory (Pompian, 2006)

Regret Aversion is a psychological error that arises out of excessive focus on feelings of regret at having made a decision, which turned out to be poor, mainly because the outcomes of the alternative are visibly better for the investor to see. The root cause of this type of error is the tendency that individuals hate to admit their mistakes. Because of suffering from this bias, investors may avoid taking decisive actions for the fear that whatever decisions they make take will be sub-optimal in Hindsight. One potential downside is that this could lead investors into holding onto a losing position for too long, because of unwillingness to admit and rectify mistakes in a timely manner. Another downside is that it can stop investors from making an entry into the market when there has been a downtrend, which is showing signs of ending, and signals that it is a good time to buy. The Fear of Regret happens often when individuals procrastinate while making decisions. Various psychology experimental studies suggest that regret influences decision-making under uncertainty. People who are regret averse tend to avoid distress arising out of two types of mistakes (i) Errors of commission – which occur as a result of misguided action, where the investor reflects on this decision and rues the fact that he made it, thus questioning his beliefs (ii) Errors of omission – which occur as a result of missing an opportunity which existed (Pompian, 2006).

2.5.7 Gamblers’ Fallacy Bias

“Perhaps the most bizarre argument for being bullish is the belief that markets can’t go down for four years in a row. This is a prime example of the Gamblers’ Fallacy.” Montier (2003).

Kahneman and Tversky (1971) describes the heart of gambler’s fallacy as a misconception of the fairness of the laws of chance. One major impact on the financial market is that investors suffering from this bias are likely to be biased towards predicting reversals in stock prices. Gamblers’ Fallacy arises when investors inappropriately predict that trend will reverse and are drawn into contrarian thinking. Gamblers’ Fallacy is said to occur when an investor operates under the perception that errors in random events are self-correcting. For instance, if a fair coin is tossed ten times and it land on heads each time, an investor who feels that the next flip will result in tails can be said to be suffering from this bias.

2.5.8 Mental Accounting Bias

Mental Accounting was coined by Richard Thaler and defined by Thaler (1999) as the *"set of cognitive operations used by individuals and households to organize, evaluate, and keep track of financial activities."*

Mental Accounting is the set of cognitive operations used by individuals and households to organize, evaluate, and keep track of financial activities. This result in a tendency for people to separate their money into separate accounts based on a variety of subjective reasons. Individuals tend to assign different functions to each asset group, which has an often irrational and negative effect on their consumption decisions and other behaviors. Mental Accounting refers to the codes people use when evaluating an investment decision.

2.5.9 Hindsight Bias

Shiller (2000) describes Hindsight bias as *"the tendency to think that one would have known actual events were coming before they happened, had one be present then or had reason to pay attention"*.

Monti and Legrenzi (2009) investigated the relationships between investment decision making and Hindsight bias. They say that economic studies consider the agent's foresight perspective only, without taking into account the Hindsight bias possible effects in the decision-making process. They collected data from 25 Master and PhD students attending courses in Finance and Economics at Bocconi University and from 35 financial managers from a leading Italian bank by circulating two sets of questionnaires. The study found strong evidence for the consequences that Hindsight bias can have on the investor's portfolio decisions: the portfolio allocation perception and therefore, the risk exposure.

2.6 More Literature

Some other literary works there were reviewed are summarized below:

Hoffmann, Shefrin and Pennings (2010) analyze how systematic differences in investors' investment objectives and strategies affect the portfolios they select and the returns they earn. The analyses in this study draw on transaction records of a sample of clients (65,325 individual accounts with over nine million trades from January 2000 until March 2006), from the largest online broker in The Netherlands. The data were obtained through an online questionnaire. The results might be useful for policy makers. It is found that investors who rely on fundamental analysis have higher aspirations and turnover, take more risks, are more overconfident, and outperform investors who rely on technical analysis. Our findings provide support for the behavioral approach to portfolio theory and shed new light on the traditional approach to portfolio theory.

Chandra (2008) explored the impact of behavioral factors and investor's psychology on their decision-making, and to examine the relationship between investor's attitude towards risk and behavioral decision-making. The research was based on the secondary data. Through this research, the author finds that unlike the classical finance theory suggests, individual investors do not always make rational investment decisions. The investment decision-making is influenced, largely, by behavioral factors like greed and fear, Cognitive Dissonance, heuristics, Mental Accounting, and Anchoring. These behavioral factors must be taken into account as risk factors while making investment decisions.

Chira, Adams and Thornton (2008) aimed at studying the cognitive biases and heuristics, which, the business students are subjected to. The main purpose of the study was to look at how influenced the students are, by biases, heuristics, and framing effects. The behavioral survey was administered to a sample of sixty-eight students at Jacksonville University in USA during November 2007 by administering a questionnaire and collecting empirical evidence about both undergraduate and graduate business students' own perceptions of bias. The findings concluded that students are less disposed to make the mistake of being overly confident and optimistic when there is more objectivity involved in making the assessment. Students did not display illusion of control tendencies and a tendency to be subject to the familiarity heuristic.

Sairafi, Selleby and Stahl (2008) in their study 'Behavioral Finance- a Student Perspective' examined the characteristics of investment interested business students and their decision-making process and choices from the perspective of behavioral finance. The research holds an abductive approach and is based on qualitative data. Data collection was done through an Internet-based questionnaire. In the study, herd behavior was found to be the most evident behavioral factor. This paper found that the behavior of respondents in the chosen population was best described as “student behavior”; a somehow irrational behavior explained by the learning process in which business students exist.

Cipriani and Guarino (2008) studied herd behavior in a laboratory financial market with financial market professionals. The study combines the advantage of the controlled experiment with that of observing the behavior of professionals, who are engaged in the day-by-day activity of trading, pricing and analyzing financial assets. This study compares two treatments, one in which the price adjusts to the order flow so that Herding should never occur, and one in which event uncertainty makes Herding possible. In the first treatment, subjects herd seldom, in accordance with both the theory and previous experimental evidence on student subjects. In the second treatment, the proportion of Herding decisions increases, but not as much as theory suggests; moreover, contrarianism disappears altogether.

Waweru, Munyoki and Uliana (2008) surveyed the institutional investors at the Nairobi Stock Exchange. The work investigated the role of behavioral finance and investor psychology in investment decision making. The study established that behavioral factors such as Representativeness, Overconfidence, Anchoring, and Gamblers’ Fallacy, Availability, Loss Aversion, Mental Accounting and Regret Aversion affected the decisions of institutional investors operating at the Nairobi Stock Exchange.

Maheran, Muhammed and Ismail (2008) intended to investigate the relationship between investment decision making of an investor and their rationality in investing in the Malaysian capital market. The findings of the study indicate that the economic condition and frame of references influence investor decision-making behavior. The study concluded that Malaysian investors are partially rational in their decision-making.

Cianci (2008) in her study conducted an experiment with 78 graduates as substitutes for real investors and results suggested that investors made higher relevance ratings and lower investment attractiveness ratings while provided with simultaneous negative information in comparison with sequential negative information(consistent with phenomena of multiple loss aversion and loss buffering). Investors’ relevance and attractiveness ratings were higher when positive information was provided sequentially (consistent with gain savoring). The study categorized investors as current and prospective. It was examined how they evaluate positive and negative information presented sequentially or simultaneously aimed to determine whether these results can be generalized to apply to investment related information and whether investor status affects this evaluation.

Grou and Tobak (2008) studied the behavioral patterns exhibited by investors in risk situations, which offered multiple choices. Two behavioral effects known as illusion of control and ambiguity aversion were studied. Through a total of eight experiments in which there were 196 student participants, conducted at the Catholic University of Brazil was shown that investors tend to exhibit these phenomena while making financial risk decisions. Decisions made by students showed that they had the illusion of control- where they thought they have better control over random events than they actually had, if there was any. However, they were not willing to pay a slight price to take advantage of this control they felt they had. To test ambiguity aversion, students were made to choose between known and unknown distributions in four experiments under various settings. Results showed that invested proportions were significantly higher in known distributions. Even though students exhibited ambiguity aversion, not many were willing to pay a price to reduce or eliminate the ambiguity

Oehler et al(2008) in their study analyze the composition of 102 funds whose assets exceed EUR100 Million in each year, actively managed by five biggest German mutual fund companies by hand collecting data from annual reports in the period 2000-2003 and come up with convincing empirical evidence of home biased portfolio selection in this duration. Three possible reasons for this behavior are listed: lower transaction costs, better hedging possibilities and advantageous information asymmetries. They find that mutual funds that are sold to private investors show high home-biased composition, but these funds invest heavily in equities from other European countries ("they term it as Europe bias"), larger funds showed more home bias than smaller and medium sized funds; and portfolio comprised by funds with global investment strategies rarely exhibits home bias, while portfolios with geographically focuses strategies deviate from optimal portfolio composition. They try to find if the local bias is driven by private investors or fund managers and results indicate that home bias are driven more by private investor demand rather than by mutual fund managers. They have also mentioned that the home bias in 2000-2003 is significantly lower than what was seen in the data from 1990s.

2.7 Behavioral Finance and Decision Making

Decision-making can be defined as the process of choosing a particular alternative from many available alternatives. It is a complicated multi-step process involving analysis of various personal, technical and situational factors. There are no exceptions in the case of making decisions in the stock markets either. Taking investment decisions is the most crucial challenge faced by investors. Some personal factors are age, education, income etc. On the technical side, investment decisions can be derived from various models of finance, for e.g. the capital asset pricing model (CAPM). Decisions should not be reached without considering situational factors that take into account the environment, the market psychology in other words.

Effective decision making in the stock market requires an understanding of human nature in a global perspective on top of financial skills. Thus cognitive psychology should be given importance in the process of decision-making (Chandra, 2008).As a result of the bull market from 2004 to 2007 and the subsequent financial crisis, there has been a lot of fresh focus on the irrational investor. Studying irrational investor behavior has become important.

"Behavioral Finance is becoming an integral part of decision-making process because it heavily influences the investors' performance". (Banerjee, 2011)

"An understanding of how our emotions result in irrational behaviour is indispensable for any investor". (Parikh, 2011)

Investors can educate themselves about the various biases they are likely to exhibit and then take steps towards avoiding it thus improving their effectiveness. Some common mistakes made by investors are selling too soon while booking profits, holding too long while facing losses, buying overpriced stocks based on market sentiments and positive evaluation by all and sundry. The key, according to Parikh, for an investor so succeed is to get in touch with the emotional indiscipline he has exhibited, and deal with it so that it is not repeated. In the words of Warren Buffet,

"It is only when you combine sound intellect with emotional discipline that you get rational behavior" (Parikh, 2011).

Chapter Three

The Role of Behavioral Factors – Analysis

3.1 Overview

There are numerous identified psychological biases in Behavioral finance literature. Each has implications on financial decision-making and behavior. Table 3.01 shows the nine biases analyzed in this study, their key effects on investors and its consequences.

Table 3.01 **Biases, Effects on Investor, and Consequences**

NAME OF BIAS	KEY EFFECTS ON INVESTOR	CONSEQUENCE
Overconfidence	Too many trades, too much risk, failure to diversify	Pay too much brokerage and taxes, chance of high losses
Representativeness	Tendency to associate new event to a known event and make investments based on it	Purchasing overpriced stocks
Herding	Lack of individuality in decision making	Bubbles, and bubble bursts
Anchoring	Tendency to consider logically irrelevant price level as important in the process of decision making	Missed investment opportunities, or bad entry timing into the market
Cognitive Dissonance	Ignore new information that contradicts known beliefs and decisions	Reduced ability to make rational and fair investment decisions
Regret Aversion	Selling winners too soon, holding losers too long	Reduced returns
Gamblers' Fallacy	Taking too much risk after a lucky win	Chance of high losses
Mental Accounting	Low or no diversification	Irrational and negative effects on returns
Hindsight	The tendency to feel that a past event was obvious when it really was not, at onset	Incorrect oversimplification of decision making

3.2 Research Design

3.2.1 Historical-Comparative Approach

After considering the possibility of holding an experimental research and realizing that it would be difficult to implement, the historical and comparative method was chosen for this study. Historical method of research in sociology tries to gather insights from the experiences of participants with regard to social behavior. The method was chosen for two main reasons:

(i) Most practical way to reach real investors to gather insights on their past experiences while making decisions

(ii) Investors were likely to provide credible information since the nature of survey was anonymous

The comparative method, as the name suggests, is used to study different types of groups and societies to analytically determine factors that could lead to similarities or differences in specified patterns of behavior. The feature under examination could occur within the same society or between different societies. The significance of the comparative-historical approach was first emphasized by Durkheim (1982), who drew up classifications of behavior to make it possible to test hypotheses about relationships between social phenomena. In this research, the comparative study is facilitated by categorizing investors as young and experienced, and further analyzing the groups for similarities and differences.

3.2.2 Questionnaire Survey

The questionnaire survey was the most convenient method for this research owing to the fact that the research had to be conducted in a remote location. According to Taylor et al (2006), questionnaires are a sensible option when information is needed from a large number of people and is a powerful method to capture their opinions and attitude.

Three main points emphasized by Taylor et al (2006) were kept in mind while designing the questionnaire[2] survey for the purpose of this thesis:

(i) Assuring the participants of confidentiality

[2] Refer Appendix A

(ii) Keeping questionnaire compact and using questions which focus on core of the research work
(iii) Gathering respondents' interest and retaining it

The questionnaire consists of 35 questions out of which 17 were meant to obtain a measure of the investor attitude, while the rest were designed to capture quantitative information. These 17 questions were constructed based on the "Likert Scale", which is a symmetric one-dimensional scale where all the items measure the same thing, however in different degrees of approval or disapproval. Likert Scales are comprised by Likert items and based on the count of these items exist in different point scales. Three-point Likert Scales have been used in the questionnaire and the three-level Likert item takes the form (i) Always/Yes (Positive) (ii) Sometimes/Maybe (Neutral) (iii) No/Never (Negative). These items are quantified by being assigned scores depending on the analysis technique used (Taylor et al, 2006). This study uses the 'Weighted Scoring Method', described later, in which weights of three, two and one are assigned to the positive, neutral and negative responses respectively to compute scores.

3.3 Sample Profile

One of the primary aims of the study was to focus on real investors, as they were more likely to have limited knowledge about the application of behavioral theories in decision-making and hence gullible to psychological errors. The sample profile was created based on two judgment criteria: age of the respondent and years of investment experience in the stock market. After an analysis of the sample, the following groups were found to be optimal:

(i) Experienced: Investors aged above 30, with at least 7 years of investing background
(ii) Young: Investors aged 30 or below, with less than 7 years of investing background

The valid number of responses collected by the questionnaire survey was 119. When the judgment criteria were applied, the sample was trimmed down to 101 primarily owing to few inexperienced respondents aged above 30. In total, there were 46 young investors and 55 experienced investors. In order to keep the sample profile even between the two groups, 9 incomplete observations, where answers to more than 6 questions were missing, were filtered and eliminated from the experienced investor sub-sample to reach the final sample profile of 92 which is given below in Table 3.02.

Table 3.02 Profile of Sample Respondents

AGE / EXPERIENCE	Below 30 years	30 years & above	Total
Up to 7 years	46	-	46
7 years & above	-	46	46
Total	**46**	**46**	**92**

Source: ***Primary Data***

To summarize, the sample used in this study consists of 92 respondents out of which:

(i) 46 were Young Investors (aged below 30 with experience less than 7 years)

(ii) 46 were Experienced Investors (aged 30 or more with experience of 7 years and above)

3.4 Limitations of the Study

The main weakness of the study is owing to the fact that it aims to study investor behavioral patterns using questionnaires. Making financial decisions can be demanding for various reasons that possibly could push many into making irrational decisions at one point or the other. However, while answering a questionnaire, the same individuals are likely to be relaxed and in a better frame of mind, hence choosing to give answers, which may put them across in different light, especially in context of questions which were presenting hypothetical situations. To overcome this problem to an extent, many questions attempted to make the participants admit mistakes they have made in the past.

A second limitation arises out of the fact that India is a vast country, and this study cannot be considered an evaluation of the average Indian investor. The sample collected is mainly from a state called Kerala, which accounts roughly for a mere 3% of the Indian population. The location was chosen mainly because it was the researcher's home state thus making data collection convenient. It remains to be seen whether investors in other parts of the country would exhibit a similar behavior as would be found out by this study.

3.5 Data Collection

The study includes only primary data which was gathered using the questionnaire which was distributed both offline and online to reach out to wider audience. All data collected was from/through the clients of ‘Trivandrum Investor Services’, a franchisee of Motilal Oswal Financial Services[3], one of the leading brokerage firms in India with presence in 555 cities in India with 738,156 members, as of Dec 31st 2011. Most investors and traders that fall into the experienced category were not likely to be as technology perceptive as the average young investor, and tend to do their trading via the brokerage floor. So, hard copies of the questionnaire were distributed among investors that frequent Trivandrum Investor Services for their trading activities. . 45 responses were gathered from October 2011 to January 2012 out of which 42 were selected. The young investor was likely to favor online trading over floor trading thus necessitating an online survey. After considering many options a free survey site, ‘kwiksurveys’ was chosen. The questionnaire was made available online at http://kwiksurveys.com?u=stocksurvey in October 2011. This online survey was distributed among personal contacts and to contacts of the franchisee head. Participants were encouraged to distribute the survey to their contacts as well. Ultimately, 113 responses were obtained by February 2012 out of which 77 were selected after filtering and elimination.

3.6 List of Hypotheses

1. There is no relationship between investor experience and losses suffered during crisis
2. Both investor types are equally affected or unaffected by the behavioral biases
3. Young investors are not likely to be more overconfident than experienced investors
4. Both investor types depend on similar factors while making judgments/analyses
5. Both investor types are equally likely to exhibit Herding behavior
6. Both investor types are equally likely to exhibit Anchoring bias
7. Both investor types are equally likely to exhibit Regret Aversion bias
8. Both investor types are equally likely to be subject to the Gamblers’ Fallacy Bias
9. Both investor types are equally likely to be subject to the Mental Accounting Bias
10. Both investor types are equally likely to be subject to the Hindsight Bias

[3] http://www.motilaloswal.com/about_us/

3.7 Analysis and Hypothesis Testing: Methods Used

3.7.1 Discriminant Analysis

According to Klecka (1980), *"Discriminant Analysis is a statistical technique which allows the researcher to study the differences between two or more groups of objects with respect to several variables simultaneously".*

Discriminant Analysis predicts the group to which a variable belongs to, with the help of a linear equation that can be written as:

$$D= v_1X_1 + v_2X_2 +...+ v_iX_i + a$$

Where D = discriminate function

v = weight of the variable (the larger the weight, the better the predictor)

X = respondent's score for the variable

a = constant, analogous to residual in linear regression

i = number of predictors

With this equation, Discriminant Analysis helps to confirm whether the function separates the groups well, by pointing out the chances of a case being misclassified into the wrong group (Anon., 2008).

In this study, the equation takes the form :

$$D= v_1X_1 + v_2X_2 + v_3X_3 + v_4X_4 + v_5X_5 + v_6X_6 + v_7X_7 + v_8X_8 + v_9X_9 + a$$

Where X_1 = Representativeness, X_2= Herding, X_3= Overconfidence, X_4= Anchoring, X_5= Cognitive Dissonance, X6= Fear of Regret,X_7= Gamblers Fallacy,X_8= Mental Accounting, and X_9= Hindsight

Klecka (1980) states some key mathematical requirements that should be met in-order to perform discriminatory analysis:

(i) There should be at least two groups

(ii) There should be at least two cases per group

(iii) Number of discriminating variables (discriminators) should be less than total number of cases minus two, and any of these discriminators should not be a linear combination of other discriminators

(iv) The covariance matrices for each group must be within statistically acceptable limits

(v) Each group should be selected from a population with a multivariate normal distribution on the discriminator

3.7.2 Weighted Scoring Method

The weighted scoring method is a type of multi-criterion analysis. Weights are assigned to the relevant attributes. Then scores are calculated based on these weights for each of the attribute to reflect how each option performs in relation to each attribute. The resulting weighted score indicates the overall performance of the options in relative terms (Anon., 2008). The following are the steps involved:

(i) Identification of the attributes

(ii) Assign weights to the attributes to reflect their relative importance

(iii) Calculate individual score to find how each option performs against each attribute

(iv) Calculate Weighted Scores for each option

(v) Test the Results (Robustness)

(vi) Interpret the Results

3.7.3 Chi-squared Test for Independence

Chi-squared test is a nonparametric statistical test analyzing method often used in experimental work where the data consists of frequencies, counts or percentages. It can be used to determine whether two or more classifications of the samples are independent or not. Chi-squared test can be applied only to discrete data. However, continuous data can also be tested by classifying it to different discrete categories or by labeling using nominally scaled variables (Maxwell, 1971). Two key concepts in the context of the Chi-squared test are:

(i) Qualitative Variables: Variables can be quantitative or qualitative. Qualitative variables indicate categorization rather than measurement. A commonly used qualitative variable in social research is the ‘dichotomous variable’, which is binary. Chi-squared test is applicable only when we have qualitative variables classified into categories.

(ii) Contingency table: In a sample, when the participants are grouped in two or more different ways, the results may be arranged in rectangular tables called 'Contingency Tables'. The entries in the table may correspond to frequencies, or its transformation into proportions or percentages.

The most common use of the test is to assess the probability of association or independence of facts. The test, as the name suggests, is based on the Chi-square (χ^2) distribution. The Chi-square value is calculated in order to compare the observed and expected frequencies using the formula:

$$X^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Where O_i = observed frequencies, E_i = expected frequencies, and i = 1...N where N is the number of cells in the contingency table (Zibran, 2007).

The significance of the calculated value of χ^2 is assessed by referring to the standard Chi-square table which contains critical χ^2 values on different degrees of freedom and levels of probability. The hypotheses are stated as:

H0: The two variables are independent in the whole the population (Independence)

H1: There is some relationship between the variables (Relationship)

If the value of χ^2 is less that the value corresponding to confidence interval, the Null hypothesis (H0) cannot be rejected. In the IBM SPSS software which has been used, three Chi-squared tests are performed, namely (i) Pearson Chi-Square, (ii) Likelihood Ratio Test, and (iii) Linear-by-linear association.

3.8 Overall Analysis and Hypothesis Testing

3.8.1 Preliminary Analysis: Multicollinearity Check

The 3-point Likert scale responses were arithmetically combined to form 9 variables, each representing a bias analyzed in this thesis. It had to be checked whether there was a problem of multicollinearity between the variables. Table 3.03 shows the correlation matrix between the bias variables. Note that the table has two parts, the first part displays the Pearson Correlation Coefficient between the biases, and the second part shows the significance of the coefficients. The second part of the table was scanned to see if any of the variables had majority of the values greater than 0.05 (95% confidence interval). It was observed that Herding and Cognitive Dissonance fitted into the category. However, on analyzing the first part of the table, low coefficients suggested that these variables did not have a high correlation with any of the variables. The determinant of the correlation matrix had a value of 0.201, was very high above the necessary value of 0.00001 thus signaling the non-existence of multicollinearity.

According to Table 3.03, the highest correlated variables were Gamblers' Fallacy and Representativeness with a coefficient of 0.555. To double-check, further multicollinearity testing was done with both Gamblers' Fallacy and Representativeness as dependent variables. The results are shown in Table 3.04.

The Variance Inflation Factors (VIF) – an indicator of how much the variance of estimated coefficients increase if there is no correlation amongst the independent variables – were very low compared to the widely accepted threshold level of 4 (which indicates multicollinearity). Table 3.04 shows that the VIF values for Representativeness and Gamblers' Fallacy was 1.585, and 1.271 thus clearly eliminating the possibility of multicollinearity between the variables. Table 3.03 also shows Anchoring and Fear of Regret to have a high correlation coefficient of 0.512. So the tests were performed again in a similar manner and the VIF values were found to be low at 1.278 and 1.430, as seen in Table 3.05, thus again clearing doubts of possible multicollinearity.

Table 3.03 Correlation Matrix for the Bias Variables

	Represent ativeness	Herding	Over Confidence	Anchoring	Cognitive Dissonance	Fear of Regret	Gamblers Fallacy	Mental Accounting	Hindsight
Correlation									
Representativeness	1.000	0.009	0.185	0.277	0.122	0.269	0.555	0.235	0.017
Herding	0.009	1.000	0.187	-0.013	0.147	0.153	-0.094	0.043	0.052
Over Confidence	0.185	0.187	1.000	0.032	0.101	0.177	0.150	0.101	0.265
Anchoring	0.277	-0.013	0.032	1.000	0.101	0.512	0.325	-0.159	0.228
Cognitive Dissonance	0.122	0.147	0.101	0.101	1.000	0.058	-0.091	0.048	-0.055
Fear of Regret	0.269	0.153	0.177	0.512	0.058	1.000	0.277	-0.141	0.190
Gamblers Fallacy	0.555	-0.094	0.150	0.325	-0.091	0.277	1.000	0.221	0.375
Mental Accounting	0.235	0.043	0.101	-0.159	0.048	-0.141	0.221	1.000	-0.119
Hindsight	0.017	0.052	0.265	0.228	-0.055	0.190	0.375	-0.119	1.000
Sig.(1-tailed)									
Representativeness		0.468	0.042	0.004	0.128	0.005	0.000	0.013	0.439
Herding	0.468		0.040	0.453	0.084	0.076	0.190	0.345	0.315
Over Confidence	0.042	0.040		0.385	0.172	0.049	0.080	0.173	0.006
Anchoring	0.004	0.453	0.385		0.173	0.000	0.001	0.069	0.016
Cognitive Dissonance	0.128	0.084	0.172	0.173		0.294	0.199	0.326	0.305
Fear of Regret	0.005	0.076	0.049	0.000	0.294		0.004	0.094	0.037
Gamblers Fallacy	0.000	0.190	0.080	0.001	0.199	0.004		0.019	0.000
Mental Accounting	0.013	0.345	0.173	0.069	0.326	0.094	0.019		0.133
Hindsight	0.439	0.315	0.006	0.016	0.305	0.037	0.000	0.133	

Source: ***Computed Data***

Table 3.04 Collinearity Statistics: Representativeness & Gamblers Fallacy

Coefficients[a]

Model	Collinearity Statistics	
	Tolerance	VIF
Investor Type	0.710	1.408
Herding	0.893	1.120
Over Confidence	0.847	1.181
Anchoring	0.607	1.647
Cognitive Dissonance	0.912	1.097
Fear of Regret	0.667	1.499
Mental Accounting	0.811	1.233
Hindsight	0.731	1.369
Gamblers Fallacy	0.631	1.585

a. Dependent Variable: Representativeness

Coefficients[a]

Model	Collinearity Statistics	
	Tolerance	VIF
Representativeness	0.787	1.271
Investor Type	0.739	1.354
Herding	0.906	1.103
Over Confidence	0.833	1.200
Anchoring	0.591	1.691
Cognitive Dissonance	0.916	1.092
Fear of Regret	0.666	1.502
Mental Accounting	0.837	1.194
Hindsight	0.800	1.251

a. Dependent Variable: Gamblers Fallacy

Source: ***Computed Data***

Table 3.05 Collinearity Statistics: Anchoring and Fear of Regret

Coefficients[a]

Model	Collinearity Statistics	
	Tolerance	VIF
Investor Type	0.745	1.342
Herding	0.895	1.118
Over Confidence	0.839	1.191
Cognitive Dissonance	0.920	1.086
Fear of Regret	0.783	1.278
Mental Accounting	0.825	1.212
Hindsight	0.691	1.448
Gamblers Fallacy	0.444	2.251
Representativeness	0.569	1.758

a. Dependent Variable: Anchoring

Coefficients[a]

Model	Collinearity Statistics	
	Tolerance	VIF
Investor Type	0.680	1.472
Herding	0.924	1.083
Over Confidence	0.847	1.180
Cognitive Dissonance	0.898	1.114
Mental Accounting	0.819	1.222
Hindsight	0.687	1.455
Gamblers Fallacy	0.447	2.238
Representativeness	0.559	1.790
Anchoring	0.699	1.430

a. Dependent Variable: Fear of Regret

Source: ***Computed Data***

To summarize, multicollinearity was not a problem for the sample. All the variables correlated fairly well without any of them having high correlation coefficients. The decision was made to retain all the variables for further analysis.

3.8.2 Effect of Financial Crisis on Portfolios

Table 3.06 Losses suffered by Investors

		Crisis _Loss					Total
Investor Type		**>50% Loss**	**30-50% Loss**	**10-30% Loss**	**Loss<10%**	**No Loss**	
Young Investor	**Count**	4	15	9	7	11	46
	% within Investor Type	8.7	32.6	19.6	15.2	23.9	100
	% within Crisis Loss	26.7	39.5	56.3	58.3	100	50.00
Experienced Investor	**Count**	11	23	7	5	0	46
	% within Investor Type	23.9	50.0	15.2	10.9	0	100
	% within Crisis Loss	73.3	60.5	43.8	41.7	0	50.00
Total	**Count**	15	38	16	12	11	92
	% within Investor Type	16.3	41.3	17.4	13.0	12.0	100
	% within Crisis Loss	100	100	100	100	100	100

Source: ***Primary Data***

The effect of the financial crisis on the average individual investors' portfolio was likely to be significant, based on insights from personal losses suffered, and losses suffered by friends and colleagues alike. The respondents were asked to reveal losses suffered in 2007 – 2009. Table 3.06 shows that 38 investors (41.3%) suffered a 30–50% loss, 23 being experienced investors, and 15 young. The number of people that suffered a loss > 50% was 15 (16.3%). Table 3.06 shows that the number of experienced investors that suffered a loss was slightly higher. It had to be checked if the losses incurred had a relationship with the experience of the investors.

There were no experienced investors who claimed to have escaped losses. 11 young investors suffered no losses. However, these participants had entered the market post the crisis. They were excluded from the analysis and the Chi-squared test for independence was performed to test the following hypotheses:

H0: There is no relationship between investor experience and losses suffered during crisis

H1: There is some relationship between investor experience and losses suffered during crisis

Table 3.07 Chi**-Squared Tests: Investor Experience & Portfolio Losses**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	4.116	3	0.249
Likelihood Ratio	4.181	3	0.243
Linear-by-Linear Association	3.794	1	0.051
No. of Valid Cases	81		

Source: ***Computed Data***

The p-value from the Pearson Chi-Square and Likelihood ratio tests were 0.249 and 0.243 (Table 3.07). This suggested that the null hypothesis could not be rejected in the 95% confidence interval. Thus, it could not be convincingly stated that a relationship existed between the experience of investors and the losses they suffered during the financial crisis. Since it was obvious that the participants in the survey had suffered losses, it made an interesting premise to check if they were susceptible to behavioral biases while making financial decisions.

3.8.3 Discriminant Analysis

The variable Investor-type (1– young, 2– experienced) was chosen as the discriminator. The aim of the analysis was to check whether the discriminator was effective. In other words, it had to be seen whether the young investors and experienced investors could be categorized as two groups exhibiting the biases in different ways.

Here is a summary of the results:

- Gamblers' Fallacy and Anchoring were seen to be the biases which were exhibited by the experienced and young investors in the most significantly different manner
- It could not be said that either investor group was more prone to being affected by behavioral biases as a whole in comparison with the other. In totality, both the young and experienced investors seemed to be affected by the biases to a similar level
- However though, it was observed that the degree to which each of the biases affected the groups varied, and it was statistically possible to separate the behavior of the experienced investors from that of the young investors

Group Statistics Table

To check whether there were any significant differences between the two groups in the dependent variable on each of the independent variables the data provided by 'Group Statistics' (Table 3.08) and 'Equality of Group Means' (Table 3.09) were examined. If differences did not exist, then investor-type could not be considered a significant discriminator, and further analysis would not be possible. However, this was not the case. In Table 3.08, it can be observed that the mean difference between the various biases in the two groups were significantly different. Two exceptions however were Overconfidence and Mental Accounting where the means were nearly identical, and the standard deviations comparable. The other seven variables, however, pointed in the direction that the chosen discriminator was indeed a good one.

Table 3.08 Discriminant Analysis: Group Statistics

Investor type		Mean	Std. Deviation	Valid N (list wise) Unweighted	Weighted
Young Investor	Representativeness	1.5455	0.66313	44	44.000
	Herding	1.6364	0.74991	44	44.000
	Overconfidence	1.6364	0.53226	44	44.000
	Anchoring	1.3864	0.65471	44	44.000
	Cognitive Dissonance	1.3636	0.61345	44	44.000
	Fear of Regret	1.7955	0.59375	44	44.000
	Gambler's Fallacy	1.7273	0.58523	44	44.000
	Mental Accounting	1.8409	0.47949	44	44.000
	Hindsight	1.7273	0.78839	44	44.000
Experienced investor	Representativeness	1.6222	0.64979	45	45.000
	Herding	1.4667	0.72614	45	45.000
	Overconfidence	1.6222	0.64979	45	45.000
	Anchoring	2.0222	0.86573	45	45.000
	Cognitive Dissonance	1.6444	0.80214	45	45.000
	Fear of Regret	2.0444	0.56228	45	45.000
	Gambler's Fallacy	2.1556	0.36653	45	45.000
	Mental Accounting	1.8667	0.34378	45	45.000
	Hindsight	2.2000	0.72614	45	45.000
Total	Representativeness	1.5843	0.65382	89	89.000
	Herding	1.5506	0.73872	89	89.000
	Overconfidence	1.6292	0.59126	89	89.000
	Anchoring	1.7079	0.82850	89	89.000
	Cognitive Dissonance	1.5056	0.72494	89	89.000
	Fear of Regret	1.9213	0.58823	89	89.000
	Gambler's Fallacy	1.9438	0.53000	89	89.000
	Mental Accounting	1.8539	0.41425	89	89.000
	Hindsight	1.9663	0.78984	89	89.000

Source: ***Computed Data***

Table 3.09 provides statistical evidence for the difference in means that was observed. The Wilks' lambda is a test statistic used in the multivariate analysis of variance to test the null hypothesis that both groups have identical means based on the discriminator. The F-values were high for most variables except for Overconfidence and Mental Accounting. Wilks' Lambda coefficients are interpreted differently, where higher values signify that the means are identical. The Wilks' Lambda coefficients were highest for Overconfidence and Mental Accounting, thus confirming that both groups exhibited these biases in a similar manner.

Table 3.09 Discriminant Analysis: Equality of Group Means Tests

	Wilks' Lambda	F	df1	df2	Sig.
Representativeness	0.997	0.304	1	87	0.583
Herding	0.987	1.176	1	87	0.281
Overconfidence	1.000	0.013	1	87	0.911
Anchoring	0.851	15.222	1	87	0.000
Cognitive Dissonance	0.962	3.430	1	87	0.067
Fear of Regret	0.955	4.128	1	87	0.045
Gambler's Fallacy	0.835	17.202	1	87	0.000
Mental Accounting	0.999	0.085	1	87	0.771
Hindsight	0.909	8.663	1	87	0.004

Source: ***Computed Data***

The p-values suggested that, at a 95% confidence interval, Anchoring, Fear of Regret, Gamblers' Fallacy and Hindsight biases were confirmed to have different means, thus implying that the investor types exhibited these biases in a different manner. Gamblers' Fallacy and Anchoring seemed to be the biases, which affected one investor category more than the other was, the most noticeably.

Box's M test

A key assumption in Discriminant Analysis is that the variance-covariance matrices are identical for the groups formed by the discriminator. Box's M test tests the null hypothesis that matrices do not differ between groups of the dependent variable.

Table 3.10 **Discriminant Analysis: Box's M test Result**

Box's M		**82.065**
F	**Approx**	1.623
	df1	45
	df2	24838.841
	Sig.	0.005

Source: ***Computed Data***

The p-value was found to be low at 0.005 (seen in Table 3.10) which suggested that the null hypothesis could not be rejected at the 99% confidence interval, thus confirming that both groups had identical variance-covariance matrices. This was a necessary condition to proceed with further tests.

Wilks' Lambda Test

Wilks' Lambda test shows the significance of the Discriminant function. The Wilks' Lambda coefficient provides the proportion of total variability that is not explained by the function.

Table 3.11 **Discriminant Analysis: Wilks' Lambda Test Results**

Test of Function(s)	Wilks' Lambda	Chi- square	df	Sig.
1	0.683	31.414	9	0.000

Source: ***Computed Data***

The value of 0.683(Table 3.11) suggested that 68.3% of the variability was unexplained by the discriminator. This result implied that there is no statistically significant difference between the behavioral patterns of young and experienced investors for the whole set of biases considered together. The following hypotheses were tested:

H0: Both investor categories are equally affected or unaffected by the Behavioral Biases

H1: Young investors are more affected by Behavioral Biases than experienced investors are

The high Wilks' Lambda statistic and the p-value < 0.001 suggested that the null hypothesis could not be rejected. However, it has to be kept in mind that the Wilks' lambda coefficients in Table 3.09 had given confirmation about biases like Anchoring and Gamblers' Fallacy that were exhibited by the investor types in a different manner.

Standardized Canonical Discriminant Function Coefficients

The Standardized Canonical Discriminant Function coefficients are analogous to the coefficients in multiple regressions. The higher values of coefficients indicate increasing importance of those variables in predicting the differences between the groups. The signs indicate direction of the relationship and can be ignored for the time-being.

Table 3.12 Discriminant Analysis: Standardized Canonical Discriminant Function Coefficients

	Function
	1
Representativeness	-0.518
Herding	-0.168
Overconfidence	-0.140
Anchoring	0.607
Cognitive Dissonance	0.170
Fear of Regret	0.045
Gambler's Fallacy	0.720
Mental Accounting	0.183
Hindsight	0.212

Source: ***Computed Data***

From Table 3.12 it can be observed that Gamblers' Fallacy and Anchoring have the highest coefficients. This is in line with the results suggested by the Wilks' Lambda coefficients. What was interesting here was that Fear of Regret, which was shown to be a significant variable in predicting differences, had a low coefficient, thus losing a bit of significance as a discriminant. Representativeness, with the third highest coefficient value, seemed to be a significant discriminator between the groups as opposed to what previous results suggested.

The Structure Matrix Table

The structure matrix table is another widely employed method for testing the relative importance of predictors. It is considered more accurate than the Standardized Canonical Discriminant Function coefficients. Table 3.13 shows that Gamblers' Fallacy and Anchoring had the highest coefficients, which was consistent with results from the other tests conducted previously. Interesting fact was that Fear of Regret regained importance as a discriminator, while Representativeness lost ground as one. This tallied with the message given by the Wilks' Lambda coefficients.

Table 3.13 **Discriminant Analysis: Structure Matrix**

	Function
	1
Gambler's Fallacy	0.653
Anchoring	0.614
Hindsight	0.464
Fear of Regret	0.320
Cognitive Dissonance	0.292
Herding	-0.171
Representativeness	0.087
Mental Accounting	0.046
Overconfidence	-0.018

Source: ***Computed Data***

* Pooled within- groups correlations between discriminating variables and standardized canonical discriminant functions

**Variables ordered by absolute size of correlation within function

Classification Table

A classification table is a very interesting representation of the behavioral pattern of experienced and young investors. Table 3.14, which shows the classification results, has the original observed categories for rows and predicted categories for columns. The footnote suggested that 75.3% of the cases were correctly classified. This can be thought of as a significant result. In the row part, the table has two sections, namely original and cross-validated. In the original classification, the interpretation was that 10 young investors were seemingly behaving like their experienced counterparts while 11 experienced investors seemed to behave like the young investors while making investments.

Table 3.14 Discriminant Analysis: Classification Table

			Predicated Group Membership		
		Investor type	**Young Investor**	**Experienced investor**	**Total**
Original	Count	Young Investor	33	11	44
		Experienced Investor	11	34	45
	%	Young Investor	75.0	25.0	100.00
		Experienced Investor	24.4	75.6	100.00
Cross-Validated[a]	Count	Young Investor	29	15	44
		Experienced Investor	12	33	45
	%	Young Investor	65.9	34.1	100.00
		Experienced Investor	26.7	73.3	100.00

Source: ***Computed Data***

a. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.

b. 75.3 % of original grouped cases correctly classified

c. 69.7 % of cross- validated grouped cases correctly classified

The second section of Table 3.14 provides cross-validated results that are more accurate. In this method, one variable is left out and then the discrimination function is developed using the other variables after which the left out variable is categorized using these results and this process is repeated for all variables. The results were different for the young investors, and said that 16 of the young investors behaved like experienced ones, while the number stayed at 11 for experienced investors. The accuracy with which the Discriminant function is able to predict the behavior of the groups is termed as the hit ratio. Going by the original results 75% of the young investors and 75.6% of the experienced investors were rightly classified, and for research purposes, a hit ratio above 75% is considered acceptable, since by default, there is a 50% chance that an investor would fall into either of the categories and it adds a 25% to it. Therefore, it could be said that young investors behave differently from experienced investors even though either category was not seen to be more biased than the other is.

Canonical Discriminant Function Coefficients

These coefficients are unstandardized and are used to create the Discriminant Function Equation can be interpreted just like the coefficients in a classic regression equation.

Table 3.15 Discriminant Analysis: Canonical Discriminant Function Coefficients

	Function
	1
Representativeness	-0.788
Herding	-0.228
Overconfidence	-0.236
Anchoring	0.789
Cognitive Dissonance	0.238
Fear of Regret	0.077
Gambler's Fallacy	1.478
Mental Accounting	0.440
Hindsight	0.280
(Constant)	-4.106

Source: ***Computed Data***
* ***Unstandardised Coefficients***

Table 3.15 can be written as:

D =	-	0.788*Representativeness	-	0.228*Herding
	-	0.236* Overconfidence	+	0.789* Anchoring
	-	0.238*Cognitive Dissonance	+	0.077* Fear of Regret
	+	1.478*Gamblers Fallacy	+	0.440*Mental Accounting
	+	0.280*Hindsight	-	4.106

'D' is the discriminate function which controlling the variables in the equation. The coefficients are indicative of the degree to which the variable contributes to the function. For instance, the highest coefficient of 1.412 for Gamblers' Fallacy indicated that the bias was exhibited by one investor category much more than the other was.

3.9 Bias Specific Analysis and Hypothesis Testing

3.9.1 Overconfidence Bias

Investors tend to be consistently overconfident in their ability to outperform the market. Some of them believe that based on information they have, they are able to predict the future movements of stock prices better than others are. Five questions were put forward to investors in the questionnaire[4]. All the questions, but one, were designed based on the 3-point Likert scale. One of the questions inquired about the levels of risk investors were ready to take, on a 7-point scale. This was re-coded in SPSS software into a 3-point scale in the following manner: 5-7 = high risk (1), 3-4 = medium risk (2), 1-2 = low risk (3). The answers from questions were summed, averaged and grouped to fit into a 5-point Likert scale. Table 3.16 shows the cross-table. It was noticed that 39% of the young investors and 46% of the experienced investors were likely to be at least moderately overconfident while making decisions.

Table 3.16 Contingency Table: Overconfidence Bias

Investor type		Level of Overconfidence					Total
		Over confident	Moderately Overconfident	Confident	Slightly Diffident	Diffident	
Young	Count	5	13	20	7	1	46
	% within investor type	10.9	28.3	43.5	15.2	2.2	100
Experienced	Count	7	14	17	4	4	46
	% within investor type	15.2	30.4	37.0	8.7	8.7	100
Total	Count	12	27	37	11	5	92
	% within investor type	13.0	29.3	40.2	12	5.4	100

Source: ***Primary Data***

[4] Refer Appendix A, Q13 – Q17

Results from Discriminant Analysis suggested that Overconfidence bias was among the least significant variables that could characteristically differentiate the young investors from the experienced ones. The Chi-squared tests were performed to confirm this.

Chi-squared Tests

The following hypotheses were tested:

H0: Young investors are not likely to be more overconfident than experienced investors

H1: Young investors are likely to be more or less overconfident than experienced investors

Table 3.17 Chi-squared tests: Overconfidence Bias-I

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3.232[a]	4	0.520
Likelihood Ratio	3.372	4	0.498
Linear-by-Linear Association	0.041	1	0.839
No. of Valid Cases	92		

Source: ***Computed Data***

a. 2 cells (20%) have expected count less than 5. The minimum expected count is 2.50.

The test results, seen in Table 3.17, could not be validated since the minimum count required in each cell is 5, and two cells had less than 5 observations. As noticed in Table 3.16, the count of diffident investors were a minority. This category was merged with the 'slightly diffident' column. The tests were repeated to obtain the results shown in Table 3.18.

Table 3.18 Chi-squared tests: Overconfidence Bias-II

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	1.330[a]	3	0.722
Likelihood Ratio	1.341	3	0.720
Linear-by-Linear Association	1.288	1	0.256
No. of Valid Cases	87		

Source: ***Computed Data***

a. 0 cells (0%) have expected count less than 5. The minimum expected count is 5.31.

The p-values from the tests were greater than 0.7, which suggested that the null hypothesis could not be rejected. Thus, it could not be observed that investor experience had an influence on overconfident behavior while making investments and the results from Discriminant Analysis were validated further. What remained to be checked was whether investors, in general, tend to be overconfident. The weighing and scoring method was employed on the results in Table 3.16.

Weighted Scoring

Weights from 5 to 1 were assigned to the various columns (5 for Overconfident and 1 for Diffident). The calculation was done in MS Excel to get the results shown in Table 3.19.

Table 3.19 Weighted Scoring: Overconfidence Bias

Investor Type	Weighted Score	Mean	Reference Score	Outcome
Young	152	25.3	23	Overconfidence Bias
Experienced	154	25.7	23	Overconfidence Bias
Total	**306**	**25.5**	**23**	**Overconfidence Bias**

Source: ***Computed Data***

The reference score is calculated by assuming a sample where all the participants were on the median line of neutrality, in the Likert scale. Both the young investors had mean scores above the reference score of 23, which pointed in the direction that investors in general had the tendency to be overconfident while making their decisions. The similarity in mean scores (25.3 and 25.7) was also consistent with the results from Discriminant analysis, where Overconfidence bias was seen to be one of the least significant variables separating the two groups of investors.

3.9.2 Representativeness Bias

Representativeness can shape up when investors either seek to buy what they think is a 'hot' stock or try to label stocks which may have performed poorly in the recent past as 'bad' and avoid them. At times, Representativeness can make investors judge based solely on past records of accomplishment, immediate and distant. This is mainly because these conceptions are among the easiest to recollect in a small timeframe without any immediate analysis. An attempt was made to check whether investors were prone to being biased because of Representativeness.

When the Discriminant analysis was performed, Representativeness was seen to have varying levels of significance in the various tests, so it was interesting to check whether the investor groups could be separated by their affinity to the bias, and also if they the investors in general had exhibited the bias in their decisions.

Representativeness in Decisions

Investors who rely on Representativeness heuristic tend to become overly pessimistic about past losers and overly optimistic about past winners. It can so happen that they will end up considering past returns to be representative of what they can expect in the future. A question[5] was put forward to the investors to check whether they consider the past performance of a stock before investment. The contingency table showed that 39% of young investors and 33% of experienced investors always checked the past performance of a stock before investing in it. To check if the sample was convincingly representative, the weighted scoring method was employed and it was seen that both the investor groups were likely to be prone to Representativeness.

Representativeness in Stock Value Predictions

When an investor feels that he can predict the future value of a share based on its past performance alone, he can be said to be subject to bias. Results from the contingency table showed that 22.8% of the survey participants, when asked[6] whether they believed that future value of a stock can be predicted by analyzing past performance, opined that it is always possible and 65% were of the opinion that it is possible sometimes. Results from weighted scoring showed that both young and experienced investors were equally likely to be affected by the bias, as their mean values were above the median reference score. Responses to the two questions were merged to fit into a 3-point Likert Scale and a conjoint analysis was performed to check if the investors were likely to exhibit the bias. First, the weighted scoring method was employed to check if convincing results on the bias could be obtained.

Weighted Scoring

Results (Table 3.20) suggested that the investors were indeed prone to Representativeness bias, owing to significantly higher means compared to the reference score.

[5] Refer Appendix A, Q6
[6] Refer Appendix A, Q11

Table 3.20 Weighted Scoring: Representativeness Bias

Investor Type	Weighted Score	Mean	Reference Score	Outcome
Young	114	19	15.33	Representativeness
Experienced	109	18.17	15.33	Representativeness
Total	**223**	**18.58**	**15.33**	**Representativeness**

Source: ***Computed Data***

What was also noticeable was that young investors had a mean of 19, higher than 18.17 for experienced investors, thus implying that they were more likely to suffer out of exposure to this bias in comparison to their experienced counterparts. It was checked whether this result could be validated further.

Table 3.21 Contingency Table: Representativeness Bias

Investor Type		Representativeness			Total
		Always	Sometimes	Never	
Young Investors	Count	26	16	4	46
	% within investor type	56.5	34.8	8.7	100
Experienced Investors	Count	21	21	4	46
	% within investor type	45.7	45.7	8.7	100
Total	Count	47	37	8	92
	% within investor type	51.1	40.2	8.7	100

Source: ***Primary data***

From Table 3.21, it can be observed that the responses were distributed in a similar manner among the various options for both groups. The results from Chi-squared tests suggested that both the investor groups exhibited the bias in a similar manner. However, since the 'Never' column lacked the recommended number of cases in SPSS software, the result lacked credibility.

To summarize, overall results suggested that investors were highly prone to suffer from the Representativeness bias which can cause them to make grave errors while investing, the young investors slightly more than the experienced ones. When a company posts poor results for a few quarters, some investors tend to write it off as a lousy company; and expect that, like all lousy companies, it will continue to deliver poor results in the future. In these instances, investors may well be overreacting to the past and ignoring sure signs of improvement in the near future, this missing a great investment opportunity. Representativeness may also lead them to overweigh recent good or bad news while trying to judge future stock performance, this hampering their chances of making the right investments with optimum market timing.

3.9.3 Herding Bias

An investor would be exhibiting Herding behavior when he relies more on information validated by a crowd, rather than on his own judgment, owing to popular perception that the crowd cannot be wrong and also due to being wary of probable ridicule which he might face if the crowd is actually right. If investors are heavily influenced by other investors, analysts etc., the ability to come up with their own analyses and judgments get hampered. For most part, Herding may work fine but the upside is limited since, when everyone is thinking alike, it is quite difficult to make abnormal profits. On the other hand, when a downside happens, it amplifies the psychological biases and can lead to abnormal losses, especially to private investors who are likely to hold on to losing stocks, out of uncertainty due to lack of own views, hence possibly ending up seeking information from many sources.

Investors were asked[7] if they trust their own judgment more than that of others and the results are shown in Table 3.22. Some interesting facts were observed:

- Only 21% of the investors trusted their own judgment more than information/analyses from other listed sources
- 24% of young investors trusted their own judgments, while only 17.4% of the experienced investors gave high importance to their judgments
- Young investors seemed to give most importance to opinions of either friends/brokers. 47.8% of them opined that they listened to friends or recommendations from brokers,

[7] Refer Appendix A, Q5

while making their investment decisions. This could possibly be owing to the fact that broker recommendations are frequently available in the trading platform and via email intraday and before/after-market. From the survey, it was clear that young investors mainly preferred online trading over trading at the brokerage

- Experienced investors were biased towards opinions from media and other so-called experts, as disclosed by 56.5% of the experienced participants. Rightly so, because they seem to have more time to follow financial news and the views of 'experts' who seem to know just about every twist and turn the market takes. On top of this many of them are technologically challenged, thus preferring to trade at the brokerage floor with the help of 'expert' traders who are more than happy to make trading calls on their behalf.

Table 3.22 Contingency Table: Herding Bias

		Herding			
Investor type		Self	Brokers/Friends	Media/Experts	Total
Young Investors	Count	11	22	13	46
	% within investor type	23.9	47.8	28.3	100
Experienced Investors	Count	8	12	26	46
	% within investor type	17.4	26.1	56.5	100
Total	Count	19	34	39	92
	% within investor type	20.7	37.0	42.4	100

Source: ***Primary Data***

Table 3.22 suggests that the young and experienced investors exhibit Herding behavior in a different manner. It seemed interesting to perform the Chi-squared test to check whether this was true.

Chi-Squared Tests

The following hypotheses were tested to check for independence of the variables:

H0: Both investor types depend on similar factors while making judgments/analyses

H1: Young and experienced investors behave differently while making judgments/analyses

Table 3.23 Chi-Squared Tests: Herding Bias – Sources of Information

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	7.748[a]	2	0.021
Likelihood Ratio	7.878	2	0.019
Linear-by-Linear Association	4.720	1	0.030
No. of Valid Cases	92		

a. 0 cells (0%) have expected count less than 5. The minimum expected count is 9.50

Source: ***Computed Data***

The p-values from the Pearson Chi-Square test and Likelihood Ratio tests at .021 and .019, seen in Table 3.23 suggested that the null hypothesis could be rejected at a 95% confidence interval. Thus, it was confirmed that young and experienced investors behave differently for the sample. Now it had to be checked whether the results were significant enough to hold for the population. The cross tabulation was done to extract the ‘adjusted standardized residuals’ – which is the difference between expected values and observed values. The results are shown in Table 3.24.

Table 3.24 Adjusted Standardized Residuals Table: Herding-I

		Herding		
		Self	Brokers/Friends	Media/ Experts
Investor type	Young Investor	0.8	2.2	-2.7
	Experienced Investor	-0.8	-2.2	2.7

Source: ***Computed Data***

The residuals follow a bell curve distribution and hence, at the 95% confidence interval ‘+’ to assigned to values greater than 2 and ‘-‘to values less than -2. Table 3.24 was modified to get Table 3.25.

Table 3.25 Adjusted Standardized Residuals Table: Herding-II

		Herding		
		Self	Brokers/Friends	Media/ Experts
Investor type	Young Investor	0	+	-
	Experienced Investor	0	-	+

Source: ***Computed Data***

Two key interpretations from table 3.25 are:

- In the whole population , young investors were more likely to listen to broker tips or friends compared to their experienced counterparts, as suggested by the '+'
- Views from popular analysts and various media like news channels, websites, newspapers etc. were likely to have a bigger impact on the experienced investors compared to young investors, for the whole population.

Influence of investment decision of others on own decisions

While making a long-term investment, daily trading volumes of the share ideally should not have much weight in the decision because high volumes usually represent speculators and day traders at work. The best case in favor of trading volume should be to select an optimum entry point where the sellers are possibly exhausted, and prices are not likely to drop much further owing to speculation swings. Participants were asked[8] if they consult, the trading volume of a stock influenced their decision to invest in it. Table 3.26 shows that only 24% of the investors were always checking the trading volume while making investment decisions.

[8] Refer Appendix A, Q7

Table 3.26 Contingency Table: Herding-Preliminary-I

		Herding			
		Always	Sometimes	Never	Total
Investor type	Young Investor	32.6	65.2	2.2	100
	Experienced investor	15.2	84.8	-	100
Total		23.9	75.0	1.1	100

Source: ***Primary Data***

Participants were also asked[9] how about the possible influence of a buying spree by people surrounding them and the responses are summarized in Table 3.27. It should be noted that the variable was re-coded in SPSS software by assigning value 2 to a neutral view and 3 to a negative view, as opposed to the reverse ordering in the questionnaire.

Table 3.27 Contingency Table: Herding-Preliminary-II

		Herding			
		Positive	No Change	Negative	Total
Investor type	Young Investor	52.2	21.7	26.1	100
	Experienced investor	58.7	28.3	13.0	100
Total		55.4	25.0	19.6	100

Source: ***Primary Data***

Table 3.27 shows that 55% of the investors were likely to exhibit Herding behavior. Interestingly, going by the results seen earlier in Table 3.22, which said that only 21% of the investors trusted their own judgments above anything else, it could be authoritatively said that at least 33% of the investors exhibit very visible Herding behavior tendency.

[9] Refer Appendix A, Q10

To perform a conjoint analysis, responses to both the questions were arithmetically combined and categorized to fit into the 3-point Likert scale. The contingency table (Table 3.28) shows that 60% of the investors were exhibiting the Herding bias.

Table 3.28 Contingency Table: Herding Bias

		Herding			
Investor type		Yes	Maybe	No	Total
Young Investors	Count	24	15	7	46
	% within investor type	52.2	32.6	15.2	100
Experienced Investors	Count	31	9	6	46
	% within investor type	67.4	19.6	13.0	100
Total	Count	55	24	13	92
	% within investor type	59.8	26.1	14.1	100

Source: ***Primary Data***

Weighted Scoring

Results confirmed that the investors were exposed to the Herding bias. The mean scores of both the investor groups were significantly higher than the reference score, as seen in Table 3.29.

Table 3.29 Weighted Scoring: Herding Bias

Investor Type	Weighted Score	Mean	Reference Score	Outcome
Young	115	19.17	15.33	Herding
Experienced	117	19.5	15.33	Herding
Total	**226**	**18.83**	**15.33**	**Herding**

Source: ***Computed Data***

The identical mean scores pointed towards the direction that experienced investors, even though averaging slightly higher, were not likely to be more overconfident than the young investors. The Chi-squared tests were performed to check it.

Chi-Squared Tests

The following hypotheses were tested based on results from the weighted scoring.

H0: Both investor types are equally likely to exhibit Herding behavior

H1: Experienced investors are more likely to exhibit Herding behavior as compared to young investors.

Table 3.30 Chi-Squared Tests: Herding Bias

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	2.468[a]	2	0.291
Likelihood Ratio	2.486	2	0.288
Linear-by-Linear Association	1.297	1	0.255
No. of Valid Cases	92		

Source: ***Computed Data***

0 cells (0%) have expected count less than 5. The minimum expected count is 6.50

The high p-values returned by all the tests, shown in Table 3.30, meant that the null hypothesis could not be rejected. It could not be said that one investor group was exhibiting Herding behavior more than the other was. These findings were consistent with that of Discriminant Analysis results, where Herding was not found to be an important variable separating the two groups of investors.

3.9.4 Anchoring Bias

When investors tend to label logically irrelevant price levels as important and cling on to them while making investment decisions, they are said to be exhibiting the Anchoring bias. When investors tend to fix a price for a share before buying or selling it based on certain information in the past, they may actually be timing it badly, thus buying it expensive or selling it too early. It can also happen that investors get fixed to a price point, which may not be reached, thus missing good investment opportunities.

When asked[10] whether they tend to fix a target price for buying or selling a stock before the start of a trading day, 29.3% said yes and 66% said that they do it sometimes. From this, it could be thought that in most cases it was likely that investors were likely to have a price range in mind, even if they were not fixing it beforehand. When asked[11] if they place stop losses in their trades, 34% of the investors said that they always do, out of which 24 were young investors and only seven were experienced investors. This question was asked to check if the investors are fixed on prices at which they enter the market, and if they have an exit-strategy in case things go wrong during the day. Participants were then presented[12] with a hypothetical question where they were asked to consider buying a share at a new low, which was 80% lower than the anchor price. 53% of the investors said that they would go for the stock, while 37% said they would not. For the sake of a binding analysis, the three questions were combined to have a composite 3-point Likert scale variable. One of the questions had to be recoded to swap the neutral and negative values of responses, in-order to facilitate proper averaging and obtaining a composite variable, which was representative of the individual responses.

Weighted Scoring

Weighted scoring analysis was performed to see whether the investor groups exhibited Anchoring in a significantly different manner, as suggested by results from Discriminant Analysis.

Table 3.31 Weighted Scoring: Anchoring Bias

Investor Type	Weighted Score	Mean	Reference Score	Outcome
Young	120	20	15.3	Anchoring
Experienced	92	15.3	15.3	No Anchoring
Total	**212**	**17.67**	**15.3**	**Anchoring**

Source: ***Computed Data***

Results seen in Table 3.31 were in line with what results from Discriminant analysis suggested. Young investors were more prone to committing the bias, and the experienced

[10] Refer Appendix A, Q18
[11] Refer Appendix A, Q19
[12] Refer Appendix A, Q22

investors could not be confirmed to be exhibiting a behavior, which could be considered at par with being affected by the bias.

Chi-squared Tests

The following hypotheses were tested:

H0: Both investor types are equally likely to exhibit the Anchoring Bias

H1: Younger investors are more prone to Anchoring, as compared to experienced investors

Table 3.32 Chi-Squared Tests: Anchoring Bias

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	12.821[a]	2	0.002
Likelihood Ratio	13.510	2	0.001
Linear-by-Linear Association	12.614	1	0.000
No. of Valid Cases	92		

Source: ***Computed Data***

0 cells (0%) have expected count less than 5. The minimum expected count is 10.50

The low p-values returned by all the tests (Table 3.32) suggested that the null hypothesis could be rejected at the 99% confidence interval and it could be confirmed convincingly that young investors were more prone to the Anchoring bias than experienced investors. Discriminant analysis had pointed out that Anchoring was one of the key variables, which separated out the behavioral pattern of the investor groups.

3.9.5 Cognitive Dissonance Bias

As human beings, investors are all likely to be blessed with different levels of self-esteem and ego. It is natural that an investor would always want to make the right decisions. Cognitive Dissonance is a bias, which is said to have occurred, when investors' beliefs are changed to be consistent with their past decisions. It so happens that sometimes people try to reduce the discomfort of having to live with the burden of a wrong decision by forgetting their past mistakes, thus improving the success rate of their past investment decisions. For these reasons, if investors try to justify mistakes made while making decisions, they can be thought of as being exposed to the bias. Investors can also experience discomfort when they acquire new information that conflicts with preexisting understandings, which is another symptom of the bias. Out of this condition, investors may tend to avoid information that conflicts with their past investment decisions, which were made. Investors are said to be subject to Cognitive Dissonance bias if they exhibit the tendency to avoid new and conflicting information. (Pompian, 2006)

When asked[13] if their minds try to justify mistakes committed while making investment decisions, 22% of the respondents admitted that it happens while more interestingly, 67% of the investors admitted that it happens sometimes. This might have been a reluctant way of admitting that they have also exhibited the bias. When asked[14] if they would accept new and conflicting information immediately, 66% of the investors said no, and 16% agreed. While combining the questions to perform a composite analysis, the positive and negative responses in the second question had to be inversed since a negative response was in fact confirming the bias. After doing the re-coding and merging in SPSS software, the analysis was performed.

Table 3.33 Contingency Table: Cognitive Dissonance Bias

		Cognitive Dissonance			
Investor type		Yes	Maybe	No	Total
Young Investors	Count	31	10	3	44
	% within investor type	70.5	22.7	6.8	100
Experienced Investors	Count	25	11	9	45
	% within investor type	55.6	24.4	20.0	100
Total	Count	56	21	12	89
	% within investor type	62.9	23.6	13.5	100

Source: ***Primary Data***

Results in Table 3.33 suggest that 63% of the investors could be considered to be subject to the bias. However, the pattern in which the investor types were exhibiting the bias seemed to be equivalent. The weighted scoring method was performed to confirm this.

[13] Refer Appendix A, Q23
[14] Refer Appendix A, Q24

Weighted Scoring

Results in 3.34 suggested that both types of investors were subject to the bias; however, it was also seen that young investors have a higher score compared to the experienced ones.

Table 3.34 Weighted Scoring: Cognitive Dissonance Bias

Investor Type	Weighted Score	Mean	Reference Score	Outcome
Young	116	19.33	15.3	Cognitive Dissonance
Experienced	106	17.67	15.3	Cognitive Dissonance
Total	**222**	**18.5**	**15.3**	**Cognitive Dissonance**

Source: ***Computed Data***

Chi-Squared tests

The tests were performed to see if the different mean scores for the investor types presented any statistically significant information. The following hypotheses were tested:

H0: Both investor types are equally likely to be subject to the Cognitive Dissonance Bias

H1: Young investors are more likely to exhibit the Cognitive Dissonance bias, as compared to experienced investors

Table 3.35 Chi-Squared Tests: Cognitive Dissonance Bias

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3.680[a]	2	0.159
Likelihood Ratio	3.820	2	0.148
Linear-by-Linear Association	3.338	1	0.068
No. of Valid Cases	89		

Source: ***Computed Data***

0 cells (0%) have expected count less than 5. The minimum expected count is 5.93

High p-values ,seen in Table 3.35, implied that the null hypothesis could not rejected, and thus it could not be statistically confirmed that young investors are more susceptible to the Cognitive Dissonance bias compared to experienced ones.

3.9.6 Regret Aversion Bias (Fear of Regret)

Regret Aversion occurs from the investor's desire to avoid the pain of regret arising from a poor investment decision. As a result of this, investors could end up holding on to poorly performing shares because avoiding the sale avoids the recognition of associated loss and in turn, of a bad investment. When asked[15] whether they have made the wrong decision 86% of the investors replied that they sometimes did it and when asked [16]whether they have put off an investment decision because of wanting more positive news about a stock, 74% of the investors admitted that they had done it sometimes. Answers to both questions were combined to perform a composite analysis of the bias. It can be seen in Table 3.36 that close to 21% of the investors seem to be confirmed subjects to the bias, while 66% of them could be thought of as possible subjects.

Table 3.36 Contingency Table: Fear of Regret Bias

		Fear of Regret			
Investor type		Yes	Maybe	No	Total
Young Investors	Count	13	29	4	46
	% within investor type	28.3	63.0	8.7	100
Experienced Investors	Count	6	32	8	46
	% within investor type	13.0	69.6	17.4	100
Total	Count	19	61	12	92
	% within investor type	20.7	66.3	13.0	100

Source: ***PrimaryData***

[15] Refer Appendix A, Q26.
[16] Refer Appendix A, Q27

Weighted Scoring

Results seen in Table 3.37 suggested that young investors, with a mean score higher than the reference score, were more susceptible to exhibiting the bias, and that experienced investors could not be thought of as exhibiting the bias, in a statistically significant way.

Table 3.37 Weighted Scoring: Fear of Regret

Investor Type	Weighted Score	Mean	Reference Score	Outcome
Young	101	16.83	15.3	Fear of Regret
Experienced	90	15	15.3	No Bias
Total	**191**	**15.92**	**15.3**	**Fear of Regret**

Source: ***Computed Data***

Chi-Squared tests

The tests were performed to see if the different mean scores for the investor types presented any statistically significant information. The following hypotheses were tested:

H0: Both investor types are equally likely to exhibit Regret Aversion Bias

H1: Young investors are more likely to exhibit the Regret Aversion bias

Table 3.38 Chi-Squared Tests: Fear of Regret Bias

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	4.060[a]	2	0.131
Likelihood Ratio	4.148	2	0.126
Linear-by-Linear Association	3.928	1	0.047
No. of Valid Cases	92		

Source: ***Computed Data***

0 cells (0%) have expected count less than 5. The minimum expected count is 6.00

High p-values, seen in Table 3.38, implied that the null hypothesis could not be rejected, and thus it could not be statistically confirmed that young investors were more susceptible to the bias compared to experienced ones.

3.9.7 Gamblers' Fallacy Bias

Gamblers' Fallacy bias arises when investors inappropriately predict a stock market outcome like a trend reversal etc. This may lead them to anticipate the end of a series of good (or poor) market returns. An investor who suffers from the Gamblers' Fallacy bias is likely to be biased towards predicting a reversal in the trajectory of a stock.

Preference in a flip-a-coin bet

A widely quoted example related to Gamblers' Fallacy theory is the prediction of the outcome of a fair coin toss. Respondents were asked to imagine a situation where an unbiased coin was flipped three times and landed heads each time. When asked[17] to share their thoughts on the outcome of the fourth flip only 37% (34 investors) said that they are neutral, as seen in Table 3.39.

Table 3.39 Contingency Table: Coin Flip Bet

		Coin Flip			
Investor type		Heads	Tails	No Preference	Total
Young Investors	Count	11	24	11	46
	% within investor type	23.9	52.2	23.9	100
Experienced Investors	Count	15	8	23	46
	% within investor type	32.6	17.4	50.0	100
Total	Count	26	32	34	92
	% within investor type	28.3	34.8	37.0	100

Source: ***Primary Data***

Out of this, 11 were young investors and 23 were experienced investors. The rest can be thought of as being susceptible to the bias, because they were forgetting the fact that each coin toss is an independent event and there was an equal chance of a head or a tail.

[17] Refer Appendix A, Q29

Anticipation of Market Reversals

The main point to be kept in mind from Table 3.39 was that 63% of the investors were likely to be preys to the Gamblers' Fallacy bias. When asked whether they are able to predict reversals in market trends, only 16% of the investors (15 of them) felt that they predict the stock reversals effectively all the time (Table 3.40) and all of them were young investors. 73% of the investors said that they are able to make the predictions occasionally. However, when interpreted in light with the coin-flip bet outcome, it could be argued that most of them do suffer from the bias.

Table 3.40 Contingency Table: Gamblers Fallacy Bias

		Gambler's Fallacy			
Investor type		Yes	Maybe	No	Total
Young Investors	Count	15	28	3	46
	% within investor type	32.6	60.9	6.5	100
Experienced Investors	Count	0	39	7	46
	% within investor type	0	84.8	15.2	100
Total	Count	15	67	10	92
	% within investor type	16.3	72.8	10.9	100

Source: ***Primary Data***

The results from Discriminant Analysis suggested that Gamblers' Fallacy was among the biases, which clearly separated the behavior patterns of investor groups. The results from Table 3.39 and 3.40 suggested that the young investors were more susceptible to the bias in comparison to the experienced ones. The weighted scoring analysis and Chi-squared tests were performed in-order to check this.

Weighted Scoring

Results shown in Table 3.41 and Table 3.42 suggest that young investors, with a mean score greater than or equal to the reference score, were more susceptible to exhibiting the bias, and that experienced investors could not be thought of as exhibiting the bias, in a statistically significant way.

Table 3.41 Weighted Scoring: Coin Flip Bet

Investor Type	Weighted Score	Mean	Reference Score	Outcome
Young	92	15.3	15.3	Borderline Bias
Experienced	84	14	15.3	No Bias
Total	**176**	**14.67**	**15.3**	**No Bias**

Source: ***Computed Data***

Table 3.42 Weighted Scoring: Gambler's Fallacy

Investor Type	Weighted Score	Mean	Reference Score	Outcome
Young	104	17.33	15.3	Gamblers Fallacy
Experienced	85	14.17	15.3	No Bias
Total	**189**	**15.75**	**15.3**	**Gamblers Fallacy**

Source: ***Computed Data***

This was in line with the results from Discriminant Analysis as the investor behavior is clearly different for the investor groups.

Chi-Squared Tests

The tests were performed to see if the different mean scores for the investor types presented any statistically significant information. The following hypotheses were tested:

H0: Both investor types are equally likely to be subject to the Gamblers' Fallacy bias

H1: Young investors are more likely to exhibit the Gamblers' Fallacy bias, as compared to experienced investors

Table 3.43 Chi-Squared Tests: Coin-Flip Bet

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	12.851[a]	2	0.002
Likelihood Ratio	13.318	2	0.001
Linear-by-Linear Association	1.067	1	0.302
No. of Valid Cases	92		

Source: ***Computed Data***

0 cells (0%) have expected count less than 5. The minimum expected count is 13.00

Table 3.44 Chi-Squared Tests: Gambler's Fallacy Bias

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	18.406[a]	2	0.000
Likelihood Ratio	24.254	2	0.000
Linear-by-Linear Association	14.440	1	0.000
No. of Valid Cases	92		

Source: ***Computed Data***

0 cells (0%) have expected count less than 5. The minimum expected count is 5.00

The p-values from all the tests, except one, were very low (seen in Table 3.43 and 3.44) and the null hypothesis could be rejected with 99% confidence. Thus, it was confirmed that young investors were more likely to suffer from the bias compared to experienced investors. These results complied with the results from Discriminant Analysis obtained previously.

3.9.8 Mental Accounting Bias

Sometimes investors tend to separate their money to separate accounts owing to various reasons. When people mentally separate money into different accounts, they usually tend to spend it in a different manner. For instance, if they set money aside for the sake of trading, it could be possible that its money they do not need for any other purpose and are willing to risk in the stock markets. This can lead to the Mental Accounting bias. Investors were asked[18] if they set aside a share of their income for investing in the share market and their responses are shown in Table 3.45. 80% of the investors amounting to 74 individuals opined that they do it sometimes, while 17% said that they always do it. These investors were likely to be to treat this money as 'trading' money and make untimely investments into their favorite stocks, if they did.

Table 3.45 Contingency Table: Mental Accounting Bias

		Mental Accounting			
Investor type		Yes	Maybe	No	Total
Young Investors	Count	10	34	2	46
	% within investor type	21.7	73.9	4.3	100
Experienced Investors	Count	6	40	0	46
	% within investor type	13.0	87.0	0.0	100
Total	Count	16	74	2	92

Source: ***Computed Data***

Based on results in the Discriminant Analysis performed earlier, Mental Accounting was not a key variable in separating the investment behavior of the two groups.

Weighted Scoring

Results shown in Table 3.46 suggest both investor types with a mean score greater than or equal to the reference score were susceptible to exhibiting the bias.

Table 3.46 Weighted Scoring: Mental Accounting Bias

Investor Type	Weighted Score	Mean	Reference Score	Outcome
Young	92	16.67	15.3	Mental Accounting
Experienced	84	16.33	15.3	Mental Accounting
Total	**176**	**16.5**	**15.3**	**Mental Accounting**

Source: ***Computed Data***

[18] Refer Appendix A, Q30

The similarity in mean scores, roughly confirmed the results from Discriminant analysis that one group of investors were not found to be exhibiting the bias more than the other.

Chi-Squared Tests

The following hypotheses were tested:

H0: Both investor types are equally likely to be subject to the Mental Accounting bias

H1: Young investors are more likely to exhibit the Mental Accounting bias, as compared to experienced investors

Table 3.47 **Chi-Squared Tests: Mental Accounting Bias**

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	3.486[a]	2	0.175
Likelihood Ratio	4.270	2	0.118
Linear-by-Linear Association	0.249	1	0.618
No. of Valid Cases	92		

Source: ***Computed Data***

2 cells (33.3%) have expected count less than 5. The minimum expected count is 1.00

The p-values (seen in Table 3.47) were high suggesting that the null hypothesis could not be rejected. Thus, the results from Discriminant Analysis were confirmed to hold.

3.9.9 Hindsight Bias

It is a common human trait to reflect on past decisions. While analyzing such decisions many things seem falsely obvious and easily predictable. When asked[19] whether it was easy to predict the collapse of Sensex in the wake of the 2008 Global financial crisis 73% of the investors said, that it was easy/very easy(Table 3.48). This could be arguably due to Hindsight bias, since it was seen earlier that around 58% of the investors suffered at least a 30% loss because of the crisis (Table 3.06). Investors were asked[20] to give a response on a scale of 1 to 5, on how easy it would be to convince them back in 2006-07, that a crisis was likely to happen in

[19] Refer Appendix A, Q12
[20] Refer Appendix A, Q32

the near future. The responses were scaled in the following manner: 1-2: not convinced, 3: maybe, 4-5: easily convinced.

Table 3.48 Contingency Table: Hindsight Bias-I

		Predicting 2008 Sensex Crash			
Investor type		Very Easy	Easy	Difficult	Total
Young Investors	Count	12	24	10	46
	% within investor type	26.1	52.2	21.7	100
Experienced Investors	Count	2	29	15	46
	% within investor type	4.3	63.0	32.6	100
Total	Count	14	53	25	92
	% within investor type	15.2	57.6	27.2	100

Source: ***Computed Data***

This aligned the responses to a 3-point Likert Scale. 33% of the investors said that they would have been easy to convince (Table 3.49). This seemed to be owing to Hindsight bias, since there were many opportunities to exit their positions before the full impact of the crisis was transmitted to India. The fact was that the Indian economy was believed to be resilient to the crisis, causing investors to be bullish in 2008 making SENSEX touch an all time high.

Table 3.49 Contingency Table: Hindsight Bias-II

		Hindsight			
Investor type		Yes	Maybe	No	Total
Young Investors	Count	21	16	9	46
	% within investor type	45.7	34.8	19.6	100
Experienced Investors	Count	9	20	17	46
	% within investor type	19.6	43.5	37.0	100
Total	Count	30	36	26	92
	% within investor type	32.6	39.1	28.3	100

Source: ***Computed Data***

Weighted Scoring

Results shown in Table 3.50 suggest the young investor lot were suffering from the Hindsight bias in a statistically significant manner, while the experienced investors were not. The whole sample was seen to be slightly subject to the Hindsight bias.

Table 3.50 Weighted Scoring: Hindsight Bias

Investor Type	Weighted Score	Mean	Reference Score	Outcome
Young	104	17.33	15.3	Hindsight Bias
Experienced	84	14	15.3	No Bias
Total	**188**	**15.67**	**15.3**	**Hindsight Bias**

Source: ***Computed Data***

Results from discriminant analysis suggested that Hindsight bias was a significant variable, which highlighted the difference in behavior patterns between the investor groups and this finding added credibility.

Chi-Squared Tests

The chi-squared tests were conducted to test the following hypotheses:

H0: Both investor types are equally likely to be subject to the Hindsight Bias

H1: Young investors are more likely to exhibit the Hindsight Bias, as compared to experienced investors

Table 3.51 Chi-Squared Tests: Hindsight Bias

	Value	df	Asymp. Sig. (2-sided)
Pearson Chi-Square	7.706[a]	2	0.021
Likelihood Ratio	7.884	2	0.019
Linear-by-Linear Association	7.087	1	0.008
No. of Valid Cases	92		

Source: ***Computed Data***

0 cells (0 %) have expected count less than 5. The minimum expected count is 13.00

The low p-values seen in Table 3.51 suggested that the null hypothesis could be rejected at a 95% confidence interval. This was only partly in line with results from previous analyses, because the Canonical Discriminant function Coefficient (Table 3.14) value for Hindsight bias rated it below various other biases when assigning significance as a factor separating the young investors from experienced one. However, results from the structure matrix table, seen in Table 3.14, suggested that younger and experienced investors exhibited Hindsight bias in a significantly different manner. Results from Chi-Squared tests confirmed that younger investors were more likely to exhibit the Hindsight bias than experienced investors were.

Chapter Four

Summary of Findings and Recommendations

4.1 Overview

The thesis attempted to analyze the effects of nine identified behavioral biases on the decision making process of investors, namely: Overconfidence, Representativeness, Herding, Anchoring, Cognitive Dissonance, Regret Aversion, Gamblers' Fallacy, Mental Accounting and Hindsight Bias. Effects of these nine factors on the decision making process of a sample of 92 investors from Kerala, India were studied. Out of this sample, two sub-samples of 46 investors each were created: (i) experienced investors – those aged above 30 with at least 7 years of investing experience; and (ii) Young investors – those aged 30 or below with less than 7 years of experience. The sample and sub-samples have been processed and analyzed using IBM SPSS Software and Microsoft Excel. 10 variables were coded into SPSS, 1 of them a dichotomous variable representing investor group, and the remaining 9, each representing a bias, were created by using scaling techniques like 3-point and 5-point Likert Scales, and arithmetic mean. An overall analysis of the sample was conducted by performing various Multicollinearity Checks and the Discriminant Analysis, which checks if the behavioral pattern of younger investors is different from that of the experienced ones. Further, effect of each bias on the two groups was analyzed separately using the Weighted Scoring Method and hypotheses were tested using the Chi-squared test for Independence.

The results from Chi-squared tests (seen in Table 4.2) suggested that 6 out of the 9 biases could not be determined to be affecting one investor category more than the other. This pointed in the direction that it would not be fair to say that younger investors and experienced investors can be separated as two entities who behave differently while investing. However the conjoint analysis results from discriminant analysis and weighted scoring revealed that, that 'investor type' indeed was a significant discriminator, based on which the investors could be separated into two groups of human beings that think differently while making investment decisions. When asked to reveal financial losses suffered in the 2007 – 2009 timeframe, 53 out of the 92 investors admitted to having faced a loss of at least 30%. It was checked if either of the investor categories had suffered more losses than the other. Chi-squared tests indicated that both young and experienced investors suffered losses, and thus were equally impacted by the crisis. Results from weighted scoring (summarized in Table 4.1), showed that investors were suffering from almost all the biases studied. In this context, it could be argued that being subject to these behavioral biases had played a significant role in the losses suffered during the crisis by both the young and experienced investors.

4.2 Summary of Findings

Some of the key findings from the study are listed below:

- A multicollinearity check was performed to see if any of the biases had high correlation. The initial test suggested that there are no multicollinearity issues for the data. The Pearson Correlation Coefficient for the Gamblers' Fallacy – Representativeness pair was 0.555, and that for Anchoring – Fear of Regret pair had a coefficient of 0.512. These were the highest values in the correlation matrix, and were chosen for further analysis. The Variance Inflation Factors were determined. The values for the Gamblers' Fallacy – Representativeness pair were 1.585 and 1.271, and that for the Anchoring – Fear of Regret pair was 1.278 and 1.430. All these values were below the threshold value of 4(which indicates multicollinearity) and hence the decision was made to include all variables in further analyzes.
- The Discriminant Analysis was performed using Investor type(young or experienced) as the discriminant function D and the following canonical discriminant function equation was obtained :

D =	-	0.788*Representativeness	-	0.228*Herding
	-	0.236* Overconfidence	+	0.789* Anchoring
	-	0.238*Cognitive Dissonance	+	0.077* Fear of Regret
	+	1.478*Gamblers Fallacy	+	0.440*Mental Accounting
	+	0.280*Hindsight	-	4.106

  - ✓ Gamblers' Fallacy and Anchoring were seen to be the biases (as suggested by the canonical discriminant function coefficients) which were exhibited by the younger and experienced investors in the most significantly different manner

- ✓ It could not be said that either investor group was more prone to being affected by behavioral biases as a whole, when compared to the other. Both the young and experienced investors were affected by the biases in a similar manner.
- ✓ Even though both young and experienced investors were equally affected by the behavioral biases together, it was observed that the degree to which each of the biases affected the group varied, and it was statistically possible to separate the behavioral of the experienced investors, from that of the younger investors.
- ✓ The Discriminant function was able to capture 75% of the behavioral pattern differences between the two groups of investors, thus gaining statistical credibility. This implied that it could be said authoritatively that younger investors exhibited a different behavioral pattern compared to experienced ones.

- In an attempt to study whether investors were prone to Herding bias, they were asked if they trust their own judgment more than that of others and the responses indicated significant exposure to Herding behavior. Some highlights are summarized below:
  - ✓ Only 21% of the investors trusted their own judgment more than information/analyses from other listed sources.
  - ✓ 24% of younger investors trusted their own judgments, while only 17.4% of the experienced investors gave high importance to their judgments.
  - ✓ Younger investors seemed to give most importance to opinions of either friends/brokers. 47.8% of them opined that they listened to friends or recommendations from brokers, while making their investment decisions. This could possibly be owing to the fact that broker recommendations are frequently available in the trading platform and via email intraday and before/after-market. From the survey, it was clear that younger investors mainly prefer online trading rather than trading at the brokerage, which is preferred by the more experienced traders.
  - ✓ Experienced investors, on the other hand, were biased towards opinions from media and other so-called experts, as disclosed by 56.5% of the experienced participants. Rightly so, because they seem to have more time to follow financial news and the views of ‘experts’ who seem to know just about every twist and turn

the market takes. On top of this many of them are technologically challenged, thus preferring to trade at the brokerage floor with the help of 'expert' traders who are more than happy to make trading calls on their behalf.

- Respondents were asked to reveal their preferences in a flip-a-coin bet where the last three flips had resulted in 'heads'. Ideally, they should have had no preference since each coin flip was supposed to be an independent event. Very surprisingly, only 37% of the respondents were found to have no preference.
- The Weighted Scoring Method was employed to serve two purposes. (i) If either of the groups were suffering from the bias; and (ii) To check if the whole sample was suffering from the bias. Results from the analysis can be seen in Table 4.1. In the case of all biases except Cognitive Dissonance, either both investor groups or one of them were seen to be prey to the bias. If the groups were biased, the Answer is 'Yes' and if both groups were not biased, the answer is 'No'.

Table 4.1 Weighted Scoring Methods: Summary of Results

NAME OF BIAS	INVESTORS BIASED? (WEIGHING AND SCORING)
Overconfidence	Yes
Representativeness	Yes
Herding	Yes
Anchoring	Yes
Cognitive Dissonance	No
Regret Aversion	Younger – Yes, Experienced – No
Gambler's Fallacy	Younger - Yes, Experienced - No
Mental Accounting	Yes
Hindsight	Younger – Yes , Experienced – No

Source: ***Computed Data***

- Results from the various Chi-squared tests are furnished in Table 4.2. The results were mainly in line with that from Discriminant Analysis where it was seen that Anchoring and Gamblers' Fallacy are the biases, which were displayed by the investors in the most different manner. Chi-squared tests confirmed that younger investors were seen to exhibit both the biases more compared to the experienced ones.

Table 4.2 Chi squared Tests: Summary of Results

NAME OF BIAS	ONE INVESTOR TYPE MORE BIASED THAN OTHER?
Overconfidence	No
Representativeness	No
Herding	No
Anchoring	Yes , Younger Investors
Cognitive Dissonance	No
Regret Aversion	No
Gambler's Fallacy	Yes, Younger Investors
Mental Accounting	No
Hindsight	Yes, Younger Investors

Source: ***Computed Data***

- Results from weighted scoring in context of Hindsight bias suggested that younger investors were suffering from Hindsight bias, while the experienced ones were not. This was interesting because the canonical discriminant function coefficient value for Hindsight bias rated it below other biases like Representativeness and Mental Accounting when assigning significance as a factor separating the younger investors from experienced ones. However, results from the structure matrix table rated Hindsight bias as the third most significant separator of groups after Anchoring and Gamblers' Fallacy biases. Results from Chi-Squared tests confirmed that younger investors were more likely to exhibit the Hindsight bias than experienced investors were.

- Results from the various hypothesis tests are summarized in Table 4.3 below

Table 4.3 List of Hypotheses: Summary of Results

NULL HYPOTHESIS	RESULT
There is no relationship between investor experience and losses suffered during crisis	Not Rejected
Both investor types are equally affected or unaffected by the Behavioral Biases	Not Rejected
Young investors are not likely to be more Overconfident than experienced investors	Not Rejected
Both investor types depend on similar factors while making judgments/analyses	Rejected
Both investor types are equally likely to exhibit Herding behavior	Not Rejected
Both investor types are equally likely to exhibit Anchoring Bias	Rejected
Both investor types are equally likely to exhibit Regret Aversion Bias	Not Rejected
Both investor types are equally likely to be exhibit the Gamblers' Fallacy Bias	Rejected
Both investor types are equally likely to be exhibit the Mental Accounting Bias	Not Rejected
Both investor types are equally likely to exhibit the Hindsight Bias	Rejected

4.3 Recommendations

4.3.1 Recommendations for Investors

As seen in Table 4.4, 89% of the investors who participated in the survey had average or less awareness on behavioral finance and the findings from the study imply that these investors are in fact prey to many of the biases, which have been identified in this field.

Table 4.4 Contingency table: Investor Awareness about Behavioral Finance

		Awareness on Behavioral Finance					
Investor type		Poor	Basic	Average	Good	Excellent	Total
Young Investors	Count	4	19	15	7	1	46
	% within investor type	8.7	41.3	32.6	15.2	2.2	100
Experienced Investors	Count	9	19	16	2	0	46
	% within investor type	19.6	41.3	34.8	4.3	0.0	100
Total	Count	13	38	31	9	1	92
	% within investor type	14.1	41.3	33.7	9.8	1.1	100

Source: ***Primary Data***

The main recommendation for investors is to make constant attempts to increase their awareness on behavioral finance by educating themselves on the field. Studying about the biases, and reflecting on their decisions are likely to help achieve better self-understanding of to extent and manner to which they gets influenced by emotions while making financial decisions under uncertainty. Even after satisfactory awareness is achieved it is highly recommended that they maintain a chart of the behavioral biases they are likely to be vulnerable to. This should be reviewed periodically in order to recollect and refresh their memory thus giving themselves a better chance to make improved financial decisions in the stock market. Most essentially, what remains unanswered is whether greater awareness of investors about behavioral biases is likely to increase the market efficiency. Awareness about behavioral biases and its application in the course of making investment decision would be increasing the rationality of investment decisions thus making way for higher market efficiency.

4.3.2 Recommendations for Economics/Finance Schools

Behavioral Finance should be given more importance in the Academic Curriculum, if it has not already been given its due. The schools do an excellent job in equipping students with knowledge of the sciences and various techniques, which definitely serves as a foundation to a great career. If they are equipped with excellent knowledge in Behavioral finance, the psychological aspect of the field would have already helped them achieve better self-understanding, and hence decision making in pressure situation might not be as challenging to them as it would be otherwise. Knowing what to do is important, but knowing when to do what is to be done, is priceless.

4.3.3 Recommendations for Academics

Behavioral finance, as a field, brings psychology and finance together. From a research perspective, behavioral finance presents a lot of fresh opportunities and challenges mainly because it is a relatively young field. Moreover, it offers numerous opportunities for creative thinking and experimental studies, since there is an opportunity to focus on the human mind and its ways. The field is closely related to behavioral economics, which focuses on understanding the rationale behind economic decisions, by researching on various identified cognitive or emotional biases, which people may be suffering from. In this study, methods like Discriminant Analysis and Weighted Scoring were used, since the idea was to gather a broad overview about nine biases, serving as a platform for more specific experimental research focusing on one or two biases. Each of these biases can be studied using multiple variables to add dimensions to the analysis, and techniques like Factor Analysis can be employed to check for variability among them, as they are likely to exhibit a high degree of correlation. The questionnaire survey method, which was the tool employed to gather data, was one of the main limitations of this study, albeit the only practical option to reach real investors. Any study undertaken in this direction with the target audience in mind as students of economics and finance, will provide limitless opportunities to come up with creative experimental premises on the lines of trying to out-think contemporaries.

Chapter Five

Conclusion and Future Research

One word, which has dominated the world of financial stock markets since 2008, has been 'Volatility'. Extreme movements in global indices and stock prices because of fear and anticipation has, as it is supposed to, made life tough for a rational investor. Market sentiments have been observed to sway wildly from positive to negative and back, in the shortest timeframes like weeks, days and hours. In this context, understanding irrational investor behavior deserves more importance that it has ever had. Behavioral finance - a relatively new field that came into relevance in the 1980s – studies the effect of psychology on financial decision-making. It studies how investors interpret new information and act on it to make decisions under uncertainty. The science does not try to label traditional financial theories as obsolete, but seeks to supplement the theories by relaxing on its assumptions on rationality and taking into consideration the premise that human behavior can be understood better if the effects of cognitive and psychological biases could be studied in context where decisions are made.

Are people (market participants) rational? Or are they likely to be driven by bouts of emotions like fear and greed, which could lead to bad decisions? The objective of this thesis was to check if the average individual investor participating in the Indian Stock Market is rational at all times. The focus is on nine identified behavioral biases, namely: Overconfidence, Representativeness, Herding, Anchoring, Cognitive Dissonance, Regret Aversion, Gamblers' Fallacy, Mental Accounting and Hindsight Bias. Effects of these factors on the decision making process of portfolio investors in Kerala, India were analyzed in this study. By distributing a structured questionnaire[21], responses were obtained from individual investors and the final sample consisted of 92 respondents out of with 46 were experienced investors – those aged above 30 and having at least 7 years of investing experience; and young investors – those aged 30 or below, with less than 7 years of investing experiences. Variables representing each bias were carefully constructed from the responses based on the Likert Scale, and techniques like Discriminant Analysis, Weighted Scoring, and Chi-squared Tests were employed to analyze the data.

[21] Refer Appendix A

The study found out that, with the exception of Cognitive Dissonance Bias, investors suffered from all biases in a significant manner. Weighted Scoring Analysis revealed that Regret Aversion, Gamblers' Fallacy and Hindsight bias were seen to be affecting the younger investors only. Anchoring, Gamblers' Fallacy and Hindsight were the three biases, which were seen to affect the younger investor lot in the most significant manner, compared to experienced investors, as suggested by results from Chi-squared tests. Tests had shown that all the investors were affected by the various biases while making investment decisions but it could not be established that one investor group had suffered more losses under the influence of these biases. Results from discriminant analysis suggested that, even though investors were equally prone to committing erroneous decisions owing to being biased, the degree to which each of the biases were affecting them were different in a significant manner to an extent that younger and experienced investors could be separated as two different groups of human beings exhibiting a different behavioral pattern. When asked to reveal financial losses suffered in the 2007 – 2009 timeframe, 53 out of the 92 investors admitted to having faced a loss of at least 30%. In this context, the study argues that being subject to these behavioral biases had played a significant role in the losses suffered during the crisis by both the young and experienced investors.

Results from the study are more indicative in nature, than confirmative. However, the findings do open up various research opportunities where the number of biases studied could be reduced and the attempts can be made to produce confirmative results under detailed experimental settings. Two recommendations are:

(i) Subjects should be randomly split into two groups. One group should be given a knowledge session about a certain bias. Then both groups should be presented with a scenario, which tries to induce the subjects into committing the bias.

(ii) Subjects should be provided with a scenario where they are likely to be influenced by a certain bias. Then they should be given a knowledge session on the bias. A similar scenario should be presented to the same group a day later, to see if the new awareness has any impact on their decision-making.

Methods like Game Theory and Probabilistic Logic can be used as inspiration while setting up the premises for a detailed and more advanced study. The nature of the field promises that a researcher would be presented with many opportunities to be innovative and creative.

Bibliography

Andersen, Jorgen Vitting. 2010. *Detecting Anchoring in Financial Markets*. Journal of Behavioral Finance 11(2): 129 – 133.

Anonymous. 2008. *Discriminant Analysis*.<http://www.uk.sagepub.com/burns/website%20material/Chapter%2025%20-%20Discriminant%20Analysis.pdf>. UK: SAGE Retrieved : January 2012

Anonymous. 2009. *Economic Appraisal Guidance*. <http://www.dfpni.gov.uk/eag-the-weighting-and-scoring-method>, Department of Finance and Personnel, Northern Ireland. Retrieved : January 2012

Banerjee, Arindam. 2011. *Application of Behavioral Finance in Investment Decisions: An Overview*. The Management Accountant 46 (10) : 869 – 872.

Barber, Brad M., and **Odean, Terrance**.1999. *The Courage of Misguided Convictions*. Financial Analysts Journal 55(6).

Barber, Brad M., and **Odean, Terrance**.2001. *Boys will be Boys: Gender, Overconfidence and Common Stock Investment*. The Quarterly Journal of Economics 116(1): 261 – 292.

Barberis, Nicholas. and **Thaler, Richard**.2003. *A Survey of Behavioral Finance.* Handbook of the Economics of Finance. Elsevier Science B.V: 1054-1056.

Belsky, Gary and **Gilovich, Thomas**. 1999. http://introduction.behaviouralfinance.net/. Retrieved: February 2012.

Bernstein, Peter L. 1998. *Against the Gods: the remarkable story of risk*. USA: John Wiley & Sons Inc.

Brabazon, Tony. 2000. Behavioral *Finance: A new sunrise or a false dawn?*. University of Limerick: 1-7.

Chandra, Abhijeet.2008. *Decision Making in the Stock Market: Incorporating Psychology with Finance*. New Delhi.

Chen, Gongmeng., **Kim, Kenneth A**., **Nofsinger, John R**., and **Rui, Oliver M**. 2007. *Trading Performance, Disposition Effect, Overconfidence, Representativeness Bias, and Experience of Emerging Market Investors.* http://papers.ssrn.com/sol3/papers.cfm?abstract_id=957504. Retrieved : February 2012.

Chira, Inga., **Adams, Michael**., and **Thornton, Barry**. 2008. *Behavioral Bias Within The Decision Making Process*. Journal of Business & Economics Research 6(8): 11 – 20.

Cianci, Anna M. 2008. *The Impact of Investor Status on Investors' Evaluation of Negative and Positive, Separate and Combined Information*. The Journal of Behavioral Finance 9: 117- 131.

Cipriani, Marco., and **Guarino, Antonio**. 2008. *Herd Behavior in Financial Markets: An Experiment with Financial Market Professionals*. IMF Working Paper, WP/08/141.

Durkheim, Emile. 1982. *Rules of Sociological Method*. New York : Free Press

Economou, Fotini., **Kostakis, Alexandros**., **Philippas, Nikolaos**. 2010. *An Examination of Herd Behavior in Four Mediterranean Stock Markets*. Athens: 9th Annual Conference, European Economics and Finance Society.

Fagerström, Sixten. 2008. Behavioral Finance: *The psychological impact and Overconfidence in financial markets*. Skövde : University of Skövde.

Fama, Eugene F. 1965. *Random Walks in Stock Market Prices*. Financial Analysts Journal 21 (5): 55 - 59.

Fama, Eugene F., Fisher, Lawrence., Jensen, Michael C., Roll, Richard.,1969. *The Adjustment of Stock Prices to New Information*. International Economic Review,10.

Fama, Eugene F. 1970. *Efficient Capital Markets: A Review of Theory and Empirical Work*. Journal of Finance 25 (2): 383 - 417.

Fama, Eugene F., and **French, Kenneth R**., 1993. *Common Risk Factors in the Returns on Stocks and Bonds*. Journal of Financial Economics 33: 3 -56

Fama, Eugene F., and **French, Kenneth R**., 1996. *Multifactor Explanations of Asset Pricing Anomalies*. Journal of Finance 51: 55 – 84.

Fama, Eugene F. 1998. *Market Efficiency, long-term returns, and behavioral finance*. Journal of Financial Economics 49 (1998): 283 – 306.

Gilovich, Thomas., **Griffin, Dale**., and **Kahneman, Daniel**.2002. *Heuristics and Biases: The Psychology of Intuitive Judgment*. Cambridge : Cambridge University Press.

Grou, Breno. and **Tabak, Benjamin M**. 2008. *Ambiguity Aversion and Illusion of Control: Experimental Evidence in an Emerging Market*. The Journal of Behavioral Finance 9: 22 -29.

Grossman, Sanford J. and **Stiglitz, Joseph E**. 1980. *On the impossibility of Informationally Efficient Markets*. The American Economic Review 70(3): 393 – 408.

Heukelom, Floris. 2007. *Kahneman and Tversky and the Origin of Behavioral Economics*. Tinbergen: University of Amsterdam. http://dieoff.org/_Economics/Origin%20of%20Behavioral%20Economics07003.pdf Retrieved: February 2012.

Hirshleifer, David., and **Teoh, Slew Hong**. 2003. *Herd Behavior and Cascading in Capital Markets: a Review and Synthesis*. European Financial Management 9(1): 25 – 66.

Hoffmann, Arvid O.I., **Shefrin, Hersh**., and **Pennings, Joost M.E**. 2010. *Behavioral Portfolio Analysis of Individual Investors*. Working Paper, Maastricht University, and Santa Clara University.

Jeng, L., Metrick, **A.,** and **Zeckhauser,R.** 1999. *The profits to insider trading: A performance-evaluation perspective*'. NBER Working Paper) #6913. Cambridge, MA: NBER.

Jensen, Michael C. 1978. *Some Anomalous Evidence Regarding Market Efficiency*. Journal of Financial Economics 6 (2, 3):95-101.

Kahneman, Daniel. and **Tversky, Amos**. 1971. *Belief in law of small numbers*. Psychological Bulletin 76(2): 105 – 110.

Kahneman, Daniel. and **Tversky, Amos**. 1972. *Subjective Probability: A judgment of Representativeness*. Cognitive Psychology 3(3): 430 – 454.

Kahneman, Daniel. and **Tversky, Amos**. 1973. *On the psychology of prediction*. Psychological Review 80(4): 237 – 251.

Kahneman, Daniel. and **Tversky, Amos**. 1979. *Prospect Theory: An Analysis of Decision under Risk*. Econometrica 47(2): 263 – 291.

Kahneman, Daniel and **Riepe, Mark W**. 1998. *Aspects of Investor Psychology: Beliefs, preferences, biases investment advisors should know about*. The Journal of Portfolio Management 24 (4): 52 – 65.

Kishore, Rohit. 2004. *Theory of Behavioral Finance and its Application to Property Market*: A Change in Paradigm. Australian Property Journal 38(2): 105-110

Klecka, William R., 1980. *Discriminant Analysis – Series: Quantitative Applications in the Social Sciences*. USA: SAGE Publications. Inc.

Kristensen, Henrik. and **Gärling, Tommy**.1997. *Anchor points, reference points, and counteroffers in negotiations*. Göteborg Psychological Reports 27(7).

Lakonishok, Josef., **Shleifer, Andrei**., and **Vishny, Robert W**.1994. *Contrarian Investment, Extrapolation and Risk*. Journal of Finance 49:1541–1578.

Maheran, Nik., Muhammad, Nik., **Ismail, Nurazleena**. 2008. *Investment Decision Behavior: Does Investors Rational or Irrational?* Faculty of Business Management, Mara University of Technology, Malaysia.

Monti, Marco and **Legrenzi, Paolo**.2009. *Investment Decision-Making and Hindsight Bias*. Annual Meeting of the Cognitive Science Society. Amsterdam.

Montier, James. 2002. *Cognitive Dissonance*. http://cognitive-dissonance.Behaviouralfinance.net/ Retrieved : February, 2012.

Montier, James. 2003. *Global Equity Strategy: The Gamblers' Fallacy*. http://gamblers-fallacy.behaviouralfinance.net/Montier2003.pdf. Retrieved : February 2012.

Nofsinger, John R.2001. *Investment madness: how psychology affects your investing – and what to do about it*. USA: Pearson Education

Odean, Terrance. 1998. *Volume, Volatility, Price, and Profit When All Traders Are Above Average*. The Journal of Finance 53(6) : 1887 - 1934

O'Hagan, Anthony., **Buck, Caitlin E., Daneshkhah, Alireza., Eiser, J Richard., Garthwaithe, Paul H., Jenkinson, David J,. Oakley, Jeremy E**., and **Rakow, Tim**.2006. *Uncertain Judgements: Eliciting Experts' Probabilities*. USA: John Wiley & Sons.

Oehler, Andreas., Rummer, Marco., and **Wendt, Stefan**. 2008. *Portfolio Selection of German Investors: On the Causes of Home-biased Investment Decisions*. The Journal of Behavioral Finance 9: 149 – 162.

Parikh, Parag. 2011. *Value Investing and Behavioral Finance*. New Delhi : Tata Mcgraw Hill.

Pompian, Michael M. 2006. *Behavioral Finance and Wealth Management*. USA: John Wiley & Sons.

Phung, Albert.2002. *Behavioral Finance*. http://i.investopedia.com/inv/pdf/tutorials/BehavioralFinance.pdf Accessed: February 2012.

Ritter, Jay R. 1991. *The long-run performance of Initial Public Offerings*. Journal of Finance 46(1) : 3 – 27.

Rozeff, Michael S., and Kinney, William Jr. 1976. *Capital Market Seasonality: The case of stock returns*. Journal of Financial Economics 3(4): 379 – 402.

Sairafi, Kamran., Ståhl, Thom., and **Selleby, Karl**. 2008. *Behavioral Finance – The Student Perspective*. Jönköping International Business School, Jönköping University.

Scharfstein, David S., and **Stein, Jeremy C**.2000. *Herd Behavior and Investment*. The American Economic Review 80(1) : 465 – 479.

Schindler, Mark. 2007. *Rumors in financial markets: Insights into Behavioral Finance*. West Sussex: John Wiley & Sons Ltd.

Sewell, Martin. 2007. *Behavioral Finance*. http://www.behaviouralfinance.net/behavioural-finance.pdf. Retrieved: February 2012.

Seyhun,H.N. 1998. *Investment Intelligence From Insider Trading*. Cambridge: MIT Press

Shefrin, Hersh. 2000. *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*. New York: Oxford University Press.

Shiller, Robert J. 1984.*Stock Prices and Social Dynamics*. Brookings Papers on Economic Activity 2: 457 – 510.

Shiller, Robert J. 2000. *Irrational Exuberance*. USA: Princeton University Press.

Shiller, Robert J. 2002. *From Efficient Markets Theory to Behavioral Finance*. Journal of Economic Perspectives 17(1): 83 – 104.

Shleifer, Andrei. 2000. *Inefficient Markets: An introduction to Behavioral Finance*. New York: Oxford University Press.

Sinha, Anand.2012. *Changing Contours of Global Crisis – Impact on Indian Economy*. <http://rbi.org.in/scripts/BS_SpeechesView.aspx?Id=678> . Retrieved: April 2012

Subrahmanyam, Avanidhar. 2007. *Behavioral Finance: A Review and Synthesis*. European Financial Management 14(1): 12-29.

Summers, Lawrence H.1986. *Does the stock market rationally reflect fundamental values?*. Journal of Finance 41 (3): 591 – 601.

Taylor, Bill., Sinha, Gautam., and **Ghoshal, Taposh**.2006. *Research Methodology: A Guide for Researchers in Management and Social Sciences*. UK: Motilal Books.

Thaler, Richard H. 1988. *Anomalies: The Winner's Curse*. Journal of Economic Perspectives 2(1): 191 – 202.

Thaler, Richard H. 1999. *Mental Accounting Matters*. Journal of Behavioral Decision Making 12(3) : 183 – 206.

Thaler, Richard H.2005. *Advances in Behavioral Finance, Volume II*. USA: Princeton University Press

Tversky, Amos. and Kahneman, Daniel. 1974. *Judgment Under Uncertainty: Heuristics and Biases*. Science: 185(4157). 1124 – 1131.

Tversky, Amos. and Kahneman, Daniel. 1981. *The framing of decisions and the psychology of choice*. Science 211(4481): 453 – 458.

Waweru, Nelson Maina., Munyoki, Evelyne.,and **Uliana, Enrico**. 2008. *The effects of behavioral factors in investment decision-making: a survey of institutional investors operating at the Nairobi Stock Exchange*. International Journal of Business and Emerging Markets 2008 1(1): 24 - 41.

Welch, Ivo. 2000. *Herding Among Security Analysts*. Journal of Financial Economics 15(3).

Zibran, M F., 2007. *Chi-squared test of Independence*. Technical Report, Department of Computer Science, University of Calgary. Canada.

Website(s)

Motilal Oswal Financial Services, <http://www.motilaloswal.com/about_us/>, Retrieved: February 2012.

www.investopedia.com

Appendix A
Structured Questionnaire

"Your honest feedback is of highest importance in the course of my academic research. This information will not be used to serve any other purpose"

ANONYMOUS SURVEY – 35 QUESTIONS

1) What is your age? ☐

2) For how many years have you been investing/trading shares on BSE/NSE? ☐

3) What price range of shares do you prefer to invest in?
High Cap ☐ Mid Cap ☐ Low Cap ☐

4) How much loss did your portfolio incur in the period 2007 – 2009?
>50% ☐ 30 – 50% ☐ 10 – 30% ☐ < 10% ☐ No losses ☐

5) Whose judgment analysis do you trust most while making investments?
Self ☐ Broker/Friends ☐ Media/Expert opinions ☐

6) Do you consider the past performance of a stock before investing in it?
Always ☐ Sometimes ☐ Never ☐

7) Does trading volume of a stock affect your investment decision?
Yes ☐ Sometimes ☐ No ☐

8) Did you subscribe to Reliance Power shares during its 2008 IPO?
Yes ☐ No ☐

9) Did you subscribe to SFS Microfinance shares during its 2010 IPO?
Yes ☐ No ☐

10) You have poor knowledge about Company X's stock and is therefore uncertain about investing in it. Suddenly many of your co-workers and competitors start buying it. How would this affect your attitude towards 'X'?
Positive ☐ Negative ☐ No Change ☐

11) Do you believe it is possible to find future value of a share through detailed analysis of past performance?

Always ☐ Sometimes ☐ Never ☐

12) How easy do you think it was to predict the collapse of SENSEX in the wake of the Global Financial Crisis?

Very Easy ☐ Easy ☐ Difficult ☐

13) How do you think your investments will perform in comparison with SENSEX?

Outperform ☐ At par ☐ Underperform ☐

14) Do you feel you can, on average, predict future share prices better than others?

Always ☐ Sometimes ☐ Never ☐

15) On a scale of 1 to 7(1: low risk), what levels of risk do you undertake? ☐

16) Would you go ahead and invest in a stock if your valuation of a stock is different from that made by a well known expert on some financial news channel or paper?

Definitely ☐ Maybe ☐ Never ☐

17) How often have your investment decisions proved to be right?

>80% ☐ 50 – 80% ☐ <50% ☐

18) Do you fix a target price for buying/selling in advance (say, before start of trading day)?

Yes ☐ No ☐ Sometimes ☐

a. If yes, which of the following criteria will you consider to fix the price?

52 Week high/low ☐

Price/Earnings Ratio (P/E) ☐

Average Price in recent past ☐

Issue Price ☐

Advice from broker ☐

19) Do you use stop losses in your trades?

Always ☐ Sometimes ☐ Never ☐

20) Between P/E ratio and intrinsic value of a stock, which has more weightage in your investment decision?

P/E Ratio ☐ Intrinsic Value ☐ Equal weightage ☐

21) How did you react to the 2008 Crisis and resulting crash in SENSEX

Sell off Shares ☐ Purchase share are low prices ☐ Hold on to existing shares ☐

22) Consider the following situation: The Price of a Blue Chip share is Rs 500. This falls to Rs 100 as a result of a crisis. Analysts are neutral and give hold signals. Will you purchase the share at the new low, keeping in mind the recent high?

Yes ☐ Sometimes ☐ No ☐

23) Does your mind try to justify mistakes committed while making investment decisions?

Yes ☐ Sometimes ☐ No ☐

24) If you hear views from a famous analyst that conflicts with your opinion about a stock, would you change your opinion immediately?

Yes ☐ Sometimes ☐ No ☐

25) What will you do if you are criticized for investing in a losing stock or for selling off a winning stock?

Justify Decision ☐ Be disappointed ☐ Re-think the decision ☐

26) Do you end up sticking with a losing stock (wrong investment decision) for too long hoping for a reversal, or book profits in a winning stock and then felt you could have waited?

Always ☐ Sometimes ☐ Never ☐

27) Have you put off an investment decision expecting new and favorable (positive) information release regarding the stock?

Always ☐ Sometimes ☐ Never ☐

28) Are you able to anticipate the ends of good/poor market returns (reversals)?

Always ☐ Sometimes ☐ Never ☐

29) Suppose an unbiased coin is flipped three times, and each time it lands on 'Heads'. What do you feel would be the outcome of the next flip?

Heads ☐ Tails ☐ No preference ☐

30) Do you save a part of your income for investing in the share market?

Yes ☐ Sometimes ☐ No ☐

31) If you win a lottery of Rs 1 Crore (Rs 10 million) which type of shares would you consider investing in?

High Cap ☐ Mid Cap ☐ Low Cap ☐

32) In 2006-07, if someone had told you that a financial crisis is about to happen in a years' time would you be convinced(On a scale of 1 to 5 : '1' Not convinced , '5' Highly) ☐

33) Can you name some stocks that have been a part of your portfolio in the past 1 year?

34) Do you favor investing in companies that are operating in Kerala, Karnataka and Tamil Nadu, since we are more familiar with their operations?

Yes ☐ No ☐ Indifferent ☐

35) On a scale of 1 to 5, how would you rate your knowledge on a relatively new field which studies financial decision making, called ' Behavioral Finance ' ('5' – Excellent , '1' – Poor) ☐

36) Suggestions (If any) :

THANK YOU FOR SPARING YOUR PRECIOUS TIME.

Rahul Subash (Student Researcher)
Institute of Economic Studies
Prague, Czech Republic