CHAPTER 3

LITERATURE REVIEW

This chapter provides a review of the literature on four behavioral biases under consideration, i.e. overconfidence, optimism (pessimism), the disposition effect and herding. It is a combination of both primary and secondary data studies. The research based on secondary data predominantly provides the background for trading pattern of investors and the impact of behavioral biases on stock markets. On the other hand, primary data based studies offer a more personal account of investors, mainly focusing on their psychology, trading sophistication and demographics. It further explores the research gaps in the literature and finally presents the research objectives.

3.1 LITERATURE OF OVERCONFIDENCE

Overconfidence is probably one of the most researched bias. Several studies consider that this bias is responsible for generating high trading volume of financial markets [95], [117], [118], [119], [60]. These researches suggest that success in past trades makes the investor overconfident of their private knowledge which leads to an increase in trading activity [160]. Some of the relevant works in this area are discussed here.

According to [95] overconfident investors have a tendency to trade more. They believe returns to be highly predictable and expect higher returns as compared to relatively less confident people. [117] defines overconfidence as the investors’ tendency to overestimate the precision of their knowledge about the value of a security.

[41] develop a model based on overconfidence of investors who overestimate the precision of their private signals and concludes that the overconfidence leads to negative serial correlation in prices (price reversals).

[60] formulate a multi-period market model to estimate overconfidence. They propose that overconfidence is enhanced in those investors who have experienced high returns. As a result, they trade more frequently. Therefore overconfidence leads to increase in trading volume. On the other hand, a loss in the market reduces overconfidence level and subsequently the
transaction volume. They assign a positive relationship between volume of transaction and delayed returns of the market.

The theoretical concept on overconfidence is empirically tested by [119], [5] and [6] who provide evidence that overconfidence leads to greater trading volume in financial markets. Using the data from individual investors’ account held with a large U.S. brokerage firm, they propose that higher trading in turn leads to lower expected utility or poor portfolio performance.

[71] investigate the persistence of overconfidence in the financial markets. It is suggested by the fact that overconfident traders trade more aggressively than their rational counterparts in order to exploit the mispricings. They find that there are two factors behind this behavior. These are: the underestimation of risk by the investors and overestimation of the success of their own trading strategies.

[165] and [111] the presence of overconfidence in financial professionals like fund managers. [165] state that professionals overestimate their ability to choose better performing stocks. They compare their result with laypeople and find that the professionals are more overconfident than layman investors. [111] adds to this knowledge by finding that 74 percent of fund managers perceive themselves to be above average in their performance.

[61] suggest that considering past returns to be a proxy for overconfidence, there will be a positive lead-lag relationship between past returns and trading volume. They elaborate that investors mistakenly attribute gains in wealth to their ability to pick better stocks. Hence, they underestimate the variance of stock returns and trade more frequently in future periods.

[64] study the relationship between current trading activity and past returns using vector autoregressions across 46 countries. They find that there exists a positive relationship between trading volume and past returns and it is much stronger in developing countries as compared to developed countries. Fagerstrom (2008) analyses the historic data of Institutional Brokers’ Estimate System (IBES) and finds that analyst’s are overoptimistic and overconfident in their expected growth estimates.
[66] combine the equity trading data of investors with their psychological profile to study overconfidence and sensation seeking tendency. They find that the investors prone to both these biases trade more frequently.

[161] conducts a survey and detects that investors of Kerala (India) are overconfident about their ability to outperform the market. The respondents believe that based on the information they have, they are able to predict the future movement of stock prices.

3.2 LITERATURE ON OPTIMISM:

The literature on optimism is far and wide and it goes back to 1930’s when [84] noted that optimism causes the illusion of boom and pessimism causes its disillusion or bust. Optimism is detected in a variety of fields. [108] acknowledges that excessive optimism in corporate management is the major cause behind their debt problems. This bias is also seen in sales forecasts by [63]. [143] find that domestic investors are more optimistic about their own equity market than foreign investors. Optimism in analysts’ forecasts is identified by [23], [50], [37], [24], [51]. [166] detect this bias in Japanese institutional investors. Various researchers explore the presence and impact of optimism in financial markets [70], [59], [139] and [12]. [72] and [15] identify the factors behind this bias. We classify this wide literature into four strands. The first strand deals with drivers of optimism. The second strand of literature focuses on optimism of analysts in forecasting expected returns and projecting target price. Third strand deals with identification of this bias in investors. And the fourth strand explores the presence and impact of this bias on financial markets. This section reviews some of the noteworthy studies done in each area.

3.2.1 Drivers of optimism (pessimism):

[72] identify the drivers of investors’ optimism and fear (pessimism) based on their return expectations, return tolerance and risk perceptions. They use a data set of brokerage records as well as monthly survey measurements to analyze the impact of the past return and past risk on the drivers of optimism (pessimism). They discover that past returns positively impact return expectations, return tolerance and negatively impact risk perceptions. They reason that investors are prone to hot hands fallacy, which means that past returns will continue in future. This makes
them more optimistic in return expectations if there past returns are positive. However, past risk has no effect on these parameters.

In Indian context [15] conduct a survey to identify the factors influencing investors’ optimism. They find that investor optimism is influenced by four factors. These are macro-economic factors, internet led access to information and trading, performance factor and confidence level of institutional investors and investors’ belief that the stock market is the best game in town.

3.2.2 Analyst optimism:

[23] and [50] reveal that analysts generally make “buy” or “strong buy” recommendations as compared to “hold” and rarely “sell”. The authors suggest that their optimistic recommendations results in an upwardly biased estimate of expected returns. [37] studies the relationship between optimism and stock returns. The author investigates that the returns of the firms for which the analysts have given optimistic forecasts, give lower return than those with pessimistic forecasts. Moreover, this relationship is unaffected by losses. [24] relates analysts’ recommendations with their earnings forecasts. The author examines that the recommendations are not consistent with the valuation of earnings forecasts as these recommendations are more optimistic. Further, the investors who act on “buy and hold” strategy should rely on analysts’ earnings forecasts rather than their recommendations. [51] find that optimism bias in the forecasted estimates differs with firm size and analysts’ recommendations.

[24] examine optimism of analysts at a global level in setting target prices. Using a dataset of 41 nationalities they observe that analyst optimism is aggravated when there are potential benefits of biased research. However, countries with good infrastructure i.e. strong investor protection transparent financial environment and strong cultural forces mitigate such optimism of analysts in target prices.

[31] analyze a sample of 3416 analyst recommendations and 3239 earning forecasts and find that analyst optimism contribute to future stock price crash in China. They suggest that when analysts are overly optimistic in their forecasts, the negative information cannot be timely revealed. Thus, negative information gets accumulated and leads to stock price crash in future.
3.2.3 Identification of optimism (pessimism) bias in investors:

[166] investigate optimism bias in Japanese institutional investors. They use survey based data and find that the optimistic investors are more sensitive towards positive market news. They selectively incorporate only good news in their decision making process. Further, investors affected by optimism bias tend to undervalue the risk of familiar investment products such that they are more optimistic towards the domestic market than foreign markets.

[122] recognizes optimism to be an emotional bias. He states that undue optimism can be financially harmful as it can create an illusion of some unique insight or upper hand for the investors. This can cause the investors to have a “rosy” outlook of their portfolio performance. His study tries to help the fund managers and investors in identifying this bias using updated case studies and psychological quizzes. He suggests that fund managers can use this knowledge in creating “behaviorally modified” investment portfolios for optimal returns.

3.2.4 Presence and impact of optimism (pessimism):

[70] state that optimistic agents overestimate their expected payoffs, while pessimistic agents underestimate it and only rational agents assess their payoffs correctly.

[26] investigate optimism in entrepreneurs. They find that a chance success of a project can make the entrepreneurs optimistic such that they start investing in more projects without gathering further information. Therefore, this bias results in excessive investments.

[59] develop a general model for optimism and pessimism to analyze the impact of these biases on financial markets. They find that optimistic traders have a tendency to buy more or sell lesser quantities whereas pessimistic traders sell more or purchase less than if they were realistic. They also find that unrealistic trader (who is either optimistic or pessimistic) earns negative, higher or lower expected profit than realistic traders.

[13] reports the case of over-optimism in dot-com era. The author suggests that the internet bubble is supported by the combination of over-optimism and momentum trading. These investors capitalized on the fact that the prices of internet stocks will rise. However, by late
1990’s a large number of investors started selling these stocks, such that the optimism of investors got converted into pessimism who began to overwhelm the optimistic ones.

[139] find that excessive optimism can create speculative bubbles in financial markets by inflating the prices of securities above their intrinsic values. They further state that if bubbles last long enough, some pessimists might become convinced that they are wrong and can convert into optimists and in the process they are likely to intensify this phenomenon.

[12] use a pricing kernel technique to measure the presence and impact of optimism. Two types of pricing kernels namely: empirical pricing kernel and theoretical pricing kernel have been used. The empirical technique provides the objective estimates of S&P 500 for the period of 2005 to 2009. The theoretical technique provides the framework for the calculation of sentiment function which is subsequently used to derive the measure of optimism. Their results reveal that time series a property of excessive optimism appears to generate a negative relationship between perceived risk and return.

3.3 THE DISPOSITION EFFECT

[136] introduce the concept of the disposition effect. It is defined as the tendency of investors to hold on to losing stocks and sell winning stocks early. This concept is built on the implications of prospect theory [83]. The possible reasons for this effect as proposed by the authors are loss aversion, seeking pride, mental accounting and regret avoidance. They stipulate that realization of gains in individual stocks can make the investors proud. The major research work in the disposition effect took place in the late 1990’s. Subsequent academic formulations to test the disposition effect are as follows.

[118] documents the presence of the disposition effect using market data on 10000 discount brokerage accounts of individual investors. In his study, the ratio of realized gains over total gains (i.e. proportion of gain realized or PGR) and the ratio of realized loss over total loss (i.e. proportion of loss realized or PLR) are taken as measures to calculate the disposition effect. He finds that a majority of investors are reluctant to realize their losses.

[175] presents an explanation for the disposition effect. The author advocates the justification hypothesis which states that individuals stick to previous unsuccessful actions
because they feel the need to justify or to rationalize their decisions. People are reluctant to admit that the prior decisions were incorrect and therefore they become prone to the disposition effect.

[65] find the evidence of the disposition effect in the Finnish stock market using a data set of shareholdings and trades of individual and institutional investors for a period of year 1994-1997. [54] analyze the presence of the disposition effect in China. They argue that investors with less trading sophistication and less trading experience are more prone to this bias. [146], using a sample of 13,460 Chinese investors note that a large majority of Chinese investors exhibit the disposition effect and that it drives momentum in Shanghai stock exchange.

[125] analyzes the trading records of 78,000 clients from the discount brokerage firm and documents the presence of the disposition effect. The author explores the relationship of firm size and the disposition effect and states that large-cap firms are more prone to this bias.

[160] differentiate between overconfidence bias and the disposition effect where the former bias should be studied at market level and the latter bias at the individual stock level. The data set comprises of monthly observations on all NYSE/AMEX common stocks. Their results are consistent with the disposition effect trading and the trading of overconfident investors in relation with trading volume. They also show that both overconfidence and the disposition effect are more marked in small-cap stocks and in prior periods where individual investors hold a higher proportion of shares. Vlcek and Wang (2007) conduct controlled experiments on the students of university of Zurich to study the disposition effect. They find that rebalancing the prospect theory with a fixed reference point or the justification hypothesis does not explain the disposition effect. [88] uses multiple measures of valuation uncertainty and behavioral bias proxies to find that individual investors exhibit stronger disposition effect when stocks are harder to value and when market-level uncertainty is higher. [46] employ a database of orders and trades of Indian investors to study the relative effects of the disposition effect and overconfidence in a unified framework. They compare the impact of these two biases within investor categories (individual versus institutional investors) and find that individual investors are more prone to the disposition effect.
3.4 THE HERD BEHAVIOR

The review of literature shows several studies have been done to analyze the herd behavior in stock markets.

One of the pioneer researches on herding is done by [91]. They study the herd behavior in conjunction with positive feedback trading in destabilizing the stock prices. They differentiate between the two behaviors by referring herding as the tendency of investors to mimic the investment activities of other fund managers at the same point of time. On the other hand, positive feedback trading refers to the tendency of buying the stocks showing winning trend while selling the losers. The use quarterly portfolio holdings of equity pension funds as the data set starting from year 1985 to 1989. The results of their study do not show any significant evidence of herding or positive feedback trading by pension fund managers except in small stocks.

3.4.1 Factors behind herding

[129] examine some of the factors that could lead to herd behavior in the investment decisions of money managers. They develop a model which separates smart managers from biased (dumb) managers. Smart managers are those who receive informative signals about the value of an investment, whereas the biased (dumb) managers receive purely noise signals. They identify that reputational concerns and ‘sharing-the-blame’ effect, were some of the factors that could drive managers to herd. In a similar study, [48] find that money managers deliberately follow the actions of a benchmark manager so as to protect their reputation.

[36] detect that herding is more likely to occur during the period of market stress. They explain that investors become anxious during these periods as the level of uncertainty is higher. In order to reduce their anxiety they seek for conformity and certainty. Thus, they become doubtful of their own beliefs and tend to follow the market consensus.

[33] and [76] argue that herding not exists during market stress, but it also occurs during normal market conditions. However, this behavior becomes more apparent during market stress.
find that informational learning and information cascade can induce herding in investors. This implies that investors learn from the actions of previous investors. They follow the footsteps of their predecessors to an extent that they ignore their own private information.

**3.4.2 Measures of herding**

[36] provide a test to identify herding behavior in the market. They measure average proximity of individual asset returns to the realized market average with the help of cross sectional standard deviation (CSSD). They analyze that market shifts between the normal phase and extreme phases. Further, they find that herding prevails in periods of market extremes. They argue that when investors follow aggregate market movement, disregarding their own judgment (herding) then individual asset returns will be close to overall market return. Thus, the value of CSSD gets reduced.

[116] use positive feedback trading as a measure for herding. They state that herding occurs when investors trade in the same direction over a period of time. They suggest that high level usage of positive feedback trading among institutional investors indicates the presence of herding.

[33] extends the work of [36] and establishes a nonlinear relationship between level of equity return dispersions and the overall market return. Cross-sectional absolute deviations (CSAD) are taken as a measure of dispersion.

[76] develop a measure to calculate the degree of herding. They term it as H-statistic which takes into account the fundamentals of the firms and the influence of time series volatility. With this they can differentiate intentional herding from spurious herding. They also evaluate the direction towards which the market may be herding.

**3.4.3 Implications of herding**

[129], [4] and [21] suggest that herding behavior feeds the speculative bubbles that can lead to substantial losses once the bubble bursts.

Herding also leads to suboptimal use of relevant information which results in inefficient decisions. This suggested by various researches that study analysts’ earning forecasts [167].
[120], [45]. [120] analyzes that herding leads to a decrease in dispersion and an increase in the mean of expert forecasts, which creates a positive bias in the earnings estimates. This form of behavior increases the unpredictability of earning. [45] affirm these results by investigating herd behavior on U.K. (1986-1997). They discover that 50 to 60 percent of herding forecasts are observed within 12 to 9 months of an earnings announcement. However, herding decreases as the actual announcement date approaches. [162] attribute herding to be the main cause of volatility in Chinese stock markets.

3.4.4 Evidence of Herding

[119] use their approach to find herd behavior in the U.S. Stock market. [78] use the measure of [119] to investigate herding in Tokyo stock exchange. They detect this bias in three groups of investors- individual, institutional and foreign. They find that Japanese individual and institutional investors tend to engage in positive feedback trading strategies while foreign investors base their decisions on the information.

[76] detect the presence of herding in herding in US, UK, and South Korean stock markets. In contrast to [36], they find that herding prevails even in normal market conditions.

[33] examine the presence of herding in 5 financial markets, including both developing and developed. These are US, Hong Kong, Japan, South Korea, and Taiwan. They find that herding prevails in emerging economies like South Korea and Taiwan, while, it is not detected in developed countries like US & Hong Kong.

[30] investigate the presence of herding in the Italian stock market. They find nonlinearity in herding pattern using methodology given by [33]. They also calculate H statistics as a measure of degree of herding which differentiates between spurious and intentional herding. Intentional herding is indicated by a decreasing H-statistics and is found to be greater in bull phases and in small-cap companies on the Italian stock market.

[47] and [162] examine the presence of the herd behavior in Chinese stock markets. They analyze the A and B shares of Shanghai and Shenzhen stock markets. However, their results are contradictory. [47] find that there is no significant herding in both the markets, whereas [162] confirm its presence in Chinese stock markets.
[93] examine herding patterns in Indian and Chinese stock markets. They find that herding behavior is greater during extreme market conditions in both markets, but the pattern is different. In the Chinese market, herding is greater when the market is down (bear phase). However, in India herding is greater when market is up (bull phase).

[92] observe that the presence of market wide herding in Indian stock markets is not very severe. They find that FII’s do not significantly impact herding, however Mutual Funds increase herding. They also find that Nifty returns have no impact on herding. They document that this bias is on a rising trend from 2003-2005. However, post 2006 it started to decline. They suggest that periods of market crisis can help return markets to equilibrium, and that herding can be more apparent before market stress, rather than during it.

3.5 LITERATURE REVIEW ON SURVEY OF BEHAVIORAL BIASES

This section explores various noteworthy survey based studies in the field of behavioral finance. These are divided into three themes; factors behind the individual investor behavior, effect of demographics on investor behavior, and the role of psychological biases on investor behavior.

3.5.1 Factors behind individual investor behavior

[115] use a questionnaire to determine that investor behavior is influenced by factors such as corporate earnings, diversification needs, feeling for firms’ products, past performance of stocks and portfolio and stock brokers’ recommendation.

[87] analyze the factors influencing the short term decisions of investors using analysts’ recommendations to hold or sell a stock. The results indicate that a strong form of analyst recommendation report can help in reducing the propensity to hold on losing stock or sell winners early i.e. the disposition effect

[1] explores the factors influencing investor behavior in U.A.E. that belongs to five categories self/firm image coincidence, accounting information, neutral information, advocate recommendations, personal financial needs.

[85] study the behavioral profile of Japanese investors and find that they were risk takers, frequent traders, make poor trading decisions and buy recent winners.
provide evidence that individual investors depend upon heuristics for making investment decisions and their behavior is highly influenced by biases like overconfidence, representativeness etc.

**3.5.2 Effect of Demographics and trading sophistication on investor behavior**

[6] report that men trade more excessively than women due to which their net returns get diminished. They conclude that women are risk averse while men are overconfident as they frequently rearrange their portfolio, which leads to unwarranted mistakes that can create losses.

[104] investigate that small (individual) investors of NYSE get more influenced by optimistic stock recommendations by security analysts as compared to large (institutional) investors. They exert positive pressure on buy and strong buy recommendations and no pressure on hold recommendations.

[54] employ account-level data from a national brokerage firm in the People’s Republic of China to detect the impact of factors like investor sophistication and trading experience. They find that investor sophistication and trading behavior together can reduce behavioral bias like the disposition effect.

[75] study the effect of several behavioral biases like disposition effect, herding and the availability heuristic on Israeli portfolio managers and find that and female investors are more highly affected by these biases than their male counterparts and past trading experience reduces this effect.

**3.5.3 Impact of psychological biases on investor behavior**

[101] analyze the risk management behavior of fund managers in Germany and detect the presence of herding in these professionals. On being asked, most of them agreed that discussion of an investment decision with colleagues reduces the pressure of being successful. The authors reason that strong incentives and “sharing-the-blame” effect promotes herding in these professionals.

[19] detect the presence of overconfidence in contribution pension plan members. They judge the level of overconfidence by matching the level of their knowledge with the level of
certainty, taking into consideration their respondents’ experience and education. They find that this bias can cause individuals to overestimate the level of certainty of their response, even if they have limited knowledge.

[105] provides a deeper insight into the mindset of investors. In his book, he provides a set of fifty psychological experiments that help the investors to detect the biases like overconfidence, herding, representativeness and home bias, in themselves as well as others.

[73] analyze the systematic differences in the investment objectives and strategies of investors. They employ transaction level and survey based data of Dutch investors to find that speculators have higher aspirations, greater risk seeking ability and greater overconfidence. They also underperform in comparison to those investors who invest for saving and retirement purposes.

[126] conduct in-depth interviews and capture eight biases in Indian investors. These are reliance on experts, overconfidence, self control bias, categorization tendency, budgeting tendency, socially responsible investing bias, and spouse effect. They also segment investors’ biases into four categories, namely: the novice learner, the competent confirmer, the cautious anticipator and the efficient planner.

It can be seen that there have been significant contributions in the field of behavioral finance. Nevertheless, lacunae still exist in the body of knowledge that leads to the necessity of research in this field.

3.6 RESEARCH GAPS

Research in behavioral finance is at an evolving stage. Each new development brings a new perspective into the picture. Researchers have captured behavioral biases and its impact on various economies like U.S., U.K., Finland, Taiwan, China, India and Japan. However, most of the research work is skewed towards the developed economies like U.S. and U.K. The developing economies like India are still untapped where the research is still at a budding stage. Thus, these regions provide tremendous scope for researchers to investigate the behavioral anomalies in individuals as well as markets. Further, taking into consideration the obvious disparities between developing economies like India and a developed ones like the U.S. with
respect to age of investors, level of sophistication, level of trading activity, norms, rules and regulations, it will be interesting to compare their behavioral aspects.

Research in emerging markets, specifically India is mostly confined to survey based studies. It is important to note that, although surveys can capture a number of biases at a time and can give a fair picture of the investors’ psyche in the current time period; they are insufficient in providing the evidences of behavioral influence on the stock market over a period of time. This can be achieved with the help of secondary data on the stock market indicators. To the best of our knowledge, there are not many studies in India that utilize the secondary data for this purpose. Thus, the present study tries to bridge this gap by combining the advantages of secondary data and survey based approaches. Accordingly the research objectives have been framed and are discussed in the next section.

3.7 RESEARCH OBJECTIVES:

Based on the literature review and gaps identified, following research objectives have been framed.

1. To investigate the presence and analyze the impact of heuristic driven biases on different stock market indicators.
   1.1. To investigate the presence and impact of overconfidence in the Indian equity market
   1.2. To investigate the presence and impact of excessive optimism (pessimism) in the Indian equity market

2. To determine the presence and analyze the impact of Frame dependent biases on different stock market indicators.
   2.1. To determine the presence and impact of herding in the Indian equity market
   2.2. To determine the presence and impact of the disposition effect in the Indian equity market

3. To investigate which bias is most pronounced in the Indian context.

The methodology used to fill these gaps has been discussed in the succeeding chapter.