An Empirical Inquiry into the behavioral Dynamics of South Asian Emerging Stock Markets

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DEDICATION

I dedicate my research work to my family and my friends. A special feeling of gratitude to my loving parents, whose words of encouragement and push for firmness ring in my ears. My whole family never left my side and are very special. This work is especially dedicated to my father who always motivated and encouraged me throughout this journey.

I also dedicate this dissertation to my friends, teachers, and to all those who believe in the richness of learning.

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ABSTRACT

An Empirical Inquiry into the behavioral Dynamics of South Asian Emerging Stock

Markets

This study traces behavioral patterns which influence the aggregate market in terms of under and overreaction. These reactions are mostly observed in the form of excess volatility and unsystematic patterns in trading volumes. Self-attribution, anchoring, herding, disposition effect, and limited attention bias are selected for this study. The study is conducted on Karachi Stock Exchange, Bombay Stock Exchange, Dhaka Stock Exchange, and Dow Jones Industrial Average for Pakistani, Indian, Bangladeshi, and U.S stock markets respectively. The study is conducted for the period 2009 to 2018 using secondary data. It was found that the overconfidence bias can be equally observed in Pakistani, Bangladeshi, and the U.S stock markets. Using nearness to a historical high and nearness to a 52-week high as anchors, it was found that all sampled stock markets under-react to new incoming information. Herding bias was confirmed in Up and Down extreme market conditions for Pakistani and Bangladeshi stock markets respectively. Similarly, the turnover effect was confirmed in low turnover stocks for Down extreme market conditions in Pakistani and Bangladeshi stock markets only. The disposition effect is also confirmed in Pakistani and Bangladeshi stock markets. The limited attention bias is tested and confirmed in terms of the significant relationship between price momentum profits and trading volume in Pakistani and Bangladeshi stock markets. Owing to the existence of these behavioral biases in the sampled stock markets, the market over hypothesis was tested through the Average Cumulative Excess Returns analysis. The results confirmed overreaction for Pakistani and Bangladeshi stock markets. This implies that losers in one testing period become winners in subsequent periods due to the investor's overreaction and vice versa. Moreover, excess volatility in relation to market reactions and trading turnover is tested. It was concluded that behavioral biases in sampled stock markets lead to excess volatility while market overreactions along with excess volatility influence the trading turnover. Interestingly, investors' decisions in such trends are dependent on behavioral biases, and as a result market overreaction becomes more prolonged and denser. In other words, the over-trading on part of investors motivated by behavioral biases results in aggregate excess volatility primarily because of the underlying momentum in trading trends. The results of the study are useful for individual investors in their general awareness of behavioral biases, for regulators in coming up with more efficient models regarding stock price estimation, and for mutual funds managers to improve the safety of their investments.

Key Words: Anomalous Behavior, Behavioral Biases, Extreme Market Conditions, Market Under and Overreaction, Momentum Profits

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CHAPTER-1

INTRODUCTION

This section is aimed to establish a sound theoretical background for the study by necessitating and elaborating on the evolution of behavioral finance. In the following sections, a funneling approach is employed starting from general economic decision-making and coming up with the role of behavioral biases in economic rational decision-making. Which leads to the Problem statement, research questions, objectives and significance of the study.

1.1 Economic decision-making

Economics can be defined as the optimal usage of limited resources. It studies how firms and ultimate consumers interact with each other to regulate the allocation of resources. Such a given relationship cannot be truly comprehended unless an underlying theory is studied that governs the said relationship along with the study of key features of the individual (traits) involved in such decision-making. In such a case, the theory of decision-making lays the foundation for any underlying economic theory. Finance and economics intellectuals are therefore responsible to describe the behavior of individuals, markets, and aggregate economies. Decision-making is therefore the core of economics and finance.

The decision-making models are assumed to render major roles. i.e to describe and then advocate the decision-making process. In such cases, the descriptive models describe or explain the actual process of decision-making while the normative models propose various sets of measures or benchmark behaviors, against which the real behavior is matched. Psychologists are concerned about both sides of the decision-making role. On one hand, they do study the actual behavior and on the other hand, they try to devise measures, benchmarks, or thresholds which can be used for the comparative analysis between actual and standard measures.

As finance and economics scholars, we do require a firm foundation in terms of an underlying theory of decision-making for financial and economic modeling. The normative models in such cases are more advisable as they are simple in presentation. However, economists and finance specialists are much eager to take the "world as it is". The positive models in normative models are more likely to give a more reasonable background in the economic modeling. It is very important to give a model that discusses the decision-making process, without compromising on the real aspects of decision-making.

Therefore, we are aiming to investigate the core foundation of economic decision-making first and then deducing towards the specificity of the issues under study. As evident from the definition of economics, the best utilization/allocation of resources poses a major question. What is best or not? Reflects the rationality or reasonableness of the individual. It is, therefore, preferable to talk about rationality first.

1.2 Rationality

Aristotle considers that rationality is what differentiates mankind from other animals (Joachim, 1951). The normative decision-making models are usually considered identical to the concept of rationality. Rationality is the measure of the pertinence of a decision. According to the Oxford dictionary, rationality is defined as "the ability to think clearly and make decisions based on reason rather than emotions synonym reasonableness." While the oxford companion to philosophy states that rationality is a "feature of cognitive agents that they exhibit when they adopt beliefs based on appropriate reasons" (Honderich, 2005).

Irrationality or non-rationality on the other hand reflects the lack of reasoning or even an individual who is capable of rationality but he/she bypasses or infringes the generally understood assumptions of rationality, which is also deemed as irrational. Similarly, judgments and beliefs are considered irrational on the same principles. Stringent principles are required for different beliefs and preferences, for instance, a large number of so-called beliefs are neither rational nor irrational because they cannot be easily assessed on the basis of reason. So, if rationality and irrationality are dependent upon reasoning and justification, it will be quite hard to call something irrational in the absence of any explanation for such behavior. As a matter of fact, a new question emerges what standards can be used to measure the reasonableness of a notion. The reason is believed to be the internal consistency of beliefs that govern our actions. The relationship between the persistence of our actions and beliefs is dubious. For instance, for an individual who faces similar conditions, the choice of actions may be inconsistent, possibly due to eagerness for variety. As stated by Gwilym, (2009) "The fact that I wear a pair of shorts one day and a pair of long trousers on another equally warm day may be a sign of irrationality, that I choose my clothing randomly, or it may be that I enjoy the variety". Therefore, reasonableness is not merely subjected to consistency only. So, logic is yet another factor that is added to the consistency factor in order to understand rationality. However, logic is based on certainty and demonstration. Conversely, most human decisions are taken on the basis of likelihood or probability.

Logic does not explain 'reasonable' sufficiently. In such instances, Aristotle's views seem more meaningful also endorsed by Gwilym, (2009). Aristotle considers an action or notion as reasonable if it creates "eudaimonia". Eudaimonia refers to happiness or virtue. According to Gwilym, (2009) "human flourishing" as meaning to Aristotle's Eudemonia looks more appropriate in this age. Nowadays, the word rationality is seen as the opposite of emotions and instincts.

Rational beliefs are the product of relevant proof or evidence. However, as mentioned earlier, formal evidence can be relevant only to some narrow fields. Demonstrative evidence when backed with mathematical justification can only result in acceptable reasonableness of some notion.

In reality, as probability or likelihood governs human life so, the theory of probability is serving as a guide to indicate the reasonableness of some underlying notion or action. In other words, individuals take into account the Bayesian rule of inference while estimating the outcomes associated with some actions or beliefs. Bayes theorem has a significant role in the updation of the decision-making process. It involves updating past probabilities based on current evidence in order to come up with new accurate subsequent probabilities.

In a nutshell, it can be deduced that rationality is based on the level of "eudaimonia" as proposed by Aristotle. Moreover, Eudaimonia can be translated to utility or satisfaction in modern terms. Furthermore, the reasonable factor in rationality is also backed by the Bayesian's new updated probabilities.

Today, most of economic and finance theories rely on the rational choice theory. The rational choice theory is linked with self-interest and the invisible hand motives. The theory testifies that individuals involved in an economy are rational hence taking rational decisions on the basis of reasonable and logical evidence. Furthermore, these rational individuals are assumed to consciously maximize their benefits and minimize their potential losses. The rationality assumption states that individuals responsible for decision-making are rational, hence undertaking rational choices based on the rational choice theory to get favorable results for self and the aggregate.

The rational choice theory was first discussed by Adams Smith in terms of the invisible hand and self-interest in 1776. The theory of the invisible hand is based on the premise of self-interest. “The invisible hand” is a symbolic manifestation of invisible forces that run the free market economy. The core underlying assumptions are self-interest, freedom of consumption and production, and the good of the aggregate society. Individual demands determine the aggregate demand and supply, leading to price movements and overall trade. The invisible hand theory implies that equilibrium is achieved without any external interference in the economy. The theory is based on the rational choice motive, self-interest, or rationality. It is inferred from the invisible hand theory that individual rationality results in aggregate rationality of the whole economy hence benefiting the overall society at large.

Now coming to finance, individuals especially investors are impassive or unemotional according to the traditional theories of finance. In other words, individuals make most decisions based on rational choice rather than emotions or instincts. Based on this notion, various models have been proposed by proponents of traditional finance. Mainly, these include the Arbitrage theory, portfolio theory, the capital asset pricing theory (CAPM), and option pricing theory proposed by miller and Modigliani, Markowitz, Linter, and Black, Black Scholes, and Merton respectively (Statman, 1999). Eugene Fama’s Efficient Market Hypothesis (EMH) is yet another most important theory in traditional finance. Traditional finance states that a rational individual will try to maximize his/her utility or return/output/benefit from his investment based on some level of risk. Therefore, Baker & Wurgler (2006) proposed that investors are rational and their core emphasis is on the trade-off between risk and return.

The efficient market hypothesis was proposed by Eugene Fama in 1960 in his Ph.D. dissertation. It states that stock prices represent all relevant and available information and is traded at the true fair price all the time. It is, therefore, that individual stocks cannot earn abnormal returns at a given time as compared to the market returns. Weak, semi-strong, and strong are the three variations of EMH.

The weak form of efficiency assumes that existing stock prices are depictive of all available information, while past information has no relevance to current prices. The semi-strong form of efficiency states that stock prices reflect all the publically available information while the strong form of efficiency states that stock prices reflect all available public and private information therefore a perfect market exists, restricting insider trading.

1.3 Arguments against Rational Choice Theory

The theory of rational choice behavior and the invisible hand is not endorsed by various economists. These economists have proposed that individuals do not necessarily make rational decisions all the time. Therefore, multiple studies have been conducted to investigate the deviant behavior existing in the rational decision-making models. The rational choice theory is thoroughly criticized by many researchers, for instance, Babajide & Adetiloye (2012) state that investors are involved in irrational decision-making because of wrong judgments, subjective interpretation of a similar situation, and biased perceptions.

The existence of perfect and complete rationality is often questioned by economists and various pieces of evidence in the form of psychological and behavioral effects are put forward against perfect rational decision-making. More studies were conducted in the later ’70s and early 80’s to compare rational behaviors with actual behaviors. Researchers found that an investor’s decision-making process is influenced by heuristics, psychological biases, social and demographic factors, hence perfect rational decisions cannot be achieved (e.g., Baker & Wurgler, 2006; Barnea et al., 2010; Gärling et al., 2009; Kumar & Lee, 2006). Various other studies found investors' partial rational decision-making (e.g., Muhammad & Abdullah, 2009).

Investors do not have access to more important information in their decision-making concerning the problem definition and the criteria (H. A. Simon, 1956). Slovic (1972) and Shefrin (2001) stated that investors are imperfect in the processing of information. Moreover, these investors undergo mistakes due to their perceptual problems. Similarly, Simon (1956) proposed that in decision-making concerning a complex situation, individuals are unable to process information adequately while the traditional finance theories provide an unjustified behavioral explanation. Ahmed et al. (2011) concluded that Pakistani investors are unable to make rational decisions by utilizing all available information. Hirshleifer & Teoh (2003) found that due to constraint concentration span, investors ignore the significant features of financial statements which are not openly disclosed. Similarly, Grossman and Grossman & Stiglitz (1980) stated that a perfect information market is impossible to exist in the real world. Letkiewicz & Fox (2014) argued that different complications may exist in the real-life market.

Statman (1995) proposed that the Assessment of risk and the underlying framing issues are the two problems associated with behavior and psychology in investment decision-making. The process of risk assessment helps to create a system regarding information for all the relevant levels of risk. Therefore, the mechanism of how information is processed by investors relies on the presentation of such information. It is well established that where risk and uncertainty are involved in decision-making, feelings act as an important influencer (e.g., Forgas, 1995; Loewenstein et al., 2001). Emotions have also an established influence on decision-making (Fenton-O’Creevy et al., 2011). The short-term constructs affect decision-making like fear, anxiety, and greed

(Statman,2011). Similarly, Kahneman & Riepe (1998) state that based on financial psychology, various irrational components of human cognition, influence investment decisions.

Daniel et al. (2001) found some major trends in the investment behavior of decision-making which stated that individual investors do not participate in various modes of investment. They found that generally, individual investors tend to be loss averse, past performance is used as an index for current investment decisions and the trading activity is often aggressive in nature. Conlisk, (1996) on the other hand, stated that individuals tend to misjudge statistical independence, are unable to incorporate new information in order to come up with updated probabilities, misinterpret the causality, use irrelevant information, exhibit over-confidence, ignore the significance of the law of large numbers. Similarly, March (1994) proposed that certain important dimensions act as important limitations to rationality. These include an individual's limited comprehension, defective memory, limited concentration, and constrained communicability.

The Efficient Market Hypothesis states that stocks are always traded at their true fair prices and therefore, mispricing cannot occur at a random time. In other words, undervalued and overvalued stocks cannot be purchased and sold respectively in the market. Hence it is impossible to beat the aggregate market through selective trading. The famous Efficient Market hypothesis (EMH) is challenged by different researchers on the basis that arbitrages fail to offset the mispricing brought by individual irrational decisions. Shleifer & Vishny (1997) stated that arbitrage is dependent upon its cost. Arbitrages may incur high costs due to the regional variations from efficient price levels. Daniel et al. (2001) add risk factors by stating that mispricing in arbitrages cannot be eliminated because of the risk aversion behavior of the arbitrageurs. De Long et al., 1990) argued that irrational individuals are over-confident in nature and they can benefit from this in terms of higher returns by higher risk tolerance. Similarly, irrational investors can earn more as compared to rational investors when share prices influence the fundamentals by affecting the corporate investments (Hirshleifer et al., 2006). Ferris et al. (1988) also state that abnormal returns for stocks having high earning yields, high book-to-price ratios, disproportionate volatility, high book-to-price ratio, and short-term momentum prices and long-term reversions contradict the efficient market hypothesis.

1.4 Bounded Rationality

In practical circumstances, deviation from rational behavior is observed especially in cases of uncertainty, complexity, or information incompleteness. Here comes another important concept called bounded rationality. It is concerned with cognitive barriers to decision-making and it works on the assumption that individuals have limited decision-making abilities (Simon, 1956). The core function of decision-making is supposed to be satisfaction rather than optimization (March, 1994). Such a situation is referred to as minimal rationality by Rubinstein (2001). Herbert A. Simon, 1997) considers bounded rationality as the main theme in the behavioral decision-making of investors.

Bounded rationality was first defined by Herbert Simon- a Nobel laureate in 1956. It was stated by Simon (1956) that no matter how intelligent are human beings in learning and decision-making, they are expected to fall short in contrast to the ideal level required for rational decision-making therefore, individuals tend to be satisfiers rather than optimizers subject to the limitations related to the use of information and computation. Individuals do not specifically avoid rationality entirely but rather they are concerned with maximum satisfaction rather than full optimization. Since optimal behavior requires relatively more resources of knowledge and capabilities to interpret such sources of knowledge, it is costlier than mere satisfaction.

Bounded rationality does not imply irrationality necessarily. In other words, individuals may not be irrational but rather bounded rational at times. Several contradictions to the rational choice theory can be explained by bounded rationality. Conlisk (1996) therefore states that human cognition is a limited resource therefore several researchers have proposed bounded rationality as another viable alternative model for explaining individual and aggregate behaviors concerning financial decision-making. For instance, Hoffmann et al. (2006) state that investors have bounded rationality in a world that is imperfect in many dimensions. Rekik and Boujelbene (2013) concluded that investors in Tunisia are not completely rational in their investment decision-making. Sevil (2007) found that the Turkish stock investors do not exhibit complete rational behavior as advocated by theories of traditional finance. Kahneman & Tversky (1979) found that individual investors deviate from rational behavior due to a persistent pressure of uncertainty. As mentioned earlier, due to scarcity of cognitive and time resources, individuals are unable to make rational decisions, therefore they resort to take imperfect decisions normally based on some mental shortcuts called heuristics. Decision-making based on mental shortcuts generally involves a lack of due concern for the principles of probability (Hirshleifer, 2001). The expected utility theory is considered the basis of rational decision-making, Barberis & Thaler (2003) found that individuals violate the expected utility approach when taking risky decisions.

1.5 Answers to causes of irrationality- Behavioral finance

Behavioral finance is the most reasonable domain that explains deviant and irrational behavior which is contradicted by the rational choice theory. So, according to Statman (1995), Such a void is filled by behavioral finance. The deviation from the rational choice hypothesis is explained on the basis of human psychology, by various researchers since the 1970s. Human psychology is the cornerstone of behavioral finance as advocated by Barberis & Thaler (2003). They state that behavioral finance tries to explain investor irrationality through a framework based on the cognitive psychology of the investor. Behavioral finance is an extension of traditional finance by integrating human psychology with traditional finance to provide a relatively better explanation of the irrational behavior of investors Shefrin (2001). Similarly, Statman (1999) argues that behavioral finance tends to identify and elucidate the role of emotions and cognitive errors in investment decision-making. Based on the literature available for behavioral finance, there are two main concerns firstly, the existence of deviations or anomalies towards the efficient market hypothesis (De Bondt & Thaler, 1987), and secondly, causes of irrational behavior in the form of behavioral and psychological biases (Odean, 1999). Etzioni (2014) states that behavioral finance is more vital in the comprehension of investor behavior in terms of the underlying cognitive biases which limit the rationality of individuals. Different market anomalies like under-reaction, overreaction, momentum profits, and herding bias were studied by different authors (e.g., Barberis & Shleifer, 2003; K. Daniel et al., 1998; K. Daniel & Titman, 1999). There are several instances concerning behavioral finance in explaining the variant behavior from rationality. In sum, behavioral finance integrates the role of human nature and behavioral domains into the traditional finance theories to come up with a more reasonable explanation of deviations from rationality. It is a relatively better gauge of comprehending the investor's nature and behaviors in its manifestation of true asset pricing. Despite the enormous importance of behavioral finance, it has been considered a trivial and useless branch of finance. The traditional economists also observed that individuals behave irrationally at times but they were unable to pose any explanation for such a variation from their set theories. Furthermore, behavioral finance has always been criticized for the notion that behavioral studies are conducted in controlled settings hence its findings cannot be generalized to the aggregate markets.

EMH assumes that investors are completely rational, they are well-equipped in assessing the required relevant information in calculating the true risk and return for securities, no cost is required to predict returns on assets and such privilege is available to everyone in the market. It is well established that all these assumptions are unrealistic. As given by the EMH, information is reflected in stock prices, the value of the mispriced stock cannot be predicted accurately as their values do not correspond with their intrinsic values. On the other hand, stock prices in an inefficient market price go down than required, or under-reacts to any new information, investors in both cases earn abnormal returns from the mispriced stocks.

Several studies have found a positive serial correlation among stock prices over many time horizons (Lo & MacKinlay, 1988). Prices of stocks can be predicted via the publicly available information although it does not represent the fundamentals of these stocks. For instance, Livnat & Mendenhall (2006) state that price estimation can be based on earning announcements of the firms. Gleason & Lee (2003)argue that prices are predicted on the basis of analysts' forecasts. Similarly, Fama & French (1992) state returns are depictive of book-to-market ratios. Although stock prices are fully sensitive to the risk and return assessment, such assessment leads to earning abnormal profits for the investors. In other words, it also indicates that past returns can help in predicting future returns. De Bondt & Thaler (1985) studied portfolio returns and found that on short to long-term horizons, previous losers persistently outperform previous winners. As mentioned earlier, rational market behavior has remained an area of special interest for researchers, stock price volatility in contrast to the volatility of variables affecting stock prices is also studied to study market rationality. The frequency of fluctuations is relatively higher as compared to the variations found in variables influencing stock prices. Pessimistic and optimistic market psychology is considered to be the reason behind such variations (Shiller, 1981).

According to Shleifer & Summers (1990) arbitrageurs or rational speculators working on the available information and traders who trade on imperfect information called "noise traders" are the two kinds of investors. The equilibrium prices are compromised whenever noise traders start trading based on imperfect information while arbitrageurs act as stabilizers for equilibrium prices. As a matter of fact, arbitrageurs can sometimes minimize the effects of price shifts rather than completely eliminate them. Owing to this argument, perfect arbitrage is considered unrealistic. Limited arbitrage theory suggests that prices of securities are not only the outcome of information but it is also affected by variations in sentiments or expectations which are not backed by information completely (Shleifer and Summers, 1990). Since stock markets are run by human beings therefore factors that govern human cognition and behavior are potentially more significant in explaining the behavior of the aggregate stock market. Therefore, Contemporary research is converging towards studies focused on human cognition and psychology to find out the impact of psychological factors on rationality in decision-making. As a matter of fact, it is evident from the literature of psychology that individuals who have relatively limited capacity in information processing are observed more to fall prey to systematic bias, are influenced by emotions, and perceptual errors, and most importantly, follow others in decision-making.

In sum, traditional finance could not cater to the explanations required for the deviant behavior of individuals and markets, behavioral finance came to the rescue by incorporating psychological and behavioral factors in the explanation of irrational behavior meaningfully. It is concerned with how individuals behave in different financial decisions. Behavioral finance has a special position in situations when traditional finance and economics are unable to explain the anomalous behavior by individuals and markets. It, therefore, involves the study of psychological and behavioral biases which leads to irrational behaviors on part of individuals and anomalous behaviors in aggregate markets. Jo and Kim, (2008) have identified regret aversion, proneness to cognitive errors, differential treatment of risk, and tendency towards value-driven features and utilitarian features as the most important areas in behavioral finance.

Daniel Kahneman and Amos Tversky are considered the pioneers of behavioral finance. Daniel Kahneman won the Nobel Prize for his remarkable work in 2002. They studied psychological biases and the interpretation of risk in relation to financial decision-making. Several papers were authored by Kahneman and Tversky in 70's and 80's. Their first paper was about the wrong beliefs about the probability and statistics that people hold, for instance, people think that a random sample is representative of the whole population (Tversky & Kahneman, 1971). Later papers investigated the important role of representative bias in the formulation of intuitive predictions (Kahneman & Tversky, 1972, 1973). Similarly, two seminal papers on availability, anchoring, and representativeness heuristics were published in 1974 and 1979. The famous work on prospect theory is the most important work by Daniel Kahneman, Tversky, and L.smith, which serves as a viable alternative to the expected utility theory ((Kahneman & Tversky, 1979; Tversky & Kahneman, 1974). Yet another paper in the year 1981 is considered as a seminal work on framing which states that framing of a specific scenario in variant ways impacts decisions, perceptions, and assessment of alternatives and outcomes of the individuals responsible for decision-making (Tversky & Kahneman, 1981). Sewell (2007) argues that framing and prospect theory is so important collectively, that rational choice theory seems incomplete and explains rational decision-making. Besides Kahneman and Tversky, Mark Schindler also significantly contributed to behavioral finance in terms of studying limits to arbitrage, sociology, and psychology.

1.6 An alternate view toward behavioral finance

Behavioral finance addresses the efficient market hypothesis by proposing various psychological factors in addition to the core factors that impact investor decision-making. As a matter of fact, human nature in terms of the underlying psychological theories cannot be generalized to understand market behavior. Due to the uncertainty associated with human psychology, it is also hard to estimate the life of financial bubbles and the periods of irrational regimes.

A certain segment of scholars evaluates behavioral finance on different grounds. For instance, they do acknowledge the existence of behavioral and judgment biases however they think that these biases do not impact decision-making in their entirety. Behavioral finance is considered as a sum of anomalies- which are primarily due to some inadequacy in methodology, any useful changes in the methodology will disappear such anomalies (Fama, 1998). Individuals undergo various biases while on the other hand, market forces are expected to offset any irrational moves on part of individuals and the prices should revert back to basic values therefore, the impact of investors' irrationality is negligible on the aggregate values (Lo, 2005).

Sarkar (2010) argued that EMH moves from theory to empirical inquiry while behavioral finance moves from empirical inquiry into theory while the real model is situated between a normative model theory and rational choice theory. Another aspect of behavioral finance states that it originated from disciplines like sociology, psychology, and anthropology. However, researchers of behavioral finance do not acknowledge the work done in these disciplines but rather refer only to the works done by fellow researchers of behavioral finance (Brooke, 2010). Similarly, behavioral finance is mainly concerned with individual behavior without regarding the role of social factors in investment decision-making as proposed by psychology and anthropology. Moreover, individuals mostly do not rely on rules or guidelines therefore, results obtained from experiments are not commonly generalizable (Curtis, 2004).

Behavioral finance accentuates the role of behavioral and psychological biases in decision-making however, so far it is unable to come up with a concrete model to substitute the rational choice model of decision-making. According to Fama (1998), behavioral finance will never replace traditional finance, especially the EMH because the anomalies contradictory to traditional finance are all due to faulty data mining approaches which can be questioned, while the models of behavioral finance are self-contradictory therefore they cannot be generalized.

Since internal contradictions exist in the results of behavioral finance, the researchers, therefore, do not possess the confidence to attribute work to themselves. According to Shefrin (2001), there is a lack of experts having expertise in both traditional finance and psychology, therefore, the models proposed in behavioral finance are fragile. Due to the criticism posed on behavioral finance, behavioral finance is shifting into purer sciences with new domains like neuro finance and neuroeconomics where the models are expected to be more consistent. In sum, it is inferred that despite the alternate views, behavioral finance is still considered a viable working alternative to the rational choice theory, and much research is conducted in behavioral finance these days.

1.7 Heuristics and biases

Heuristics are defined by Kahneman as efficient and simple rules of thumb which reflect how individuals solve problems, establish views and make decisions. Heuristics are therefore specific tools or mental shortcuts which are used in times of uncertain and complex situations for speedy decision-making. Humans tend to avoid facts and figures which will certainly require some time, therefore, mental shortcuts are used to avoid cumbersome and time-consuming systematic decision-making. These shortcuts are evolved over a period of time, through experiences and instincts, although these mental shortcuts can work well in a few instances, they can also lead to systematic cognitive errors which in turn influence the decision-making and result in irrational decision-making. A heuristic-mental shortcut that works most of the time is referred to as an algorithm. Therefore, heuristics assists in making sense of the world more reliably while reducing the mental load. As a matter of fact, heuristics do not work all the time and their inappropriate use can lead to certain human errors. Systematic errors resulting from the use of heuristics are called cognitive biases. According to Tversky & Kahneman (1981) heuristics are used to reduce uncertainty and complexity in choices and judgments while biases represent the difference between "normative behavior and the heuristically determined behavior". Below given is a brief overview of major heuristics and biases followed by their importance respectively.

1.7.1 MAJOR HEURISTICS

Tversky & Kahneman (1974) identified three core heuristics anchoring, availability, and representativeness. While Gilovich et.al (2002) proposed six general purposed and six special purposed heuristics. The general purpose heuristics are availability, affect, similarity, causality, surprise, and fluency while the special purpose heuristics are: substitution, prototype, attribution, outrage, choosing by choice or default, and attribution. Sewell (2007) regards similarity, availability, and affect as the most significant of all.

Similarity: similarity heuristic implies that “like causes like” while “appearance equals reality”. It helps to relate similar situations with each other based on similarity or prototyping similar situations (Sewell, 2007). The objective of the similarity heuristic is productivity maximization while getting help from identical positive experiences while avoiding negative experiences. In our day-to-day life, we use the similarity heuristic, for instance, we prefer to watch a movie, which is starred by an actor whose movies we have enjoyed in the past.

Availability: it is referred to as the heuristic, where the available information regarding decision-making is preferred rather than assessing any other alternative or substitutes (Sewell, 2007).

Affect: Affect is concerned with the goodness and badness of some outcomes. Therefore, their affect response is spontaneous and involuntary (Sewell, 2007). For example, hearing the words, love, and hate, very peculiar good and bad vibes come into our minds respectively.

1.7.2 IMPORTANCE OF HEURISTICS

As in the words of Kahneman and Tversky, a heuristic is referred to as a rule of thumbs or mental shortcuts. These mental shortcuts are primarily aimed to manage uncertainty and facilitate the decision-making process. Therefore, these shortcuts are expected to provide a more viable solution. However, the outcomes may not be as per expectations that’s why its use may become unreliable. As heuristics are experience-oriented and concerned with human beings, they are developed on the basis of experiences, available knowledge, or similarity in situations (Subash, 2012). However, these heuristics may often result in irrational or suboptimal decisions while dealing with relatively more complex and uncertain situations. Heuristics are associated with behavioral finance because of the fact that modern-day financial markets are opaque, complex, and very agile, therefore, the information processing speed is ever increasing than in the past while the response to such information is of vital importance in profitable trading. Owing to such circumstances, heuristics play a significant role in prompt decision-making however these heuristics need to be analyzed and used carefully in order to avoid the ultimate irrational decisions. Traditional finance, suppose that investor decision-making is based on rational choices, using the available information through statistical and mathematical models, therefore, supporting the inexistence of heuristics. Contrary to that, empirical evidence suggests the existence of heuristics as one of the core factors in irrational decision-making. Therefore, it is very important to delineate and understand the role of heuristics in investors' decision-making.

1.7.3 MAJOR BIASES

As mentioned earlier, biases are human errors that emerge as a result of using heuristics. Various kinds of biases exist that have been empirically tested by experts in behavioral finance. Some of these mentioned are given as:

Overconfidence bias: overconfidence bias is the over-valuing or over-relying on one's own knowledge in the estimation of financial factors like risk and return. Overconfidence is the unnecessary trust in one's intuitive reasoning and mental abilities. It has already been well established that individuals, in general, are not very good at assigning probabilities to the events, they do not comprehend the limits of their knowledge and abilities and they assume they have full control over the events therefore their behavior is based on inaccurate assumptions hence leading to irrational decisions (Pompain, 2006). Similarly, Subash (2012) states that generally, overconfidence is the most primate trait of investors in investment decision-making, while a selection of a specific financial security is more affected by overconfidence.

Representativeness bias: it is the magnitude of correspondence or resemblance between the sample and population (Gilovich et al., 1983). It is concerned with assessing conditional probabilities, for instance, determining whether a specific event belongs to a certain class of events. (Subash, 2012). An example of representativeness is an investor's assumption that positive attributes of a company are embodied in its stock prices. Contrary to this assumption, such investment decisions are normally inefficient (Subash, 2012).

Herding bias: herding refers to when financial market participants imitate or follow each other's behavior or behavior of a larger group rather than relying on the fundamental values associated with security prices. Most of the time, herding is done in order to align investing decisions with that of a larger group or popular opinions on the assumption that the majority are less prone to mistakes. While Peer pressure is yet another cause of herding behavior. As a matter of fact, individual investors are highly influenced by financial analysts in their investment decision-making. Interestingly, while formulating their recommendations, these analysts can also fall prey to herding. Herding is a high concern for the financial market because it results in the creation of financial market bubbles which depicts an extreme risk of collapse for individuals and the market in total.

Anchoring bias: anchoring bias is the tendency of individuals to refer to a base value while estimating. Such base value or initial value is called an anchor. The final estimated value is made after making adjustments with the anchor. The adjustments made to the anchor are not depictive of the information therefore the ultimate estimated value is somewhat near to the initial anchors. The creation of an initial value called anchor may also be inaccurate, it may be based on an inadequate, uneducated guess with no prior experience of giving the anchors. Interestingly, anchoring does influence security prices even though the given anchors are completely random.

For example, an investor is ready to pay for a security that is relatively less known to him/her therefore the investor's decision is influenced by any random anchor.

Cognitive Dissonance bias: It is the feelings of discomfort or stress experienced by individuals when they realize that due to the new information/events, the belief that they already held is not true. Cognitive dissonance is the feelings when acting against or events that emerged are against the already set beliefs. According to Pompian (2006), selective perception and selective decision-making are the two aspects of cognitive dissonance. Selective perception emerges when only specific information that conforms with the existing set of beliefs is processed while selective decision-making is the tendency of individuals to replicate past decisions even though are not rational.

Regret Aversion bias: it is caused by intensive feelings of regret in the form of a psychological error while a decision is already taken and that has proved to be a poor decision. In other words, a wrong decision taken by an investor will result in regrets for the investor in the future. Owing to this bias, an investor's decision-making is affected where the investor is unable to conduct a rational analysis of the situation at hand for investment. The error of omission and error of commission are the two types of regret aversion bias. When an investor regrets not buying specific security is the error of omission while when the investor regrets buying specific security is the error of commission. In both cases, the decision turns out to be poor (Subash, 2012).

Loss Aversion bias: loss aversion bias is the propensity of investors to value expected losses more than expected gains therefore investors have a strong tendency to avoid losses than acquire gains. Kahneman and Tversky first studied loss aversion, it was found that losses are weighted two and half times greater than the gains. According to Benartzi and Payne, (2015) loss-averse behavior is totally natural in human beings however, it is important to comprehend how indifferent interpretation of potential losses influences our investment decisions. Benartzi and Payne (2015) conducted an experiment with 400 respondents, the study was aimed to know about the preferences of individuals concerning perceived risk and investment choices in order to overcome the psychological stress of loss rather than led by the rational factors like risk, returns, and variance. Because risk is most of the time interpreted in terms of loss rather than variance or standard deviation by individuals. Various other biases have been examined in the literature. These include mental accounting, gambler's fallacy disposition effect, etc.

1.7.4 IMPORTANCE OF BIASES

Psychological and behavioral biases include the foundation of behavioral finance, aimed at explaining the anomalous behavior of financial markets. Investors tend to behave in a certain manner hence resulting in different cognitive errors. Behavioral finance has the therefore the privilege of proposing such financial markets which include these deviant factors of rationality (Barber & Odean, 2000). Similarly, Subash (2012) also proposed that investors come along with two major biases one is overconfidence and the other is regret aversion.

As a matter of fact, these are not the only biases, various behavioral and psychological studies have identified almost fifty other biases relevant to an investor's behavior. Heuristics and biases are used interchangeably across the whole literature by many researchers, others propose a slight differentiation by referring to biases as beliefs, and others call them relevant frameworks only (Subash, 2012). On the other hand, Pompian (2006) states that no unified theory can be proposed which explains the irrational behavior of individuals in the presence of variant nomenclature for existing heuristics and biases. Therefore, behavioral finance studies have to depend on a combination of empirical evidence which shows irrationality on part of the individual investor in different situations. Market anomalies in the form of irrational exuberance are depicted in many forms, market under-reaction and overreactions are two such anomalies given below.

1.8 Reactions of Stock Market: Overreaction and Underreaction

Under-reaction and overreaction are the two most important types of market reaction mostly cited in the behavioral finance literature. Market reaction is a concept truly related to the irrationality of investors. Under-reaction is the short reaction of investors than what is expected of them. In other words, under-reaction is the reaction of the market to certain news in a current period and even in subsequent periods (Prast, 2004). Conversely, in overreaction, the investor's reaction is greater than what is actually expected from them.

The terms overreaction and under-reaction were first coined by De Bondt & Thaler (1985). They found that today's winners will lose tomorrow and today's losers are the winners of tomorrow in their portfolios of past winners and losers in 3-5 years' monthly returns. It was found that where investors overreact to certain news they will win in the current period but in the long run, they will lose because the returns will revert back to the actual values in the long run. The investors do not give proper attention to the mean reversion, therefore, their overreaction costs them in long run.

Reversion and momentum strategies are usually recommended to an investor on the basis of market reaction. Barberis et al. (1998) categorize the movement of a firm's earnings into two regimes – the mean-reverting regime and the trending regime. It is assumed that a firm's earnings will remain in the current state. And therefore, an investor is more likely to change his beliefs with the upcoming news. In case of a series of good news in the market, the investor will be in the trending regime while if good news is followed by bad news, then investors are in a mean-reverting regime. Where momentum is the short-term (≤ 01 years) persistence of a trend whether it is positive or negative. Reversions and momentums are also connected with under and overreaction. A positive momentum implies that an investor under-reacts to bad and non-conforming news while a negative momentum indicates that investors overreact to negative information and undermine the positive signal (Spellman, 2009).

The momentum traders give attention to only past prices while the news watchers rationally assess any significant news regarding the basics of a firm. As soon as bad or good news hits the market, the news watchers underreact because the news about fundamental (company-specific) information moves slowly in the market. While the momentum traders overreact and raise market returns above the equilibrium in the form of high volumes of stock trading (Hong & Stein, 1999).

Most of the previous studies on market efficiency have limited their analysis to the short-term horizon of stock returns on the basis of the assumption that only a short-term lag exists between an event and a price adjustment. However, the focus has now shifted to the notion that market efficiency must be tested in the long run as stock prices require some time to adjust to any information or event. Since, the long-term market under-reaction and overreaction must be studied in a long term (Fama, 1998).

Another perspective on an investor reaction is that investors, most of the time react differently to the same bits and bytes of information in different market conditions. Cooper et al. (2004) defined market conditions for stock performance in the last 36 months as UP and Down. When the three years lagged market return is positive, the market is in UP condition while when the three years lagged return is negative, the market is in DOWN condition. Similarly, for Chen et al. (2012) UP is represented when the market return for the last 03 consecutive months is positive. While DOWN market condition is represented by negative market returns for the last three consecutive months before the portfolio holding. Such under/overreaction of the investor in a response to some news also helps in the estimation of future returns.

1.9 Biases, Market Behavior, and Reaction

The ever-growing behavioral finance can be broadly categorized into four significant areas. These are framing, heuristics, market impact, and emotions. Heuristics being the subject matter of this study is referred to the mental shortcuts or rules of thumb that an investor uses in financial decision-making in order to reduce uncertainty. These shortcuts are used to simplify complex decisions, for example, the financial decision-makers come across various options or choices with attached uncertainty. In such cases, the heuristics are utilized by the decision-makers hence managing the associated uncertainty and the cognitive resources. With each passing day, many new types of these heuristics are added to the behavioral finance literature as these are related to the human mind and behavior. Till now the famous heuristics identified are overconfidence, status quo, familiarity, anchoring, availability, regret and loss aversion, conservatism, mental accounting, disposition effect, and limited attention. These heuristics are sometimes also referred to as cognitive errors or biases. And these errors generally result in different market anomalies. As the aggregate impact of irrational investors will result in the mispricing of financial securities (Wouters, 2006).

Overreaction and under-reaction are themselves the embodiment of market anomalies. While an investor's behavior is a function of all the biases and heuristics. Irrational investor uses mental shortcuts as the basis of their decisions and as a result, they commit errors in these decisions. Therefore, it is implied that the anomalous behavior of the market in the form of over and under-reaction is a consequence of the cognitive errors in investors' processing of information and their decision-making.

The study of heuristics and biases is justified in the question that why investors react differently to the same set of information. It is proposed that the investor's anomalous behavior is due to heuristics-driven biases (Fama, 1998). Factors responsible for the irrational decision-making proposed by Shefrin (2001) are heuristic-driven biases, frame dependence, and inefficient markets. Heuristics-driven biases and frame dependence are considered the types of biases while the inefficient market is the consequence of heuristics and frame dependence.

1.10 Problem statement

Since information is the core element of efficient markets, such information is expected to be handled in a very diverse manner based on the belief set, perceptions, attitudes, experience, knowledge, cognitive abilities, social factors, and moods of an individual investor. This non-uniform processing of the same information will lead to individual biases and ultimately to anomalous market behavior. Based on the divergent and competing theoretical frameworks regarding the existence of perfect or efficient markets, it is important to delineate the role of behavioral and psychological biases in the existence of market imperfections. Moreover, it is also important to differentiate developed and emerging markets in terms of market anomalous behavior (if any) and to investigate the relation of such market anomalies and investors behavioral and psychological biases. The sampled south Asian countries share a similar historical and cultural background and people from these countries have lived together for hundreds of years. Moreover. The corresponding stock markets in these countries are considered emerging by the Standard and Poor (S&P). The interest of this study is in relation to the cognitive and social diversity that exists in the south Asian investor in contrast to that of a developed economy like the U.S, the impact of biases must be studied to ascertain the causes of any market anomalies (if exist) in the sampled south Asian stock markets. Therefore, this study is aimed to investigate market reactions on the basis of investor biases.

1.11 Research Questions

This study is aimed to answer the following research questions:

- Do the Pakistani, Indian, Bangladeshi and the U.S stock markets show anomalous behavior?
- Do the behavioral and psychological biases have any contribution to market reaction?
- Does market under and overreaction cause excess volatility in the Pakistani, Indian, Bangladeshi and the U.S stock markets?
- Can the Pakistani, Indian, Bangladeshi and the U.S stock markets be considered efficient in the presence of heuristic biases, trading volume, volatility, and market reactions?

1.12 Research Objectives

Our study is aimed to achieve the following objectives.

- To study the existence of self-attribution, anchoring, herding, and limited attention bias in Pakistani, Indian, Bangladeshi and the U.S stock markets.
- To relate the existence of self-attribution, anchoring, herding, and limited attention bias with market reactions in Pakistani, Indian, Bangladeshi and the U.S stock markets.
- To study the relation of market reaction with volatility in Pakistani, Indian, Bangladeshi and the U.S stock markets.

- To compare the performance of Pakistani, Indian and Bangladeshi stock markets with each other and with that of the U.S in the presence of various biases.

1.13 Significance of the study

Beliefs, perceptions, desires, attitudes, and cognitive abilities of individual investors determine the outcome of an individual's financial decision. The cognitive process is reflected in the decisions of an investor. This study will contribute to the existing literature by investigating the market anomalies in the sampled South Asian stock market, furthermore, the inter countries' differences in the sampled South Asian region will also provide a comparative explanation for any inter-countries differences. This study will also provide a comparative analysis of trading turnover, market returns, and volatility in relation to the overall market efficiency along with sound theoretical support.

Behavioral biases are relatively more studied in developed countries, however; it has never been studied widely in developing economies, especially in the sampled South Asian context. There is no integrated study available that confirms the existence and nature of these biases in the selected sampled South Asian stock markets. Therefore, this study is aimed to investigate the nature and existence of these biases which result in irrational market decisions with a special focus on the comparison of results among markets.

This study is expected to produce comparative results between the selected south Asian stock markets and a developed market like the U.S. The study will investigate the contribution of various biases to the efficiency of each stock market in South Asia. Since very little research has been conducted in emerging economies like Pakistan, Bangladesh and India, this study will act as a foundation for future comparative researches.

Countries in the sub-continent region of South Asia share a mutual history although the diversity is always there in religions, customs, values, etc. since, the sub-continent remained a common dwelling for these different nationalities therefore, these nationalities have a very stronger impact on each other. The south Asian region has also faced different upheavals for example floods, tsunamis, terrorism, and extremism in our sample period. In addition to that, these economies are largely relying on the IMF and World Bank which extends the credit with ever stringent conditions. Political stability is also one of the turbulences that adversely affect the sampled South Asian financial market. This study will lay a foundation for the above-mentioned factors in investor rational financial decision-making and aggregate anomalous market behavior.

Markets are composed of individuals and such individuals are governed by their beliefs and value system. Individuals in the sampled south Asian countries are generally more inclined to their religions, they are more risk-takers and they live in a collectivistic society. To this effect, the colonial mindset is a predominant factor in the political and social lives of individuals. Moreover, beliefs are shaped by specific features of a society which in turn are manifested in decision making. On the other hand, the U.S society is based on western culture, predominantly influenced by Britain in terms of language, culture, and legal system while the rest of the features are supposed to be influenced by immigrants and general evolution. Cultural diversity and openness to pluralism is the strength of American society. However, the aggregate society is driven by individualistic philosophy. Therefore, markets are dominated by individuals with relatively more education and sophistication. Similarly, individuals are less sentimental, objective, and capitalistic. It is therefore expected that this study will accentuate the necessity for further researches to investigate various drivers of behavioral and psychological biases especially in relevance to financial decision making.

Inclusion of a developed stock market like that of U.S is significant mainly for two reasons. Firstly, to consult an immediate benchmark which remained a major source of testing theories empirical works. Secondly, the methodologies employed in the study are mostly tailored for western stock markets including the U.S. Therefore, comparing the empirical results for emerging markets with that of a developed markets provides a nexus between theory, empirical work and anecdotal evidence.

This study is organized as chapter 2 discusses the literature review regarding various behavioral and psychological biases and their implications in finance. Chapter 3 discusses the methodology pertinent to various research hypotheses, chapter 4 summarizes our results for the proposed hypotheses and chapter 5 leads us to the conclusion of the study with policy implications and future research directions.

CHAPTER-2

LITERATURE REVIEW

The literature review section summarizes earlier studies on market reactions with special relevance to the role of behavioral biases in such reactions. In the later section, based on various underlying theories associated with different biases from literature, hypotheses of this study are developed. Literature starts from the discussion of emerging markets as under:

Since our study is aimed to investigate the south Asian emerging stock market. It is important to review the literature about the emerging stock markets, especially the south Asian emerging stock market.

Emerging markets being a differentiated investment classification is a relatively new concept (Fifield et al., 1998). For instance, the international finance corporation was founded for the sole purpose of supporting and nourishing financial markets in developing countries. The IFC aimed to mobilize resources for registered companies on stock exchanges in developed countries. Because of this shifting trend, institutional investors started taking interest in such companies (Mobius, 1994).

‘Emerging market’ is a term, which was first coined in the early ’80s. While Templeton's emerging markets fund was the premier fund made in 1987. Although the term ‘emerging market’ existed till 1987, there was no exact definition of the classification of emerging markets (Mobius, 1994). The IFC for the first time, classified countries on the basis of their national incomes, endorsed by the World bank’s classification of countries based on income. (Mobius, 1994).

The problem arose when the definition of developed markets came under suspicion. Based on the definition, some of the oil-producing countries like Kuwait, United Arab Emirates, and

Saudi Arabia were removed from the developing markets group because of the prevailing high per capita income in these countries. As a matter of fact, although these countries had the highest per capita income, the real income was stagnant in the hands of the few. Therefore, it was unjust to generalize the standards of life of these wealthy individuals to the general masses that's why the living standards of the general masses essentially differed from the developed countries. Similarly, capital markets in these countries are also not that developed, where trading is comparatively low, with lower levels of liquidity and insufficient use of technology (Al-Abdulqader et al., 2007). And most importantly, these countries strictly regulate the flow of capital in their stock markets in the form of discouraging foreign investors as compared to the local investors (Mobius, 1994).

Owing to the above-stated situation, Mobius (1994) defined emerging markets as those markets situated outside North America or Europe, Australia, or Fareast. According to Mobius, emerging markets must have an adequate supply of securities accessible to international investors, there should be no restrictions on the flow of capital from these markets hence these markets must be well established. According to Errunza (1983), There are three classes of emerging markets- the first class includes those markets which are well-established for example India, Brazil, Greece, Spain, Mexico, Argentina, and Portugal, these stocks are established for almost one century however they have a minor contribution in developing equity corporate investment. The second class of emerging markets is the one where the markets are developed due to some special circumstances, for instance, the stock market of Jordan was established to accommodate OPEC money due to the prevailing crisis at that time in the Middle East. The third class of emerging markets includes relatively new stock markets for example stock markets of the Philippines and Korea which were aimed to fuel the economic growth of those specific countries.

Even though the categorization does not provide a specific definition for emerging markets, it thoroughly acts as a guide to the financial markets encompassed by the term emerging markets. (Fifield et al., 1998). A practitioner's perspective is adopted by Divecha et al. (1992) and Mobius (1994). According to them, an emerging market is the one that adopted an alternative definition of an emerging market from the practitioner perspective that was employed by Mobius (1994). They considered an emerging market as one which is available for international investors, the market is operated through a reliable source of data, securities are freely traded and the market is not situated in a developed country as declared by the Morgan Stanley capital international indices (MSCI). This definition of the emerging market takes into account an academic and the practitioner's perspective – the academic perspective sheds light on the developmental stage of the country and the practitioner's perspective focuses on the practicability of investment.

The emerging-market database (EMDB) provides yet another definition of emerging markets which is also endorsed by the standard and poor's. According to the standard and poor's an emerging market is the one that is situated in a low-to-middle income declared by the world bank, has a market capitalization that is relatively low to the gross national income (GNI) and is regulated by less strict rules concerning investments from international investors. (Standard and Poor's, 2011).

The definition given by the international finance corporation is generally used to identify emerging markets however, it certainly lacks the practitioner's confidence because of the notion that it has a restricted or limited scope and investors do consider other factors in their investment decisions (Hartmann & Khambata, 1993). In this context, Burton et al. (2007) conducted a survey of practitioners for the definition of an emerging market in the eastern European and central European regions. It was found that most practitioners primarily consider investment restrictions from the stock market in their investment decision-making. Similarly, these practitioners also consider the relative size of the company and the liquidity of the market where investment is to be made.

In a nutshell, it can be concluded that no definition of emerging markets is universally acceptable however, the IFC's definition of an emerging market based on the per capita income is more widely used by researchers. Researchers have limited the definition of emerging markets to those where foreign investment is more encouraged with fewer restrictions on foreign investments.

The study at hand includes India, Pakistan, and Bangladesh, these are the major countries situated in the region called South Asia. As proposed by Standard and Poor the comparison of gross national income with market capitalization for the south Asian countries show a relatively lower market capitalization to GNI ratio. Similarly, the GNI as compared to the per capita income indicates whether the country is in the high middle or low category. The market capitalization to GNI ratio highlights the importance of a stock market within a country. Interestingly, a country having low to middle-income level, also have a low level of market capitalization to GNI ratio. Therefore, its stock market is considered as an emerging market.

Khan (2013) provides comprehensive information regarding the member countries of South Asia in terms of GNI, market capitalization, and GNI per capita income from 2000 to 2011. It was found from the analysis that the economic performance of the South Asian countries varies from time to time and from country to country. For instance, Indian GNI had a growth rate of 125 percent from 2000 to 2011. Similarly, Pakistan, Bangladesh, and Sri Lanka had a growth rate of 83, 91, and 76.2 percent respectively from 2000 to 2011. In contrast, the GNI growth rate was observed to be much smaller in developed countries for the same time period. Despite a high growth rate of GNI, the poverty level did not significantly improve in these countries. The GNI per capita income analysis revealed that Sri Lanka (1440 US $) had the highest GNI per capita income while Bangladesh (482 US$) had the lowest GNI per capita income in South Asia. On the other hand, the UK had an average GNI per capita income of 3217 US$ for the same period. It is important to note that the GNI per capita income increased for all countries of South Asia but at varying rates. India had the highest growth rate of 213 percent in GNI per capita income for the sampled period. Interestingly, although the south Asian countries had an impressive growth rate in GNI and GNI per capita income, these countries could not come out of the low to middle-income category given by the World Bank. According to the world bank figures for 2018, south Asia had an average GNI per capita of 1915 US$ while India, Pakistan, Sri Lanka, and Bangladesh had 2010, 1590, 4040, and 1940 US$ respectively. According to the threshold given by World Bank, Sri Lanka falls under the upper-middle-income category while India, Pakistan, and Bangladesh still fall under the low-income category. So according to the definition of IFC, the sampled countries are rightfully considered emerging countries. According to khan (2013), India had the highest GNI to market capitalization ratio for the period 2001-2011, Pakistan, Sri Lanka, and Bangladesh were second, third, and fourth in GNI to market capitalization respectively. Although, the GNI to market capitalization ratio grew for all south Asian member countries. It did not reach the threshold level required for developed countries. For instance, the UK had a ratio of 1.305 as compared to India (0.86) (highest among the South Asian countries)

In yet another perspective, a decline in market capitalization to GNI ratio indicates stock market volatility. For example, a gradual decline in market capitalization to GNI for India and Pakistan from 2006 to 2008 resulted in a stock market collapse in 2008. Pakistani and Sri Lankan market capitalization to GNI ratios decreased by 70 and 50 percent. The average growth rate fell due to this decline in 2008 however, it started recovering in 2009 and 2010.

It can be inferred that the Indian, Pakistani, and Bangladeshi stock markets, constituting the south Asian stock market, is considered emerging market. As these markets fall under the low to middle GNI class and the GNI to market capitalization ratio is relatively low. These markets are relatively more volatile even though international investors are allowed to invest.

Now that a foundation about the south Asian emerging market is established, literature regarding investment decisions influenced by various behavioral and psychological biases will be reviewed that lead to irrational decision-making on part of an investor. As discussed in the introduction part, behavioral finance is seen as a more accurate explanation of the irrational decision-making of investors. According to Fromlet (2001), the behavior of an investor is the sole focus of behavioral finance which is viewed as the core factor in the psychological decision-making process of such investors. Therefore, behavioral finance narrowly focuses on human behavior with market dimensions in addition to the framework offered by psychology and standard finance.

Various other psychological illusions govern the behavior of investors besides emotions. According to Thaler (2016), Adam Smith can be credited with explaining various psychological biases like overconfidence and loss aversion. Behavioral finance has evolved since the contribution of Adam Smith into a framework that can identify and categorize different irrational moves.

The theory of market efficiency proposed by Fama (1970) remained a center of attraction for researchers till now. However, various anomalies found so far have influenced the claims posed by the EMH. Contemporary research is therefore aimed to investigate the motives behind such anomalies. In times of equilibrium in prices caused due by the irrationality of individual investors, arbitrageurs are expected to intervene by bringing security prices to their intrinsic values. As a matter of fact, it does not occur that often because of the limitations in arbitrage. Major transaction costs and borrowing costs are two such restrictions that make arbitrage ineffective. The firm-specific risk cannot be mitigated other than in situations where opportunities for diversification are available for the investor. In case of mispricing, reversion of prices to their intrinsic values takes some time, within such time the arbitrage process becomes ineffective (Bondt and Thaler, 1985). Arbitrageurs in such situations, when prices take some time in mean reversion, are expected to incur losses and eventually liquidate. Consequently, the untimely liquidation leads the arbitrageur to purchase overvalued stocks and sell them with forced losses, such a situation further hampers the anomaly. Below is a detailed review of the literature concerning various behavioral and psychological biases which lead to market anomalies.

2.2 Market Reactions

2.2.1 Market Overreaction

Investor Under and overreactions are the two important anomalies frequently mentioned in the literature. De Bondt and Thaler (1985) conducted their premier study on market reactions. They studied monthly stock returns for the New York stock exchange (NYSE) for the period 1962 to 1982. Two portfolios were formulated, where one portfolio constituted past winners for three years while the other portfolio included past extreme losers for the last three years. It was found that past losers outperform past winners in the subsequent four years. The results showed only 5 percent low returns for past winners while 19 percent high returns for past losers in contrast to the average market returns. It was proposed that investors are responsible to misprice stock values from the fundamentals hence resulting in inefficient markets. Similarly, Bayes' rule came into question as investors overreacted to unexpected and new information. Investors made decisions while ignoring the tendency of returns to revert back to their mean values, it implicates investor overreaction towards previous returns. According to Fama (1998), the overreaction hypothesis can therefore be considered as a substitute for the market efficiency theory. The investor’s overreaction was confirmed by De Bondt and Thaler (1985) in terms of supporting the price-earnings ratio hypothesis. Additionally, risk differences (beta) and firm size were also incorporated to study the winner and loser’s portfolios, the results still supported the investor’s overreaction hypothesis. While studying the seasonal effect, the excess return was observed in January as a product of the previous year’s market returns and long and short-term performance.

Spanish investor was studied by Alonso & Rubio (1990) in relation to the extreme stock price levels. They also followed (De Bondt & Thaler, 1985, 1987) using a testing period of at most three years or 36 months. The results showed that past losers outperform past winners hence reflecting the investor's overreaction. The results were also symmetric as losers gained as much as lost the winners. While no seasonal effect was found.

Financial indicators as a measure of a firm’s financial performance were used by Lakonishok et al. (1994) to test the overreaction hypothesis. Firm stocks having high earnings to price ratios, book to market ratio and cash to price ratio are perceived by investors as more profitable even on the basis of their past performance hence overreacting to such stocks. Investors anticipate that these stocks will continue their best performance in the future therefore, such stocks are purchased more hence overpricing them. On the other hand, stocks having relatively lower earning to price, book to market, and cash to price ratios, are expected to perform low in the future therefore, investors overreact and such stocks are oversold and hence they are underpriced. In reality, contrarian strategies are more efficient and profitable because they tend to invest more in underpriced stocks which are more profitable in reality due to the aggregate market overreaction. (Bondt and Thaler,1985).

A study conducted by Kahneman and Tversky (1982), suggested that investors overreact to either bad or good news. If evidence of investor overreaction is found, contrarian strategies are found to be more profitable hence it's better to sell off past winners and buy past losers.

The overreaction hypothesis is studied by Clare & Thomas (1995) in the UK from 1955 to 1990. It was found that returns revert back in two to three years period, while losers outperform previous winners. The results also indicated a statistically significant but small overreaction effect. Another study on UK's stock market by Campbell and Limmack (1997) studied the reversion of abnormal returns in long run from 1979 to 1990, confirming the overreaction hypothesis.

The overreaction hypothesis is also studied in France, Japan, Italy, Germany, and Canada (Baytas & Cakici, 1999), China (Fang, 2013), Brazil (da Costa, 1994), Australia (W.T Leung & li, 1998), and New Zealand (Bowman & Iverson, 1998). The overreaction hypothesis is also confirmed for Ukraine by studying stock reactions in relation to changes in stock prices (Mynhardt & Plastun, 2013). However, yet another study in Australia by Beaver & Landsman (1981) could not confirm the overreaction hypothesis. Similarly, the overreaction hypothesis could not be confirmed in the US (Baytas & Cakici, 1999).

Furthermore, investor overreaction is also supported in studies conducted by (Atkins & Dyl, 1990; Bremer & Sweeney, 1991; K. C. Brown et al., 1988; Howe, 1986). While reversion patterns are more relevant to a decline in prices. A study conducted by Vega (2006) revealed that stocks reliant on private information for trading, incorporating public news, and experiencing low post-earnings drift affect the post-event returns.

2.2.2 MARKET UNDER-REACTION

Under-reaction is basically the tendency of investors to slowly update their beliefs about stock investment. Therefore, under-reaction is caused by anchoring bias, investors tend to stick with the initial estimates or baseline values. Generally, the underreaction is weaker for bad news and relatively stronger for good news (Welfens & Weber, 2011). As opposed to the overreaction hypothesis, Jegadeesh & Titman (1993) suggested buying stocks that have a good past performance while selling stocks having a bad past performance, the holding period was from 3 to 12 months. It was found that stocks that performed well in the past year, tend to give higher returns in the future six months. Such tendency was attributed to the momentum effect. It implies that stock prices react to earnings announcements after a period of six months (Ball & Brown, 1968). A positive autocorrelation was found in excess returns of the stock by Summers (1991) from 1960 to 1988. The autocorrelation effect was consistent with the underreaction hypothesis which implies that information is slowly updated in stock prices.

Short-term underreaction and overreaction were studied by Schnusenberg & Madura, (2001), for six major US stock indices. A short-term one-day and sixty days' under-reaction was found for all the given six indices. When the holding period is extended, the abnormal returns are changed from negative to positive for losers while showing a reversion of returns over the sixty days. therefore, it is inferred that the reaction of markets is seen in the short run while it reverses its direction in long run. Asian stock markets just like global markets remained under the focus of researchers in studying the under-reaction anomaly. Mazouz et al. (2009) studied ten major Asian stock markets including Indonesia, Hong Kong, India, Pakistan, Korea, Singapore, Malaysia, Thailand, Taiwan, and the Philippines. The study investigated price behaviors in contrast to price shocks through GARCH and OLS for estimating CARs. Significant differences were found in price shocks across all major indices, implying that reactions to price shocks may vary from country to country because investors process information in a diverse manner. The results also confirm return continuity patterns in markets. Similarly, Rastogi et al. (2009) studied the monthly prices of all stocks listed on the National Stock Exchange of India, S&P CNX-500 from 1996 to 2008. Winner and loser portfolios were formed on the basis of past average returns. A short-term under-reaction was observed for the NSE, indicating a momentum effect and a long-run overreaction for midcap stocks. Using ANAR-TGARCH, the Chinese stock market was found to underreact to good news and overreact to bad news, regardless of the size of the firm.

Reversion of returns towards mean value is considered to be linked with market overreaction or a contrarian strategy. Weekly returns were analyzed by Kelley (2004) and found that past weekly winners outperform past losers despite a short reversal in a whole year. As, reversals in the short run do not happen that often, the underreaction hypothesis in a market is confirmed. A systematic pattern of under-reaction to positive and negative information is confirmed by Stevens and Stevens & Williams, (2004). It was noted that the under-reaction for negative information is lesser while it is stronger for positive information.

Under is a brief review of various behavioral and psychological biases which may possibly lead to market under and overreaction.

2.3 Behavioral and psychological biases leading to market reactions

Researchers have found plenty of reasons for the market under and overreactions. K. Daniel et al. (1998) believed that market under and overreaction are due to the investor's overconfidence and self-attribution bias. They suggested that overconfidence implies a negative autocorrelation for longer lags, and returns predictions on the basis of some public event where decisions of the management are also associated with stock mispricing and excess volatility. While self-attribution bias indicates positive autocorrelations for shorter lags, for instance, earnings drift in short term and momentums. Furthermore, a negative correlation between past long-term firm performance and the future returns was found. Larson and Madura (2003) studied whether extreme stock prices can lead to under and overreaction and that such can be considered an uninformed event or an informed event, in the wall street journal. It was found that since releasing public information decreases uncertainty, the uniformed winners overreact while the informed winners do not. Similarly, K. Daniel et al. (1998) conclude that overreaction is observed for private information while under-reaction is observed for any public information. The results also confirm the self-attribution and overconfidence bias in market reactions.

Momentum strategies on part of the investor are also seen as one of the causes of market under-reaction (Chan et al., 1996). Momentum is caused by gradual updation of beliefs which leads to under-reaction of investors as relatively more time is required for stock prices to revert back to the true intrinsic value. Hong & Stein (1999) studied two groups of investors- momentum traders and news-watchers, they found that gradual dissemination is the only factor that influences the whole model. Momentum traders are prone to utilize any previous price changes while news-watchers tend to use any private information. It was found that for only news-watchers, under-reaction is prominent while when adding the momentum traders to the model, overreaction is noted. It indicates that any short-run under-reaction will be translated into a long-run investor overreaction owing to the emergence of public and private information. Where an overreaction on part of an investor is given by the overconfidence bias, as overconfident investors extrapolate an array of bad and good news. Du (2005) proposed their model based on the confidence levels of diverse investors. According to Du (2005), more confident investors consider every earning announcement as stable therefore, they tend to purchase more stocks and consequently leading to high average returns and increased trading volumes. Such a pattern in return boosts the confidence level of investor who has low confidence and ultimately they also start purchasing the stocks.

Therefore, a positive autocorrelation in short-term returns due to the gradual updation of information results in market under-reaction. As a matter of fact, the news that arrived in the market is non-stationary, however, investors with high confidence take it as permanent. Prices move upwards and revert back to their intrinsic values after some corrections hence leading to market overreaction. Self-attribution bias and confirmation bias are considered responsible for such patterns. It reflects only screening for conforming evidence and associating or attributing the success with self only. Both biases lead to a high propensity for market overreaction. It also endorses the notion that aggregate market behavior is influenced by herding where investors with limited knowledge and confidence, follow the market trend and hence resulting in a long-run market overreaction. To investigate the explanation for post-earnings announcement drift, Frazzini (2006) studied the market under-reaction. It was found that the disposition effect is the core reason for market under-reaction. Investors tend to realize gains while carrying forward losses to the next periods, resulting in the post-earnings announcement drift and ultimately in investors' under-reaction. Individual investors are more anxious to account for gains, slow down the informational dissemination, and therefore result in the slow adjustment of prices. Aguiar et al. (2006) suggested a model based on fuzzy sets which in their opinion was close to behavioral finance. In their study, two distinctive portfolios were made for the textile and petrochemical sectors. The textile sector portfolio demonstrated under-reaction while the petrochemical sector portfolio showed an overreaction to the Brazilian stock market. According to the fuzzy model, anchoring and representativeness biases are considered responsible for market reactions. Mental accounting, self-deceptions, framing, emotional judgments, and attribution bias are a few of the reasons identified by other researchers which influence an investor's psychology in investment and asset pricing decision-making (K. Daniel et al., 2002).

Below is a detailed review of literature for various psychological and behavioral biases which may result in the market under and overreaction.

2.3.1 SELF-ATTRIBUTION

Self-attribution bias is associated with Heider (1958, 2013), who studied the behavior of individuals that how people regard the best outcomes to their own actions while attributing bad outcomes to some external factors. The self-attribution bias arises from two core human traits: self-enhancement and self-protection. The prior refers to the desire of an individual to be seen positively by others while the latter trait refers to the desire of an individual to have a favorable self-image. These traits lead an individual to take biased decisions.

Literature of psychology favors the notion that individuals try to overvalue their own abilities and wrongly associate their success with their own decisions. An Ohio state university psychology Professor-Mark Alicke, the human tendency of considering himself better than others, is quite common (Alicke et al 2001). Confidence and overconfidence can be differentiated by a very clear line. Confidence is the realistic trust of an individual over his/her capabilities while overconfidence reflects an overly optimistic and unrealistic guestimate of one's abilities and knowledge or control over an event. Werner De Bondt and Richard Thaler can truly be considered the pioneers of behavioral finance. The propensity of being more privileged as compared to others is also supported by De Bondt & Thaler (1995). They consider the finding of overconfidence as a significant contribution to the psychology of judgment. Overconfidence is a driving motive that enables an investor to think that he/she can control the outcomes. This "illusion of control" was first introduced by Langer & Roth (1975) when the probability of an objective outcome is less than the expected subjective probability of success of an individual.

The idea of the imperfect rationality of an investor was proposed by K. Daniel et al. (1998). Self-attribution bias and overconfidence bias were the two major behavioral irregularities considered responsible for pricing anomalies. A self-attribution bias results in overconfidence and ultimately in the market under-reaction against any public information while the under and overreaction anomalies result in corrections in fundamentals and excess market volatility in the long run. They suggested that investors tend to overvalue their own capabilities while undervaluing variance in forecast errors. It indicates that investors associate any potential gain with their own wisdom in stock picking and any potential loss to external factors including luck. Self-attribution bias states that investor confidences rise when his private information is confirmed by any public information, resulting in a market overreaction. Interestingly, investors' confidence does not fall especially when the private information held by the investor contradicts with any public information. And this is because individual investors attribute their success to their own abilities and any failure to external factors (Langer & Roth, 1975; Miller & Ross, 1975; Taylor & Brown, 1988).

Two new proxies for self-attribution and overconfidence were used by Cremers & Pareek (2012) to support the results of K. Daniel et al. (1998). The institutional holding period of stocks or stock duration was used by Cremers & Pareek (2012). As overconfidence is associated with the trading patterns of the investor (Barber & Odean, 2000). While the performance of institutional investors was used as a proxy for self-attribution which otherwise, cannot be explained through momentum, value, or size. The results supported the presence of momentum returns, shares issue anomalies of investors of short horizons with past good performance, and reversion of returns. Self-attribution is normally linked with overconfidence. Self-attribution leading to overconfidence makes an investor attribute all gains and success to his personal efforts, and any failure is attributed to external factors (Bradley, 1978). Therefore, self-attribution or overconfidence is the overvaluation of personal abilities. The self-attribution theory was presented by Bem (1965), proposing that individuals are more likely to associate those events which endorse their capabilities while decisions with bad outcomes are associated with external noise factors.

According to Statman et al. (2006), self-attribution leads to overconfident investors because of persistent gains in trading. It is important to note that overconfidence does not result in high wealth but rather high wealth results in overconfidence of investors (Gervais & Odean, 2001). Soll & Klayman (2004) stated that overconfident investors do not account for the accuracy of information but rather rely too much on their own instincts. This concept is called "miscalibration" because the subjective probabilities assigned by an investor are somewhat far from correct probabilities. Such miscalibration results in over-trading of stocks, which in turn, leads to condensed profitability (Barber & Odean, 2001). Similarly, rational investors will be outperformed by overconfident investors, since overconfident investors expect a higher return from higher risk. An overreaction in the market is caused when private information is validated through public information. A persistent overreaction produces momentum in stock prices. While in the long run, with the emergence of more public information, stock prices revert back to their true intrinsic value. Therefore, a self-attribution bias leads to momentum in short term and a long-term reversal in price (K. Daniel et al., 1998a).

When an investor gets information that is aligned with his beliefs and personal understanding, his confidence boosts, and his trust in personal capabilities strengthens. Consequently, over-trading is observed among such investors. According to Statman et al. (2006) investor confidence increases with an increase or growth in average stock returns. investor associate this growth in average returns with his own stock-picking abilities, which in return motivates him to trade even more. Generally, it is observed that individuals who are more experienced, possess more knowledge and are experts in their field, are expected to be more overconfident as compared to individuals with less experience and knowledge (Griffin & Tversky, 1992).

The aggregate hike in investor confidence results in market momentum while investors overreact to personal information when it is validated by the subsequent public information. Odean (1998)concluded overconfidence in informational precision without ascertaining whether the information is public or private. Over-trading is the result of overconfidence in investors, this results in the market overreaction in the form of a negative autocorrelation in returns and excessive volatility (Odean, 1998)

Bertella et al. (2017)studied the variations in stock prices, and their returns in a hypothetical stock market chartists and fundamentalists also found the overconfidence bias. it was found that relatively more fluctuations in stock prices were created by confident chartists as compared to less confident chartists. On a self-drawn confidence index, it was concluded that the self-drawn confidence index is not influenced by the sock prices but rather stock prices influence the confidence index. García et al. (2007) conducted their study on the effects of behavioral biases in stock markets by evaluating the rational traders in contrast to the irrational traders on overconfidence, by combining the two main features of the market "coexistence of rational and overconfident traders and information acquisition by agents". It was found that due to the initial overconfidence of irrational investors and subsequent market overreaction, rational investors decline the demand for information so as to trade off the impact of overconfidence on rational agents, their expected welfare, and profits. It implies that the overconfidence possessed by new irrational investors does impact the rational investors. While market prices and depth, trading volume information in prices are expected to positively increase investors' overconfidence (Barber & Odean, 2001; Benos, 1998). Using the VAR model for four mutually associated concepts of overconfidence, Abbes Boujelbene et al. (2009) conducted a study on the French stock market. It was found that overconfident investors are more likely to underreact to public information while overreacting to any private information. Similarly, the Granger-causality test indicated that investors with profits/gains over trade stocks. While two GARCH models indicated self-attribution bias resulting into investor over-trading and overconfidence. It was also found from analyzing returns in contrast to excessive volatility and trading volume that excess volatility is the product of over-trading by overconfident investors.

Yet another study by Odean, (1998) suggested that high returns result in high trading, because of the investor's overconfidence. However, the lead-lag relationship between trading and stock returns was not explained. Harris & Raviv (1993) investigated the lead-lag relationship. They investigated the lead-lag relationship between trading volume and concurrent return volatility. The trading volume and returns relationship is also established by Karpoff (1987). Llorente et al. (2002), also confirmed trading volume as a measure to predict future returns. Investors who fall victim to biases are more likely to under-react to any new information and use past signals. Such inclination in information processing creates momentum in returns (Barberis et al., 1998; K. Daniel et al., 1998b). Various biases have been identified in this regard, for instance, K. Daniel et al. (1998b) link momentum returns with self-attribution bias which forms a base for the confirmation bias. Hirshleifer (2001) state that Self-attribution results in overconfidence, when added with adjustment and anchoring, which leads to conservatism on part of an investor hence creating momentum through an under-reaction to the new information.

Overconfidence in addition to the confirmation bias is studied by Park et al. (2012). It was suggested that confirmation bias leads to overconfidence and therefore, high investor expectation and high trading volume while the realized returns are low in contrast. The confirmation bias and overconfidence bias were established after studying 502 investor reactions in South Korea. Overconfident investors are expected to make more investment and judgment errors (Barber and Odean, 2001). Rabin & Schrag (1999) found that confirmation bias will result in overconfidence of investor who is hesitant to learn despite the availability of significant information.

The overconfidence bias is also confirmed by Metwally (2015). The study was conducted in the Egyptian stock market; it was concluded that the overconfidence bias has a positive significant impact on trading volume. As high trading volume leads to high investor overconfidence. Jlassi et al. (2014) concluded that overconfidence is the prime reason behind the global financial crisis. The study was conducted in eleven developed markets, four were Latin American markets and seven were Asian markets. A high level of overconfidence was observed in developed markets as compared to the developing or emerging markets in DOWN and UP states of the market. While for some Latin American and Asian markets, overconfidence bias could not be found.

A meta-analysis was used by Miller & Ross (1975) and provided evidence of self-attribution while explaining the ordinary methods of testing the bias. Respondents within the experiment are directed to complete a task and then a random win or lose outcome was assigned to such respondents. Respondents are afterward interviewed about why they thought they have lost or won. The respondents usually attributed their winning status to themselves while they deemed their failures associated with some external factors.

Self-attribution is also studied outside the psychological domain. For instance Skaalvik, (1994) provide evidence of self-attribution in sports, and found self-attribution bias in students' performance while they were learning. While Stewart (2005)found that in accidents the drivers attribute external factors to the accidents while ignoring their own faults.

Many finance-related studies have investigated the self-attribution bias of individual investors or any other financial market participant. While others have studied the market-based self-attribution bias. For instance, K. Daniel et al. (1998b) & Gervais & Odean (2001) developed a theoretical model for self-attribution to show, how individual investors turn overconfident. An individual investor successfully predicts a dividend payout for the coming period, such success is regarded as the personal skills of an investor while ignoring the external factors like luck and chance. Such behavior leads those investors to become overconfident in their coming decisions. Gervais and Odean proposed that in a financial market that is composed of young or new traders largely in bull conditions, over-confidence is expected to be much higher all due to self-attribution. It was found that past financial experience will moderate the self-attribution bias.

Studies on acquisitions and the role of CEOs have found that past experience is the moderator in their self-attribution bias. A study conducted by Choi & Lou (2012) on fund managers found that low-performing managers exhibit self-attribution. These managers are expected to enhance their portfolios which have different values from the benchmark proceeding a time of increased volatility. It is established that the frequency of positive and negative outcomes increases in a time of high volatility. Choi and Lou conclude that poor-performing managers are those who have not yet learned to overcome their self-attribution bias. Therefore, in times of peaked volatility, managers regard the positive outcomes to their own skills and decisions while they attribute the negative outcomes to some external factors. This leads to increased overconfidence which in turn results in over-investment.

Overconfidence has also been studied in some recent studies. For instance, some recent studies (e.g., Areiqat et al., 2019; Chhapra et al., 2018; Keswani et al., 2019) studied overconfidence from a global perspective and found that investment decisions are positively impacted by overconfidence bias. Similarly, using primary data, Rasheed et al. (2019)found that overconfidence is significantly related to investment decision making with a moderating effect of locus of control hence pointing out the individual-specific components in the overconfidence bias.

2.3.2 Anchoring Effect

The term anchoring bias was first coined by Daniel Kahneman and Amol Tversky in 1974 in behavioral finance. It is defined as that individuals estimate values by using some baseline value which is refined for the final value, such baseline value or an initial value comes from some calculations or from a problem at hand. Any adjustments to the initial baseline value are based on the initial value however, these adjustments must converge to the starting value. This inclination in adjustments of estimates towards a baseline or initial value is referred to as the anchoring effect.

Anchoring is only significant when it is more accurate, it defines the true direction of an investor otherwise, it may also result in the investor's misguidance. Since anchoring reflects adjustments or corrections to a baseline or initial value, the corrections made to the initial value are ultimately inadequate because it still does not reflect the true value (Lichtenstein & Slovic, 1971)

Kaustia et al. (2008) studied the anchoring effect on 213 university students and 300 finance professionals in Scandinavia. The study showed a low significant anchoring effect for finance professionals and a highly significant anchoring effect for stock return expectations in long term. Furthermore, it was found that professionals are not highly bothered by past values in estimation. Anchoring bias was also confirmed by Khan et al., (2017) in the Pakistani and

Malaysian stock markets by using primary data tools. Historical average values are used by most investors as anchors in order to forecast the performance of a firm (Cen et al., 2013).

Campbell & Sharpe (2009) conducted a study on monthly data from 1990 to 2006. They found a significant anchoring effect. The results also indicated a biased expert opinion towards the previous month's data. Bond returns were found to strongly react toward the unexpected part of the information which depicted that bond yields are not in any way linked to the estimation error caused by anchoring.

The anchoring effect in stock market returns is measured through the use of 52-week low and 52-week high anchors. These anchors assume that stocks will never cross the threshold range of 52-week high and 52-week low. Nearness to a 52-week high is also used by George & Hwang, (2004) & Li & Yu, (2009). Similarly, nearness to a historical high is also used as another measure of the anchoring effect (Li and Yu, 2009). As previous information is included in current prices, estimation of future prices relies on previous information and prices (Campbell & Sharpe, 2009).

Nearness to a 52-week high is a relatively better measure as compared to nearness to the historical high in the estimation of future returns (George & Hwang, 2004). In long run, 52-week high returns are not expected to revert back. Therefore, it can be inferred that a 52-week high more robustly measures the under-reaction in contrast to some novel information. Since under-reaction indicates the slow updation of information by investors, a 52-week high anchor is considered a more suitable anchoring measure in the estimation of increments in the stock market. Similarly, a 52-week high anchor is also supported by George and Hwang (2004). They propose that a 52-week high is a relatively better measure as the existing price level best defines the momentum effect as compared to any changes in prices due to the behavioral aspects of the anchoring theory.

Furthermore, it is believed that a 52-week anchor acts as the best measure of anchor in estimating future returns.

Proximity or nearness or closeness to a 52-week high of stock returns reflects that good news has recently arrived in the market. Investors are reluctant to invest in such stocks although the information at hand depicts price hikes in the future. However, in the long run, the information results in high prices. Conversely, if the stock prices are somewhat close to a 52-week low, stocks will be purchased instead of selling by investors at low prices. The prices will fall down due to the dissemination of information. The same results were also validated by Grinblatt & Keloharju, (2000) in a study conducted on the Helsinki stock exchange. Prices for stocks close to the 52-week high, yield better performance because investors, in general, use the 52-week high anchor, which is used in stock valuation. Investors are seen as less interested in purchasing such stocks regardless of the good news that arrived in the market. Ultimately, investors are more likely to under-react to a situation where prices are somewhat near to the 52-week high anchor. In contrast to the investor's expectations, stock prices close to the 52-week high are, Therefore, as opposed to investor's expectations, stocks near to the 52-week high are devalued.

Closeness to the 52-week high is considered a measure of underreaction where positive returns in the future are expected while closeness to the historical high is considered a measure of market overreaction where negative returns are expected in short horizons of 1-12 months (Li and Yu, 2009). These proxies when added with macroeconomic variables, lead to an overall 46 percent estimation of market returns, attributed to the underreaction of the market in response to a broken series of information and overreaction in response to a series of some good news. So, the current level of prices of stocks near the 52-week high reflects the under-reaction of the market to positive information while the farness of stock prices from the 52-week high depicts overreaction of the market against some bad news. On the other hand, stock prices near to or far from the historical high show overreaction of a market to a negative or positive set of information.

Anchoring bias is seen as the investor's reliance on previous prices and experience. Where the investor does not pay any special attention to the recent news, while prices are made fixed before selling and buying and the investor is in search of the right time to trade stocks also influenced by a variety of moods. Various factors can be proposed, that influence the anchoring tendency of an investor. For instance, bad, sad or discouraged moods are linked with the tendency of an investor to be more precise in the assessment of some issue at hand (Bodenhausen et al., 2000). Therefore, as a consequence of this, literature provides that individuals with bad moods are less prone to the anchoring bias as compared to those with good moods. Some other researchers have shown a variant conclusion, for instance, Englich & Soder (2009) found that individuals with good moods will demonstrate an anchoring effect more as compared to individuals with bad moods. Roberto Luppe & Paulo Lopes Fávero, (2012) conducted their study in Brazil on the relationship between the anchoring heuristic and the prediction of financial indicators. The major task of the study was to explore positive accounting in Brazil and to show different aspects of a variety of variables on investor behavior. Evidence of the anchoring bias was found in the prediction of the given indicators.

Many studies following Tversky and Kahneman's have demonstrated the anchoring effect in most human decisions. The anchoring effect is established in different domains. For instance, the Anchoring effect from a general knowledge perspective is studied by Epley & Gilovich, 2001 & Mcelroy & Dowd, 2007). While probability estimates in relation to anchoring are studied by Chapman & Johnson (1999). In general, the knowledge's perspective, anchoring effect is studied through asking basic questions like "how many states are there in the U.S"? (Epley and Gilovich,

2001) or “the length of the Mississippi River” (McElroy and Dowd, 2007). Since most of these studies were conducted in a laboratory setting, therefore, the generalizability of these studies comes under question. However, studies conducted in more realistic scenarios, for instance, legal judgments, valuations, purchasing decisions, negotiations, forecasting, and self-efficacy in relation to the anchoring bias have proved to generate more robust results. (e.g., Critcher & Gilovich, 2008; Englich & Soder, 2009; Galinsky & Mussweiler, 2001).

Similarly, Thorsteinson et al. (2008) applied both laboratory and field studies to establish the relationship between performance judgments and the anchoring bias. Oppenheimer et al. (2008) studied the boundary limitations of anchoring effects in relation to the use of anchors working across different dimensions of the judgment bias. Interestingly, most of the studies have shown robust results for anchoring bias in relation to various judgments.

Yet another study by van Exel et al. (2006) showed that higher ambiguity, lower familiarity, weightage of personal involvement, and trustworthiness in the estimation of response result in a relatively stronger anchoring effect.

A recent study conducted by Shin & Park (2018) investigated anchoring bias in relation to foreign investors in the Korean Stock market. The results showed that anchoring proxy and Post earnings announcement drift (PEAD) are positively related to each other. Interestingly, the relationship was insignificant for those stocks which were owned by foreign investors. It was concluded that global investors are more sophisticated and they are able to overcome the anchoring bias.

According to Parveen & Siddiqui (2018), investors prefer to invest in stocks with recently declined prices with the hope that these stocks will appreciate once again. Therefore, such investors anchor on the current prices which they expect will appreciate in the future. Such preference of investors is based on reputed firms and seasonal cycles.

Since anchoring is closely associated with forecasting and estimation, it has a significant role in financial markets. According to Tversky and Kahneman (1974), individual investors utilize decision strategies that are ‘cognitively tractable’. Such strategies called heuristics are aimed to deal with uncertain and complex situations. Heuristics are expected to decrease the circumference of relatively sophisticated and complex events into simple and easy cognitive activities. As a matter of fact, although these heuristics are targeted toward dealing with uncertain circumstances, these may also result into systematically biased outcomes. As mentioned earlier, anchoring is one such mental shortcut that is used by investors to forecast values by starting with an easily available baseline or reference value. Investors tend to anchor their purchasing price with historically high prices of the stock. Shiller, (1999) proposed that new stock prices will be closer to the old stock prices if past prices are used as an indicator of the new prices. Therefore, in the case of high uncertain prices of securities, a stronger anchoring is expected. In other words, such a relationship indicates a return flow in the negative direction. As investors would consider stocks economical when the stock prices fall. A 52-week high momentum was observed by George & Hwang (2004) associating it with anchoring bias. A 52-week high price is used as an anchor by the investor in decision-making. Investors are hesitant to trade stocks at an adequately high price especially when the prices are close to the highest value which are then influenced by subsequent positive news. These studies reflect that while evaluating the incremental value which includes any novel information, investor forecasting is significantly affected by the past time-series variations in prices due to anchoring bias and heuristics.

2.3.4 HERDING BIAS

Herding behavior is the propensity of an individual to imitate the activities of another individual or group regardless of the fact that whether it is sensible or not? Herding behavior in most instances is a set of decisions and activities that is based on the action of some other individual or a group.

In the financial context, the dot-com bubble is an example of herding behavior. As in the late '90s, a very large number of investors made investments in digital companies even though many of such companies had a feasible business model, the main reason for investors' over-investment was the security that they received by looking at other people doing the same. Even today, some experts point out a probable financial bubble in the cryptocurrencies financial markets.

Herding is normally seen in a time of large market stress or price movement. Large investors and institutional investors have a significant impact on price movement. Even though institutional investors are expected to be relatively rational, are also seen to undergo a herding effect. Christie & Huang (1995) suggest that individual investors are expected to undervalue their private preferences in favor of large group behavior in times of rapid market movement. While the frequency of herding enhances with information risk (Boortz et al. 2013).

An analytical model was developed by Banerjee (1992) which stated that asymmetrical information and its associated high cost of acquisition, leads investors to ignore the basic value of an asset and rather follow the market trend, which consequently results in market inefficiency. Domestic and foreign investors of the Korean stock exchange were studied by Kim & Wei (2002). It was found that foreign investors were more prone to herding behavior as compared to domestic investors. Similarly, Chen et al. (2003) analyzed A-share and B-share markets to investigate any difference in the behavior of foreign and domestic investors. It was confirmed that foreign investors are inclined to more herding as compared to domestic investors. These findings suggest that the case of uncertainty and non-availability of worthy information encourages investors to resort to herding behavior. Italian stock market was investigated by Caparrelli et al. (2004), where no evidence was found for herding behavior. The study was conducted for the period 1988-2001.

Herding behavior was investigated by Tan et al. (2008) on a-share and b-share firm stocks listed on Shanghai and Shenzhen stock exchanges. Herding behavior was found for both A-shares and B-shares however, herding for weekly and monthly time intervals was weaker indicating the short-term nature of the phenomenon. It was also found that in case of high volatility, high trading volumes, and rising stock market herding is stronger for A-shares in the Shanghai stock market. In contrast, no such asymmetry for B-shares was observed. A study in the Athens stock market by Caporale, Economou and Philippas (2008) investigated herding behavior in extreme market conditions from 1998 to 2007. The results showed a more intense herding behavior.

A more comprehensive study was conducted by Chiang & Zheng (2010) using daily data from 1988 to 2009, for 18 different countries. These countries included Thailand, Australia, Singapore, the United States, Malaysia, Chile, France, South Korea, Germany, Mexico, Hong Kong, Brazil, Argentina, Japan, and United Kingdom. Significant evidence of herding behavior was found in all countries except Latin America and the U.S. the findings were in contrast to the earlier studies which stated that herding in advanced countries does not exist.

Herding behavior was also found in the Indian and Chinese stock markets by Lao & Singh (2011). The study used the CSAD approach proposed by Tan et al. (2008) while using daily data of the top 300 stocks from both markets from 1999 to 2009. It was found that herding is stronger in extreme market conditions but only with different patterns. In bearish Chinese markets, herding was relatively stronger. While in the Indian stock market, herding was stronger in bullish or trending market situations. However, Lakshman et al. (2013) found that herding behavior in the Indian stock market is not that much stronger indicating that Indian investors are rational and therefore they behave rationally. Additionally, it was proposed that a market crisis can result in equilibrium, herding is more evident before a crisis rather than in the middle of such a crisis. Herding behavior was also found in the Tunisian stock market, especially in the downward market trend (Gabsia, 2011).

According to Bikhchandani & Sharma (2000) there are three reasons for institutional herding. Firstly, assuming that others may have more accurate information about the returns and their trading patterns may reflect such information. Secondly, the fund managers who invest on behalf of others, are subject to the incentive plans offered by the employer which motivates the managers to replicate and follow others, and thirdly, investors as individuals have an innate tendency to validate and align their actions with others. Yet another reason for herding is that individual investors follow the trending forecasts (Clement & Tse, 2005).

As the same time frame and the same set of information are used by analysts in estimation, it is more likely that these analysts may follow the same estimation trends. Therefore, having an underlying trend or consensus does not necessarily reflect herding behavior at all (Zitzewitz, 2005).

Herding maybe because of uncertain valuation according to Prechter & Parker (2007) Investors who are undergoing any financial distress, are unable to systematically analyze the required data for decision-making and are therefore more prone to herding behavior. Similarly, due to the non-availability of the required information, individual investors are left to rely on their own instincts. As every market participant is liable to incur the cost necessary for the acquisition of some information, observing others in decision-making does not involve any cost. That’s why individuals are expected to resort to free and easy mediums hence herd. Even a small-scale increase in the observation cost results in the discontinuation of herding (Kultti and Miettinen, 2006). In extreme market conditions, information reaches within its due time but investors are unable to acquire such information due to time constraints. Therefore, investors herd in extreme market conditions where information is not readily available or it has certain associated costs.

N.Jegadeesh et al. (2004) suggested that stocks having higher growth rates in returns, trading volume, and positive momentum are valued high by the analysts. It can be inferred that herding being an irrational move is strengthened by a low level of information. Similarly, stocks with relatively low turnover are linked with less availability of information. As mentioned earlier, stocks with relatively low turnover are more prone to herding in contrast to stocks with high turnover (Gregoriou & Ioannidis, 2006). A study conducted by (N. Jegadeesh & Kim, 2006) studied the behavior of sell-side analysts, and whether they herd while making recommendations. It was found that, when a stock recommendation is different from the market trend, reaction to such recommendations varies from the trend, and it is greater when the recommendation is nearer to the market trend. It indicates that the market is able to recognize herding behavior.

'Home bias' was investigated to be the reason for international herding through adjustments to the ICAPM (Hachicha et al., 2010). 'A home bias equity' was the preference to hold domestic stocks regardless of being familiar with the potential gains from international diversification. Hachicha et al. (2010) introduced the 'international dynamic herding' and investigated its impact on financial markets in the Eurozone. A strong relationship between herding behavior and market return was found. The ICAPM significantly improved when herding was included for adjustment while herding provided the psychological justification for home bias in the eurozone financial markets.

While studying the U.S mutual funds for the period 1994-2003, Wei, Brown, and Wermers (2007) probed two major questions. Firstly, do the mutual funds herd in the direction of the analyst's recommendations and revised recommendations? And secondly, what is the impact of such revision-induced herding on stock prices? It was found that the herding in mutual funds, in relation to the analyst recommendation, leads to a market overreaction in terms of the resultant trading impact. Mutual fund managers show overreaction to the information included in the trending indications of the analyst. Such revised recommendations induced herding indicates that herding is observed for a reason other than information.

The impact of noise in relation to the market returns was studied by Hoitash & Krishnan (2008). The term noise referred to herding implying the response of the investor caused by factors other than the information. They used a measure of speculative intensity based on the autocorrelation in trading volume, depicting the available information as a proxy for herding. It was evident from a highly significant positive relationship between speculative intensity and market returns that firms with high speculative intensity provide greater momentum strategies while the investors overreact to these firms with high speculative intensity.

Herding pushes the stock prices away from basic values, leading to momentum in the market where winners continue earnings while losers keep on losing till mean reversion starts to occur or some new information arrives that corrects the existing prices. Yan et al. (2012) examined the combined effect of momentum effect and herding. It was found that weaker herding enhances the momentum effect. The presence of momentum threatens the validity of EMH and signifies investors' overreaction in response to public signals. According to Cooper et al. (2004) high momentum effects related to UP market conditions are linked with market overreaction implying that the momentum effect reverts in the long run since market prices are adjusted in the long run.

A study conducted by Javed et al. (2013) examined herding in the Pakistani stock market. The KSE-100 with its monthly returns was analyzed. The results showed no evidence of herding in the Pakistani stock market. The absence of herding would mean that a Pakistani investor is a rational investor however, it is assumed to be contradicting. The study necessitated more comprehensive studies in the future. Furthermore, it was also suggested that since herding is a short-term concept, therefore, it must be studied in short horizons.

Many studies have concluded different opinions about the underlying motives of herding. It is established that investors are attracted by the similarity of securities, historical returns, liquidity, and size of the firm Gompers & Metrick, (2001). While Barberis & Shleifer (2003) consider fashion as yet another important factor in explaining herding behavior. Herding most commonly occurs in managers, investors, analysts, and portfolio managers as these financial market participants depend upon the performance of their concerning stocks and portfolios (Trueman, 1994). To show accurate forecast, these financial stakeholders feel not to vary their opinions from each other. For example, whenever analysts feel less confident about their forecasting, they tend to follow large and experienced analysts even though their available information does not confirm the forecast (Trueman, 1994). Similarly, when investors have less time to acquire and analyze information or if the cost of information is not feasible, especially in times of financial distress, investors resort to the herding as a completely free ride in extreme market conditions (Kultti and Miettinen, 2006). Another argument in favor of herding is that it is generally assumed that crowd decisions are less likely to go wrong. Therefore, a herding behavior reflects increased confidence in the mass judgments.

Yet another study by Chang et al. (2000) studied the herding behavior of financial market participants in global markets. They proposed the cross-sectional absolute deviation (CSAD) to study the dispersive relationship between stock returns and market returns. The CSAD decreases or increases at a diminishing rate for a possible herding behavior. No herding behavior was found in the U.S and Hong Kong. While slight evidence of herding was found in South Korea, Japan, and Taiwan. Furthermore, it was found that macro-economic information had a greater role than any firm-specific information in the herding effect.

The Indian and Chinese stock markets were investigated by Lao & Singh, (2011) for a herding effect. It was found that both stock markets are inefficient based on menial information disclosure. While the Chinese stock market had relatively more herding than the Indian stock market. However, the herding effect was stronger in bigger market movements. While the asymmetry test showed a greater extent of herding effect in times of low market returns and high volumes of trading. While in the Indian stock market herding was found in high market conditions. No relationship was found between the herding effect and trading volumes in the Indian stock market. Factors responsible for herding behavior in china were found to be short-term investor horizon, analyst recommendation, and the level of risk in decision-making (Chong et al., 2017).

A study conducted by Christie & Huang (1995) used the cross-sectional standard deviation (CSSD) for the measurement of the herding effect. They proposed that when investors do not rely on their own judgment but rather follow the market trends in times of extreme volatility, the value of CSSD will be small in the form of deviation between individual security returns and market returns. The Istanbul stock exchange was investigated by Ayhan Kapusuzoglu (2011) using the model of Christie & Huang (1995). The results revealed that when the market index returns increase, the cross-sectional absolute deviation (CSAD) also increases. Furthermore, a non-linear relationship was found between the index return and cross-sectional volatility.

K. C. Gleason et al. (2004) followed the methodology of Christie and Huang (1995) by using the intraday data prices of nine sectors ETFs on the AMEX from 1999 to 2002 to examine whether traders undergo herding in times of extreme market conditions. The results indicated that no herding behavior by investors is observed during extreme market conditions. Similarly, no herding behavior was found in the “New Securities Stock Exchange of Montenegro” by Kallinterakis & Lodetti (2011).

Using the daily data of NIFTY-50 from 2006 to 2011, Prosad et al. (2012) also failed to find any herding behavior in the Indian stock market. The results were in contradiction to that of earlier studies. On the other hand, studies on herding in bearish and bullish markets reveal that herding is stronger in bull market conditions as proposed by Lao and Singh (2011).

The turnover effect was studied by Fu (2010) in relation to herding behavior. The results found a significant turnover effect for low turnover stocks as compared to the high turnover stocks. Low turnover stocks are less attention-grabbing for the investors therefore, very little information about these stocks arrives in the market. Due to insufficient information, the investors tend to show herding for low turnover stocks in contrast to high turnover stocks (Gregoriou & Ioannidis, 2006). A recent study conducted in the Indian stock market by Satish & Padmasree (2018) investigated herding behavior through secondary measures from 2003-2017. The results showed no indication of the herding effect especially in relation to before crisis, in crisis, and after the financial crisis.

In the Pakistani context, herding behavior was found in several studies, for instance, using quantile regressions, Jhandir & Elahi (2015) found evidence of herding behavior in normal bearish and bullish market conditions. Similar results were also found by Shah et al. (2017) between firms with large capitalization in extreme market conditions.

Corona pandemic has clearly halted the economic and social lives across the globe during the past year. An interesting study was conducted by Kizys et al. (2021) to investigate government response to tackle herding behavior across the corresponding stock markets. The results showed the existence of herding in international stock markets. However various regulations like a ban on short-selling seemed to contribute to mitigating herding in international stocks.

2.3.5 LIMITED ATTENTION BIAS

Limited attention is an important outcome of the cognitive hurdles and the wide set of available information. The significance of time and mental operations in the valuation of a firm cannot be undermined. While the investors need to evaluate plenty of firms for investment decision-making these individuals, as well as analysts and mutual funds managers, are equally affected by neglecting the required information. Whenever investors face limited attention, they only use a small portion of information publicly available. Such information ignored earlier is incorporated into the stock prices at a later stage.

It is argued that a limited attention bias may involve a vast array of stylized research findings like stock price-return movements, an underreaction to some public news, and the long-term behavior of corporate managers. A relatively simple model exhibits the impact of limited attention on capital markets. Such a model is expected to demonstrate that stock prices do not necessarily reflect the amount of information especially when investors do not give due attention to such stocks. Similarly, the model will show that the prediction power of returns increases as long as the investor's attention increases.

The accruals anomaly and the post-earnings announcement drift are the two of the most frequently studied anomalies. The accruals anomaly is the negative abnormal stock return of a company with the highest accruals. It proposes that investors show overreaction to accruals which is after all a constituent of earnings (Teoh et al., 1998). While the post-earnings announcement drift states that stock prices show under-reaction to earnings announcements, as it will affect the investor if they fail to give proper attention to the earnings announcements.

The model proposed by Hirshleifer et al. (2009) proposed a model that corrects the underlying differences. Whenever a group of investors reacts to some earning news, an under-reaction to the earnings announcement is shown. Some of the investors do not give proper attention to the application of variant persistent expected cash flows from the accruals and operational cash flows. The frequency of expected cash flows is smaller if the earnings form a major part of accruals as compared to the operational cash flows. It is still argued that both anomalies can co-exist based on the relative frequencies of the investor type.

Past studies have well established the limited attention bias concerning the availability of public information resulting in stock momentum, accruals anomaly, and post-earnings announcement drift while having an impact on stock prices (K. Daniel et al., 2002). Different accounting fundamentals estimate the expected abnormal returns like returns on net operating assets (Hirshleifer et al., 2004). Financial ratios specific to identify the operating performance and distress of a firm (Lev & Thiagarajan, 1993) and cash-flow-to-price ratio (Desai et al., 2004).

The role of investor attention in the market reaction was studied by Hou et al. (2011) using trade volumes and the market state as a measure of investor attention. They used market state based on the study conducted by Karlsson, Loewenstein, and Seppi (2005), these states were in the form of up and down market conditions. The results revealed a robust underreaction to earnings announcements in low turnover stocks in a down market, representing a larger extent of investor attention.

Sonya and Teoh (2010), suggested that the degree of incorporation of information in stock valuation is expected to be greater, especially if the competing stimuli or the distractions are less in number while the information at hand is prominent and easy in processing. The empirical proxies for limited attention bias, used by various studies are based on three factors firstly, the role of competing stimuli which are expected to divert investor's attention from the relevant information secondly, the importance of the underlying information and its processing and thirdly, other variables like internet search volumes and trading volumes which reflect the extent of investor's attention. Under is a brief detail of these three factors in shaping a proxy for an investor's attention.

2.3.5.1COMPETING STIMULI AS A MEASURE OF INVESTOR INATTENTION

It is a general observation that individual investors face difficulty in paying attention to any relevant information, especially in the presence of other competing stimuli. This is also supported by Kahneman and Tversky (1973) by stating that attention required by one task must be compensated for or substituted by another task. For example, in studies of dichotic listening as quoted by Sonya and Teoh (2010), a different message is played in each ear of the respondent simultaneously (Moray, 1959). The respondents are required to attend to at least one of the messages and repeat one message. The message not attended by the respondent is generally not remembered by the respondent, especially in the case when extra time is sanctioned for them to recall the message. This experiment indicated that individual listeners face difficulty in deciphering a specific message especially when they are bothered by an equally compelling message. Such an alternative message is considered a competing stimulus for the attention of the listener.

In yet another study by Dellavigna & Pollet (2009) they proposed that on Fridays, investors are less accurate in stock valuations due to inadequate attention toward earnings announcements. They observed a relatively less noting market reaction in response to the earning announcements on Fridays. Similarly, a stronger under-reaction was observed in response to the earning announcements during the non-trading hours (Bagnoli et al., 2011). Hirshleifer et al. (2009) studied the extent of information overload due to the earning announcements on a specific day. Furthermore, it was found that in the case of an earnings announcement, market reaction is relatively weaker while the drift is relatively stronger on a specific day where several other competing announcements are also made. While the announcement from within the same industry is less distracting than announcements from non-related industries.

2.3.5.2 SALIENCE OF INFORMATION AND PROCESSING EASE

Some of the stimuli are more attractive and salient as compared to others, therefore they are more easily processed by individuals. The more prominent information is also more salient and people tend to more readily process salient information as compared to the non-salient information. It is evident in the form of stock prices reaction to the availability of any public information (Huberman & Regev, 2001). Attention is also diverted to an easily accessible and processable set of information. Investors are expected to pay attention and evaluate event probability on the basis of their tendency to recall confirmatory situations. These individual investors also tend to acquire information that lies within logical and systematic patterns. Stimuli that are more closed proximally, in a spatial and temporal way are considered salient. The psychology literature suggests that salience effects are more widespread and robust (Fiske and Taylor, 1991). The literature also proposes that investors face more difficulty in processing less salient and harder processing information. Lower investor attention reflects greater return expectations based on such information.

Dellavigna & Pollet (2009) studied the impact of demographic attributes on cross-sectional returns. As demographic information estimates potential profits or demand shifts for age-sensitive assets. So, if investors give full attention, the expected changes can timely be included in the stock prices. It was also found by the researchers that long-term forecasted growth may indicate abnormal returns in the industry, reflecting that investors do not give attention to the implications of demographic changes in the long run. These changes are harder in processing and less salient in contrast to the short-term orientation.

According to Cohen et al. (2008) a market under-reaction is observed in response to specific news that is economically related to firms, and such relation is discovered through customer-supplier linkages. It was also suggested that returns predictability is based on the level of investor's attention. Investors can pay attention to the economic relation especially when these investors possess stocks in both customer and the supplier's firms. Cohen et al. (2008) also stated that the predictability of the returns is stronger when a small number of total investors hold stocks in economically inter-linked firms.

Earning news is categorized into hard and soft information by Engelberg (2011) these are also called quantitative and qualitative information respectively. Furthermore, Engelberg also investigated the relationship of such earning information with post-earnings announcement drift. Soft information was measured through the negative words included in the earnings press release, it was found that such information has incremental predictability. The return predictability is extendable to longer periods as compared to the quantitative information. Similarly, Peress (2008) found a more robust market reaction and a less drift for the earning announcements covered by the wall street journal, which is more salient as compared to other sources.

Experimental accounting studies conclude that categorization, placement, and labeling influence the perceptions of financial statement users. The salience of information affects the judgment of causality and the relevance of such information. Therefore, variations in the presentation and disclosure of a specific set of information about a firm influence the investor's aptitude in stock valuation and trading. Accounting information presented on the face of financial statements is valued greater than the information mentioned in notes and disclosures. Similarly, these investors also give more weightage to the recognized information written down in determining the net income in contrast to the information written down in disclosures and notes to the accounts in the oil and gas industry (Aboody, 1996).

According to Davis-Friday et al. (1999), investors overvalue non-pension retiree benefits as compared to the presented liabilities. Experimental studies are more important in investigating the perceptual differences regarding the respective significance of the accounting information based on its classification and presentation.

Hopkins (1996) reported that when the same hybrid financial instrument is presented as equity, debt, or a mezzanine item in the balance sheet, it is treated differently by the experimental subjects. Similarly, the users of financial statements give more value to the 'pooling of interest method' over the 'purchase method' (Hopkins et al., 2000). As the 'purchase method' leads to lower earnings since the merger premium is diluted over several future periods. As stated earlier, the users of financial statements overvalue income items more especially when they are presented on the face of financial statements as compared to when it is presented in relatively less visible parts of financial statements like 'statement of changes in owner's equity (Dietrich et al., 2001).

A study conducted by Cai et al. (2011) reported that stock prices do not indicate the costs of option grants unless they emerge on exercise. Furthermore, they also reported that the predictability of the returns is reduced in response to the implementation of accounting standards which implies that firms must report the fair market value of stocks in contrast to their earnings.

2.3.5.3 OTHER PROXIES OF INVESTOR ATTENTION

Trading volume is used as yet another proxy for investor attention (Hou et al., 2011). Trading volume is used as a proxy because investors tend to trade more when they pay more attention to the stock price variations, therefore, high trading volumes indicate high investor attention. Similarly, Google search volume is also used as a measure of investors' attention. Da et al. (2011) state that Google search volume indicates a more precise measurement of investors' attention. interestingly, the above-mentioned measures i.e competing stimuli and salience of information serve as the determinants of investor attention while trading volume and google search volumes are regarded as the outcomes of investor's attention.

Hou et al., (2011) studied the impact of investor attention on the market over and under-reactions while measuring investor attention through market state and trading volumes. They followed Karlsson et al. (2011) in using the market state as a proxy which was based on the notion that investors exert more attention in times of market up conditions than in down conditions. The results included a strong under-reaction to earning information in stocks with low trading volume in down markets, implying that high levels of investor attention result in speedier market reactions towards the earning information.

Loh (2010), studied the impact of investor attention in relation to market reaction and stock recommendations. Recommendations by analysts are supplemented by the following drift, representing investor under-reaction to stock recommendations. Loh (2010) used trading volume as the main proxy for investor attention. He also used institutional ownership, analyst coverage, and the numbers of earnings announcements on the same day as various other proxies for investor attention. The results indicated a stronger recommendation drift for low turnover stocks, institutional ownership, the number of an announcement on the same day, and analyst coverage.

Limited attention is a bias that is equally performed by financial analysts. These analysts demonstrate a lack of attention, especially when developing reports in other words these analysts overweight industry information rather than going for firm-specific information. (H. M. Choi & Gupta-Mukherjee, 2016). Similarly, Driskill et al. (2020) found that analysts covering concurrent announcements tend to exert limited attention on firms that have already rich information.

2.3.6 DISPOSITION EFFECT

The disposition effect is the tendency of investors to sell stocks that have appreciated in value while retaining those stocks which have depreciated in value. The stock trading decisions of investors generally rely on the future variations in prices of the asset rather than its historical price patterns. However, this notion is contradicted by the behavioral finance theories which state that investors' trading patterns depend upon the historical performance of the stock. According to the famous prospect theory, Individuals generally tend to opt for those options which are less loss-yielding or which do not involve any loss. The reason attributed to such a risk-averse tendency is that individuals assign relatively lesser weights to options involving high levels of uncertainty based on the probability of the underlying event. However, in contrast, investors behavior tend to sell those stocks which are expected to devalue in the future, and stocks having the chance of price appreciation are purchased. According to the behavioral finance aspect, individuals realize gains by disposing of worthy stocks and retain losing stocks in the prospect of reversion. Such tendency of individual investors is called the disposition effect by Shefrin & Statman, (1985). The disposition effect is commonly observed across multiple stocks around the world. For instance, a study conducted in Finland by Grinblatt & Keloharju (2000) studied five categories of investors. These were insurance companies, financial and non-financial companies, households, foreign investors, and government institutions. Foreign investors were excluded due to time limitations while the rest of the categories were observed to significantly demonstrate that these investors would not sell stocks having capital losses. Strong evidence of the disposition effect was found by Odean (1998) who conducted his study in the USA from 1987 to 1993 by examining 10,000 investor accounts. Similarly, stocks realizing capital gains were sold by Australian investors, indicating the presence of the disposition effect (Jackson, 2004). The disposition effect was also confirmed in the Korean stock market and the Estonian stock market by Choe & Eom (2009). A study conducted by B. Li et al. (2014) also confirmed the existence of the disposition effect in the Chinese stock market. The researchers made a multi-agent model, where investors were classified into fundamentalists, inactive traders, and chartists based on the trading strategies. the results showed asymmetric volatility in the Chinese stock market indicating that volatility is more subject to bad news than good news.

A vast literature is available that confirms the existence of the disposition effect experimentally and empirically. For instance, Dhar & Zhu (2006) and Barber et al. (2007) empirically and T. Y. Chang et al. (2016) experimentally confirm the disposition effect. While Odean (1998) contends that drivers of disposition effect are still not clear. Interestingly, different approaches have been used to measure the disposition effect which is not justified. As a matter of fact, these approaches have led to different results.

Out of the two pioneering principles concerning the measurement of the disposition effect, Weber & Camerer, (1998) measures disposition effect as the difference in trading of winner and loser stocks while Odean (1998) measures disposition effect as the difference in magnitude of losses and gains which are realized. Both measures range from -1 to +1. Where positive 1 indicates that the investor will sell a winning stock and vice versa. The results given by the two approaches vary for different approaches. Similarly, the same researcher may employ different methods. The realized paper gains and paper losses are calculated on the day of a sale of the stock by Barber & Odean (1999) while paper gains and losses are calculated daily by (Barber et al., 2007)

Odean (1998) examined the trading history of 10,000 investors for six years in the USA. In a comparison of the realized gains with realized losses, it was found that investors realize a lower magnitude of losses than gains. After controlling for the 'rebalancing of the portfolios' which was represented by partial sales, the results still indicated a disposition effect. The study also tested a mean reversion strategy of investors by monitoring the performance of the subsequent portfolios. One and two-year periods being the holding periods on average, for securities listed on NSE, the ex-post returns were noted and it was found that the excess returns for the unsold stocks over the sold stocks were 3.4%. similarly, the study also confirmed the existence of the December effect. December is the month when more losing stocks are sold than the winner stocks and such behavior is attributed to the investor's tendency to curtail their taxes. As mentioned earlier, the study conducted by Odean (1998) is followed by many researchers while studying the disposition effect.

On the other hand, an experimental approach is employed by Weber and Camerer (1998) on the disposition effect. Their study was conducted on 100 students from two prominent universities in Germany. Respondents were given the option to trade in six given risky assets at the start of the period. Subsequently, the prices of the given securities fluctuated from their initial values to delineate the disposition effect from the formation process. The results showed that as proof of the disposition effect, respondents tended to hold losing stocks while they disposed of winning stocks. In other words, stocks having higher prices were traded more frequently in order to realize gains that's why a positive stock return implies a high turnover of the stocks. The trading behavior of the participants was examined for fourteen trading sessions with two major hypotheses. Firstly, to check for the existence of disposition effect in relation to the purchase and last trading price of the security. And secondly, to note the investor's behavior on the last trading day. The results showed a significant disposition effect for the first hypothesis while in the case of the second hypothesis where the investor is compelled to sell stock on the last trading day, could not be validated. The trading pattern of investors involving the disposition effect is identical to the mean reversion phenomenon of the investors. In actuality, it is not the case, many experimental and empirical studies imply that trading patterns do not necessarily, reflect the mean reversion tendency of the investor. As, on the fewer instance, the ex-post returns for the stocks retained or purchased at a later time, underperform the currently retained portfolio and attributes to the tendency of regret aversion (Barber and Odean, 1999). The experimental researches also negate the mean reversion factor due to the persistent trend in already traded stocks (Weber and Camerer, 1998).

According to the overconfidence bias, investors' overconfidence is primarily due to their over-optimism in-stock selection. Even though overconfidence and disposition effect both are directly associated with stock turnover, overconfidence indicates a transaction involving rationality on both sides while the disposition effect accounts for one side where gains are realized by selling stocks to rational individuals. According to Statman et al. (2006) overconfidence is a market-oriented approach while the disposition effect is more closely related to specific securities.

Ferris et al. (1988) suggested that the disposition effect is the determinant of the trading volume of stocks. While few studies have tried to establish the importance of the reference price as mentioned by the prospect theory. Kaustia (2004) stated that their study provided evidence on the relative significance of minimum and maximum stock prices in the form of reference points. So, reaching new highs and lows as compared to the previous months is expected to a relatively high turnover. Such effect was noted to be stronger for positive and negative IPO returns. Such effect is incremental in nature for larger changes in stock prices. New highs are considered more vital because their resultant effect is 1.5 times larger than new lows. Disposition effect on the basis of prospect theory has also some built-in challenges mostly in the form of their explanatory power. There is a disagreement that the disposition effect is observed even for those investors who generally do not purchase stocks. Similarly, the disposition effect is seen in ex-post investments and rarely observed in the ex-ante investments, therefore producing contradiction with the basic theory (Hens & Vlcek, 2011).

The disposition effect is also questioned by Ranguelova (2001). The study was carried out by delineating 78000 investors from a big retail discount brokerage firm. The disposition effect was related to the size of the firm and empirically establishes that even in the presence of the disposition effect, the breakup of the trend by firm size indicates a distinctive variance in the trend.

Similarly, the proportion of realized gains grows one-sided in contrast to the quintile stocks separated by market capitalization. While the extent of realized losses grows in terms of quintile size number, therefore the disposition effect also becomes weaker with relatively less market capitalization and small firm size. In other words, investors tend to dispose of their larger portion of large-cap and small-cap losses in stocks. In sum, several studies validate the existence of the disposition effect however, its existence does not come under question whether it is justified by any explanatory rationale? The below section will present a summary of studies on disposition effect in respect of the geographical location.

2.3.6.1 THE UNITED STATES OF AMERICA

Shefrin & Statman (1985) used the monthly purchase and redemption of mutual fund transaction data for the period 1961-1981 in order to study the overall trade patterns. It was assumed that mutual funds will represent the market trend while utilizing such information to build propositions for market gains and losses which would be based on the aggregate trade patterns. Considering a rational individual, who will try to minimize the tax burden, as opposed to the disposition effect, investors are expected to dispose of their losses and delay their potential gains. Therefore, mutual funds which are incurring losses in January and February are sold in February. While funds that result in gains for the same period are retained. The study shows that an investor's propensity to dispose-off gaining funds rather than losing funds, would increase the tax burden and therefore against the rational behavior assumption in the financial market.

Historical trading patterns of investors were for the first time studied by Odean (1998) in the U.S as discussed earlier, his study concluded with significant evidence of the disposition effect. Similarly, Kaustia, (2004) tested the disposition effect in the U.S IPOs. A stronger disposition effect in terms of post-listing trading trends was noted. It was suggested that the trading volume of a specific security should be high when it trades over the offer prices as compared to when it is traded below the issued price. In the price-volume relation, a kink is observed at the offered price for negative, initial returns for the IPO, indicating that trading volume is stagnant under the offer price. Similarly, when the price of the security is higher than the issue price and remains higher for an average time of two weeks, the trading volume significantly increases.

2.3.6.2 EUROPE

The disposition effect is also found in various studies, carried out in the European continent. For instance, Weber & Camerer (1998) used an experimental design for the disposition effect, the results of their study are already mentioned above. Similarly, the disposition effect was also validated in the European context by different authors (e.g., Grinblatt & Keloharju, 2000; Oehler et al., 2005). Mirjam Lehenkari & Perttunen (2004) examined the data that represented a total of 99% market capitalization on the Helsinki stock exchange. It was noted that losses in stocks demotivate investors to dispose-off their stocks. While only partial evidence was found for the proposition that investors retain loser stocks and sell winning stocks. In conclusion, it can be inferred that individuals, in general, avert losses, which is based on prospect theory and the disposition effect.

Another study conducted at Vienna university of economics and business administration by Kirchler et al. (2010) reported that investors who had secured some gains sold their securities relatively earlier as compared to those individuals who incurred losses. The participants were observed through trading software. While the mentioned effect was influenced due to positive framing. Therefore, individuals with positive framing were observed to dispose-off their securities as compared to the ones with negative framing.

2.3.6.3 THE ASIA PACIFIC

Various studies on the disposition effect are conducted in different regions of the Asia pacific. For example, Chui (2001), followed the methodology of Weber and Camerer,(1998) with slight modifications. The study was conducted in Macau, which showed significant evidence of a stronger disposition effect. The effect was still stronger even after controlling for the mean reversion patterns. Additionally, the researchers established a link between disposition effect and personality factors. It was concluded that ‘locus of control’ was considered as an important factor in the disposition effect. IPO’s and index stock’s Share registry data was analyzed by P. Brown et al. (2006). It was reported that the disposition effect can be observed in all different groups of Australian investors. Similarly, the disposition effect in Israeli investors was validated by Shapira & Venezia (2001). The study was conducted on clients of a large Israeli brokerage firm. In China, Feng & Seasholes (2005) analyzed clients of a Chinese brokerage firm. The disposition effect was also found for the Chinese investors. The same results were also confirmed by Chen, et al (2007) in China.

A study conducted by Barber et al. (2007) investigated the trading behavior of four million stock traders. The study was conducted on the Taiwan stock exchange (TSE) from 1994 to 1999. The results concluded that 84 percent of the investors tend to dispose of winner stocks more readily as compared to the losers’ stocks. Furthermore, foreign investors and mutual fund managers are less prone to the disposition effect in contrast to corporations, individuals, and dealers who were more reluctant to book losses, hence exhibiting a high level of the disposition effect. Interestingly, foreigners and mutual fund managers were only involved in trading of less than 5 percent.

The disposition effect in relation to the accounting conservatism was also studied by Zhao et al. (2011). The study used capital gains as an index of disposition effect in terms of lagged returns and turnover. Capital gains were defined as the closing price and price on a specific day over the closing price. Cumulative returns from past one month to past one year, cumulative returns from post one year to post three years, natural log of market capitalization, and the corresponding turnover. The results indicated that all independent variables exhibited negative significant values furthermore, the accounting conservatism was found to settle under and over estimation generated by disposition effect.

Based on the extant literature, it is inferred that the disposition effect is caused due various individual characteristics, tax aversion tendency, and future expectations of the investor. Primarily, the investment decisions of an individual are influenced due to the characteristics of the individual. The financial literacy of the investor and past trading experience of the investor determines the propensity of individual trading decisions. Hence, the disposition effect is exercised to a lesser extent by individuals with more financial literacy and investment experience (Dhar & Zhu, 2006).

The gender-oriented approach was studied by other researchers. They reported that risk aversion based on gender depends upon income, age, marital status, wealth, race, and the number of minor children. Furthermore, it was noted that the same level of risk is taken by individuals with the same educational level. Women are by nature impatient and more optimistic, therefore, they tend to hold losing stocks for more time while selling the winning stocks as soon as possible (Feng & Seasholes, 2005). Similarly, according to Shu et al., (2005) females with more age, are more likely to treat their gains variant as compared to losses.

Even though, investor's sophistication is considered of major importance in relation to the disposition effect (Grinblatt and Keloharju, 2001; Dhar and Zhu, 2006). It is differently interpreted by different researchers across the whole literature. Investor's income and job experience are used to proxy investor sophistication (Dhar and Ahu, 2006). While age, gender, trading patterns, and diversification are used by Feng and Seasholes (2005) for an investor's sophistication.

The tax-loss selling hypothesis is also considered an important factor in the disposition effect. The tax-loss selling hypothesis states that investors dispose-off the loser stocks and utilize such losses to offset their capital gains to minimize their tax liability at the end of a financial year (Badrinath & Lewellen, 1991). Investors sell their loser stocks especially in December, to enter losses in their tax returns and secure tax benefits (Shefrin & Statman, 1985). Constantinides,

(1983) also endorsed the proposition that investors continue trading with tax minimization objectives all year long, however, such trend reaches its highest level especially in December. Investors sell loser stocks in December to offset losses against capital gains for less tax liability. While such same investors in most cases re-purchase the same security at the beginning of the next year to come up with the previous portfolio composition. In sum, the tax-loss selling hypothesis work as a driving force for the disposition effect.

2.3.6.4 FUTURE EXPECTATIONS

According to the prospect theory, abnormal gains do not add to a proportionate joy towards investors. Similarly, abnormal losses also do not result in a proportionate pain for the investor (Kahneman and Tversky, 1979). It indicates that generally, investors do not expect abnormal gains, as it does not result in the highest joy for an investor and vice versa. Therefore, such less responsiveness towards expected returns acts as one of the reasons for the disposition effect.

Loser stocks are retained while winning stocks are sold with the hope that today’s losers are tomorrow's winners and future performance of stocks will compensate for current losses. Such a position can only be justified if, returns from tomorrow’s winning exceeds the returns from today’s returns. on the other hand, there is a stronger probability of investor misguidance when the investor hopes for a mean reversion while neglecting that he is currently incurring losses Odean, 1998).

The disposition effect can be due to be certain psychological factors that cannot be explained otherwise. Investors undergo regret aversion and bad feelings in the shape of judgment error, caused by losses in investments. Disposing of winner stocks results in investor’s pride while selling loser stocks results in regrets for the investor (Shefrin & Statman, 1985).

The mean reversion phenomenon implies earnings of investors above-average gains, with expectations of a future reduction in returns, depicted in the form of negative autocorrelation. A wrong interpretation of the mean reversion phenomenon results in a market disposition effect (Weber & Camerer, 1998). Investors overvalue their stock-picking ability hence show overconfidence resultantly, they purchase undervalue stocks in the prospect of future price appreciation. A price appreciation in stock will result in its sale to realize gains. Therefore, the investor's overconfidence results in the disposition effect.

Besides the behavioral and psychological factors, stock markets are also affected by major macroeconomic events. Political uncertainty and terrorism are two of such factors especially relevant to the sampled South Asian stock markets.

Any political or terrorist mishap giving rise to uncertainty directly deteriorates investor's confidence and hence influences the stock market. Similarly, governments are more prone to invest in security and stability measures which also curtails the GDP of the economy (e.g., Buesa et al., 2007; Drakos, 2004). Researchers are therefore also interested in investigating the impact of terrorist incidents which sometimes involve a great deal of losses to mankind and the corresponding economy. As a matter of fact, research studies before 9/11 were less common. However, the threat proved to be more resilient therefore it got the attention of researchers. Interestingly, the terrorist attacks famously known as 9/11 had chain effects. In other words, several countries were also impacted besides the U.S from such attacks. One of the core reasons is that many economies around the world are directly linked with the U.S economy, mainly in terms of their monetary policies and foreign exchange reserves. According to Ulick, (2001) 9/11 was the biggest incident in the history of the U.S which caused a loss of 3000 human lives in addition to a 7% worst drop in Dow Jones leading to a loss of one trillion dollars. Various studies have been conducted to investigate the impact of 9/11 on various aspects of the economy. For instance, Goodrich (2002) studied the consequences 9/11 attacks on the U.S tourism industry. The study reported significant levels of shocks from the 9/11 attacks on the tourism industry. Which led the U.S government to issue a relief package of direct 15 billion U.S dollars and loan guarantees to hospitality and the airline industries. and to the tourism industry. A similar study was conducted by Bonham et al. (2006) They investigated the effect of 9/11 and other terrorism incidents on the tourism industry in the U.S. It was found that travel spending significantly dropped down in the U.S post 9/11 incident. Moreover, the attacks resulted in a significant level of unemployment- a 5 percent surge in unemployment in the time period 2000-2004. Some other studies also investigated the impact of various global terrorist activities on some of the prominent indices worldwide. For example, Abadie & Gardeazabal (2003) found a 10 percent drop down in the GDP of the Basque region. The study was conducted to measure pre and post conditions of the 1998-99 ceasefire on the Basque and non-Basque firms. It was found that Basque firms perform non-Basque firms in other words the non-Basque firms showed negative returns as compared to their Basque counterparts. In yet another study by A. H. Chen & Siems (2004) they investigated the impact of terrorism on global financial markets. They studied the impact of 14 militants and terrorist invasions dating back to the year 1915. They found that the U.S market is the most resilient market which was able to recover more efficiently as compared to many other global markets. Another study conducted on ten major global markets by Charles & Darné, (2006) investigated the impact of global terrorist attacks. They used GARCH models to study the volatility shocks. They concluded that macroeconomic variables have a significant impact on the European and the U.S stock markets respectively.

A more extensive study was conducted in the same year by Crain & Crain (2006). They analyzed 147 stock markets from 1968-2006. They concluded a loss of 3.6 trillion dollars over the sampled period in the year 2002. Moreover, Buesa et al. (2007) the impact of the Madrid attacks of 2004 which caused the death of 291 and 1600 injuries. It was found that the Spanish economy incurred a loss of 211.584 million euros. Yet another similar study conducted by Greenbaum et al. (2007) found that areas that face terrorist attacks face direct costs however the impact of terrorist events is sometimes overlooked in terms of indirect costs within the economy. The study was conducted in 95 Italian provinces from 1985-1997.

As already mentioned the focus of research shifted to developing countries more specifically after 9/11. Following such a trend, Aslam & Kang, (2015) used time-series data to study the impact of 300 terrorist attacks from 2000-2012 in the Pakistani context. The results showed that the Karachi Stock exchange incurred an average negative return of -0.32% specifically on the day of the attack. However, the shock was seen to be absorbed after one trading day of the attack. Another study conducted on the Colombian stock market was conducted by Mapa & Jayasinghe (2014). The study was conducted for the period 1985-2007. A negative statistically significant relationship was found when all terrorist attacks were aggregated however only a negative weakly significant relationship was found for stand-alone attacks on the Colombian stock market. Besides the monetary and human losses, a study conducted by D. Kim & Albert Kim, (2018). concluded that terrorism may have a less monetary impact in the developed countries however, it has a substantial effect on the mental health of the residents. Interestingly, the survey results showed a stronger trend for immigrants and low-income individuals as compared to natives and high-income individuals.

Political factor is yet another reason which may add to the prevailing uncertainty in a country. Political events drive future economies as a change in governments is responsible to ensure consistency in economic policies or even paradigm shifts aimed for some transformational change within the economy. Political events have a direct effect on the stock market. As a matter of fact, political events drive investor's confidence, leading to stock market volatility and as a result into grand uncertainty of expected cash flows (Kongprajya, 2010). Moving forward, another study conducted in South Africa by Brooks et al. (1997) found that political instability is one of the most important predictors of stock market volatility in the south African economy. Similar results were observed by Vuchelen (2003) and concluded that stock prices are affected by political events. The study was conducted in the Belgian context. It was found that besides other political events, elections and coalitions among governments affect stock prices. Moreover, an effective stock market is also determined by the composition of governments. A study conducted in the Turkish stock market by Aktas & Oncu (2006) found that political events have a weaker influence on stock markets. The study was based on the relations between Turkey and U.S where the U.S army was deployed in Turkey back in 2003. The results were economically insignificant negating any market under and market overreactions. Similarly, Kyereboah-Coleman & Agyire-Tettey (2008), studied various macroeconomic variables as predictors of the stock market performance in Ghana for the period 1995-2005. Using error correction models and the cointegration test, it was concluded that lending rates and inflation rates among other macroeconomic variables have a negative effect on stock market performance. In another study conducted by Lehkonen & Heimonen (2015), studied the relationship between political risk and democracy. The study was conducted on 49 emerging stock markets from 2000-2012. Using a pooled OLS, the results showed that market returns are determined by the extent of democracy in a country. Moreover, market returns are high in those countries which have a low level of political risk. A relatively recent study conducted by Tabassam et al. (2016), investigated the political instability and the underlying associated volatility in the Pakistani economy for the sample period 1988-2010. Using GARCH models, it was found that regime-changing, elections, strikes, and terrorist events have a negative significant impact on Pakistani GDP for the sampled period. Nazir et al. (2018) focused on a rather broader sample for the period 2005-2016. Their study investigated the effect of various political and terrorist activities along with the duration required to absorb the aftershocks of such events. The results showed a significant negative association of political events on stock markets in south Asian emerging stock markets. Moreover, it was found that the stock markets under study are inefficient on a 15-day event window.

Ahmad et al. (2021) investigated the impact of various global terrorist activities in relation to their impact on the Pakistani stock market. They used KMI-30 and KSE-30 indices in their analysis. Daily closing stock prices were collected for both indices from 2010 to 2019. Twelve main terrorist incidents were selected from the South Asian Terrorism Portal. These events were selected on the basis of damages they created. The study was based on pre, event, and post-event windows. It was found that most of the incidents had a significant impact on both sampled indices. Mainly the events which were significantly related to stock indices included, Attack on the Jamia masjid Madina, a Suicide attack on political offices, Twin suicide assaults at Parachinar, Paris, France bombing at a bar, an assault on the Army Public School, a Suicide bombing at Quetta's Civil Hospital, a Suicide bombing in Belgium, Attack on the political rally of the Balochistan Awami Party and Attack on Shrine of Lal Shahbaz had a significant effect on both indices. While, Bomb blast at Karbala Maula Imambargah, the attack on Shias at Alamdar road in Quetta, and the attack on the New Sariab Police Training College had an insignificant impact on both indices. Moreover, the sampled indices were found slow in absorbing noisy information promptly. The results of the study negated the Efficient market hypothesis. The results also proposed that local events have a more immediate and severe influence on both sampled indices in contrast to the global terrorism events.

Another important aspect of literature is the integration of stock markets across different regions. This implies that since markets are interdependent on each other, any event on the global level is expected to impact the constituent markets equally or proportionally in the region. It is already established from the literature that the south Asian stock market is less integrated in contrast to the other global trade blocks. Barriers pertaining to Policy especially focused on investments and regional trade are one of the core reasons for the lack of integration in the south Asian region (e.g., Masha & Ding, 2012). As far as trading blocks are concerned, Western trading blocs especially the European Union are more integrated as compared to the Asian economies which bring synergic efficiency in the long run (Naeher, 2015). An analysis provided by Kousar et al. (2019) show that the south Asian block has a trade of less than 5.6 percent, 36 percent, 47 percent, 9 percent 16.40 percent, 18.20 percent, 24.56 percent, and 63 percent less than the east Asia, Asia Pacific, ASEAN, Central Asia, Latin America, Middle East, North America, and European Union respectively. Trade barriers are rooted in the controversial history of the region. However, Pakistan, India, and Bangladesh are the three major fast-growing economies therefore these countries are listed as the emerging economies by the World Bank.

Various studies have examined the regional integration in the south Asian region. For instance, Narayan et al. (2004) examined regional integration among Pakistani, Indian, Bangladeshi, and Sri Lankan economies, using a multivariate co-integration approach. The results showed that the long-run stock prices in Bangladeshi, Indian, and Srilankan stock markets Granger cause stock prices in the Pakistani stock market. while in the short run, a one-sided Granger relationship existed between Sri Lanka to India Pakistan to Sri Lanka, and Pakistan to India. In another study, Mukherjee & Bose (2008) studied linked movements of the Indian stock market in contrast to other Asian markets and the U.S stock market. The study was more narrowly focused on capital market reform including liberalization of markets. It was found from the analysis that all other markets including Asian markets are affected by the U.S stock market. Moreover, the Japanese stock market was found to have a central role in the integration of Asian stock markets. Similarly, Rahman & Uddin, (2009) examine the co-movement of stock prices and exchange rates in Pakistani, Indian, and Bangladeshi economies. Their study used listed indices and the corresponding exchange rates for each country. Using Granger causality and con-integration tests, they did not find any evidence of stock prices and exchange rate integration. R. Kumar & Dhankar (2012) examined the short-term integration between Indian and U.S stock markets using the GARCH (1,1) model. The results concluded that the Indian stock market (market volatility) is equally affected by the U.S stock market in both the short and long run. Singhania & Prakash (2014) deployed a GARCH model and examined conditional volatilities and the corresponding correlation between unexpected and expected volatility for south Asian stock markets. The results showed an economically insignificant relationship between stock market volatilities. Using structural breaks, Rajwani & Mukherjee (2013) examined co-integration features among key Asian stock markets including Japan, Hong Kong, South Korea, Malaysia, China, Taiwan, and India. The results showed that the Indian stock market is not co-integrated with other Asian stock markets. Stock market integration is also studied in relation to various non-economic variables. For instance, Yartey (2008) studied economic and non-economic determinants of the emerging stock market with a panel of 42 emerging economies. It was found that different economic variables including capital flow, banking capital, and income level along with various non-economic variables including law and order, political risk, and bureaucracy are the most important predictors of stock markets across almost all emerging economies. Yet another study conducted by Sriananthakumar & Narayan (2015) investigated the stock market association between the Srilankan stock market with Pakistani, Indian, Chinese, Malaysian, Singaporean, and the U.S stock markets with special relevance to the prevailing at the time, civil war. The results showed that the Srilankan stock market has a significant but weak association with other stock markets.

In a recent study conducted by Kousar et al. (2019) they examined the spillover effects among south Asian stock markets with a special focus on the impact of terrorism. The study was conducted in Pakistani, Indian, Bangladeshi, and Srilankan stock markets. The monthly panel of data was created for the sample period 2000-2016. Using R-programming, the DCC GARCH model was used for the spillover effects. The results showed a significant negative relationship between terrorism and stock prices of the corresponding sampled stock markets. Moreover, Pakistani, Indian and Bangladeshi stock markets are significantly correlated with each other except for the Srilankan stock market.

2.4 Gap Identification

Majority of studies in the literature showed that the strength of integration among different stock markets has increased over the years. However, few researchers, for example, Azman-Saini et al. (2002) do not contend with the underlying phenomenon which leads to such a conclusion.

Importantly, traditional measures of market co-integration assume that adjustment to prices remains the same for the short run and long run in negative and positive shocks. while different researchers have established that stock price adjustment is relatively slow against any positive or negative shocks. (e.g., Chiang, 2001; Sarantis, 2001). According to Enders & Siklos (2001), when the relationship between variables is asymmetric, the corresponding co-integration can be ineffective. Shen et al. (2007) studied and found an asymmetric relationship in Chinese stock markets.

As mentioned earlier, there are abundant studies on symmetric stock market interdependencies however, asymmetric or non-linear interdependencies are relatively less studied. Based on the importance of asymmetric reaction of stock markets to some news Shahzad et al. (2015) studied the impact of dynamic efficiency in symmetric and asymmetric dependencies among the south Asian stock markets. They used monthly data from 1998 to 2013. The results showed that markets are efficient in at least the weak form. Asymmetric error correction and cointegration were used to assess the dynamic relationship among different markets. It was found that in long run, the Indian stock market affects the Pakistani stock market. while the Bangladeshi stock market was observed to influence the Srilankan stock market. However, the intensity of adjustment to a negative shock is less than that of a positive shock. Moreover, the non-linear error correction model produced one-sided causality from the Indian stock market to the (Bangladeshi stock market) to the Pakistani stock market (Sri Lankan stock market).

On an individual level, most of the recent work on behavioral biases is based on primary data. These studies have investigated behavioral biases in contrast to investment patterns, stock prices, market anomalies, and investment returns (e.g., Asad et al., 2018; Rehan et al., 2021). Subject to a thorough study of the literature, we select self-attribution, anchoring, herding, the disposition effect, and limited attention bias for our analysis. The prime underlying reason for that lie in the fact that these biases are somewhat chronologically related to each other. For instance, Self-attribution leads to overconfidence bias, which eventually leads to the disposition effect resulting in market overreaction, high volatility, and low turnover. Similarly, anchoring bias results in conservatism bias and hence under the reaction of the corresponding market.

Based on the researcher's knowledge, there is no such previous study that investigates the role of various behavioral and psychological biases in the south Asian emerging economies. The study at hand is therefore aimed to fill this research gap.

2.5 Development of Hypotheses

The study at hand is aimed to validate the existence of various behavioral biases viz self-attribution bias, anchoring bias, herding bias, limited attention bias, and the disposition effect in the selected South Asian and the U.S stock markets. The existence of these biases will contribute to the core behavioral finance proposition that negates the efficient market hypothesis and rational decision-making theory. Given below, First, the existence of these biases is to be ascertained, and then the relationship between such biases and investor irrational decision-making is to be studied. For this purpose, the following section provides the theoretical background and hypotheses for the proposed variables of the study.

Biases and market reaction

2.5.1 SELF-ATTRIBUTION AND MARKET REACTION

Self-attribution is associated with the self-attribution theory in psychology. Self-attribution has already been found as the major source of an investor's overconfidence. According to Hirshleifer (2001) self-attribution and over-confidence work side by side-where self-attribution acts dynamically and leads individuals to become over-confident rather than driving them towards rational decision-making.

Self-attribution is the tendency of an individual's biasedness where such individuals attribute every success to their own actions and any bad outcome to some external factors. The theory of self-attribution is associated with Heider (1958, 2013). The foundation for self-attribution lies within two basic human traits: Self-enhancement and self-protection. Self-enhancement refers to the desire for others to look at us positively while self-protection is the desire to have a favorable self-image. Such motives of the favorable image among others and self may sometimes result in biased or irrational decisions. Many studies have applied the self-biased attribution theory to the financial horizons. Most of these studies have focused on individual investor behavior while aggregate market behavior has been considered by very limited studies. For instance, K. Daniel et al., (1998a) and Gervais & Odean (2001) developed a theoretical model regarding self-attribution explaining how an investor becomes over-confident. This model was based on the predictability of dividend payout for the coming periods. Investors usually attribute their successful prediction to their set of skills and overlook any probable external factor. Such behavior leads them to become over-confident and ultimately they make irrational decisions. Gervais and Odean propose that a market that contains a large number of new or young traders and who have prior experience of bullish market conditions only is more likely to exhibit over-confidence due to a biased self-attribution.

A piece of contrary evidence to the self-attribution was found by Coval & Shumway (2005).They found that self-attribution was an opposing phenomenon for the Chicago board of trade professional traders. They hypothesized that if self-attribution had to take place, the traders who had made profits in the morning (winners) will become over-confident and hence increase trading in the afternoon. While the presence of loss aversion was to be exhibited when winning traders would not tend to increase their trading in the afternoon to avoid any potential loss and end with an overall profit for the day. The results showed that the winner traders of the morning tend to exhibit risk aversion behavior in the afternoon by taking only a below-average risk in the afternoon. These findings do not essentially negate the existence of self-attribution bias. It is evident from the study conducted by Einhorn (1980) where it was found that self-attribution bias is relatively low when the feedback on a specific decision is prompt and as a matter of fact, future markets reflect quick feedback. Hilary & Menzly (2006) found that the annual earnings are most successfully predicted by the stock analysts and these analysts underperform the median analyst subsequently. Hilary and Menzly (2006) attribute such underperformance to the self-attribution bias which in turn results in over-confidence.

In nutshell, self-confidence can be used as a measure of self-attribution. Cesarini et al. (2006) propose that over-confidence is subject to an investor’s response function and therefore it must be measured in terms of a response format. Similarly, the proxies used to measure investor over-confidence may also create different results (Juslin, 1994). Presumably, self-attribution results in overconfidence and it directly affects the stock returns and trading volume. Therefore, the trading volume returns, and the association between trading volume and stock returns can be considered the most robust techniques for investor confidence (e.g., Gervais & Odean, 2001; Odean, 1998)

Based on the theoretical models of investor over-confidence and self-attribution, many testable propositions can be deduced. Our focus is on the contribution of overconfident investors in stock trading. We try to center our attention on two testable implications. Firstly, we study how past returns are positively associated with current trading turnover. And secondly, we focus on the fact that overconfident investors tend to trade high volumes of stocks and hence resulting in excessive returns volatility. These propositions are based on two assumptions- investors are overconfident regarding the accuracy and precision of their private information and an investor's confidence varies in contrast to the market returns due to the self-attribution bias (Sheikh & Riaz, 2012).

As proposed by Statman et al. (2006) market turnover and security turnover are positively associated with market lagged returns representing the over-confidence bias. To investigate the self-attribution bias or overconfidence bias in the selected south Asian and the U.S stock markets, various underlying trends may be studied regarding the trading volumes and lagged market returns for a true picture. Therefore, we would hypothesize for each south Asian country under study as:

H1a: Trading turnover rises directly with the lagged market returns in the Pakistani stock market.

H1b: Trading turnover rises directly with lagged market returns in the Indian stock market.

H1c: Trading turnover rises directly with lagged market returns in the Bangladeshi stock market.

H1c: Trading turnover rises directly with lagged market returns in the U.S stock market.

2.5.2 ANCHORING AND MARKET REACTIONS

Anchoring refers to the bias when an investor makes estimates on some base value called an anchor and such anchor is adjusted in the investor's final decision-making. Anchoring and adjustment both measure the role of some base value in an investor's decision-making. Such anchor may be in the form of the current rate of growth, return, inflation, etc.

According to Peng & Xiong (2006) public information which is easily available, is more assertively dealt with by investors as compared to any information, related to a specific firm. Investors are attracted to stocks, whose prices have declined from all-time highs or their respective historical highs. Such stocks are seen as an opportunity by the investors. Such an approach is governed by the belief of the investor where the investor anchors his predictions on the previous historical high prices therefore, they believe that the prices will revert to their highest values. In actuality, if a decrease in stock price is attributed to the overall market behavior rather than any firm-specific information, the investment decision will ultimately pay off the investor. Anchoring to a specific low price is also used by investors where investors expect that the stock prices will fall in the future to the historical low. In such a case, investors sell stocks at relatively high prices with a mean reversion to the historically low prices of stocks. The investor tries to hold such stocks till it reaches a price level, after which it is expected to decline in value.

According to Griffin & Tversky (1992) investors under-react to single news while overreacting to a series of multiple news. In other words, it implies that the stock price close to a 52-week high indicates that recently, some good news has arrived in the market regarding the stock therefore, investors are more likely to under-react to this news. While using the historically high price as an anchor by Li & Yu, (2009) for Dow Jones, it was found that the closeness of stock prices with the historical high for a stock represents an investor's under-reaction towards a series of good or bad news. In sum, nearness to the 52-week high represents under-the reaction of the investor with expectations of positive returns while nearness to the historical high represents overreaction for the investor with negative future returns.

Based on previous studies, we establish the proximity to historical high stock prices, as a proxy for investor overreaction with expectations of negative future returns. While proximity to 52-week high stock prices is developed as a proxy for investor under-reaction with an investor's expectations of positive future returns. Therefore, this study has used two anchors in the sampled stock markets-The 52-week high which covers a period of one year, and the historical available high stock prices. Using two different anchors, our hypotheses for this study are:

H2a: Proximity to Historical high represents negative future returns for the Pakistani stock market.

H2b: Proximity to Historical high represents negative future returns for the Indian stock market.

H2c: Proximity to Historical high represents negative future returns for the Bangladeshi stock market.

H2d: Proximity to Historical high represents negative future returns for the U.S stock market.

H3a: Proximity to a 52-Week high represents positive future returns for the Pakistani stock market.

H3b: Proximity to a 52-Week high represents positive future returns for the Indian stock market.

H3c: Proximity to a 52-Week high represents positive future returns for the Bangladeshi stock market.

H3d: Proximity to a 52-Week high represents positive future returns for the U.S stock market.

2.5.3 HERDING AND MARKET REACTION

Herding means the tendency of following others' judgments and forecasts, considering them right. Investors try to rely on others rather than their assessment and valuations of the basic fundamentals of an investment option. Such behavior of investors is expected to induce irrational decision-making in the market and hence leading to an aggregate market inefficiency Prechter & Parker (2007), Investors are generally assumed to react to some information on a prompt basis in an efficient market, therefore, such information is reflected in the overall stock index and the prices of the relevant stocks. However, in highly volatile or extreme market conditions, investors rely on market movement rather than their own calculations. Thus, an individual investor return is somehow identical to the overall market return. That's how the analysis of dispersion for a difference between security returns and market returns can act as a reliable measure of herding bias. The following hypotheses have been formulated to find out the existence of herding behavior in the sampled stock markets.

H4a: Dispersion between individual stock returns and market returns decrease in extreme market conditions in the Pakistani stock market.

H4b: Dispersion between individual stock returns and market returns decrease in extreme market conditions in the Indian stock market.

H4c: Dispersion between individual stock returns and market returns decrease in extreme market conditions in the Bangladeshi stock market.

H4d: Dispersion between individual stock returns and market returns decrease in extreme market conditions in the U.S stock market.

A study conducted by Fu (2010) on the Chinese stock market found that stocks having a low turnover are more prone to a market herding behavior from the investor. While for high turnover stocks, the investors generally do not account for the trends in the market but rather rely on their estimation. Such behavior is called the turnover effect in herding. Investors do not have access to adequate levels of information therefore, they can simply follow other individuals to avoid such uncertainty Avery & Zemsky (1998). As a matter of fact, less amount of information is available for low turnover stocks that's why these stocks are more exposed to herding. And thus the dispersion between low turnover stock returns and the market returns is expected to be lower. Our hypothesis for the turnover effect is as follows:

H5a: Dispersion between low turnover stock returns and market returns decrease in extreme market conditions for the Pakistani stock market.

H5b: Dispersion between low turnover stock returns and market re- turns decrease in extreme market conditions for the Indian stock market.

H5c: Dispersion between low turnover stock returns and market returns decrease in extreme market conditions for the Bangladeshi stock market.

H5d: Dispersion between low turnover stock returns and market returns decrease in extreme market conditions for the U.S stock market.

2.5.4 LIMITED ATTENTION AND MARKET REACTION

It is worth noting that the nature of limited attention bias is not behavioral but rather it represents hindrances in an investor's information processing. Therefore, the limited attention-driven under-reaction is somewhat different from the cognitive biases-driven under-reaction Barberis et al. (1998), A limited attention bias is based on investor conservatism bias and it provides a perspective explanation for the slow-information diffusion used by Hong & Stein (1999). As far as the relationship between investor attention and trading volume is concerned, empirical evidence is provided by Lo & Wang (2000). They found that large stocks have high volumes of trading, luring more investor attention. Size, analyst coverage, and trading volume have been used as proxies for measuring limited attention however, trading volume is considered a better measure of limited attention bias. The size of information and the analyst coverage only caters to the availability of information in the public domain. How efficiently an investor utilizes such information is another matter. Gervais et al. (2001) propose that high trading volumes of stock raise its visibility and hence attract more investor attention. Similarly, Barber & Odean (2008) argue that since investor attention is a direct consequence of trading volumes, therefore, its relationship with trading volume is also self-explanatory. Therefore, a stock’s abnormal trading daily volume is a good measure for an investor's attention.

Investors can also use their attention in addition to behavioral biases, for example, overconfidence bias and extrapolation bias to result in an overreaction-driven price momentum Hou et al. (2011) Such investors try to extrapolate their past returns into the expectations of upcoming returns. De Long et al. (1990) suggest that generally, investors purchase shares whose prices have recently gone high, leading to further increase in prices and ultimately towards a price momentum.

The self-attribution bias leads to a higher confidence level whenever their private news is aligned with public news while there is no effect on investor confidence whenever private and public news is disconfirming. It implies that initial price responses are proceeded by further price hikes thus making a price momentum. Investor attention has significant importance in such overreaction-driven price momentums. As, in absence of investor attention, there would be no extrapolation of previous returns and hence no overreaction-driven price momentums. However, if there is a larger investor reaction the extrapolation and overconfidence can lead to stronger price momentum.

Based on the theoretical justification, our hypothesis is based on the fact that limited attention toward fundamental information about stock results in a stock price-under-reaction. Conversely, more attention to stock returns will lead to high trading turnovers and overreaction-driven price momentum.

So, our hypothesis becomes:

H6a: Higher Investor attention causes stock prices to overreact in the Pakistani stock market

H6b: Higher Investor attention causes stock prices to overreact in the Indian stock market

H6c: Higher Investor attention causes stock prices to overreact in the Bangladeshi stock market

H6d: Higher Investor attention causes stock prices to overreact in the U.S stock market

2.5.5 Disposition Effect

Odean (1998) studied the trading patterns of investors to study the disposition effect. It was found that winner stocks were disposed-off more quickly than the losing stocks in other words loser stocks were held for longer periods. The main proposition was the confirmation of the disposition effect specifically when realized capital gains are more as compared to the realized capital losses while realized capital gains were defined as realized gains over realized gains plus the paper gains. Realized losses were calculated on the same principles.

As mentioned earlier, Zhao et al. (2011) measured the disposition effect in relation to accounting conservatism, The effect was found through a negative relationship between capital gains with stock turnover and stock returns.

Based on the literature review, it is inferred that most of the past studies have relied on stock turnovers and lagged returns as proxies for the disposition effect. The same is also endorsed by the theory of disposition effect. The theory of disposition effect states that disposing of security with high profits indicates the mean reversion belief of the investor- the investor tries to sell high performing stocks expecting that stock will lower the profits in the future rather than increase. Eventually, such a trend leads to over-trading or a higher value of stock turnover. Based on this notion, we have framed the following hypothesis for the disposition effect:

H7a: Security lagged returns and security turnover are positively associated with each other in the Pakistani stock market.

H7b: Security lagged returns and security turnover are positively associated with each other in the Indian stock market.

H7c: Security lagged returns and security turnover are positively associated with each other in the Bangladeshi stock market.

H7c: Security lagged returns and security turnover are positively associated with each other in the U.S stock market.

2.5.6 MARKET REACTION

Market under and overreaction are the two frequently discussed market anomalies in behavioral finance literature. De Bondt & Thaler (1985) are the pioneers who first studied the market reaction to monthly stock returns of the NYSE. The two portfolios were constructed from the stocks, these portfolios were the past winners and past losers based on the performance of the preceding three years' stock returns. It was found that past winners will lose in the current period while the past losers will gain in the current period. It was concluded that investors are responsible for the overreaction and under-reaction hence leading to aggregate inefficiency. Investors generally ignore the returns reversion in the long run which indicates an overreaction on part of the investor.

Market overreaction is one of the possible answers to market inefficiency as a contribution of behavioral finance Fama (1998). As the price-earnings ratio hypothesis is confirmed by De Bondt & Thaler (1985), it also represents the overreaction hypothesis. In addition, De Bondt & Thaler (1985) considered the risk differences and firm size while studying the winner and losers portfolios. This time, their findings were again confirming the overreaction hypothesis. It was also found that the returns are excessively high in January due to the long-term and short-term performance of previous years. The behavior of Spanish investors was studied by Alonso & Rubio (1990) in relation to extreme stock prices. They also used the methodology, earlier used by De Bondt & Thaler, 1985, 1987), Using 12, 24, and 36 months portfolios, their results were also consistent with De Bondt & Thaler (1985). Although the existence of the overreaction hypothesis was proved, symmetry was also found in the magnitude of gains and losses, P/E ratio, and EPS. While the seasonal effect was not found.

Yet another study by Lakonishok et al. (1994) confirmed the investor overreaction hypothesis. They used financial ratios like BE/ME (book to market ratio), C/P (cash to price ratio), and E/P (Earning to price ratio) for the valuation of stocks. It was found that investors overreact to stocks having good performance in past, as a result, they purchase such stocks with the hope that these will continue their good performance. As a result, these stocks are over-priced. On the other hand, stocks that have shown bad performance on BE/ME, C/P, and E/P are underpriced with expectations that such stocks will not improve their performance. The market losses its equilibrium because the investors tend to inadequately invest in underpriced and overpriced stocks (De Bondt & Thaler, 1985).

A UK-based study by Clare & Thomas (1995) found that the returns reverse over two and three years and ultimately losers outperform the winners. They concluded that a statistically significant small overreaction may affect the UK stock market. Similarly, Campbell and Limmack (1997) studied the long-term reversion of returns in UK stocks from 1979 to 1990. Overreaction has already been verified in many countries like Japan, Germany, Canada, France, the UK, and Italy. Brazil, China (e.g., Baytas & Cakici, 1999; da Costa, 1994; Fang, 2013). Ukraine is an emerging market was studied by Mynhardt & Plastun (2013), where the overreaction hypothesis was confirmed by analyzing the short-term reactions to a one-day abnormal price change.

No evidence was found for the overreaction hypothesis in the Australian stock market Beaver & Landsman (1981). Similarly, in US stocks, the overreaction anomaly was also not proved (Baytas & Cakici, 1999). While a short-term overreaction was confirmed in New Zealand from 1976 to 1986 by Bowman & Iverson (1998), They used the weekly returns for their analysis. An overreaction was found for losers with a significant change in the initial prices proceeded by the same magnitude of reversion.

Where the under-reaction hypothesis states that information is slowly incorporated into stock prices, (Summers, 1991)found a positive autocorrelation in stock excess returns, foreign exchange market, and bond markets from 1960 to 1988. Good news usually leads to a stronger under-reaction than bad news Welfens & Weber (2011) & Narasimhan Jegadeesh & Titman, (1993), analyzed the strategies in which the buyer purchases the past good performing stocks and sells stocks that have performed poorly in the past three to twelve months. It was found that due to the momentum effect the past good performing stocks will also yield higher returns in the coming six months. It implies that stocks only react to high earnings or returns for only about a year after their announcement Ball & Brown (1968), Six US major equity market indices were studied by Schnusenberg & Madura (2001), for a short term over and under-reaction. The results showed a one-day under-reaction among winners and losers of all stock indices. While overall a sixty-day under-reaction was found for winners. However, with an extended time period, the abnormal returns translated from negative to positive and significantly reversed over a period of sixty days.

Asian stock markets have also been studied for the underreaction hypothesis. For example, Mazouz et al. (2009) conducted a broad study of ten Asian countries including Pakistan, India, Hong Kong, Korea, Indonesia, Malaysia, Singapore, Philippines, Thailand, and Taiwan. The results showed price shocks or large price changes through the use of GARCH and OLS. This indicates that price reaction is different for different countries as an investor in different countries, processes information differently. The results confirm the consistency of the returns in different markets.

Constructing two portfolios of winners and losers for S&P CNX 500 index from 1996 to 2008, Rastogi et al. (2009) analyzed the monthly stock prices, and a short-term market under-reaction was found in the Indian stock market. Using the ANAR-TGARCH the momentum effect also indicated a long-run overreaction of investors to the mid-cap stocks.

Fang (2013), concluded that regardless of the size, the Chinese equity market shows under-reaction to good news and overreaction to bad news. While mean reversion was observed for the market over and under-reaction. Kelley (2004) studied the weekly returns and found that winners in a week outperform the losers in a whole year with a slight reversion. Furthermore, the absence of a short-term reversion indicates market under-reaction. Similarly, Stevens & Williams (2004) found under-reaction to positive and negative information. However, the under-reaction for positive information exceeds the under-reaction for negative information.

The south Asian stock market is an emerging market dominated by large investors. The investors are also not rational enough, in order to keep the market at equilibrium. This study is aimed to investigate an investor's under-reaction or overreaction in a long run. So we hypothesize:

H8a: Investors tend to overreact to a series of good news in the Pakistani stock market.

H8b: Investors tend to overreact to a series of good news in the Indian stock market.

H8c: Investors tend to overreact to a series of good news in the Bangladeshi stock market.

H8c: Investors tend to overreact to a series of good news in the U.S stock market.

CHAPTER-3

DATA AND METHODOLOGY

This section starts with an explanation of the sampled stock markets, sampled period, and the general research methodology. In the subsequent part, the methodology for each corresponding bias is presented.

3.1 Sample and data description

Stock indices of KSE-100, DSE-30, and BSE Sensex-30 are gathered to test the hypotheses of the study. Further, the DJIA index is also selected for comparative analysis of the developed and developing markets. These indexes are assumed to be opaque and highly volatile hence representative of the South Asian stock markets. KSE-100 index is a market floating index adjusted for dividends and right shares, developed in 2006. Similarly, the DSE-30 index comprises of the top 30 best-performing companies from across Bangladesh. While BSE Sensex-30 is composed of the 30 best-performing companies listed on the Bombay Stock Exchange (BSE). As these stock markets represent almost the same geographical area, traditionally called the South Asian subcontinent, major portions of these stock markets are held by large investors who supposedly define the aggregate behavior of the market in the form of their underlying patterns of trading. Moreover, to compare and contrast the results of emerging markets with developed markets this study also takes the DJIA-30 (Dow-Jones Industrial average index). DJIA is one of the oldest indices representing the top 30 major companies in the U.S. In order to validate the biases under study in relation to market reaction, those individual stocks are selected which are most frequently traded on their respective stock exchanges.

Table 3.0 summarizes the number of observations across all sampled markets for each bias under study. A total of 9851 daily observations are taken for all stock markets especially while investigating self-attribution, anchoring and disposition effect. The Break-up for sample selection is given as follows in table 3.0

Table 3.0: summary of sample selection

Biases	**Pakistan**	**India**	**Bangladesh**	**U.S**	**Total**
Self-Attribution	2460	2469	2406	2516	9851
Anchoring	2460	2469	2406	2516	9851
Herding	2454	2476	2387	2516	9833
Disposition effect	2460	2469	2406	2516	9851

Since the core purpose of this study is to contribute towards behavioral finance and add to the explanation of market anomalous behavior. Secondary data is a more feasible option to study aggregate markets. Moreover, the Efficient market hypothesis theory deals with aggregate markets, and our study is expected to provide empirical evidence for any potential deviations from the EMH. Therefore, this study has used secondary data for the sampled emerging markets to come up with more generalizable results in explaining such deviant behavior. Moreover, since the major contribution of this work is to provide empirical evidence for the underlying theory which is backed up by behavioral finance, the study at hand clearly relies on relatively older methodologies. For this purpose, the daily turnover and daily closing share prices of KSE-100, DSE-30, BSE SENSEX-30 and DJIA are gathered from the digital archives of the respective stock exchanges. Similarly, stock market indices and overall market turnover are also collected from the sources already mentioned. Our data is collected for a period of 10 years starting from January 2009 to

December 2018. The analysis of the study uses the daily reported returns for stocks and the market as daily data is expected to give reliable results.

Table 3.1 summarizes our study as:

Table 3.1: *Summary of the proposed study's Variables and their measurement*

Variables	Proposed Hypotheses	Earlier studies	Equation/Measurement
Self-attribution bias	H1: Trading turnover rises directly with the lagged market returns in the sampled South Asian stock markets.	(K. Daniel et al., 1998a; Gervais & Odean, 2001; Miller & Ross, 1975)	$Y_t = \alpha + \sum_{k=1}^{K} A_k Y_{t-k} + \sum_{l=0}^{L} B_l X_t + e_t$
Anchoring	H2: Proximity to Historical high represents negative future returns for the sampled South Asian stock market. H3: Proximity to 52-Week high represents positive future returns for the south Asian stock markets.	(Campbell & Sharpe, 2009; George & Hwang, 2004; Kaustia et al., 2008; Tversky & Kahneman, 1974)	$R_t = \alpha + \beta_1 R_{t-1} + \beta_2 X_{HH} + \mu$
Herding	H4: Dispersion between individual stock returns and market returns decrease in extreme market conditions in the sampled South Asian stock market. H5: Dispersion between low turnover stock returns and market returns decrease in extreme market conditions for the sampled South Asian stock market.	(Barberis & Shleifer, 2003; E. C. Chang et al., 2000; Christie & Huang, 1995; Fu, 2010; Lao & Singh, 2011)	$CSSD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t$
Limited attention	H6: Higher Investor attention causes stock prices to overreact in the south Asian stock market	(K. Daniel et al., 2002; Hirshleifer et al., 2004; Hou et al., 2011)	$P_{mp} = \mu_w - \mu_l$

Disposition Effect	H7: Security lagged returns and security turnover are positively associated with each other in the south Asian stock market.	(Choe & Eom, 2009; Grinblatt & Keloharju, 2000; Odean, 1998b; Shefrin & Statman, 1985; Weber & Camerer, 1998; Zhao et al., 2011)	$\delta_{m,t}^2 = \sum_{i=1}^{N_t} r_{i,t}^2 + 2\sum_{i=1}^{N_t-1} r_{i,t}\,(r_i + 1, r)$ $R_t = ln(\frac{P_t}{P_{t-1}})$
Market overreaction	H8: Investors tend to overreact to a series of good news in the long run in the sampled South Asian stock market.	(De Bondt & Thaler, 1985; Kaestner, 2006)	$ACAR_{w,t} < 0$ $ACAR_{L,t} > 0\ and$ $(ACAR_{L,t} - ACAR_{w,t}) > 0$

The proposed methodology for the research hypotheses is as follows;

3.2 Self-attribution

This model is comprised of market return and market turnover as the endogenous variables. An endogenous variable is a variable that is explained by the functions within a model. For this purpose, daily data of our variables is used to reach the monthly values. While, for the calculations of market returns, monthly index values are used. Generally, market turnover is represented by the daily total market capitalization and calculated to form monthly values. As a matter of fact, the daily trading turnover varies from time to time based on the availability of new information, for instance, the announcement of a new regulation or an earnings surprise.

On the other hand, exogenous variables are those variables that lie outside the causal model, and any change in the endogenous variables does not affect such variables at all. Therefore, the value of the exogenous variable is found independently outside the causal model.

We use two exogenous variables Namely-Dispersion (Disp) and Market volatility (Mvol) the same was also used by Statman et al. (2006). Dispersion (Disp) is defined as the cross-sectional standard deviation between the returns on daily basis. Dispersion is used as an exogenous variable in order to control the re-balancing effect of portfolios on the trading activity (Statman et al., 2006). Dispersion is calculated as follows:

$$s_t = \sqrt{\sum_{t=1}^{N}\left[\frac{(x-\mu)^2}{N_t}\right]}$$

Where,

St = Standard Deviation for the day t

μ = Sample mean for the day t

X = Daily return for day t

Nt = Number of days in a month

While market volatility (Mvol) is the chronological volatility of market returns on a daily basis. Daily volatility is calculated by using the daily market returns. Similarly, we use the methodology suggested by French et al. (1987) as follows:

$$\delta_{m,t}^2 = \sum_{i=1}^{N_t} r_{i,t}^2 + 2\sum_{i=1}^{N_t-1} r_{i,t}\,(r_i + 1, t)$$

Where,

$\delta_{m,t}^2$= Volatility for the day

$r_{i,t}^2$=Daily return of market at day t

Nt = Number of trading days in a month

A vector auto regression model (VAR) is employed to investigate the relationship between endogenous variables i.e market returns (Returns) and market turnover (Turn) and exogenous variables Dispersion (Disp) and market volatility (Mvol) on a time-series data for each data set representing a separate stock market.

As it is a well-established requirement for a time series analysis that the time series data must be de-trended or stationary to overcome any spurious results. Therefore, several statistical techniques can be used. However, we use the unit root test through the ADF (augmented Dicky-Fuller) and PP (Philip Perron) tests. The ADF as an autoregressive model can be expressed as:

$$Y_{t=\beta Y_{t-1}} + \mathcal{E}_t$$

Where,

Yt = Variable understudy

β = Coefficient of the lagged value of Yt

εt = Error term

Generally, before the application of the VAR model, various pre-tests for co-integration and unit root tests are employed in order to know about the underlying transformation that may potentially cause the data stationarity. While a unit root test tells us which tool is best for the stationary series. The ultimate benefit of incorporating the co-integration in the VAR model is that it helps in the reduction of uncertainty of estimation regarding small sample bias in impulse response function. While these pre-tests are more disposed to the lack of robustness (Gospodenov, et al., 2013). VAR can be expressed as:

$$Y_t = \alpha + \sum_{k=1}^{K} A_k Y_{t-k} + \sum_{l=0}^{L} B_l X_t + e_t$$

Where,

Yt = n×1 vector for Market Returns and Turnover (endogenous variables)

Xt = n×1 vector of volatility and dispersion (exogenous variables)

et = n×1 vector of residuals

Ak = Coefficient of endogenous variable vector

Bl = Coefficient of exogenous variable vector

For each dependent variable, The VAR model presents a single equation. All the dependent variables in the equation have lagged values. It is considered as one of the most reliable ways for a multivariate time series analysis. The VAR model for this study addressing the self-attribution behavioral bias would be as:

$$\begin{bmatrix} Turn_t \\ Return_t \end{bmatrix} = \begin{bmatrix} \alpha_{Turn} \\ \alpha_{Return} \end{bmatrix} + \sum\nolimits_{k=1}^{3} A_k \begin{bmatrix} Turn_{t-k} \\ Return_{t-k} \end{bmatrix} + \sum_{l=0}^{2} B_l \begin{bmatrix} Mvol_{t-1} \\ Disp_{t-1} \end{bmatrix} + \begin{bmatrix} e_{Turn,t} \\ e_{Return,t} \end{bmatrix}$$

Where,

$Turn_t$ = Market Turnover for day t

$Return_t$ = Market Returns for day t

$Mvol_{t}$ = Cross-sectional standard deviation of daily returns

$Disp_t$ = Dispersion of returns from the mean for a day t

k = Lag length for endogenous variables

l = Lag length for exogenous variables

3.3 Anchoring

Based on previous studies, we establish the proximity to historical high stock prices, as a proxy for investor overreaction with expectations of negative future returns. While proximity to 52-week high stock prices is developed as a proxy for investor under-reaction with an investor’s expectations of positive future returns. Therefore, this study has used two anchors in the sampled South Asian stock markets-The 52-week high which covers a period of one year, and the historical available high stock prices.

The 52-week high is computed simply as the maximum share price of a stock over the last one-year period while the historically high value is calculated from the available computerized data of a specific stock. Additionally, we also control for the effect of some macro-economic variables e.g inflation rate, include interest rates, and exchange rate in predicting stock returns. Moreover, following George & Hwang, (2004) the authors also use two dummy variables indicating when the nearness to historical high and 52-weeks high equates (I_t) and the second dummy (D_t) represents the situation when the corresponding index reaches a historical high.

Proxies for overreaction and under-reaction i.e nearness to historical high and nearness to the 52-week high can be computed from the following formula.

$$X_{(HH)} = \frac{P_t}{P_{max,t}} \qquad and \qquad X_{(52w)} = \frac{P_t}{P_{52,t}}$$

Where,

X (52) = Nearness to 52-Week high

X (HH) = Nearness to Historical high

Pt = Index point at day t

P52, t = 52-Highest value in the week

Pmax, t = Highest historical index

The daily returns are calculated from the stock index as:

$$R_t = ln(\frac{P_t}{P_{t-1}})$$

Where,

Rt = Daily Return on day t

Pt = Closing price at day t

Pt−1 = Closing price at last trading day

In order to test the relationship between historical high, 52-week high, and future returns, an ordinary least square regression (OLS) is used. It is represented as:

$$R_t = \alpha + \beta_1 R_{t-1} + \beta_2 X_{HH} + MacroEco + \mathrm{It} + \mathrm{Dt} + \mu$$

Where,

Rt = Returns at day t

Rt−1 = Return at day t−1

X(HH) = Nearness to Historical High

β = Coefficient of variables

MacroEco =Inflation, interest rate and exchange rate for the corresponding market

I_t=When historical high equates 52-week high

$D_{t=}$ When the corresponding index reaches a historical high

μ = Error term

3.4 Herding

Investors are generally assumed to react to some information on a prompt basis in an efficient market, therefore, such information is reflected in the overall stock index and the prices of the relevant stocks. However, in highly volatile or extreme market conditions, investors rely on market movement rather than their own calculations. Thus, an individual investor return is somehow identical to the overall market return. That's how the analysis of dispersion for a difference between security returns and market returns can act as a reliable measure of herding bias.

The difference between market returns and individual security returns is measured through CSSD (cross-sectional standard deviation) and CSAD (cross-sectional absolute deviations). For the first time, Christie & Huang (1995) used CSSD in order to measure herding behavior. While the CSAD was proposed by E. C. Chang et al., (2000) as a refined version of CSSD. The CSAD measures the herding behavior in extreme market conditions connotating that investor's returns from a specific stock are nearer to the market returns. The CSSD has been used as a robust measure for herding behavior by several authors (e.g., (Ahsan & Sarkar, 2013; E. C. Chang et al., 2000; Demirer & Kutan, 2006; Fu, 2010) . Whenever the market is undergoing extreme conditions, herding behavior is more likely to occur. The CSSD is represented as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{Nt}(R_{i,t} - R_{m,t})^2}{N_{t-1}}}$$

Where

Ri,t = Stock return at time t

Rm,t = Stock market index returns at time t

Nt-1 = Number of stocks listed in the equity market during time period t

The model for this study may be expressed as:

$$CSSD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \mathcal{E}_t$$

Where,

DUt = 1 when the return on the market for time period t belongs to the extreme upper tail of the returns distribution. A value of zero “0” would be assigned otherwise.

DLt = 1 when return on the market for time period t falls in the extreme lower tail of the returns distribution. A value of zero “0” would be assigned otherwise.

We follow the methodology used by Zafar and Hassan, (2016). Extreme market conditions are defined through 5% and 10% of the return distribution. For this purpose, the market returns are arranged in a descending order, where upper 5% and 10% returns would represent extreme upper market conditions while the bottom 5% and 10% would represent the extreme low market returns.

3.5 Limited Attention

Limited attention is what appears to be the availability of a large amount of information as a cognitive constraint. Usually, a significant amount of information and sophisticated operations are required in the valuation of a firm. A large number of institutional investors undergo almost the same levels of hardships. It is an established fact that individual investors are more prone to limited attention bias, mutual funds managers and analysts have also been observed to fall prey to the limited attention bias. For instance, Teoh & Wong (2002) found that analysts do not utilize the information indicated by financial ratios and they also do not efficiently discount discretionary accruals of a new firm respectively. Similarly, according to Barber & Odean (2008) the stock trading decisions of individual investors are affected by prominent, attention-grabbing events. While according to a study by Corwin & Coughenour (2008) the NYSE specialist’s attention constraints affects the transaction costs and price movements for securities, who are the market-makers. An experimental study conducted by Hirst & Hopkins (1998) shows that analysts are unable to respond appropriately to information in complex financial disclosures.

The hypothesis is tested by the profits from price momentum strategies in relation to different levels of trading volumes. For this purpose, we developed two-way sorted portfolios for KSE-100, DSE-30, BSE-30, and DJIA's stock returns and stock trading volumes. The price momentum profits are measured as the average return difference between past return losers and past return winners within each group. To examine the relation between trading volume and price momentum, we follow the methodology proposed by Hou et al. (2011).

Price momentum profits=Average returns of past winners- average returns of past losers.

$$P_{mp} = \mu_w - \mu_l$$

Where,

P_{mp}= profits from price momentum

μ_w=Average returns of past winners

μ_l= Average returns of past losers.

All the KSE, DSE, and BSE stocks are sorted into quintiles based on their average monthly turnover in the previous year at the beginning of each month. Then we sort out the stocks based on their cumulative returns over the past 12 months within each turnover quintile. Equal weighted returns of these portfolios are computed for the following month. The profits from the momentum strategy are the difference between the loser and winner portfolios. In other words, it is the difference between quintile 1 and 5 within each turnover quintile. If the profits from price momentum increase with trading volume, it would indicate an overreaction-driven price momentum or converse otherwise.

3.6 Disposition Effect

Vector Auto Regression (VAR) is used to test the relationship between stock turnover and market returns. According to Statman et al. (2006) Investor's overconfidence is differentiated from the disposition effect by delineating the positive association of security turnover with its lagged returns considering it as a disposition effect through studying the Autoregressive VAR estimates. Using the autoregressive VAR model, returns are calculated through the use of corresponding previous day closing prices as:

$$R_t = ln(\frac{P_t}{P_{t-1}})$$

Rt= Return of security on month t

Pt= Closing price of the stock at last trading day of month t

Pt-1= Closing price of the stock at last trading day of previous month

Market returns and security returns are used as the endogenous variables while security volatility is the only exogenous variable in the autoregressive model. As monthly data is used, therefore, all daily values are converted into monthly values. An average of Security returns (overall) is obtained from each month's returns for all individual securities.

On the other hand, overall security turnover is defined as the average monthly trading volume for each corresponding security. So, monthly security turnover is the total sum value of daily turnover on the last day of a month for individual security. As iterated earlier, overconfidence and disposition effects are generally used closely with each other. Due to the overconfidence bias, an investor becomes too much confident, relying on his/her instincts, leading to overtrading and high turnovers. In reality, such investors with overconfidence bias, tend to sell winning stocks and hold the losing stocks in order to exhibit their confidence hence leading to the emergence of the disposition effect. Yet another question arises that overall positive market returns have any influence on the disposition effect or not? Market return another endogenous variable is included in the model to answer the question. Security volatility being the only exogenous variable is referred to as the monthly chronological volatility of returns for the respective security. The methodology proposed by French et al. (1987) is used for converting daily volatility for each security into monthly volatility for the corresponding security. The methodology is given as under:

$$\delta_{m,t}^{2} = \sum_{i=1}^{N_t} r_{i,t}^{2} + 2\sum_{i=1}^{N_t - 1} r_{i,t}\,(r_i + 1, r)$$

Where,

$\delta_{m,t}^{2}$= Volatility for the month

$r_{i,t}^{2}$=Daily return of market at day t

Nt = Number of trading days in a month

The next step is to test the stationary of proposed variables. Security and market returns are stationarized by taking their natural log. As natural logs and first difference are generally used to stationarize data where a non-stationary series contains variable mean and variance hence leading to inaccurate results. As mentioned earlier, other variables are stationarized through their natural logs, only security turnover is taken as it and checked for stationarity. PP and ADF tests are used to detect unit root among all variables. A vector autoregression (VAR) test is used to test the relationship between returns and turnover.

3.7 Market Overreaction

The stock market is a constituent of rational and irrational investors. Rational investors rely on the fundamentals of the market, estimations, facts, and figures while irrational investors base their investment decisions on perceptions, emotions, imitations, cultures, experiences, and other important factors. Whenever some information hits the market, both kinds of investors become active. The irrational investors overtake the rational investors and as a result, the market equilibrium is compromised. In such situations, two prominent concepts occur which are the short term under-reaction and long term overreaction.

Under-reaction indicates a slow adjustment of prices in response to some event or news. While the overreaction refers to the extreme reactions of stock prices in response to past performance, past events, or some past information. In other words, when investors underreact to some information, the prices react to such information or event. On the other hand, future prices exhibit a negative correlation with past prices.

Whenever a news arrives in the market, several investors are found to exhibit underreaction and overreaction simultaneously. These investors show short-term underreaction to earnings announcements and long-term overreaction to prior unexpected earnings (Kaestner, 2006).

One of the premier studies conducted on the market reaction by De Bondt & Thaler (1985) showed empirical evidence of investor overreaction. They analyzed portfolios of past winners and past losers and found that investors overreact to an array of good news unless the share prices revert back. This results into the loss of past winners in the subsequent periods.

As stated earlier, a negative correlation between past and future returns shows an investor's overreaction to some news in a long run. While a short-run positive correlation between past and future returns indicates investor under-reaction. For autocorrelation, the residual returns must be calculated from monthly returns through the following equation.

$$\mu_{i,t} = R_{i,t} - R_{m,t}$$

Where,

$\mu_{i,t}$=Excess residual return of stock at day t

$R_{i,t}$=Continuously compounded return of stock on day t

$R_{m,t}$ =Moving average return of stock on day t

We follow the methodology used by De Bondt & Thaler (1985). We deploy the 2/2 years non overlapping strategy which uses two years holding and two years' formation periods.

The cumulative excess residual returns are presented as:

$$CAR_i = \sum_{t=0}^{n} \mu_{i,t}$$

Where,

CAR_i= Cumulative Excess Residual Returns for stock i

$\mu_{i,t}$= Excess return of stock for month t

In portfolio formation, the stocks are ranked based on CARs (Cumulative excess returns). The winner's portfolio includes the top 10% best performers having the highest CARs while the bottom ten percent stocks with the lowest performance are assigned to the loser portfolios. Both portfolios are tested for the next two years or 24 months on the basis of CARs. Where the portfolio formation date is (t=0) for both portfolios. The Cumulative average returns for the winner (CAR w, n, t) and looser portfolios (CAR l, n, t) are calculated as:

$$CAR_{p,z,t} = \sum_{t} \left[\left(\frac{1}{N}\right) \sum_{i=1}^{N} \mu_{i,t} \right]$$

$CAR_{p,z,t}$= Cumulative Average Excess Return for test period z at time t

$\mu_{i,t}$= Excess return of stock for month t

N = Number of stocks in the portfolio

The average CARs for winner and loser portfolios from all test periods is calculated as:

$$ACAR_{p,t} = \sum_{z=1}^{z} CAR_{p,z,t \div z}$$

Where,

ACAR= Average Cumulative Abnormal Returns of the portfolio at time t

CAR p, t = Cumulative Average Abnormal Return for test period z at month t

Z = Test periods that is 2

Overreaction Hypothesis estimates that for any t > 0:

$$ACAR_{w,t} < 0$$

$$ACAR_{L,t} > 0 \; and$$

$$(ACAR_{L,t} - ACAR_{w,t}) > 0$$

A t-test is used in order to investigate the statistical significance of the difference in winner and loser portfolio performance. Similarly, we also want to know that whether the ACAR contributes to the winner or a loser portfolio for any month t. t-statistic is given as under:

$$T_{p,t} = \frac{AR_{p,t}}{S_p / \sqrt{N}}$$

Where,

Tp= t-value of the month t in portfolio

ARp, t = Average cumulative abnormal return of the portfolio at time t

N = Number of observations

Sp= Standard deviation of average returns of the portfolio

The standard deviation is defined as:

$$S_p = \sqrt{\frac{\sum_{n=1}^{N}(CAR_{p,z,t} - AR_{p,t})^2}{N-1}}$$

Also for the study, a pooled estimate of population variance in CAR is required which is estimated as:

$$S_t^2 = \frac{\sum_{n=1}^{N}\left(CAR_{w,n,t} - ACAR_{w,t}\right)^2 - \sum_{n=1}^{N}(CAR_{L,n,t} - ACAR_{L,t})^2}{2(N-1)}$$

Where

ACAR w, t= Average Cumulative Abnormal Returns of winner portfolio at time t

CAR W, n,t = Cumulative Abnormal Return for winner portfolio at month t

N= Number of observations

CHAPTER 04

RESULTS AND DATA ANALYSIS

Member countries of the Sampled South Asian region performed well from 2009 to 2018. Many of the economic indicators showed a favorable trend during the sampled period including GDP, inflation, capital account balance, and current account balance. It is interesting to observe that the GDP growth is also linked with price hikes, for instance, the inflation rate for all countries in the sampled period was high. Sri Lanka and Pakistan had relatively highest inflation rates of 22.8 and 19.6 in 2010 and 2011 respectively. The balance on capital account remained positive throughout the sampled period hence indicating a positive flow of funds within the respective countries. It is evident that the foreign investment in domestic assets is relatively higher than the domestic investment in foreign assets, indicating that foreign investment in domestic assets remained greater than domestic investment in foreign assets. It reveals that capital inflows from abroad were higher than capital outflows from the sample countries. On the other hand, the current account was in deficit for all countries in the sampled period. Bangladesh was the only country to exhibit a positive current account balance. Sri Lanka and Pakistan had a relatively high percentage of GDP as compared to Bangladesh.   Foreign exchange reserves increased for India, Bangladesh, and Srilanka except for Pakistan. Pakistan had a mixed trend in the growth rate of foreign exchange reserves. Similarly, a mixed pattern was observed for exports and imports of goods and services for the four South Asian countries for the sampled period.

Interestingly, foreign investors have demonstrated interest and confidence in the south Asian stock markets in recent years. The portfolio investment in stocks and foreign direct investment has grown. The proportion of investment varies from country to country which is based on the country's risk and volatility in stock markets. The volatility of stock markets can be attributed to the prevailing political and economic uncertainty in the south Asian member countries (Aggarwal et al., 1999). Among the four countries, India is seen to be more attractive for foreign investment in the form of portfolio equity investment while other member countries do not have as much attraction as India.

Under and overreactions are two of the major anomalies faced by the proponents of behavioral finance. It is proposed that non-representative stock prices are actually due to the investor's overreaction and under-reaction towards new information. Such a trend of investors is due to the investor’s over-sensitivity towards new information arriving in the market and less emphasis on the fundamental values hence exhibiting irrationality. Eventually, such imbalance or deviation from the fundamentals is settled in the long run. Interestingly, while looking at the whole picture, current losers are the future winners while current winners are the future losers. Contrarian strategy is the most viable solution to such mean reversion theory. Results regarding different biases of this study are stated as below:

4.1 Self-attribution bias

Conventional finance fails to answer various questions regarding different financial anomalies including the self-attribution and overconfidence bias. Overconfidence and self-attribution are more attractive to researchers because these result in over-trading in stock markets hence resulting in financial crisis and financial bubbles. Different variations in the stock market may impact the availability of information and asymmetric pattern in investor’s behavior. This points out the underlying causes of variations in decisions of informed and uninformed investors. As a matter of fact, investors or traders do interact with each other directly or indirectly in the presence of different strategies. Such interaction of investors is considered an important predictor of stock market movements leading to high or low levels of trading volumes. As established from the literature review, conventional models of finance are unable to explain over trading, therefore, behavioral finance is expected to answer such patterns while exempting the role of rational agents.

Irrationality on part of an investor makes the investor to over-rely on their instincts and assign more value to their personal information in contrast to the basic available information. Odean (1998) considers overconfidence as the prime reason for such behavior of investors where they rely more on their own skills and instincts. As a result, such investors overtrade stocks till incurring losses. The over-confidence theory can be checked through two underlying propositions. One is that high stock trading is observed for overconfident investors especially following high market returns in the recent past. Second is the eventual effect of over-trading i.e excessive returns volatility. As a matter of fact, volatile, opaque, and developing markets are more prone to establish a positive relationship between trading volume and lagged returns (Griffin and Tversky, 1992). Owing to such a claim, a study of overconfidence is much relevant in the sampled south Asian countries. Therefore, KSE, BSE, and DSE representing Pakistani, Indian, and Bangladeshi stock markets respectively are investigated for the self-attribution bias. Additionally, the results are also compared with the results of one developed market i.e the DJIA (U.S market).

Data stationarity is checked by using the ADF (Augmented Dickey-Fuller) test. Initially, the unit root test is employed with an intercept at a level however the results indicated unit root for 4 variables, therefore, eventually, unit root with intercept and trend was run for all variables. Now, the results proposed to reject the null hypothesis indicating that data for all variables is stationary and no unit root exists. The results for unit root analysis are given in appendix-01:

The given table in annexure-01 demonstrates that the sampled variables show a non-constant pattern over the period from 2009 to 2018 at a 1% significance level, also indicating non-stationarity of variables. Although taking a natural log is the simplest method to remove data stationarity, however, there is always a possibility of a non-linear secular trend in logged values. That's why the ADF test is used for unit root and data stationarity.

4.1.1 DESCRIPTIVE STATISTICS

To better understand the long-run behavior of variables under study, table 4.1 reports as below:

Table:4.1 Descriptive Statistics-Self attribution bias

	Countries	Mean	Med	Maximum	Minimum	Std. Dev.	Skew	Kurt
Dispersion	Pakistan	0,0015	0,0011	0,0140	0,0000	0,0015	2,2566	11,2022
	India	0,0007	0,0005	0,0055	0,0000	0,0006	1,7599	8,0177
	Bangladesh	0,0019	0,0011	0,0426	0,0000	0,0026	5,0753	50,0796
	U.S	0,0006	0,0004	0,0062	0,0000	0,0006	2,3018	11,0667
Returns	Pakistan	0,0007	0,0008	0,0488	-0,0692	0,0098	-0,4541	6,7054
	India	0,0002	0,0002	0,0220	-0,0266	0,0043	-0,0819	4,9164
	Bangladesh	0,0002	0,0003	0,2038	-0,0933	0,0148	1,2065	28,5656
	U.S	0,0002	0,0003	0,0201	-0,0299	0,0041	-0,4942	7,3141
Market Turnover	Pakistan	8,0607	8,0170	8,5843	6,6482	7,7726	0,8953	3,9145
	India	7,8330	7,6220	9,2041	5,2771	7,9937	5,6682	55,1335
	Bangladesh	3,4924	3,4863	3,8694	2,5642	3,0231	0,2017	2,8765
	U.S	9,5809	9,5635	10,0253	9,0128	8,9484	1,1239	7,0062
Volatility	Pakistan	0,0001	0,0000	0,0096	-0,0015	0,0004	10,4660	215,1733
	India	0,0000	0,0000	0,0010	-0,0003	0,0001	4,6267	52,8999
	Bangladesh	0,0002	0,0000	0,0344	-0,0169	0,0013	10,3560	252,7643
	U.S	0,0000	0,0000	0,0016	-0,0005	0,0001	7,7606	133,2220

The table given above summarizes the descriptive analysis for four variables naming dispersion, returns, trading volume, and volatility for the sampled four countries i.e Pakistan, India, Bangladesh and U.S. results for dispersion mean values of 0.15, 0.07, 0.19, and 0.06 percent for Pakistan, India, Bangladesh, and the U.S respectively. Similarly, the spread between the maximum and minimum values is also under the acceptable range. While the standard deviation also ranges from 0.06 % and 0.26% for dispersion.

Returns have mean values of 0.07, 0.02, 0.2, and 0.02 percent for Pakistani, Indian, Bangladeshi, and U.S stock markets respectively. Bangladeshi market has yielded a maximum return of up to 20.38% while the Pakistani stock market yielded a negative return of -6.92 percent greater than other sampled countries. Among the standard deviation values, the Bangladeshi stock market offers the highest up to 1.48 % indicating still less volatility.

Out of the total mean values for the turnover series, U.S has the highest mean value for trading turnover followed by India, Pakistan, and Bangladesh with the corresponding highest standard deviation value. Values moving between maximum and minimum values indicate more sharp deviations in the trading turnover.

Volatility series indicate low volatility for all stock markets however Bangladeshi stock market shows a relatively high level of volatility as compared to Pakistani, Indian, and U.S markets. Indian and U.S markets have the least volatility. The maximum volatility shown by the Bangladeshi market is 3.44% for the sampled period. Such a trend is also shown by the standard deviation values.

As skewness and kurtosis are used for the normality of data, the table above shows that kurtosis values for all sampled countries are mostly greater than their corresponding skewness values. Moreover, skewness value also includes negative values, hence indicating that most of the values have longer tails on the left side. As shown by the table, almost all values of kurtosis are greater than 3, showing that the curves for all variables across the sampled stock markets are peaked from the mid-point and drops down with heavy tails.

4.1.2 CORRELATION ANALYSIS

A correlation analysis is an important prerequisite for certain statistical analysis. Therefore, a correlation analysis is conducted for the sampled variables over the sampled period. Correlation analysis is also used to assess collinearity among different variables while multi-collinearity is not a favorable feature of data for further statistical analysis. Table 4.2 reports the results of correlation analysis for all the sampled countries with variables relevant to self-attribution bias.

Table:4.2 Correlation analysis

PAKISTAN				
	DISPERSION	RETURNS	TURNOVER	VOLATILITY
DISPERSION	1			
RETURNS	-0.08	1		
TURNOVER	0.07	0.16	1	
VOLATILITY	0.54	-0.04	0.07	1
INDIA				
	DISPERSION	RETURNS	TURNOVER	VOLATILITY
DISPERSION	1			
RETURNS	0.01	1		
TURNOVER	-0.05	0.21	1	
VOLATILITY	0.52	0.03	-0.07	1
BANGLADESH				
	DISPERSION	RETURNS	TURNOVER	VOLATILITY
DISPERSION	1			
RETURNS	0.11	1		
TURNOVER	-0.07	0.09	1	
VOLATILITY	0.52	0.27	-0.02	1

U.S

	DISPERSION	RETURNS	TURNOVER	VOLATILITY
DISPERSION	1			
RETURNS	-0.09	1		
TURNOVER	0.3	-0.05	1	
VOLATILITY	0.44	-0.09	0.15	1

The analysis was performed for dispersion, returns, turnover, and volatility. All the tables presented above show that weak relationships exist among all variables of the study. The weakest relationships were found for returns and volatility (r=-0.04), returns and dispersion (r=0.01), volatility and turnover (r=-0.02), and returns and volatility (r=0.05) for Pakistan, India, Bangladesh, and the U.S respectively. On the other hand, relatively a stronger correlation was found between dispersion and volatility (r=0.54, 0.52, 0.52, 0.44) for the four countries respectively. A strong correlation among the independent variables indicates the presence of collinearity implying that the existence of both variables will not result in any significant contribution and one variable needs to be dropped from the analysis. We, therefore, move one step forward and calculate the variance inflation factor VIF where VIF is calculated as, VIF=1/1-R^2. R^2 is the coefficient of determination achieved when an auxiliary regression is run for market volatility and dispersion.

The VIF values for all countries were all well under the reference value of 10, hence indicating that no multicollinearity exists between dispersion and volatility for the sampled countries, hence both variables can be included for analysis.

4.1.3 Vector Autoregression (VAR) Analysis

Before running VAR, is important to know whether the variables under study are co-integrated or not? Generally, if the variables are co-integrated with each other, then a long-term relationship is assessed through long-run Vector error correction (VEC). On the other hand, if the variables are not co-integrated, only a short-run VAR is applied.

Keeping in view the above notion, Johnson co-integration test is used and the results are given in the following table 4.3

Table 4.3 Summary of Johansen co-integration test

		None	At most 1	At most 2
Pakistan	critical value	47.86	29.80	15.49
	trace-statistics	1952.38	1205.12	552.20
India	critical value	47.86	29.80	15.49
	trace-statistics	2455.26	1465.02	748.63
Bangladesh	critical value	47.86	29.80	15.49
	trace-statistics	1096.71	621.23	258.31
U.S	critical value	47.86	29.80	15.49
	trace-statistics	1819.41	982.07	524.58

Criteria: If trace-statistics is greater than critical values, Reject the null hypothesis

The results for all sampled countries show that the variables naming dispersion, returns, turnover and volatility are co-integrated with each other (as evident from the trace-statistics with their corresponding critical values, Criteria: If trace statistics is greater than critical values, Reject null hypothesis that there is no co-integration). As stated earlier, since co-integration exists for the sampled variables a long-run VAR is considered for all countries.

A vector auto regression (VAR) is generally considered an efficient tool for estimating a linear relationship between multiple time series variables. All variables in a VAR model are symmetrically structured, with their corresponding equation based on lag values of the variable and other variables. A VAR model is, therefore, employed to estimate the interdependencies of dispersion, returns, turnover, and market volatility. Dispersion and volatility are taken as the exogenous variables while market returns and market turnover are taken as the endogenous variables. The results are given in Table 4.4

Table:4.4 Vector Auto-Regressive Estimates for Endogenous and Exogenous Variables.

	T/over(-1)	T/over(-2)	Returns(-1)	Returns(-2)	Disp(-1)	Disp(-2)	Vol(-1)	Vol(-2)	C	R2	F-value
PAKISTAN											
Turnover	0.61	0.18	0.52	0.11	0.29	-0.33	0.76	-5.94	0.26		
	-0.02	-0.02	-0.79	0.88	-0.63	-0.62	-3.24	-2.24	-1.20	0.41	456.14
	(28.73)*	(8.81)*	(6.55)*	(1.68)**	(0.46)	(0.93)	(-0.17)	(1.96)*	(12.65)*		
Returns	0.00	0.00	0.09	0.02	-0.01	0.90	1.03	-5.30	0.40		
	0.00	0.00	-0.02	-0.02	-0.17	-0.17	-0.64	-0.64	0.31	0.21	12.05
	(1.62)***	(1.64)***	(-0.13)	(-1.45)	(-0.04)	(-0.41)	(0.60)	(-2.25)*	(2.66)*		
INDIA											
Turnover	0.21	0.15	-0.17	-0.32	-0.10	-0.75	0.54	0.74	0.55		
	-0.02	-0.02	-0.39	-0.39	-0.31	-0.31	-0.20	-0.20	-0.39	0.09	31.61
	(10.52)*	(7.23)*	(-0.43)	(-1.11)	(-1.28)	(-2.43)*	(2.67)	(0.36)	(14.31)		
Returns	0.00	0.00	0.07	-0.01	0.46	0.52	-1.41	-5.72	0.00		
	0.00	0.00	-0.02	-0.02	-0.16	-0.16	-1.06	-1.06	0.00	0.28	7.04
	(-1.42)	(0.05)	(3.19)	(-0.54)	(2.87)	(3.21)	(-1.32)	(-5.38)*	(-1.17)		
BANGLADESH											
Turnover	0.40	0.26	0.12	-0.14	-0.68	0.83	0.23	-0.14	0.10		
	-0.02	-0.02	-0.12	-0.13	-0.88	-0.88	-0.17	-0.17	-0.64	0.35	157.79
	(20.31)*	(13.18)*	(0.09)	(-1.59)***	(-1.47)	(0.94)	(3.14)	(-2.82)	(16.03)		
Returns	0.00	0.00	0.02	0.05	0.24	1.04	0.36	-4.00	0.00		
	0.00	0.00	-0.02	-0.02	-0.14	-0.14	-0.27	-0.27	0.00	0.16	30.74
	(-1.10)	(1.59)***	(1.109	(2.55)	(1.66)	(7.23)	(1.30)	(-14.63)*	(-0.28)		
U.S											
Turnover	0.54	0.26	0.80	0.64	0.38	-0.45	0.16	0.81	0.71		
	-0.02	-0.02	0.29	-0.29	-0.23	-0.23	-0.17	-0.17	-0.55	0.63	520.81
	(27.09)*	(13.16)*	(2.76)*	(2.24)*	(1.03)	(-1.96)**	(1.92)	(1.60)	(12.90)		
Returns	0.00	0.00	-0.05	0.02	0.79	-0.20	-8.14	4.05	0.00		
	0.00	0.00	-0.02	-0.02	-0.16	-0.16	-1.21	-1.21	0.00	0.26	9.16
	(-3.07)*	(2.35)*	(-2.59)	(0.83)	(4.91)	(1.229)	(6.71)*	(-3.33)*	(2.67)*		

**significant at 01%, **significant at 5%, ***Significant at 10%, t-values in parenthesis*

Table 4.4 summarize the results of VAR for all the sampled countries in order to predict the association between turnover and returns. Turnover and returns are the two dependent variables appearing in rows while the lagged values of turnover, returns, dispersion, and volatility are the independent variables appearing in the corresponding columns. Each variable is explained by its respective standard error, coefficient, and t-values.

Firstly, the endogenous variable turnover (lagged values) are analyzed in contrast to the dependent variables turnover and returns. The results given in the above tables reveal that market turnover is significantly related to lagged turnover for all the sampled countries at 1 percent of significance level (t-values>2.00) however the positive association becomes relatively weaker while moving from the first lagged value to the second lagged value of turnover.

The relationship between returns and turnover yields different results for the sampled countries. For Pakistan, returns and lagged turnover (both lags) show a significant relationship at 10 percent of significance level. For India, returns are insignificantly associated with first and second lags of turnovers. For Bangladesh, returns and lagged turnover (-2) have a significant association at 90 percent of confidence interval while the returns are insignificantly associated with the first lag of turnovers. This indicates that any previous value (t-1) does not have any impact on current returns indicating a slow diffusion and underreaction of information as the relationship is more valid for the second lag of turnovers. And for the U.S, returns and lagged turnovers (-1, -2) have a significant relationship at 99 percent of confidence interval. Lee and Swaminathan (2000) proposed future returns can be estimated through past trends in trading turnover, they conducted their study on individual stocks. The same is confirmed in Pakistani and U.S stock markets as evident from significant values between returns and the first lag of turnovers.

Secondly, the lagged values of returns are analyzed in contrast to the dependent variables turnover and returns. The results are somewhat different for all the sampled countries. Turnover has a significant (at 1 percent of significance level) relationship with first lag of returns and a weekly significant relationship with the second lag of returns for the Pakistani stock market. Interestingly, the turnover and lagged returns (-1, -2) have insignificant relationships for the Indian stock market however second lag of returns show a significant relationship with turnover for the Bangladeshi stock market while for the U.S stock market, the relationship among turnovers and lagged returns is significant for both lags (where t-value>1.59).

As already established for the self-attribution and overconfidence bias, due to higher stock returns, investors attribute these returns to their own ability of wise decision-making consequently, they start over trading and this increased trading leads to high turnovers. Based on the results, it is thus concluded that past returns significantly determine the current market turnovers.

Analysis of the relationship between returns and lagged returns reveals that Pakistani and U.S stock markets exhibit significant relationships between returns and first lag of returns at 10 percent and 1 percent of significance level respectively. While the Bangladeshi stock market shows a significant relationship of turnovers and the second lag value of returns (-2). (Significant relationships, t-value=1.59).

For Pakistani, Indian, and Bangladeshi market returns in relation to lagged market volatility exhibit a significant relationship for the second lag of volatility only (at 1 percent of significance level) however, the U.S stock market shows a significant relationship for both lags of market volatility only. These results comply with the volume and volatility relationship proposed by Karpoff (1987) and French, Schwert, Stambaugh (1987). This implies that volatility of the immediate previous time (t-1) does not influence the current turnover however the second lag volatility (t-2) or volatility preceding the previous volatility negatively affects returns in the current period (evident from the t-value and negative sign). Moreover, it also indicates that as long as market volatility rises, returns are expected to drop as a rise in volatility leads to uncertainty and therefore the investors prefer to trade less. As a matter of fact, the said impact strengthens while moving from lag 01 to lag 02 in the sampled stock markets except from the U.S market where both lagged values of market volatility show a significant relationship with returns.

Turnover shows a mixed relationship for both lagged values of volatility for all the sampled countries at 99 percent of confidence interval (As t-values>2.00).

The relationship between dispersion and turnover also yielded mixed results for the sampled countries. Among all the sampled countries, the Pakistani and Bangladeshi stock markets show an insignificant relationship between turnover and lagged dispersions while, Indian and U.S stock markets exhibited a significant negative relationship of turnover on the second lag of dispersion (-2) at a 1 percent of significance level (Where all t-value>2.00) indicating that as long as dispersion increases among stocks, their corresponding turnover falls. Dispersion and returns also showed mixed results across all the sampled stock markets.

Summing the relationship between endogenous (Turnover and Returns) and the exogenous variables (dispersion and volatility), it is concluded that market volatility in the form of cross-sectional standard deviations and dispersion in the form of cross-sectional variations do have a statistically significant relationship on returns and trading turnover for all the mixed lags. Significant relationship in second lags represents under reaction or slow information diffusion and vice versa. While more deviations in stock returns may be the result of investor's anticipation regarding some information in the future.

4.1.4 GRANGER CAUSALITY TEST

Regression only studies the dependence of variables on each other, it does not essentially represent causation. In other words, the relationship among variables is not explained in terms of direction.

A Granger causality test is used in such a case. It involves the existence of correlation among one variable and the past values of other variables. A Granger causality exists if the past values of a variable help in estimating the other variable. Therefore, the null hypothesis is stated as: “Variable X does not cause variable Y”. Wald test is a common tool for the Granger causality test.

Table 4.5 given below reports the results for VAR Granger causality. Results are given for when the dependent variable is “Returns” and when the dependent variable is “turnovers” for each sampled country.

Table 4.5 VAR Granger Causality/Block Endogeneity Wald Test.

Dependent variable: D(Returns)												
	Pakistan			**India**			**Bangladesh**			**U.S**		
Excluded	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.
D(Returns)	2.13	2.00	0.04	1.16	2.00	0.56	1.36	2.00	0.51	15.84	2.00	0.00
All	2.13	2.00	0.04	1.16	2.00	0.56	1.36	2.00	0.51	15.84	2.00	0.00
Dependent variable: D(Turnover)												
Excluded	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.
D(Turnover)	6.86	2.00	0.03	0.46	2.00	0.80	4.19	2.00	0.09	17.64	2.00	0.00
All	6.86	2.00	0.03	0.46	2.00	0.80	4.19	2.00	0.09	17.64	2.00	0.00

The first portion, where the dependent variable is returns, indicates that for the Pakistani and U.S stock markets, turnover Granger causes returns at 95 percent and 99 percent of confidence interval respectively. (alpha<0.05, and 0.01). The results are in accordance with the results produced by the regression analysis.

On the other hand, when Turnover is the dependent variable, the results indicate that returns are related to turnover for Pakistani, Bangladeshi, and the U.S stock market (where p-values are 0.03 and 0.00 respectively). The null hypothesis is rejected and it is therefore concluded that Turnover Granger causes returns only in Pakistani and the U.S stock market. The results are in accordance with the results given by the VAR model. Owing to the given results, it can be concluded that the hypothesized relationship mandatory for the overconfidence bias can only be confirmed in Pakistani and the U.S markets. (evident from the VAR and Granger causality test).

Results regarding self-attribution bias are consistent with literature for Pakistani and the U.S stock markets respectively (e.g., Zia et al., 2017; Parker et al., 2012) However, for Bangladeshi stock market self-attribution is effective at the second lag only which implies slow information diffusion or conversely relatively sensibility of the investors. However, for the Indian stock market the results are insignificant which is converse to the literature (e.g., Prosad et al., 2017). Moreover, the results are contradictory for the south Asian region probably, implying the importance of individual value system driving financial decisions rather than cultural homogeneity and social norms.

4.2 Anchoring

Anchors are the initial values or reference values that are used by individuals while estimating something. The process of using these anchors is referred to as anchoring. Additionally, an investor’s decision is sometimes based on in-accurate estimation along with the use of anchors after few essential adjustments. As a matter of fact, anchoring is seen as one of the forms of irrational decisions, efficient markets cannot exist in such cases.

Various measures have been used for anchoring, out of such measures, the study at hand utilizes two measures nearness to 52-week high and nearness to historical high returns. The first measure represents under-reaction while the second measure represents overreaction of investors. The same measures have been used by various researchers (George and Hwang, 2004; Grinblatt and Keloharju, 2001; Kartano, 2013; Li and Yu, 2009).

As mentioned earlier, this study investigates the impact of anchoring on different south Asian stock markets over daily, weekly, monthly, quarterly, and yearly time horizons.

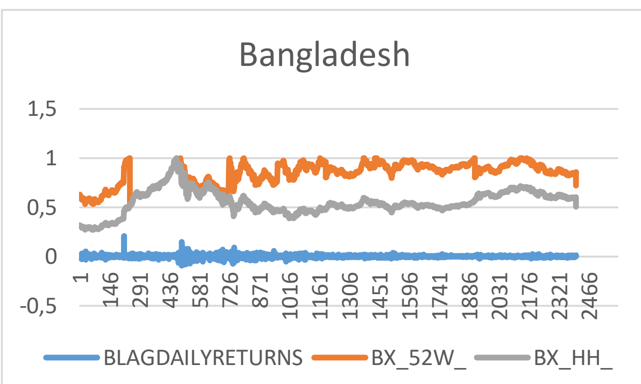
Moreover, based on the literature, anchoring is one of the psychological moves to reduce uncertainty. It is very important to control for the effects of certain macroeconomic variables which also leads to uncertainty and ultimately anchoring bias. Moreover, these macroeconomic variables have been found to predict stock returns. Some of these variables include interest rates, inflation rate, and exchange rate. Since we are dealing with financial markets, these factors are expected to influence the business conditions and the corresponding stock market. That's why inflation rate, exchange rate, and interest rates are included to control their impact in predicting future returns.

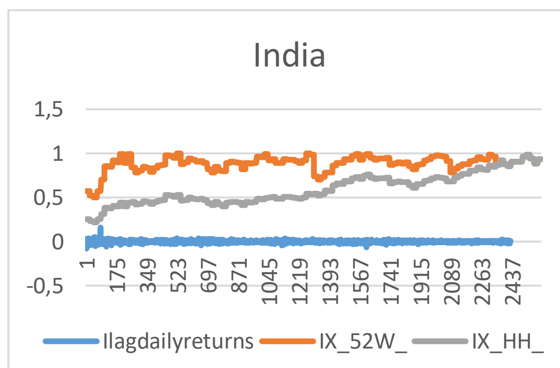
Nearness to 52-week high (X52W) and nearness to historical high (XHH) have been hypothesized to measure the anchoring effect, indicating investors under-reaction and overreaction respectively. Figure 4.1 shows a comparative graphical presentation of all four indices while Figure 4.2 shows a graphic presentation of trends in X52w and XHH and for all the sampled countries.

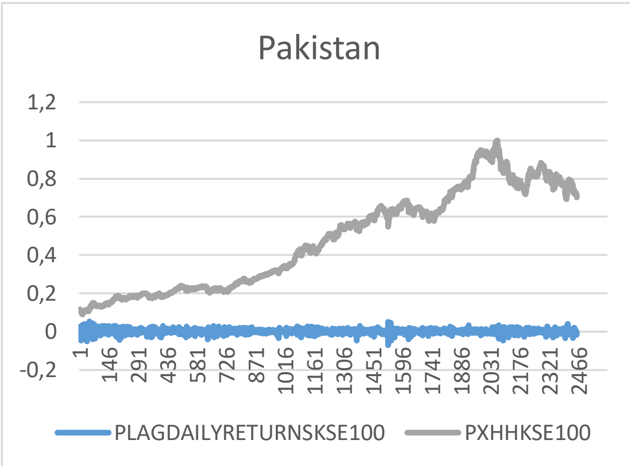
Figures 4.1 to 4.4 show the graphical relationship between lagged returns, X52w (nearness to 52-week high) and XHH (nearness to Historical high) from January 2009 to December 2018 for Bangladesh, India, Pakistan, and the U.S respectively. The historically high index observed were

8918, 38896, 52877, and 2930 for Bangladesh, India, Pakistan, and the U.S on 05th October 2010, 28th August 2018, 24th April 2017, and 20th September 2019 respectively.

A mixed trend was observed across all indices over the sampled period. It is evident from the data collected that Dhaka stock exchange (DSE) that despite the crash in 2009, DSE has shown favorable growth till 2015. The negative returns (change) were however less in proportion as compared to previous years. Returns are less variant across all sampled countries evident from the graphical presentation similarly, nearness to 52-weeks high and historical high for all indices show the same pattern over the period of time for all four countries. Nearness to historical high move along the opposite direction as nearness to 52W high for all other countries. Both nearness indices move in opposite directions in the beginning, in the second stage, both indices seem to move in the same direction till a point where they meet with each other and afterward the directions are again changed.







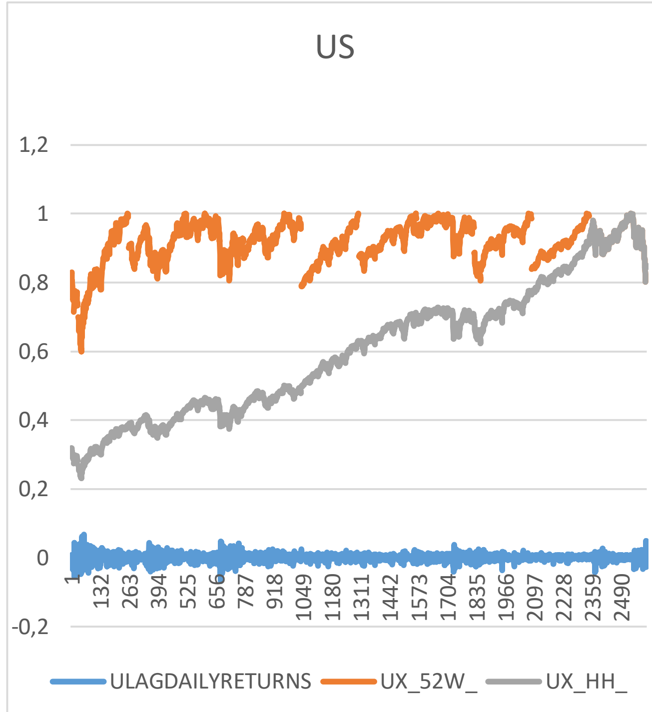


Figure 4.1

Figure 4.2

Figure 4.3

Figure 4.4

4.2.1 Descriptive Analysis

As it is evident from the literature, that nearness to 52 weeks and nearness to the historical high are two robust measures for anchoring effect. Both these measures estimate converse market reactions- nearness to 52w reflects market under-reaction towards random news while nearness to the historical high represents market overreaction. Theoretically, it is also established that when nearness to 52 weeks equates with nearness to nearness to a historical high, the investor tends to use nearness to the 52-week high anchor in investment decision-making. Table 4.6 summarizes the descriptive statistics for anchoring bias.

Table 4.6 Descriptive statistics

Country	Variables	Mean	S.D	Skewness	Kurtosis	JB-test	P-value	Obs
Bangladesh	Returns	0.00	0.02	0.44	33.00	90348.33	0.00	2407.00
	Exch.Rate	0.01	0.00	0.87	2.93	305.20	0.00	2407.00
	Infl.Rate	6.97	1.77	1.51	4.39	1110.73	0.00	2407.00
	Intr.Rate	4.96	1.11	-0.17	2.36	53.41	0.00	2407.00
	X52w	0.83	0.12	-0.85	2.73	298.04	0.00	2407.00

	XHH	0.55	0.12	0.29	3.93	119.98	0.00	2407.00
India	Returns	0.00	0.01	0.90	20.88	32700.66	0.00	2431.00
	Exch.Rate	0.00	0.00	1.57	7.34	2903.29	0.00	2431.00
	Infl.Rate	7.79	3.03	-0.22	1.79	168.14	0.00	2431.00
	Intr.Rate	7.36	1.26	0.21	1.28	316.88	0.00	2431.00
	X52w	0.89	0.09	-2.00	8.78	5008.02	0.00	2431.00
	XHH	0.60	0.17	0.30	2.25	93.44	0.00	2431.00
Pakistan	Returns	.01	.01	- .27	6.56	1326.39	.00	2458
	Exch.Rate	.01	.00	.03	2.79	5.00	.00	2459
	Infl.Rate	7.79	3.72	.31	1.72	206.25	.00	2459
	Intr.Rate	7.79	3.72	.31	1.72	206.25	.00	2459
	X52w-kse100	.80	.20	-1.80	5.28	1863.67	.00	2459
	XHH-kse100	.48	.26	.17	1.61	209.24	.00	2459
US	Returns	0.00	0.01	-0.33	8.01	2678.38	0.00	2515.00
	Infl.Rate	1.80	0.69	0.00	2.20	67.35	0.00	2515.00
	Intr.Rate	1.90	0.50	-0.28	1.41	298.72	0.00	2515.00
	X52w	0.92	0.06	-1.38	6.06	1777.80	0.00	2515.00
	XHH	0.60	0.19	0.20	1.98	127.42	0.00	2515.00

In addition to the inflation rate, exchange rate, and interest rate, two dummy variables naming It and Dt have also been used. “It” represents the dummy variable when nearness to 52 week high equals nearness to historical high (1 otherwise 0). On the other hand, the dummy variable “Dt” is used when the index reaches a historical high. Summary statistics are not included for both dummy variables.

Nearness to 52 week (X52w) has mean values of 0.83, 0.89, 0.80 and 0.92 with a standard deviation of 0.12, 0.09, 0.20, 0.06 and kurtosis values 2.73, 8.78, 5.28, 1.38 for Bangladesh, India, Pakistan and U.S respectively. As mentioned earlier, it shows a flat tail, leptokurtic distribution for Indian, and Pakistani stock indices only. The normality assumption is therefore rejected. On the other hand, nearness to historical high XHH has mean values, 0.55, 0.60, 0.48, and 0.60, with standard deviations 3.93, 2.25, 1.61, and 0.20 while the kurtosis values are 3.93, 2.25, 1.61, and

0.20 for Bangladesh, India, Pakistan, and the U.S respectively. XHH values show platykurtic distribution except for Bangladesh.

The table given below summarizes the relationship between various predictor variables. these variables include returns, exchange rate, inflation rate, interest rate, nearness to 52 weeks high, and nearness to a historical high. The dummy variables “It” and “Dt” are once again excluded from the correlation analysis. Returns are taken as lagged returns. Additionally, the analysis was only made for the daily horizon. The exchange rate has not been included in the correlation analysis for the U.S.

It is clear from the table that the two anchors namely X52w and XHH have no significant correlation with the macroeconomic variables except than with the exchange rate. Interestingly, the Exchange rate has -0.56 and -0.37 correlation values with X52w and XHH respectively for the Bangladeshi stock market.

XHH and exchange rates have the strongest negative correlation(r=-0.91). Similarly, inflation has also strong negative(r=-0.88) relationship with XHH. On the other hand, XHH and X52w have a significant positive relationship with each other (r=0.48). Moreover, exchange rate and inflation rate have relatively

As far as the Pakistani stock market is concerned, no significant correlation is observed between the proposed anchors (X52w and XHH) and the macro-economic variables (Inflation rate, interest rate, and exchange rate). Among the macro-economic factors interest rate and inflation rate have a relatively stronger correlation with each other(r=0.43). While the two anchors (X52w and Xhh) have a weak positive correlation(r=.35)

4.2.3 CORRELATION ANALYSIS

Table 4.7 summarizes the correlational analysis for all variables relevant to anchoring bias.

Table 4.7 Corelation matrix

Horizon	Variables	Returns	Exch.Rate	Infl.Rate	Intr.Rate	X52w	XHH
Bangladesh	Returns	1.00	0.05	-0.02	0.00	0.03	0.02
	Exch.Rate	0.05	1.00	-0.11	0.26	-0.56	-0.37
	Infl.Rate	-0.02	-0.11	1.00	0.29	-0.26	0.34
	Intr.Rate	0.00	0.26	0.29	1.00	0.00	-0.36
	X52w	0.03	-0.56	-0.26	0.00	1.00	0.29
	XHH	0.02	-0.37	0.34	-0.36	0.29	1.00
India	Returns	1.00	0.00	0.01	0.00	0.03	0.00
	ExchRat	0.00	1.00	0.75	-0.23	-0.67	-0.91
	Infl.Rate	0.01	0.75	1.00	-0.04	-0.27	-0.88
	Intr.Rate	0.00	-0.23	-0.04	1.00	0.20	0.09
	X52w	0.03	-0.67	-0.27	0.20	1.00	0.48
	XHH	0.00	-0.91	-0.88	0.09	0.48	1.00
Pakistan	Returns	1	.02	.03	- .01	- .02	- .04
	Exch.Rate	.02	1.00	.28	- .31	- .16	- .49
	Infl.Rate	.03	.28	1.00	- .40	- .19	- .43
	Intr.Rate	- .01	- .31	- .40	1.00	- .19	.37
	X52w	.02	- .16	- .19	- .19	1.00	.35
	XHH	- .04	- .37	- .43	.37	.35	1.00
US	Returns	1.00	-	0.00	-0.01	0.07	0.00
	Infl.Rate	0.00	-	1.00	0.10	-0.25	-0.30
	Intr.Rate	-0.01	-	0.10	1.00	-0.12	0.35
	X52w	0.07	-	-0.25	-0.12	1.00	0.39
	XHH	0.00	-	-0.30	0.35	0.39	1.00

X52w and XHH have a relatively stronger association with each other(r=0.39). The correlation matrix does not include any other value greater than 0.39. Hence all other macro-economic variables have a relatively weaker correlation in the U.S stock market.

Despite the correlation between X52W and XHH, it is inferred that the predictive power of the variables is not affected at all. Moreover, the use of least square regression method is more effective in case of high collinearity among the predictors (Stewart, 1987).

4.2.4 REGRESSION ANALYSIS

In the first step, in order to check the predictive power of individual variables, lagged returns, X52w, XHH, Dummy variables (“Dt” and “It”) are regressed with future market returns. In the second step, various macro-economic variables (inflation rate, interest rate, and ex

change rate) are added with lagged returns and regressed against future returns.

The following table 4.8 shows Non-linear Least-squares and Autoregressive, moving average NLS-ARMA results for lagged returns, nearness to 52w high (X52w), nearness to historical high (XHH), dummy variable “It”- when the corresponding stock index historical high equals to 52-week high index (entered 1 and 0 otherwise). While the dummy variable “Dt” indicates when the

Table 4.8 Empirical results NLS-ARMA (Future returns on past returns, X52w, XHH, It, Dt,)

Market	Horizon	Past returns	X52w	X_{HH}	It	Dt	R^2
KSE	Daily	0.10	0.02	0.00	-0.01	-0.02	0.01
		(5.06)*	(2.34)*	(-3.47)*	(-1.55)	(-1.18)	
	Weekly	0.05	.00	- .00	- .03	- .00	0.02
		(1.21)*	(3.4)*	(-4.60)	(-1.51)***	(-1.79)**	
	Monthly	0.01	.00	- .00	.09	.00	0.08
		(.28)	(3.55)*	(-4.14)*	(-1.64)***	(-1.92)*	
BSE	Daily	0.06	0.00	0.00	-0.01	-0.00	0.00
		(2.84)*	(0.01)	(0.35)	(-1.62)	(-0.56)	
	Weekly	0.03	0.01	-0.02	-0.00	-0.00	0.01
		(0.74)	(1.07)	(-0.96)	(-1.03)	(-0.20)	
	Monthly	0.04	0.01	0.02	-0.01	-0.03	0.03
		(0.47)	(0.26)	(0.77)	(-1.21)	(-1.13)	
DSE	Daily	0.01	0.01	-0.01	0.00	0.01	0.01
		(1.71)	(3.02)	(-1.80)	(-3.53)	(-1.36)	
	Weekly	0.03	0.05	-0.04	-0.01	-0.00	0.04
		(0.66)	(3.79)	(-3.84)	(-3.81)	(-0.25)	
	Monthly	0.00	0.00	0.02	-0.00	-0.01	0.03

		(0.05)	(0.02)	(1.55)	(-0.47)	(-0.49)	
DJIA	Daily	-0.07	0.02	0.00	-0.00	-0.01	0.01
		(3.46)	(4.04)	(-0.77)	(-0.91)	(-0.70)	
	Weekly	-0.08	0.00	0.00	0.00	0.01	0.01
		(-1.84)	(1.04)	(-0.23)	(-1.15)	(-0.50)	
	Monthly	0.00	0.00	0.00	-0.00	-0.01	0.02
		(0.05)	(0.25)	(-0.31)	(-1.12)	(-0.30)	

corresponding stock index reaches the historical high (entered 1 and 0 otherwise). The results for the Pakistani stock market show that nearness to historical high (XHH) has a significant relationship with expected future returns. Similarly, when the corresponding stock market index reaches its historical high (It=1), returns on the next day are expected to be lower as shown by a significant negative sign. Moreover, the results deteriorate while moving from the daily horizon to monthly horizons (evident from the t-values). Results for the Indian stock market (BSE) are relatively bad as compared to the Pakistani stock market (KSE) furthermore, the results keep deteriorating while moving from daily to monthly horizons. The same trend is observed for the Bangladeshi and U.S stock market.

In order to improve the prediction power of the model, macro-economic variables are added and future returns are regressed with past returns, X52w, XHH, D_t, $I_{t,}$ Exchange Rate, Inflation rate, and Interest rate. Results are reported in table 4.9. The model yields better predictive power for the sampled countries while moving from daily to monthly time horizons. Similarly, after the macroeconomic variables are included in the model, all variables have improved their significance values for countries other than the U.S hence indicating the robustness of the model. Even after including the macro-economic variables in the model, the prediction power of the model does not improve in daily and weekly horizons. This pattern differentiates developed stock markets from emerging stock markets.

Table 4.9 Empirical results NLS-ARMA (Future returns on past returns, X52w, XHH, It, ExchR, InflR, Dt,)

Market	**Horizon**	**Past returns**	**X52w**	**X_{HH}**	**I_t**	**Exch. R**	**Infl.R**	**Int.R**	**Dt**	**R^2**
KSE	Daily	0.012	0	0	0.01	0	0	0	0.19	0.012
		(4.19)	(2.57)*	(-3.48)*	(1.69)*	(-1.18)	(-2.98)	(-1.73)	-0.45	
	Weekly	0.05	0	0	0.03	- .00	.00	2.9E-05	-0.19	0.0176
		1.17	(2.82)*	(-3.65)*	(1.68)***	(-2.55)*	(-3.69)*	(-1.16)*	(- .71)	
	Monthly	0.02	0	-0.001	0.09	0	-0.12	-0.01	0.18	0.091
		(0.24)	(2.79)*	(-3.42)*	(1.53)***	(- .22)	(-1.65)***	(- .84)	(-0.35)	
BSE	Daily	0.06	0.01	0.01	0.00	0.00	79.81	0.00	0.00	0.01
		(2.78)	(2.01)**	(1.08)	(-0.69)	(0.27)	(1.47)	(0.45)	(-0.13)	
	Weekly	0.03	0.02	-0.06	0.00	0.00	-139.70	0.00	0.00	0.01
		(0.60)	(1.59)***	(-1.06)	(-1.28)	(0.18)	(-0.87)	(0.88)	(-1.17)	
	Monthly	0.05	0.08	-0.12	0.00	0.03	-1497.46	0.00	0.01	0.13
		(0.57)	(1.59)***	(-1.69)**	(0.21)	(1.17)	(-3.43)	(1.08)	(2.43)	
DSE	Daily	0.01	0.02	0.00	0.00	0.00	2.29	0.00	0.00	0.01
		(0.52)	(3.51)*	(-0.56)	(1.06)	(0.26)	(3.20)	(1.25)	(-1.46)	
	Weekly	0.02	0.02	0.02	0.01	0.00	12.93	0.00	0.00	0.05
		(0.41)	(1.42)	(0.58)	(1.52)	(0.13)	(1.64)	(-1.99)	(-0.05)	
	Monthly	-0.03	-0.01	0.03	0.00	-0.01	-31.36	0.00	0.00	0.05
		(-0.34)	(-0.65)	(1.40)	(-0.61)	(-0.58)	(-0.73)	(-0.79)	(0.14)	
DJIA	Daily	-0.07	0.02	0.00	0.00	0.01	-	0.00	0.00	0.01
		(-3.49)	(4.24)*	(-0.66)	(-1.30)	(0.69)	-	(0.85)	(0.99)	
	Weekly	-0.08	0.00	0.00	0.00	0.01	-	0.00	0.00	0.01
		(-1.86)	(1.15)	(-0.25)	(-1.24)	(0.49)	-	(0.22)	(0.45)	
	Monthly	0.00	0.00	0.00	0.00	0.01	-	0.00	0.00	0.03
		(0.00)	(0.44)	(-0.27)	(-1.28)	(0.29)	-	(0.44)	(0.54)	

Expected future returns are positively associated with nearness to a 52-week high and negatively associated with nearness to a historical high. In other words, as long as the corresponding index is somewhat near to the 52 weeks high, returns on the next day are expected to be positive. According to Li and Yu (2009), such a pattern is due to the emergence of the latest good news in the market creating a selling pressure hence a rise in the market whenever the index value is near to the 52-week high. Such pattern is referred to as investor under-reaction towards recent favorable news and overreaction towards any previous bad news. As a matter of fact, it applies only in short term and it tends to revert back in the long run.

Looking at the overall results across all sampled countries, as long as the corresponding stock index has an upward trend, the dummy variable Dt may not be considered a viable measure for any good news in the long run (Li and Yu, 2009). It is evident from the results that when 52 week high equals the historical high, returns will be insignificantly negative for the next day. Although, it was hypothesized that investors under-react to recent good news in such a case.

We have used nearness to 52-week high (X52w) and nearness to the historical high (XHH) as proxies for under-reaction and overreaction respectively. As a matter of fact, an investor's under-reaction is observed against random short-term news, and overreaction is observed for long-term good news. Therefore, the results show that investors under-react while using the 52-week high anchor and overreact while using historical high anchors.

In sum, the Pakistani stock market (KSE-100) exhibited under-reaction and overreaction significantly in daily, weekly and monthly horizons. (t-values for Xhh and X52w are significant at 1% of confidence interval)

Indian stock market (BSE) shows under-reaction (where X52w has a positive sign with t-value=2.01, 1.59, and 1.59) on daily, weekly and monthly horizons. However, on monthly horizon nearness to historical high XHH also shows significant negative values (t=-1.69) indicating overreaction of investors in the long run.

The results for the Bangladeshi stock market (DSE) shows market under-reaction only in the daily horizon with t-value=3.51 while the overreaction was insignificant in daily, weekly and monthly horizons (t-values for XHH are insignificant)

While the results for the U.S stock market(DJIA) also showed under-reaction on part of investors only for the daily horizon (where for X52w, t-value=4.24) while no significant over and under-reaction was observed in weekly and monthly horizons.

The results indicate that all of our sampled stock markets demonstrate anchoring tendencies of their corresponding investors. Moreover, Nearness to 52-week high is used more frequently across all markets as compared to nearness to the historical high which is also a proxy for long term orientation of the investors. The results are consistent with the literature for Pakistani and the U.S stock markets respectively (e.g., e.g., Parveen & Siddiqui, 2018; Campbell & Sharpe, 2009) .

4.3 Herding

In highly volatile or extreme market conditions, individuals are more prone to follow the market trend rather than using the fundamentals in investment decision-making. Such reliance of investors on market trends is termed as "herding". As already discussed in the literature review and the methodology section, cross-sectional absolute deviation (CSAD) and cross-sectional standard deviation (CSSD) are the two measures used for herding. Since CSSD is considered a more robust measure, this study uses the cross-sectional standard deviation (CSSD) between individual stock returns and market returns. For the additional hypothesis regarding the turnover effect, analysis is conducted for high turnover stocks and low turnover stocks using the CSSD. The results obtained are discussed as under:

4.2.1 DESCRIPTIVE STATISTICS

Table 4.10 below illustrates the summary of mean, max, min, standard deviation, skewness kurtosis, etc. for market returns, cross-sectional standard deviation (CSSD), High turnover, and low turnover cross-sectional deviations (HTCSSD and LTCSSD) for Pakistani, Indian, Bangladeshi and U.S Stock markets. The mean value of market returns, CSSD, HTCSD, and LTCSD are all under 1 percent. The standard deviation in market returns shows that Pakistani and Bangladeshi stock markets are relatively more volatile as compared to the Indian and U.S stock markets.

Table 4.10 Descriptive statistics

Variables		**Mean**	**Maximum**	**Minimum**	**Std. Dev.**	**Skewness**	**Kurtosis**	**p-value**	**Obs**
Mkt Returns	Pakistan	0.00	0.05	-0.07	0.01	-0.27	6.59	0.00	2453.00
	India	0.00	0.07	-0.03	0.00	0.96	20.69	0.00	2475.00
	Bangladesh	0.00	0.20	-0.09	0.01	1.18	28.15	0.00	2386.00
	U.S	0.00	0.00	0.00	0.00	1.56	3.83	0.00	2515.00
CSSD	Pakistan	0.00	0.00	0.00	0.00	2.99	15.46	0.00	2453.00
	India	0.00	0.01	0.00	0.00	8.69	188.38	0.00	2475.00
	Bangladesh	0.00	0.01	0.00	0.00	1.52	5.05	0.00	2386.00
	U.S	0.00	0.00	0.00	0.00	0.20	38.42	0.00	2515.00
HTCSSD	Pakistan	0.00	0.00	0.00	0.00	3.24	18.21	0.00	2453.00
	India	0.00	0.02	0.00	0.00	10.59	266.38	0.00	2475.00
	Bangladesh	0.00	0.02	0.00	0.00	1.53	4.69	0.00	2386.00
	U.S	0.00	0.20	0.00	0.00	50.06	2508.91	0.00	2515.00
LTCSSD	Pakistan	0.00	0.00	0.00	0.00	2.76	13.61	0.00	2453.00
	India	0.00	0.00	0.00	0.00	8.32	146.06	0.00	2475.00
	Bangladesh	0.00	0.01	0.00	0.00	5.22	53.77	0.00	2386.00
	U.S	0.00	0.36	0.00	0.01	50.10	2511.91	0.00	2515.00

The skewness and kurtosis values with the corresponding p-values for market returns, CSSD, HTCSSD, and LTCSSD represent a normal distribution across all the sampled countries. Generally, skewness and kurtosis of investments indicate how the patterns differentiate from a normal distribution hence provide reliability based on standard deviation. Only market returns show a negatively skewed distribution for Pakistan only while all other variables for the sampled countries are positively skewed. For Pakistan, the negatively skewed distribution implies that most values of market return fall on the right side of the mean value. On the other hand, kurtosis values for all variables are greater than 03 (kurtosis>03) indicating a leptokurtic distribution with a concentration of values around the mean. It depicts that the distribution includes extreme values.

In other words, all variables have peaked distribution while the given deviations may be due to the existence of some extreme values.

4.2.2 TEST FOR HERDING

In order to test the hypothesis regarding herding, cross-sectional standard deviation (CSSD) has been used as a measure of herding for all the sampled countries. The following table shows the regression results for cross-sectional standard deviation (CSSD) involving extreme market conditions. Two dummy variables have been used in the analysis:

DUt = 1 when return on the market for time period t belongs to the extreme upper tail of the returns distribution. A value of zero “0” would be assigned otherwise.

DLt = 1 when return on the market for time period t falls in the extreme lower tail of the returns distribution. A value of zero “0” would be assigned otherwise.

Extreme market conditions have been defined as the top and bottom 10% of market returns. β1 and β2 are the coefficients used for extreme market conditions. The results indicate a significant negative relationship of -0.0006, -0.0012 for Pakistani and Bangladeshi stock markets respectively in upmarket situations(DuT) All the values are significant at 1 percent of significance level (t-values>2.00). While the Indian and U. S markets exhibit a positive relationship among returns and CSSD as shown in table 4.11 below:

Table 4.11 CSSD on DuT and DLT

Variable	Pakistan	India	Bangladesh	U.S
DUT	-0.0006	0.0005	-0.0012	0.0001
	-26.6744	1.5306	-9.7370	0.6043
DLT	-0.0005	0.0001	-0.0010	0.0000
	-25.2244	1.2750	-7.9900	1.1104
C	0.0004	0.0006	0.0020	0.0017
	55.3326	54.0100	49.3460	784.3937

R2	0.3312	0.0973	0.0567	0.0931
Adj R2	0.3307	0.0966	0.0559	0.0924
F-value	606.7066	133.2386	71.5832	128.9723

On the other hand, β1 and β2 in Down extreme market conditions (DLT) exhibit an insignificant relationship for the Indian and U.S stock markets (t-values=-1.27 and 1.11 respectively) while the coefficients have significant negative values for Pakistani and Bangladeshi stock market (t-values= -25.2 and -8.0). All values are significant at 99 percent of confidence interval.

It is clear from the results that in the case of high returns (DuT) and low returns (DLT) for Indian and U.S stock markets, the cross-sectional standard deviation (CSSD) between market returns and stock returns also increases which is against the herding bias. Hence, based on the statistical insignificance, it can be inferred that there is no evidence of herding for top 10 % returns or upper extreme market conditions in Indian, and U.S stock markets. Conversely, CSSD and returns show a significant negative relationship in both extreme market conditions hence leading to the evidence of herding in Pakistani and Bangladeshi stock markets. Additionally, the R-square values indicate the joint contributions of independent variables in the dependent variable (33.0, 9.66, 5.59, and 9.24 % for Pakistani, Indian, Bangladeshi, and the U.S stock markets).

4.2.3 The Turnover Effect

It is generally observed that low turnover stocks are more prone to herding because relatively less amount of information exists regarding such stocks that’s why the dispersion and market returns move in opposite directions for such stocks indicating the herding phenomenon.

The additional hypothesis is to be tested in order to find out the relationship of herding with stocks categorized on the basis of their turnovers. For this purpose, stocks included in the indices of each sampled country, are divided into low turnover and high turnover stocks. The corresponding high turnover standard deviation (HTSD) and low turnover standard deviation (LTSD) are used in the testing of the proposed hypothesis.

Table 4.12 summarizes the regression results for the turnover effect. High turnover cross-sectional standard deviation (HTCSSD) and low turnover standard deviation (LTCSSD) are the two dependent variables used in the first and second parts respectively while DuT and DLT are the dummy variables for market extreme conditions where DuT is the market Up condition while DLT is considered as the market DOWN condition. 10% top(DUT) and 10 % bottom(DlT) returns are considered as the market extreme conditions. Regression results when the dependent variable is high turnover, cross-sectional standard deviation (HTCSSD) show that both coefficients (β1 and β2) for the extreme market conditions show a significant relationship with HTCSSD in both extreme market conditions except the U.S stock market. All values are significant at a level of 1 percent, except for the U.S stock market in UP market conditions.

Table 4.12 Regression model: HTCSSD vs DuT, DLT and LTCSSD vs DuT

	HTCSSD				LTCSSD			
Variable	**Pakistan**	**India**	**B.desh**	**U.S**	**Pakistan**	**India**	**B.desh**	**U.S**
DUT	0.0006	0.0006	0.0014	0.0001	0.0006	0.0002	0.0010	0.0001
	23.6699	10.969	6.0041	0.3328	28.8044	13.8787	28.2735	0.2406
DLT	0.0005	0.0004	0.0010	0.0008	-0.0005	0.0002	-0.0010	0.0014
	22.5300	8.0981	4.2428	3.0763	-27.0523	15.6475	-28.1038	3.0232
C	0.0004	0.0008	0.0034	0.0030	0.0004	0.0002	0.0005	0.0002
	50.9750	43.421	44.9903	34.031	57.3697	54.9900	38.9268	1.1582
R2	0.2818	0.0637	0.0202	0.0038	0.3646	0.1375	0.3751	0.0036
Adj R2	0.2812	0.0630	0.0193	0.0030	0.3641	0.1368	0.3746	0.0028
F-value	480.6770	84.147	24.5036	4.7319	702.9517	197.0772	715.3476	4.5744

It is evident from the results that high turnover cross-sectional deviation (HTCSSD) has a significant positive relationship between stock returns and market returns for all countries (except U.S in DUT only) in both extreme market conditions (DuT and DlT). The relationship is significant at a 99 percent of confidence interval (Where t-values> 2.00). It means that in as long as returns increases to the top 10% of extreme market conditions of high turnover stocks, the cross-sectional deviation also increases. Similarly, as evident from the sign, when the returns of high turnover stocks move down to the Down extreme market conditions, the cross-sectional deviation between stock returns and market returns also decreases hence indicating the non-existence of herding in high turnover stocks in both UP and DOWN market conditions. The results for high turnover stocks are uniform across the sampled countries.

On the other hand, regression results for low turnover stocks in UP and DOWN market conditions across the sampled countries are shown in the second part of the table. Coefficients for UP market conditions in low turnover are positively significant at 99 percent of confidence interval. It means that as long as returns move up into the top 10% of the market extreme market conditions, the cross-sectional standard deviation among market returns and stock returns also increases for all the sampled countries (In UP conditions). However, for DOWN market conditions, the beta values are significant at 99 percent of confidence interval across all the sampled countries (t-value>2.00) however the values have a negative sign indicating that in DOWN market conditions the cross-sectional standard deviation for low turnover stocks decreases as long as the market returns move into the DOWN market conditions hence providing evidence of herding. As a matter of fact, the herding tendency was only observed for low turnover stocks of Pakistani and Bangladeshi stock market while no conclusive evidence of herding was found for the Indian and U.S stock markets. The R-squared value for the Pakistani, Indian, Bangladeshi, and U.S stock markets was observed to be 36.42, 13.68, 37.46, 0.28 percent respectively.

In nutshell, the analysis was conducted on UP and DOWN 10 percent of market returns. The first regression was run with the cross-sectional standard deviation as the dependent variable and two dummy variables representing market extreme conditions. It is found from the analysis that herding behavior can be observed for Pakistani and Bangladeshi stock markets (evident from the negative significant values). In the second part, regression is run for high turnover and low turnover stocks in both market extreme conditions. It is clear from the results that herding is observed in low turnover stocks more specifically in market DOWN conditions but only for Pakistan and Bangladesh. Although almost all relationships were significant, a negative sign in coefficients and t-values validates the turnover effect for Pakistan and Bangladesh only.

Results regarding Pakistani stock markets are in line with earlier empirical works (e.g., Zafar & Hassan, 2016). For Bangladeshi stock market, the results conflict earlier work in the literature (e.g., Ahsan & Sarkar, 2013). Bhaduri & Mahapatra (2013) find evidence of herding in the India stock market however, this couldn't be confirmed in this study. Similarly, our results are not also backed by the literature for the U.S stock market. Previous Studies show herding effect in the U.S stock market (e.g., Clements et al., 2017). One reason that seems plausible in this situation is the existence of variant methods to arrive at conclusions for example, Clements et al. (2017) use Gragner causality with macroeconomic news announcements as the conditioning variables to estimate the extent of Herding in DJIA. Future research studies are expected in this vein to fill this gap by testing the herding proposition with varying methodologies to come up with conclusive evidence in different stock markets.

4.4 Limited attention bias

Limited attention is generally associated with the outcome of various cognitive constraints and the availability of a large amount of information. Such information is more useful in the stock valuation and therefore, the cognitive activities important in processing such information are highly important. In reality, investors are prone to evaluate thousands of stocks for their investment decision-making. That's why limited attention truly affects individual investors in their investment decisions. Based on evidence, mutual fund managers and analysts also undergo limited attention bias. Several instances have been mentioned in the literature review part. Among many, Abarbanell and Bushee (1997) concluded that analysts widely ignore the scope of information provided in the form of financial ratios. Similarly, Teoh and Wong (2002) concluded that analysts are unable to correctly discount accruals of new issue firms.

The attention provided by an investor depends upon the existence of competing stimuli. In other words, more is the investor's attention when the distractions or competing stimuli are less in numbers and vice versa in addition to the fact that the information is salient for the stock concerned. As mentioned earlier, various proxies can be used for limited attention on the basis of relevancy, strength, and ease in processing such information. Trading volume, analyst coverage, internet search volumes and the number of earnings announcements are proxies used to measure investor's attention. Among all measures, trading volume is somewhat an established logical proxy used, therefore this study is using stock trading volume as a proxy for investor's attention.

Another aspect of the limited attention bias is that; investor's attention interacts with different behavioral biases to result in price overreaction. Which is a logical explanation for the price momentum effect. The literature delineates two major behavioral biases namely overconfidence and extrapolative bias as a cause of the market overreaction. As overreaction is primarily dependent on the degree of investor attention, it is expected that stocks that exhibit more price momentum profits with overreaction indicate more investor's attention. Which is also the proposed hypothesis for this section.

In order to test the above-stated hypothesis, the monthly stock returns and stock monthly trading volume are studied for two years non-overlapping formation periods as 2011-2012, 2013-2014, 2015-2016, and 2017-2018. Within each period, all sampled stocks for KSE, DSE, BSE, and DJIA are divided and sorted into five equal parts called quintiles. The top 10 percent of total stocks within the formation period make the first quintile and so on. Stocks within each quintile are sorted again on the basis of average returns for the period. Price Momentum profits are calculated for the period as the variance between the winner and loser stocks or it is calculated as the difference between quintile 1 and quintile 5. The hypothesized relationship between trading volume and price momentum profits is assessed in the form of correlational analysis. The following tables 4.13 to 4.16 summarize the results of correlation analysis for all the sampled stock markets.

Table 4.13 Correlation matrix for trading volume and price momentum profits

	Pakistan							
	2011-2012		**2013-2014**		**2015-2016**		**2017-2018**	
	Tr.V	PMPs	Tr.V	PMPs	Tr.V	PMPs	Tr.V	PMPs
Tr.V	1.00		1.00		1.00		1.00	
PMProfits	0.44	1.00	0.39	1.00	0.44	1.00	0.00	1.00
	(3.24)		(2.77)		(3.21)		(-0.03)	
	0.00		0.01		0.00		0.98	

Table 4.13 shows the direction and strength of relationship between trading volume and price momentum profits across all four formation periods for Pakistani stock market. It is evident from the above table that a positively significant but moderate association exists among trading turnover and the price momentum profits in three formation periods from 2011 to 2016. While an insignificant weak positive association exists for trading volume and momentum profits in the last formation period in Pakistani stock market.

Table 4.14 Correlation matrix for trading volume and price momentum profits

	India							
	2011-2012		**2013-2014**		**2015-2016**		**2017-2018**	
	Tr.V	PMPs	Tr.V	PMPs	Tr.V	PMPs	Tr.V	PMPs
Tr.V	1.00		1.00		1.00		1.00	
PMProfits	-0.14	1.00	0.57	1.00	0.40	1.00	0.41	1.00
	(-0.61)		(3.14)		(1.95)		(2.02)	
	0.55		0.01		0.07		0.06	

For the Indian stock market (table 4.14), the association is contradictory across all four formation periods with varying signs however as evident from the significance and t-values the relationship shown above is also insignificant.

Table 4.15 Correlation matrix for trading volume and price momentum profits

	Bangladesh							
	2011-2012		**2013-2014**		**2015-2016**		**2017-2018**	
	Tr.V	PMPs	Tr.V	PMPs	Tr.V	PMPs	Tr.V	PMPs
Tr.V	1.00		1.00		1.00		1.00	
PMProfits	0.73	1.00	0.33	1.00	0.53	1.00	0.65	1.00
	(3.89)		(1.28)		(2.21)		(3.09)	
	0.04		0.22		0.08		0.01	

As shown above, in table 4.15, the results for the Bangladeshi stock market show a somewhat strong positive relationship between the trading volume and momentum profits. The relationship is positive and significant in formation periods one, three, and four respectively.

Table 4.16 Correlation matrix for trading volume and price momentum profits

	U.S							
	2011-2012		**2013-2014**		**2015-2016**		**2017-2018**	
	Tr.V	PMPs	Tr.V	PMPs	Tr.V	PMPs	Tr.V	PMPs
Tr.V	1.00		1.00		1.00		1.00	
PMProfits	0.29	1.00	0.17	1.00	0.05	1.00	0.04	1.00
	(1.59)		(0.88)		(0.28)		(0.23)	
	0.12		0.38		0.78		0.82	

The correlation analysis in the U.S stock market shows an insignificant relationship between trading volume and momentum profits as shown in table 4.16. Although the direction of the relationship is positive, it is statistically insignificant across all four formation periods (evident from the t-values and significance values).

Overall, the results show that out of total four formation periods, a significant positive association can be observed for at most three periods for Pakistan, India and Bangladesh respectively. However, for the U.S stock market, the positive Corelation between momentum profits and the corresponding trading volume is insignificant across all sampled periods. This trend points out an interesting pattern, as it can be inferred that investors in Pakistan, India and Bangladesh exhibit over-confidence which in turn leads to over-attention and consequently there is a grand over reaction in the corresponding stock market in terms of high turnovers. For the U.S stock market the results conflict with earlier study (e.g., Hou et al., 2011). Hou et al. (2011) find a positive association of momentum profits and stock turnovers monotonically and in context of low and high turnover stocks.

4.5 Disposition Effect

Generally, it is a more logical stance to hold winner stocks for a larger period to realize more gains and sell looser stocks in order to avoid incurring losses. However, the Disposition effect is the converse phenomenon that takes place due to investors, it has been defined as the propensity of investors to dispose of winning stocks and retain losing stocks in the prospect of regains, for a relatively long time. As mentioned earlier, this behavior on part of investors can be attributed to the investor’s expectations or optimism where they think that the loser stocks may start recovering and turn losses into gains. That’s why they tend to hold such stocks. In addition to that Kahneman and Tversky (1979) found in their study that individual investors are attracted by confirmed gains rather than uncertain or riskier options even though the actual realized gains are less than the expected gains.

Loser stocks on the other hand are retained with anticipation of improvements in the future. In reality, it does not happen that way. These variances in investor behavior are catered by Kahneman and Tversky (1979) in their prospect theory. The disposition effect is a part of the prospect theory and it is defined as the tendency of an investor to dispose of winning stocks and retain the losing stocks. The disposition effect is studied for the south Asian emerging countries viz- Pakistan, India, Bangladesh, and U.S stock markets. The Results are presented as under:

4.4.1 DESCRIPTIVE STATS

Descriptive statistics are summarized in table 4.17. Market returns, security returns, security volatility, and security turnover are included in the analysis. The following table shows mean, median, max, min, standard deviation and skewness, kurtosis for the variables mentioned above.

It is evident from the table that all values are well under 1 percent for all the sampled countries except skewness and kurtosis. Among all the sampled countries, Bangladesh shows a relatively high level of volatility among the market returns and security returns although the volatility is less than one percent. The null hypothesis regarding skewness is rejected as the skewness values for all variables across the sampled countries, are less than 3. Generally, normal distributions have skewness values equal to zero or near to zero. A negatively skewed distribution indicates left-sided skewness while a positively skewed distribution indicates right-sided skewness in distribution. The skewness values given in the following table show a slightly positively skewed distribution for most of the variables. On the other hand, kurtosis is a measure of tails in data distribution, in other words, kurtosis indicates the presence of extreme values in data distribution. The kurtosis values for most of the variables across all sampled countries are somehow greater than 3 which indicates the rejection of the null hypothesis regarding kurtosis.

Table 4.17 Descriptive statistics

Variables		Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
Mkt Return	Pakistan	0.0010	0.0010	0.0090	-0.0060	0.0030	-0.2260	3.5830
	India	0.0000	0.0000	0.0050	-0.0020	0.0010	1.0080	6.3350
	Bangladesh	0.0000	0.0010	0.0490	-0.0350	0.0120	0.5760	5.5340
	U.S	0.0000	0.0000	0.0000	0.0000	0.0000	0.0380	2.6130
S. Returns	Pakistan	0.0000	0.0000	0.0030	-0.0030	0.0010	-0.1970	3.2520
	India	0.0000	0.0000	0.0050	-0.0030	0.0010	0.4330	5.2290
	Bangladesh	0.0010	0.0070	0.0580	-0.1160	0.0430	-1.5720	4.7530
	U.S	0.0350	0.0350	0.0360	0.0330	0.0010	-0.4730	3.3450
S.Volatility	Pakistan	0.0000	0.0000	0.0010	0.0000	0.0000	1.3380	4.9500
	India	0.0010	0.0010	0.0020	0.0000	0.0000	1.9050	8.2890
	Bangladesh	0.0020	0.0020	0.0070	0.0000	0.0020	1.3060	3.8830
	U.S	0.0020	0.0020	0.0020	0.0020	0.0000	0.7190	3.1690
Security T/O	Pakistan	0.0064	0.0044	0.0275	0.0001	0.0056	1.5700	2.5700
	India	0.0277	0.0204	0.0316	0.0185	0.0044	9.3000	16.0400
	Bangladesh	0.0042	0.0031	0.0052	0.0034	0.8210	2.0800	7.6700
	U.S	0.0480	0.0465	0.0541	0.0416	0.0031	1.4050	2.7400

Looking at the security returns, it is observed that the U.S stock market offers the highest return (3.5 percent per month) for securities. Similarly, stock volatility is also more for the U.S and Bangladeshi stock markets (also evident from the corresponding standard deviations).

Generally, mesokurtic, leptokurtic, and platy-kurtic distributions have kurtosis values of zero, positive and negative respectively. The kurtosis values indicate a leptokurtic distribution for almost all variables across the sampled countries (Kurtosis>+3)

4.4.2 CORRELATION ANALYSIS

Table 4.18 given below shows correlation analysis for market returns, security returns, security volatility, and security turnover. Correlation analysis is intended to know about the direction of relationships and the strength of relationships among variables. The table given below shows the correlation values among the above-mentioned variables.

Table 4.18 Correlation Analysis

	M.Returns	S.Returns	S.Volatility	T/O
Pakistan				
M.Returns	1.000			
S.Returns	0.368	1.000		
S.Volatility	-0.005	-0.046	1.000	
T/O	0.469	0.459	0.179	1.000
India				
M.Returns	1.000			
S.Returns	0.350	1.000		
S.Volatility	-0.150	-0.232	1.000	
T/O	0.113	0.088	0.062	1.000
Bangladesh				
M.Returns	1.000			
S.Returns	0.150	1.000		
S.Volatility	-0.025	-0.610	1.000	
T/O	-0.046	-0.057	0.026	1.000
U.S				
M.Returns	1.000			
S.Returns	0.129	1.000		
S.Volatility	-0.258	-0.152	1.000	
T/O	0.422	-0.084	0.352	1.000

Generally, correlation values range from +1 and -1. Where +1 indicates perfect positive correlation, -1 indicates perfect negative relationship while 0 indicates no correlation among variables. The correlation analysis yield slightly variant results for all variables however the sign associated with each relationship does indicate the reasonableness of the relationship. the correlation matrix for each country shows that correlation among market returns and security returns is the highest for the Pakistani stock market(r=0.36) and least for the U.S market (r=0.13) however the positive sign shows that as long as the overall market increases or decreases, returns for the stock also move in the same direction.

Correlation among market returns and security volatility was observed to be -0.005, -0.150, -0.0250, -0.258 for Pakistan, India, Bangladesh, and U.S stock markets respectively. The negative sign indicates that any increase in volatility will adversely affect the market returns.

The correlation between security returns and security volatility shows values of -0.046, -0.23, -0.610, -0.152 for Pakistan, India, Bangladesh, and the U.S respectively. The negative sign shows the same relationship as market returns and volatility. However, the relationship was relatively stronger for the Bangladeshi stock market as compared to other countries.

The correlation between security volatility and security turnover was found as 0.179, 0.062, 0.026, and 0.35 for Pakistan, India, Bangladesh, and U.S stock markets respectively. Among the stated values, U.S exhibited a relatively stronger association between volatility and turnover. No two variables have a perfect or near to 1 correlation therefore it is inferred that there is no multicollinearity among the given variables. Generally, in the case of collinearity among variables, an auxiliary regression is deployed, or variance inflation factor (VIF) is calculated. The variance inflation factor (VIF) for all variables in our case is greater than 1 and less than 10 so the variables under study do not exhibit any multicollinearity.

4.4.3 STATIONARITY TEST

Before running the main analysis of the study, it is important to ensure stationarity of the time series variables. There are multiple ways of checking and transforming nonstationary data into stationary data. These include taking natural logs and taking the first and second difference of the time series variable. Variables under study are market returns, security returns, security turnover, and security volatility.

Augmented Dickey-Fuller (ADF) has been employed to check stationarity for the above-mentioned variables across all the sampled countries. The test is employed at level and individual intercepts. No unit root was found among all variables across the sampled countries where p-value<0.05 and t-statistics> 3 in all cases. The null hypothesis is therefore rejected stating that unit root does not exist for the given series. Results for the unit root analysis are reported in appendix-02.

As taking natural logs of a series is a common method of removing data stationarity, there is always a chance of a non-linear trend among the logged values, therefore, the most suitable technique in such conditions is an ADF test. It is evident from the table that market returns, security returns, security volatility, and security turnover exhibit non-stationarity at a 1 percent significance level from 2009 to 2018 for all the sampled countries (Appendix-2)

4.4.4 VECTOR AUTO REGRESSION (VAR) ANALYSIS

Disposition effect is the investor's inclination towards selling profiting stocks and retaining losing stocks. As a matter of fact, trading turnover and its corresponding returns are more relevant to disposition effect (Shefrin and Statman, 1985). This study investigates trading turnover, returns, and volatility for individual stocks across all the sampled stock markets to look for any disposition effect. Additionally, market returns are also added to the model to delineate its role in predicting the stock's turnover. Any such potential relationship is expected to relate the overconfidence bias to the disposition effect. In other words, high stock returns in times of bearish market conditions are considered as a fruit of an investor's own ability in the selection of stocks. Consequent to such high returns, investors tend to sell stocks with relatively high gains, hence leading towards the emergence of the disposition effect (Statman et al., 2006).

The study at hand has employed Vector Auto Regression (VAR) with security volatility as the exogenous variable while market returns, security returns, and security turnover as the endogenous variables. Table 4.19 given below shows the lagged values of the variables as independent variables and their current values as dependent variables. These three variables are security return, security turnover, and market return. The Akaike Information Criteria (AIC) is used to set a number of lags as 1 and 2 for the endogenous variables.

Table: 4.19 VAR estimation of Endogenous and Exogenous Variables

	Panel-I		**Panel-II**		**Panel-III**					
					Pakistan					
	MR(-1)	MR(-2)	SR(-1)	SR(-2)	S.T/O(-1)	S.T/O(-2)	C	S.Volt	R-squared	F-statistic
M.Returns	-0.26	-0.09	0.87	0.52	-0.00	0.00	0.00	-0.25	0.255	4.60
	-0.10	-0.10	0.24	-0.24	0.00	0.00	0.00	-1.37		
	(-1.50)	(-2.91)*	(1.91)**	(-1.19)	(-1.27)	(2.57)*	(0.23)	(-4.18)*		
S.Returns	-0.04	0.05	-0.07	-0.11	0.00	0.00	0.00	-0.72	0.234	3.68
	-0.05	-0.05	-0.12	-0.12	0.00	0.00	0.00	-0.68		
	(-0.79)	(1.94)**	(0.56)	(0.89)	(1.66)***	(1.95)**	(0.71)	(-1.07)		
S.Turnover	1.27	2.20	1.91	3.24	0.23	0.20	2.10	6.42	0.81	9.87
	1.29	1.27	-1.33	1.39	-0.11	-0.11	-5.39	-7.20		
	(2.03)*	(1.25)	(1.91)**	(3.24)*	(1.98)**	(1.87)**	(3.90)*	(2.88)*		
					India					
	MR(-1)	MR(-2)	SR(-1)	SR(-2)	S.T/O(-1)	S.T/O(-2)	C	S.Volt	R-squared	F-statistic
M.Returns	-0.27	-0.08	0.43	0.16	0.00	0.00	0.00	0.46	0.31	7.10
	-0.10	-0.09	-0.07	-0.08	0.00	0.00	0.00	-0.41		
	(-0.75)	(-1.03)	(0.04)	(1.97)**	(0.19)	(1.09)	(0.52)	(1.12)		
S.Returns	-0.13	0.01	0.17	0.14	0.00	0.00	0.00	1.68	0.14	2.64
	-0.13	-0.12	0.10	-0.11	0.00	0.00	0.00	-0.56		
	(-1.03)	(0.11)	(1.73)***	(-1.27)	(-0.85)	(1.03)	(-2.76)*	(3.01)*		
S.Turnover	3.76	6.59	7.40	1.87	-0.01	0.03	5.45	2.34	0.05	0.81
	-7.10	-6.50	-5.30	-6.10	-0.09	-0.09	-2.10	-3.10		
	(0.52)	(1.02)	(1.39)	(0.30)	(-0.09)	(0.27)	(2.54)*	(0.07)		
					Bangladesh					
	MR(-1)	MR(-2)	SR(-1)	SR(-2)	S.T/O(-1)	S.T/O(-2)	C	S.Volt	R-squared	F-statistic
M.Returns	0.03	0.03	0.01	0.01	0.00	-0.00	0.00	-0.10	0.00	0.06

	-0.10	-0.10	0.03	-0.03	0.00	-0.00	0.00	-0.64		
	(0.29)	(0.31)	(2.29)*	(0.20)	(0.21)	(-0.11)	(0.002)	(-0.15)		
S.Returns	0.03	-0.07	0.31	-0.06	0.00	0.00	0.04	15.22	0.47	13.69
	-0.24	-0.24	0.07	-0.07	0.00	0.00	-0.01	-1.62		
	(0.13)	(-0.27)	(4.25)*	(-0.82)	(1.61)***	(1.90)**	(5.74)*	(-1.40)		
S.Turnover	4.50	1.09	-7.32	2.99	0.90	-0.08	2.55	-4.36	0.73	43.03
	4.61	4.60	-1.39	-1.41	-0.09	-0.09	-1.20	-3.10		
	(0.97)	(2.36)*	(1.61)***	(2.12)*	(9.72)*	(-0.81)	(2.16)*	(-0.14)		
U.S										
	MR(-1)	MR(-2)	SR(-1)	SR(-2)	S.T/O(-1)	S.T/O(-2)	C	S.Volt	R-squared	F-statistic
M.Returns	-0.39	-0.16	0.00	0.00	0.00	0.00	0.00	0.00	0.34	8.18
	-0.09	-0.10	0.00	0.00	0.00	0.00	0.00	0.00		
	(-1.12)	(-0.62)	(1.95)**	(-0.51)	(0.85)	(1.48)	(4.39)*	(-1.11)		
S.Returns	-142.14	57.74	-0.03	-0.15	0.00	0.00	0.05	3.08	0.10	1.84
	-95.50	-99.23	-0.09	-0.09	0.00	0.00	-0.01	-1.63		
	(-1.48)	(0.58)	(-0.29)	(1.40)	(0.55)	(1.16)	(7.58)*	(1.89)**		
S.Turnover	2.08	2.76	2.05	3.18	0.43	0.25	-9.88	4.67	0.84	85.20
	5.70	5.90	5.60	5.40	-0.09	-0.08	-3.70	-9.70		
	(3.65)*	(1.56)	(0.36)	(0.59)	(4.79)*	(3.16)*	(-2.68)*	(4.81)*		

**Significant at 01%, **Significant at 5%, ***Significant at 10%, t-values in parenthesis*

Table 4.19 can be divided into three panels. Panel-I includes market return, security return, and security turnover as the dependent variables while the lagged values of market returns are the independent variables. Panel-II show values when market return, security return, and security turnover are the dependent variables while the lagged values of security returns are the independent variables while Panel-III show values when market return, security return and security turnover act as the dependent variables while the lagged values of security turnover act as the independent variables. The same pattern is followed for each corresponding stock market.

The first parts of table 4.19 in Panel-I indicate market returns as dependent variables while its first and second lags act as the independent variables. For Bangladeshi, Indian stock markets, and the U.S stock markets, the relationship is insignificant in both lags and negatively significant in the second lag for the Pakistani stock market. The negative relationship implies that any past upward movement in returns decreases current market returns.

The second part of Panel-I in table 4.19 shows the relationship between security return and lagged market returns. The results indicate a negatively insignificant relationship in first lags for Pakistani and the Indian stock markets while a positively significant and positive insignificant relationship for Pakistani and the Indian stock markets in the second lag respectively. While the results are insignificant for Bangladeshi and U.S stock markets respectively. It implies that any increase/decrease in past market returns will result in an increase/decrease in current security returns.

The third part Panel-I show values for security turnover in relation to the lagged values of market returns for each corresponding stock market. For Pakistan, market returns have a positive significant value with the first lag of market returns however, the relationship turns insignificant in the second lag. For the Indian stock market, the relationship is insignificant in both lags. The Bangladeshi stock market shows an insignificant positive relationship in the first lag and a positive significant relationship in the second lag. Similarly, the U.S stock market shows a significant positive relationship in the first lag and an insignificant relationship in the second lag.

Investor's overconfidence is differentiated from the disposition effect in the form of a relationship between lagged market returns and security turnovers. As mentioned earlier, high stock returns are attributed by investors to their own stock-picking abilities hence leading to over-trading. Such tendency on part of the investor enables the investor to sell winning stocks and retain losing stock in order to reinforce their beliefs. This proposition is established from the results showing that security turnover is significantly associated with lagged market returns for Pakistani, Bangladeshi, and the U.S stock markets respectively.

Panel-II present results where market returns, security returns, and security turnover are taken as the dependent variables in relation to the lagged security returns as the independent variables.

In the first part of Panel-II, market returns in contrast to the lagged security returns are regressed through VAR. The results indicate a positive significant relationship for Pakistani, Bangladeshi, and U.S stock markets in first lags while an insignificant relationship for the first lag in the Indian stock market. The results indicate that good past security returns positively predict returns for all stock markets.

The second part of the Panel-II relates security returns with the lagged values of security returns. The results for the sampled stock markets are likewise mixed. In other words, for the Pakistani stock market, the relationship is positively insignificant in both lags. The Indian and Bangladeshi stock market shows a positive significant relationship in the first lag and negative insignificant in the second lag. However, the relationship is negatively insignificant in both lags for the U.S stock market. Interestingly, the data does not support the proposition about the relationship between returns and lagged returns. Probably the reason that can be associated with such a pattern is the possible existence of other variables which are not included in the model here. The said relationship among security returns and lagged security returns were only found in the Indian stock market (at lag 02) and Bangladeshi stock market (at lag01).

Panel-III summarizes the vector auto regression results where market returns, security returns, and security turnover act as the dependent variables while the lagged values of the security turnover are the independent variables.

In the first part of Panel-III, market return is the dependent variable while the lagged values of the security turnover are the independent variables. For the Pakistani stock market, the relationship is significantly positive at lag 2 and insignificantly negative at lag 1. For India, the relationship is positively insignificant at both lags. The Bangladeshi stock market shows a positive insignificant and negative insignificant relationship at lag 1 and lag 2 respectively. Interestingly, the U.S market exhibits a positive insignificant relationship between the dependent and independent variables on both lags. In most cases above, the relationship between market returns and security turnover is insignificant which implies that overconfidence is finely segregated from the disposition effect.

The second part of Panel-III show regression results for lagged security turnover and security returns. The results are positively significant in the first lag and second lag for the Pakistani stock market, positively insignificant in both lags for the Indian stock market, positively significant in the first and second lags for the Bangladeshi stock market, and positively insignificant for the U.S stock market in both lags. Thus the notion that security returns can be estimated through past returns, is validated only for Pakistani and the Bangladeshi stock markets. It is inferred that investors consider specific security as a winner if it is yielding higher returns in the past two periods (months) as a result such security is sold which results in high levels of trading volumes. Conversely, if security is yielding negative returns in the past two months, it is considered as the loser stock and it is held in the hope of positive returns in the future. The disposition effect is hypothesized as such that security turnover is positively and significantly related to the lagged returns of the security. Therefore, the hypothesis for disposition effect is accepted for Pakistan and Bangladesh while the hypotheses are rejected for the Indian and U.S stock markets.

The third part of Panel-III shows the results for security turnover and lagged security turnover. The results are positively significant for Pakistan with both lags, positively and negatively insignificant at first and second lag respectively for India and Bangladesh, and positively significant at both lags for the U.S stock market.

Mix results are found when security return is regressed with the cross-sectional security volatility. For instance, positive significant results were found for Indian, and U.S stock markets. However, the Pakistani and Bangladeshi stock market show a negative insignificant relationship for security returns with security corresponding volatility.

The results show an insignificant relationship for Pakistani and Bangladeshi stock markets which is in deviation with the relationship between security turnover and volatility proposed by Lo & Wang (2000) and Karpoff (1987). However, for the Indian and the U.S stock market the relationship was positively significant, which is in accordance with the literature.

4.4.5 GRANGER CAUSALITY TEST

As stated earlier, the Granger causality test is used to establish the causation effect among different variables. For this purpose, the Wald test is used for VAR estimates. Wald test is supposed to measure the combined effect of all lagged variables in causing the dependent variable. The ultimate decision rests on significance values of all variables which are considered endogenous variables.

The following table 4.20 summarizes Granger causality results for market returns, security returns, and security turnover as the dependent variables. As the model is assumed to have the causation of independent variables (combined) on the dependent variable, the null hypothesis will become as Ho: security returns (Lag01=lag02) do not jointly cause market returns. The null hypothesis for other variables is also created on the same lines.

The first part of table 4.20 presents market returns as the dependent variable while security return and security turnover are the independent variables. Given the significant value, the null hypothesis can only be rejected for India that security returns do not cause market returns and the alternate hypothesis is accepted that is: lag 1 and lag 2 of security returns jointly causes market returns (only India). The same pattern is also observed for security turnover (at 10 percent significance level).

Table 4.20 VAR Granger Causality test

Dependent variable: D (M.Ret)												
	Pakistan			**India**			**Bangladesh**			**U.S**		
Excluded	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.
S.Retr	1.11	2	0.57	20.15	2	0	0.11	2	0.94	1.11	2	0.57
S.T/O	0.04	2	0.97	1.86	2	0.39	0.06	2	0.96	0.046	2	0.97
All	1.23	4.00	0.87	21.91	4.00	0.00	0.15	4	0.9973	1.23	4.00	0.87
Dependent variable: D (S.Ret)												
Excluded	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.
M.Ret	12.32	2	0.00	2.07	2	0.35	0.09	2	0.95	12.32	2	0.00
S.T/O	7.05	2	0.02	0.29	2	0.86	0.33	2	0.84	7.05	2	0.02
All	16.11	4	0.00	2.34	4	0.67	1.31	4	0.32	16.11	4	0.00
Dependent variable: D(S.T/O)												
Excluded	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.	Chi-sq	df	Prob.
M.Ret	3.04	2	0.02	0.93	2	0.62	6.64	2	0.03	13.93	2	0.20
S.Ret	10.10	2	0.00	1.20	2	0.54	5.343	2	0.06	0.47	2	0.79
All	16.10	4	0.00	2.47	4	0.64	11.23	4	0.024	14.47	4	0.34

The second part of table 4.20 illustrates security return as the dependent variable while the null hypothesis is set as lagged market returns and lagged security turnover jointly and respectively do not cause security returns. As evident from the table, the null hypothesis is rejected for Pakistani and the U.S stock markets as the significance level is well under 5 percent. So, it is inferred that lagged values of market returns and joint lagged values of security turnover cause security returns for Pakistani and the U.S stock markets.

The third part of table 4.20 presents security turnover as the dependent variable with the null hypothesis that: lagged market returns and lagged security returns jointly and respectively do not cause security turnover. The results reveal that lagged values of market returns jointly cause security turnover only in Pakistani and Bangladeshi, stock markets at 5 percent of significance level. Therefore, the null hypothesis is rejected. Similarly, the values indicate that the jointly lagged values of security return cause security turnover in Pakistani and Bangladeshi stock markets at 1 percent and 10 percent significance levels respectively.

Therefore, the null hypothesis can only be rejected for Pakistan and Bangladeshi stock markets. These results are also consistent with the VAR estimates as obtained earlier. This pattern also depicts that the disposition effect takes place in Pakistani and Bangladeshi stock markets only among the four sampled markets. The results confirm earlier work on disposition effect in Pakistani and Bangladeshi context (e.g., Parveen & Siddiqui, 2018; Arif & Bhuiya, 2016). However, results for Disposition effect in the U.S and Indian context contradict earlier work (e.g., Prosad et al., 2017; Odean, 1998).

4.6 Overreaction hypothesis

The results reported above showed a mixed trend regarding the existence of various behavioral biases across all the sampled countries. The presence of some biases indicates irrationality on part of investors and inefficiency of the market in general. This section is aimed to find out the role of biases in the aggregate under-reaction and overreaction of the corresponding stock market.

For this purpose, the methodology proposed by De Bondt & Thaler (1985) is followed by using returns and excess returns on monthly basis from 2009 to 2018. Stock returns and excess stock returns have been studied for two years non-overlapping formation periods by segregating winners and loser portfolios based on top and bottom 10 percent threshold criteria. Table 4.21 summarizes the results obtained:

Table 4.21: Average Cumulative Excess Returns for Loser and Winner Portfolios.

Pakistan			
	ACARw	ACARl	ACARL-ACARw
Period			
jan2011-dec2012	0.0074	0.0005	-0.0069
jan2013-dec2014	-0.0044	0.0119	0.0163
jan2015-dec2016	-0.0048	0.0336	0.0384
jan2017-dec2018	-0.0046	0.0365	0.0411
India			
	ACARw	ACARl	ACARL-ACARw
Period			
jan2011-dec2012	0.0044	-0.1397	-0.1441
jan2013-dec2014	0.0074	-0.086	-0.0934
jan2015-dec2016	0.0041	-0.0304	-0.0345
jan2017-dec2018	0.0098	-0.0624	-0.0722
Bangladesh			
	ACARw	ACARl	ACARL-ACARw
Period			
jan2011-dec2012	0.0134	0.038	0.0246

jan2013-dec2014	0.0511	0.0395	-0.0116
jan2015-dec2016	0.009	0.018	0.009
jan2017-dec2018	0.0132	0.0424	0.0292
	U.S		
	ACARw	ACARl	ACARL-ACARw
Period			
jan2011-dec2012	0.0102	-0.1012	-0.091
jan2013-dec2014	0.0723	-0.0093	-0.063
jan2015-dec2016	0.0096	-0.0721	-0.0625
jan2017-dec2018	0.0012	-0.0609	-0.0597

Table 4.21 given above summarizes average cumulative excess returns for winner and loser portfolios across the four given formation periods from 2009 to 2018. Each period consists of a time frame of 24 months starting from 2011. We follow the strategy of De Bondt & Thaler (1985) with two years formation period, where they suggest that overreaction can be manifested if ACARL-ACARWL> 0. As shown in the table above, all values of winner and loser portfolios are positive except for the Indian Stock market.

For the Pakistani stock market, results show ACARw with negative values for the two years of formation period. On the other hand, ACAR for loser stocks shows positive values. However, ACARL-ACARw shows mixed values with the negative sign for formation periods 2011-2012 and positive values for the other three formation period. Based on the analysis of loser and winners' portfolios, it can be inferred from the negative values of the winner stocks that winner stocks lose in three out of four formation periods. This indicates the overreaction hypothesis (ACARw<0). Loser stock depicts positive values indicating gains in the subsequent formation periods. These values imply the existence of market overreaction. While positive values as a difference between winner and loser portfolios show that the scale of winning is higher than losing in the portfolio formation periods.

For the Indian stock market, the overreaction hypothesis cannot be confirmed as the values are positive for winner portfolios and negative for loser portfolios. As a result, the difference between loser and winner portfolios is also negative which implies that the scale of losing is greater than winning in the portfolio formation periods.

Bangladeshi stock market yielded results with positive values for winning and losing portfolios however, the difference between loser and winner portfolio is positive, hence depicting that the magnitude of winning is greater than that of losing. This pattern indicates the existence of overreaction in Bangladeshi and the U.S stock markets.

In the U.S stock market, the results do not confirm the existence of the overreaction hypothesis. As the winner portfolio has positive ACAR, the loser portfolio has negative ACAR and the resultant difference between a loser and winner ACARS is also negative. These all conditions clearly indicate the non-existence of overreaction in the U.S stock market.

The tables given below summarizes the average cumulative excess returns with their statistical significance for winner and loser portfolios in the two formation periods across the sampled stock markets. The values represent mean values with their corresponding t-values across the 24 monthly formation periods.

Table 4.22 given below presents the formation periods with 24 months of 2011-2012, 2013-2014, 2015-2016, 2-17-2018. The proposed threshold given by the literature for overreaction is the existence of conditions where ACARL>0 and ACARW<0 resultantly, ACARL-ACARW>0. It is evident from the tables that ACARW is negative for three formation periods, ACARL is positive for all four formation periods and the difference between ACARL and ACARW is negative for three formation periods in the Pakistani stock market. These results are consistent with the overreaction hypothesis. While analyzing the ACARS for winner and loser portfolios of four different formation periods on the basis of the previous two years holding periods, it can be concluded that winners in the holding periods lose in the subsequent formation period as manifested in the form of negative values. In contrast, positive values for loser portfolios depict that loser stocks have started gaining and became winners in the subsequent all four formation periods. Similarly, a positive value for the difference between loser and winner portfolios affirms that the scale of winning is larger than losing in all formation periods. All results are in accordance with the conditions of the overreaction hypothesis.

Table 4.22 ACAR Analysis for Pakistan

			Pakistan			
Periods	**Mean(W)**	**t-value(W)**	**Mean(L)**	**T-value (L)**	**Mean(L-M)**	**T-value (L-w)**
1	-0.019	-8.949	0.021	5.850	0.039	12.130
2	-0.014	2.257	0.021	7.126	0.035	3.492
3	-0.016	-3.325	0.016	4.180	0.033	-0.333
4	-0.017	-4.982	0.017	-2.190	0.034	2.604
5	-0.017	-4.582	0.017	-3.569	0.034	1.211
6	-0.014	2.495	-0.020	3.340	0.033	0.404
7	0.012	5.449	0.021	5.837	0.033	-0.227
8	-0.015	-0.692	0.021	5.971	0.036	5.142
9	-0.014	2.563	0.017	-3.866	0.030	-5.142
10	0.014	1.392	0.016	-6.246	-0.030	-5.951
11	-0.014	1.205	0.020	3.667	0.034	1.760
12	-0.015	0.252	0.021	7.924	0.036	5.819
13	-0.014	1.212	0.019	2.566	0.033	0.915
14	-0.015	0.178	0.019	1.520	0.033	1.005
15	-0.011	8.076	0.019	1.350	0.030	-5.897
16	0.010	10.914	0.021	6.110	0.030	-4.705
17	-0.013	3.825	0.017	-2.999	0.030	-5.565
18	-0.014	0.459	0.016	-5.117	0.031	-4.291
19	-0.015	0.340	0.015	-7.638	0.030	6.109
20	-0.017	-6.044	0.015	-6.697	0.033	0.082
21	-0.017	-5.240	0.017	-3.753	0.034	1.635
22	0.019	-9.583	0.019	1.027	-0.038	9.000
23	-0.015	0.154	0.017	-2.256	0.032	-1.850
24	-0.013	2.626	0.017	-3.777	0.030	-5.128

The following table 4.23 summarizes the results for the Indian stock market. The table comprises the average excess cumulative returns for winner and loser portfolios and the difference between loser and winner portfolios. It is evident from the table that, all ACAR values for the winner portfolio are positive, for loser portfolios the values are negative and the difference between loser and winner portfolio is also negative across all four formation periods. All three conditions are against the threshold for the overreaction hypothesis. Hence, the overreaction hypothesis cannot be confirmed in the Indian stock market.

Table 4.23 ACAR Analysis for India

			India			
Periods	**ACARw(mean)**	**T-value (w)**	**ACARL(Mean)**	**T-value (L)**	**Mean(L-W)**	**T-value (L-w)**
1	0.005	-4.950	-0.015	-13.069	-0.020	-4.118
2	0.004	-4.143	-0.016	-11.975	-0.020	-1.097
3	0.004	-4.198	-0.017	-6.717	-0.022	0.177
4	0.003	0.126	-0.020	1.373	-0.023	3.406
5	0.001	8.629	-0.020	0.213	-0.021	-0.022
6	0.003	1.561	-0.020	0.834	-0.023	11.316
7	0.003	0.334	-0.018	-6.531	-0.021	-0.010
8	0.004	-3.098	-0.016	-9.997	-0.021	-8.040
9	0.002	4.269	-0.019	-0.678	-0.022	1.121
10	0.003	0.907	-0.020	2.031	-0.023	3.406
11	0.005	-5.293	-0.016	-12.149	-0.020	-9.056
12	0.005	-7.130	-0.017	-7.145	-0.023	0.281
13	0.004	-2.320	-0.017	-9.136	-0.021	-5.029
14	0.004	-3.231	-0.015	-13.809	-0.019	-1.231
15	0.004	-3.973	-0.017	-8.428	-0.021	3.079
16	0.003	-0.096	-0.017	-9.600	-0.020	-0.150
17	0.004	-1.040	-0.017	-8.378	-0.021	-3.046
18	0.003	-0.138	-0.018	-4.247	-0.022	0.128
19	0.003	1.451	-0.017	-8.081	-0.020	-6.138
20	0.002	4.075	-0.017	-8.475	-0.019	-3.272
21	0.001	9.499	-0.020	1.088	-0.021	-7.015
22	0.001	9.365	-0.018	-6.252	-0.018	-9.387
23	0.005	-6.575	-0.016	-10.864	-0.021	14.066
24	0.002	5.968	-0.018	-5.321	-0.020	-2.192

Table 4.24 given below presents the ACAR values for the winner, loser portfolios and the difference between the two portfolios with their corresponding t-values, for Bangladeshi stock

markets. As evident from the tables, the average cumulative excess returns (ACARs) for winner portfolios show positive signs in most of the monthly formation periods which is against the conditions of the overreaction hypothesis however, the loser portfolios show a positive sign for almost all monthly formation periods which is in accordance with the overreaction hypothesis. Similarly, the difference between a loser and a winner ACARs is also positive in most cases. In sum, two out of three conditions of overreaction are full filled. Therefore, it can be inferred that overreaction exists in the Bangladeshi and the U.S stock markets.

Table 4.24 ACAR Analysis for Bangladesh

			Bangladesh			
Periods	**ACARw(mean)**	**T-value (w)**	**ACARL(Mean)**	**T-value (L)**	**Mean(L-W)**	**T-value (L-w)**
1	-0.043	-3.549	-0.119	9.753	0.162	11.739
2	0.045	-3.828	0.035	2.419	0.081	5.148
3	0.000	1.032	0.064	-6.321	0.064	-6.646
4	0.020	-1.087	0.074	-7.161	0.054	-5.819
5	0.027	3.940	0.003	-0.968	0.030	-3.887
6	0.003	0.721	-0.014	0.581	-0.017	-0.008
7	0.003	0.737	-0.055	4.170	0.058	3.309
8	-0.046	6.004	-0.124	10.181	-0.077	4.889
9	0.058	-5.158	0.022	-2.597	0.036	1.505
10	0.045	-3.738	0.076	-7.346	0.032	-3.978
11	-0.023	3.503	0.040	-4.208	0.063	-6.561
12	0.026	3.814	0.007	-1.239	0.032	-4.043
13	0.033	-2.464	-0.038	2.686	-0.071	4.361
14	0.010	2.141	-0.093	7.536	0.083	5.366
15	-0.064	7.884	-0.040	2.888	0.023	-3.302
16	0.086	-8.184	0.042	-4.360	-0.044	2.165
17	0.057	-5.111	0.029	-3.196	0.028	0.912
18	-0.020	3.222	0.016	-2.062	0.036	-4.357
19	0.059	7.371	0.017	-2.165	0.076	-7.600
20	0.032	-2.396	-0.039	2.785	-0.071	4.402
21	0.013	-0.319	-0.026	1.655	0.039	1.777
22	-0.072	8.718	-0.050	3.712	0.022	-3.171
23	0.081	-7.676	0.030	-3.317	-0.051	2.747
24	0.062	-5.575	0.031	-3.425	-0.030	1.053

For the U.S stock market, ACAR for winner portfolios is positive while for loser portfolios these are negative. Similarly, the difference between a loser and a winner ACARs are also negative. This implies that all three conditions required for the overreaction hypothesis are not full-filled in the U.S market, hence representing the non-existence of overreaction in the US stock market. The following table 4.25 summarizes the results for the overreaction hypothesis.

Table 4.25 ACAR Analysis for the U.S

			U.S			
Periods	**ACARw(mean)**	**T-value (w)**	**ACARL(Mean)**	**T-value (L)**	**Mean(L-W)**	**T-value (L-w)**
1	0.005	1.889	-0.011	2.375	-0.016	1.876
2	0.006	-1.227	-0.010	-0.885	-0.016	-0.367
3	0.006	0.907	-0.010	-0.809	-0.015	-1.625
4	0.006	-0.125	-0.010	-0.214	-0.016	-0.198
5	0.005	1.536	-0.011	3.374	-0.017	3.396
6	0.005	4.827	-0.012	5.544	-0.017	4.115
7	0.006	-2.040	-0.011	2.514	-0.017	4.555
8	0.007	-6.841	-0.010	0.155	-0.017	4.550
9	0.007	-5.153	-0.008	-6.346	-0.014	-4.947
10	0.007	-7.983	-0.005	-12.551	-0.012	-11.188
11	0.007	-6.551	-0.007	-8.961	-0.014	-7.447
12	0.005	3.539	-0.011	1.709	-0.016	-0.035
13	0.005	3.208	-0.013	7.642	-0.018	7.863
14	0.006	0.564	-0.013	8.009	-0.019	10.020
15	0.005	1.844	-0.011	1.333	-0.016	0.555
16	0.005	2.644	-0.011	2.466	-0.016	1.514
17	0.004	7.286	-0.010	-1.069	-0.014	-6.017
18	0.006	-0.092	-0.008	-5.888	-0.014	-7.570
19	0.007	-4.179	-0.009	-2.971	-0.015	-1.193
20	0.007	-6.289	-0.009	-2.056	-0.016	1.334
21	0.007	-6.181	-0.009	-2.195	-0.016	1.086
22	0.005	2.754	-0.010	1.063	-0.016	-0.374
23	0.004	11.308	-0.012	4.062	-0.015	-1.925
24	0.005	4.355	-0.011	3.698	-0.016	2.023

The market over reaction hypothesis was aimed to validate the existence of reactions in the sampled stocks. The results already confirm that Pakistani and Bangladeshi stock markets overreact. On the other hand, evidence regarding the existence of self-attribution, anchoring, herding, limited attention and disposition effect substantiate the grand claim that behavioral biases are related with overall market reactions at least in Pakistani and Bangladeshi contexts. However, future researches are expected to develop such a framework which incorporates the role of various other factors (macro-economic etc.) to gauge the contribution of each behavioral bias in stock market reactions in the corresponding market.

4.7 Excess Volatility, Market Reaction and Turnover

As an objective of this study, volatility, and turnover are studied in relation to market reactions. The same is also proposed by Shiller (1990). By stating that social and psychological variants have a great impact on the general price level in markets. Furthermore, Shiller (1990) confirms the certain existence of excess volatility in markets and concludes that such volatility cannot be justified by the efficient market hypothesis. Excess volatility can be defined as volatility exceeding the level of volatility given by the theorists of the efficient market hypothesis. The explanation for excess volatility is given through the existence of an investor's irrationality which results in the market under and overreaction. The following section studies the proposition stated by Shiller (1990) that how excess volatility and stocks turnover in a market is impacted by under and overreaction of the investor.

4.7.1 DESCRIPTIVE STATISTICS

Table 4.26 given below summarizes the descriptive statistics for volatility, turnovers, and market reactions. MR in the given table represents market reaction and it is calculated as the difference between a loser and winner ACARs. Where positive values for MR represent market overreaction while zero or less than zero values represent the investor's under-reaction. Table 4.26 summarizes descriptive statistics for market reactions, turnover, and volatility.

Table 4.26 Descriptive statistics

	Markets	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
MR	Pakistan	0.4330	1.0487	-0.1310	0.3590	0.5995	-0.8409
	India	-0.0209	-0.0148	-0.0305	0.0032	-0.6892	3.1790
	Bangladesh	0.0172	0.9580	-0.3269	0.1420	-0.2178	2.7257
	U.S	-0.0158	-0.0094	-0.0257	0.0029	-0.4863	4.1613
Turnovers	Pakistan	31.8800	30.0010	34.4600	29.2360	0.8643	-3.8520
	India	39.2200	38.8520	43.7510	37.4500	0.8300	5.6682
	Bangladesh	21.8800	21.0840	23.4610	14.8230	0.9840	5.2017
	U.S	44.2100	43.8290	45.3380	42.1740	0.6520	6.2714
Volatility	Pakistan	0.0835	0.4607	0.0001	0.0911	2.7059	4.2896
	India	0.0001	0.0038	-0.0007	0.0004	6.5543	57.0766
	Bangladesh	0.0320	0.1201	-0.0005	0.0425	2.4819	11.4909
	U.S	0.0039	0.0096	0.0034	0.0009	4.1188	23.0716

As evident from table 4.26 given above, the mean value for market reaction is 0.4330 for Pakistan and 0.0172 for Bangladeshi stock markets. As, it is already laid down that if the value for ACARL-ACARW is greater than 0, it depicts market overreaction. Therefore, the mean value of 0.4330 and 0.0172 for the Pakistani and Bangladeshi stock markets respectively, indicates a market overreaction towards any unexpected news from 2009 to 2018. Standard deviation represents 35.9 and 14.20 percent of variations for both markets respectively.

Out of the total mean values for the turnover series, U.S has the highest mean value for trading volume followed by India, Pakistan, and Bangladesh with the corresponding highest standard deviation value. Values moving between maximum and minimum values indicate more sharp deviations in the trading volume.

As far as excess volatility is concerned, the mean value is 0.0835 and 0.0320 with a standard deviation of 9.11 and 4.2 percent. The skewness and kurtosis values indicate that data has a leptokurtic distribution with a positively skewed tail (skewness= 2.70, 2.48 respectively).

4.7.2 CORRELATION ANALYSIS

The following correlation matrix summarizes the relationship between market reaction, turnover, and volatility. For this purpose, Pearson correlation has been calculated and summarized in table 4.27 below:

Table 4.27 Correlation Analysis

Market	Variables	MR	TURNOVER	VOLATILITY
Pakistan	MR	1	-0.5471	0.5696
	TURNOVER	-0.5471	1	-0.4190
	VOLATILITY	0.5696	-0.4190	1
India	MR	1	-0.08481	0.252419
	TURNOVER	-0.08481	1	-0.14339
	VOLATILITY	0.252419	-0.14339	1
Bangladesh	MR	1	-0.47356	0.761580
	TURNOVER	-0.47356	1	-0.376158
	VOLATILITY	0.39580	-0.376158	1
US	MR	1	-0.060411	0.043816
	TURNOVER	-0.060411	1	-0.088899
	VOLATILITY	0.043816	-0.088899	1

It is visible from the table above that a negative association exists between turnovers and market reactions where the relationship is relatively stronger in Pakistani and Bangladeshi stock markets followed by the Indian and U.S stock markets. Similarly, market reaction is positively associated with volatility. The relationship is stronger in Pakistan and Bangladesh. While the relationship in Indian and U.S stock markets is somewhat weaker.

4.7.3 REGRESSION ANALYSIS

Regression analysis is performed to figure out the contribution of market reactions on turnover and excess volatility. Table 4.28 below summarizes regression results for market reactions on turnover:

Table 4.28 Regression-I (Market reaction on turnover)

Market	Intercept	Turnover	R^2
Pakistan	0.012 (2.053)*	-0.007 (-5.128)*	0.227
India	0.119 (8.290)*	0.046 (1.770)**	0.062
B.Desh	0.110 (3.110)*	-0.006 (-12.305)*	0.319
U.S	0.125 (1.660)***	0.314 (1.901)*	0.004

As mentioned already, market reaction is the positive variance of the loser and winner ACARs. It was found that the winners in the formation period become losers in the subsequent period and losers become winners in the subsequent period. Such tendency is also visible in the form of a negative relationship between market reaction and turnover as shown in the table above. This overreaction pattern is only observed for Pakistani and Bangladeshi stock markets however, the Indian and U.S stock markets show under-reaction as evident from the positive sign. It is therefore implied that as long as market overreaction increases in Pakistani and Bangladeshi stock markets, trading volume for the winner stocks decreases, and consequently, the future returns also turn negative and vice versa.

Table 4.29 given below summarizes the regression for turnover and market reaction on excess volatility.

Table 4.29 Regression-II(Turnover and market reactions on volatility)

Market	Intercept	Turnover	MR	R^2
Pakistan	0.0454	-3.9190	0.1352	0.3255
	(5.3776)*	(-1.5854)***	(2.6201)*	
India	0.0002	-0.8408	0.0690	0.145
	(0.8021)	(-0.9070)	(1.5964)***	
B.Desh	0.0002	-1.4472	0.2125	0.4761
	(1.7186)**	(-1.9730)**	(4.7484)*	
U.S	0.0035	-0.0000	0.0116	0.0094
	(3.7645)*	(-0.8372)	(0.3732)	

Results for the second regression show that market reactions have a significant contribution to excess volatility in all stock markets except the U.S. Where results are significant at 5 percent for Pakistan and Bangladesh and 10 percent for the Indian market. Furthermore, a positive sign indicates that as long as market reactions increases, volatility in the market also increases. It is therefore implied that a one percent increase in market reactions results in 13.5, 6.90, and 21.25 percent increase in volatility of Pakistani, Indian and Bangladeshi stock markets respectively.

Table 4.29 above also shows a negative significant relationship between volatility and turnovers for Pakistani and Bangladeshi stock markets only. For Pakistan, the relationship is negatively significant at 10 percent of significance level while for the Bangladeshi stock market. It is negatively significant at 5 percent of the significance level. However, the negative relationship proposes that as long as turnover increases, market volatility decreases. The coefficient of determination R^2 value is 32.5, 14.5, and 47.61 for Pakistan, India, and Bangladesh respectively. The R^2 value indicates that 32.5, 14.5 and 47.61 percent of contribution in volatility is due to the existence of market reactions and turnover. This proposition is also justified by the corresponding f-values.

As stated earlier, excess volatility is volatility that cannot be justified by earning fundamental values. Excess volatility was for the first time diagnosed by LeRoy & Porter (1981) and Shiller (1981) who found that prices change too readily to be justified by the future forecasts through rationality or stock fundamentals. It was proposed by Shiller (1981) that the existence of behavioral and psychological biases leads to irrational investment decision-making by the investors and consequently results in market under-reaction or market overreaction. De Bondt & Thaler (1985) propose the overreaction hypothesis as ACARL> 0 ACARW< 0, and resultantly ACARL-ACARWL> 0. Based on the data analysis for the period 2009-2018, this study shows that the south Asian stock markets do not validate the efficient market hypothesis. As the variance between loser and winner ACARs is positive for Pakistani and the Indian stock markets indicating market overreaction while the Indian stock market seems to have under-reacted in the sample period.

Furthermore, the regression results show that as long as market reaction increases, volatility of the corresponding stock market also significantly increases. The market reaction here implies market overreaction as the same has been confirmed in the overreaction hypothesis section. Therefore, it can be implied that an increase in market overreaction leads to an increase in volatility. According to Hong & Stein (1999) market under and overreaction can be tested through one single event and that is the steady incorporation of any new information regarding the security fundamentals. In such an event, one group of investors tend to create price momentum profits by arbitraging the misprice while the other group tends to under-react towards private information. Several biases like anchoring, herding, self-attribution, mental accounting, and others have been proposed as the cause of under and overreaction. Lee & Swaminathan (2000) concluded that high turnover stocks exhibit more momentum therefore turnover determines the scope and strength of momentum. However, momentum strategy best works in times of low volatility. Hence, a trend in turnovers can estimate the extent of market volatility. The table given above reports a negative relationship between volatility and turnovers. This implies that an increase/decrease in turnover leads to a decrease/increase in stock market volatility. This pattern can be attributed to momentum trading (Lee & Swaminathan , 2000).

The U.S stock market is a relatively more stable market. As based on the results of self-attribution bias, the results are significant but it does not lead to a sequential disposition effect and market overreaction as a result. This indicates that the U.S stock market is a relatively efficient market. On the other hand, the significant self-attribution bias for Pakistani and Bangladeshi stock markets leads to disposition effect and overreaction in aggregate. The results are in confirmation with the literature.

The relationship between overreaction and volatility can also be explained by the prevailing uncertainty in the market. Over the sampled period, Pakistan has faced several political, terrorist, and economic setbacks. These include, the killing of Osama bin Laden in 2011, the Memogate scandal in 2012, disqualification of the prime minister by the Supreme Court in 2012, the Malala incident in 2012 Peshawar APS incident in 2014, many terrorist activities during the period, and many more events resulted into political instability, worsening law and order situations, and military operations. Consequently, high levels of foreign and domestic debt, low economic growth, and decreased capital formation and foreign investment in the Pakistani stock market. Within the sample period, the economy started stabilizing in the prime minister's Nawaz sharif era. However, the uncertainty remained intact when Nawaz Sharif was disqualified.
Bangladesh has also faced some drastic events like the mutiny killings of 2009, the collapse of a factory killing 1100 in 2013, trials of jamaat-e-Islami, and the tug of war between Bangladesh National Party of Khalida Zia and Sheikh Hasina Wajid of Awami league. These events have a similar effect on the stock market.

These significant events do affect human psychology resulting in stress and cognitive turmoil on an individual basis (Khan, 2013). It seems difficult for an investor to rationally assess the technical and fundamental values corresponding to the investment decisions. Therefore, an investor’s decisions are based on his beliefs, fears, and intuitions. In order to tackle the underlying uncertainty, investors are more prone to undergo several psychological and behavioral biases. These biases are formed in reaction to the market conditions or new information which leads to the emergence of momentums and financial bubbles.

In sum, market reactions and excess volatility prevailing in the south Asian stock market can be attributed to the existence of uncertainty in political, economic, psychological, and social conditions.

CHAPTER-5

CONCLUSION AND FUTURE RESEARCH IMPLICATIONS

5.1 Conclusion

Individuals and markets rationality remained a hot topic in academic debates for a longer period of time. Traditional finance proposes various theories based on the assumption of rational humans also called Homo Economicus. A rational human is expected to always make rational decisions which is also an underlying assumption of traditional finance. Behavioral finance, on the other hand, deals with an individual decision in consideration of these human behaviors and psychological variations.

In other words, traditional finance reflects an ideal behavior of the investor while behavioral finance represents a more practical or realistic approach towards individual investors. The Efficient market hypothesis is one such theory representing traditional finance while limited arbitrage theory is proposed against the EMH stating that security valuation does not depend upon the information but is also determined by any variations in sentiments or expectations which may not be reflected in the information. Owing to such irrationality on part of the investor leads to under-reaction or overreaction to any new information. Under-reaction is the immediate response of the market to some new information which even continues in the subsequent periods while overreaction is a market reaction to some new information that is counterbalanced by a similar change in the subsequent periods. Since these under and overreactions are market anomalies that are triggered by inefficient rules of thumb called heuristics. Heuristics exist in the form of various beliefs, tendencies, and biases which induce individuals to commit mistakes in their decision-making. In a nutshell, it can be inferred that under and overreaction are two market anomalies that are caused by heuristics in the form of various underlying behavioral and psychological biases.

The study at hand was aimed to identify and validate the psychological and behavioral biases which result in irrational decision-making in the form of market under and overreaction. In aggregate, such irrationality leads to volatile market conditions. It is therefore inferred that an individual's decisions are not primarily based on the fundamentals- psychology, fear, perceptions, and biases also play a vital role. Self-attribution, Anchoring, herding, disposition effect, and limited attention bias are a few of the mental shortcuts which are investigated in this study. These biases are studied in relation to the market anomalous behavior in the form of the market under-reaction and market overreaction. The study is carried out using three south Asian stock markets namely Karachi stock exchange, Bombay stock exchange, and Dhaka stock exchange in addition to the Dow Jones Industrial average (U.S market). This is a premier study that takes into account the given variables for a comparative study in the south Asian context.

Daily, weekly, monthly and quarterly data has been taken for various variables under study from the archives of KSE, BSE, DSE, and DJIA stock exchanges. The data has been collected for a period of 10 years starting from 2009 to 2018. Each index is a representative index of the concerned stock market. Data is analyzed to investigate the existence of self-attribution, anchoring, herding, disposition effect, and limited attention bias across all three south Asian stock markets in contrast to the U.S stock market. The relation between the above-mentioned biases and market reaction, turnovers, and excess volatility has also been investigated.

Self-attribution bias is initially tested using the vector autoregression (VAR) model to establish the long-term relationship between exogenous and endogenous variables. Where dispersion was considered as an exogenous variable while market turnover and market returns were considered as the endogenous variables. Results show that a statistically significant relationship between turnover and lagged returns exists for Pakistani, Bangladeshi, and the U.S stock markets. Moreover, the cross-sectional standard deviation in the form of volatility and cross-sectional variation in the form of dispersion have a statistically significant impact on trading turnovers. Based on VAR, the results confirm self-attribution or overconfidence bias in Pakistani, Bangladeshi, and the U.S stock markets. This implies that investors in the above-mentioned countries attribute high returns in stocks to their own stock-picking ability and resultantly they start over-trading which represents market overreaction.

Two anchors have been used for anchoring bias as suggested by the literature namely nearness or proximity to historical high XHH and nearness or proximity to the 52 weeks high X52w. Nearness to the historical high represents market overreaction while nearness to the 52-week high represents investors or market under-reaction. Regression analysis is conducted on dummy variables when the index reaches its historical high and when the historical high equates 52-week high, along with nearness to historical high and nearness to 52-week high, macro-economic variables like exchange rate, inflation rate, and interest rate. The regression results confirm that when nearness to historical high and nearness to 52-week high is used as an anchor by Pakistani and Indian investors, they overreact and under-react towards any new information respectively. While significant results were found only for underreaction in Bangladeshi and the U.S stock markets. However, the significance of the results worsens while moving from daily to monthly horizons.

Results confirming the existence of self-attribution bias, disposition effect, and overreaction hypotheses across Pakistani and Bangladeshi markets indicate irrationality on part of the investor which is against the proposition of homo economicus. Rather these investors exhibit bounded rationality based on the contribution of their beliefs, perceptions and emotions. As a matter of fact, the investor's decisions are mostly based on psychological and behavioral factors rather than fundamental values, the aggregate pattern in trading and investments results into grand market irrational behavior.

Herding yet another deviance of rational decision-making is tested by measuring the cross-sectional standard deviation (CSSD) between market and individual stock returns. Additionally, the turnover effect is tested through the use of cross-sectional standard deviation for low turnover stocks (LTCSD) and high turnover stocks (HTCSD). It was proposed that investors undergo herding in extreme market conditions where extreme market conditions are considered as the top and bottom 10 percent of returns. The results indicate the existence of herding bias in both extreme market situations only in Pakistani and Bangladeshi stock markets. However, no significant evidence of herding was found for extreme market conditions in the Indian and U.S stock markets. Similarly, the turnover effect was tested in extreme market conditions for all sampled countries. It was found from the results that herding can be traced only in low turnover stocks in the low extreme market situation or DOWN conditions only in Pakistani and Bangladeshi stock markets. This is evident from the negative sign with corresponding t-values. The negative sign indicates the inverse relationship or deviation between individual stock and market returns. The trading turnover also indicates the tendency of investors that they do not use stock fundamentals but rather follow the market trend hence overreacting to the prospective bad news in the market.

The phenomenon when investors hold loser stocks for a longer period and sell winner stocks early is termed as the disposition effect. Positive returns enhance an investor's confidence and resultantly the trading turnover also increases. In the study at hand, the application of VAR indicates a statistically significant association between security turnover and lagged security returns for Pakistani and Bangladeshi stock markets hence necessitating the existence of herding in these stock markets. Yet this tendency of investors to hold losing stocks and selling winning stocks represent investor's under-reaction to any new positive information. The existence of herding and disposition effects in Pakistani and Bangladeshi stock markets represents market anomalous behavior. These markets are mostly owned by large institutional investors or family firms which can influence these markets at any time. Therefore, any irrational move from these investors is considered reliable and a benchmark by other individual investors and as a result, the irrationality is viciously replicated in a very shorter period of time. Resultantly, the investors may exhibit under-reaction or overreaction in the market based on the market conditions at hand.

Following the methodology, as proposed in the literature, the market overreaction hypothesis is tested by making four testing periods ranging from 2011 to 2018. The Average cumulative excess returns (ACAR) analysis for all four sampled stock markets was conducted. The necessary conditions required for the overreaction hypothesis were full filled only in Pakistani and Bangladeshi stock markets.in other words, the difference between a loser and winner ACARs is positive which implies that winner stocks in the testing periods become loser stocks in the subsequent periods (evident from the negative values) while the positive values indicate that stocks have started gaining and became winners in the subsequent periods. Similarly, the positive difference between a loser and winner ACARS indicates a larger magnitude of winning than the losing in all testing periods.

The study of ACARs for winner and loser portfolios across all 24 monthly periods also confirms the existence of overreaction in most of the periods.

Additionally, market overreaction has a significant relationship with excess volatility and market turnover reflecting the notion that section of excess volatility which cannot be justified by the efficient market hypothesis is a result of investor biases which in turn result in market overreactions in response to some particular new information. Similarly, the negative relationship between volatility and turnovers indicates that high market turnovers result in price momentums which have a negative impact on excess volatility. This study has confirmed the existence of behavioral biases and it is also proved that these biases cause a market overreaction in the Pakistani and Bangladeshi stock markets.

The primary condition for the overreaction of investors is proposed as ACARL>0, ACAR W<0, and resultant positive value for ACARL-ACARW. Data analysis for this study reveals that the stated difference between loser and winner portfolios is greater than zero hence representing investor's overreaction to any new news for Pakistani and Bangladeshi stock markets. One reason for such a pattern may be the existence of various psychological and behavioral biases, these are self-attribution, anchoring, herding, disposition effect, and limited attention bias. Decisions taken in the presence of these biases directly influence security prices and their corresponding returns. As a result, the effect is multiplied several times in the market. This study also concluded a statistically significant positive relationship between excess volatility and investor overreaction which implies that bounded rationality driven by various biases causes' excess volatility.

Based on the results of this study, it can be inferred that traditional finance is unable to cater answers to the market anomalous behavior. In such context, behavioral finance comes to the rescue since security fundamentals along with specific attributes of the investor including sentiments, emotions, and behaviors determine stock valuations therefore, the stock market may be considered as a balance of behavioral and traditional finance. Another aspect is that traditional finance is used to estimate market dynamics including market returns, bounded rationality intermingles and makes it very complex and volatile to predict such dynamics. The core reasons for overreaction and excess volatility in Pakistani and the Bangladeshi stock markets can be attributed to the socio-political and economic conditions of these countries. As causes of uncertainty in these markets, self-attribution, anchoring, herding, disposition effect, and limited attention bias have also played a significant role in the aggregate uncertainty involved.

Another aspect is that under and over market reactions result in stock price momentums for shorter periods while investors can predict potential trends in the market through these momentum trading. Pakistani and Bangladeshi investors are more prone to overreaction in the long run which indicates the presence of upward momentum till excessive trading starts and as a result, returns reduce. Regression results indicate that turnover and market reactions have a negative relationship. As long as market overreaction rises, market turnover falls in the long run. On the other hand, excess volatility and trading turnover have a positive relationship with each other. In other words, as turnover rises due to momentum, the persistent market overreaction leads to an increase in excess volatility. As market overreaction has been linked with behavioral and psychological biases it is inferred based on the established relationship between turnover, market reaction, and excess volatility in south Asian stock markets that excess volatility can be attributed to the bounded rationality of investors and momentum-driven stock trading.

This study has extensively investigated the relationship between market reactions, turnover, and excess volatility and their role in stock valuation. The biases under this study have shown an established relationship with market turnover. Most of the biases under study are measured through stock turnover. These biases lead to investor's overreaction and overreactions result in the emergence of excess volatility. On the other hand, market overreaction in addition to excess volatility has a significant relationship with market trading turnover. Investors in such trading trends depend on their investment decisions which are exposed to behavioral biases. This cycle continues to operate and as a result market overreaction becomes denser and lengthy. This is a possible cause that Pakistani and Bangladeshi stock markets have shown overreaction from 2009 to 2018.

Behavioral finance is an efficient combination of classical economics and the psychology of decision-making. The study at hand confirms irrational decision-making on part of individual investors in the form of various biases and as a result, such irrationality is translated to the whole market and markets start exhibiting anomalous behavior (under and overreaction). The study at hand has also investigated the rationale which is taken by investors by giving weightage to different underlying factors like self-attribution, anchoring, herding, disposition, and limited attention. As the magnitude and existence of these traits vary from individual to individual, no single unifying policy can be given. These notions are against the efficient market hypothesis. Which states that all investors do use the security fundamentals for their valuation and investment decision-making, all investors will earn equal returns.

This study has also concluded that due to the variations in heuristics and behaviors, average returns also vary from person to person and country to country as investors decisions rely upon the underlying heuristic while the use of these mental shortcuts can always act as a gamble, sometimes it may work but often it does not work due to which uniform returns are not found in markets. As a sum, the existence of self-attribution, anchoring, herding, disposition effect, and limited attention bias confirms heuristics in investor's decision-making. Self-attribution bias leads to market overreaction while anchoring bias results in the market under-reaction towards any sporadic news. Herding results in the market overreaction on the same pattern while due to the disposition effect an investor under-reacts in the form of disposing of winner stocks and holding loser stocks. Similarly, more attention in the form of high trading from investors represents an overreaction of the market. As a matter of fact, the explanation proposed by these biases is more logical and acceptable unlike the presumptions of efficient market hypothesis. The EMH assumes rational investors which is far from reality and rather being idealistic. Additionally, the existence of market under and overreaction and its contribution to excess volatility also justifies the non-existence of EMH in south Asian countries. As a matter of fact, Pakistani and Bangladeshi stock markets demonstrated anomalous behavior mostly due to the role of underlying psychological and behavioral biases. These have also impacted trading volumes, excess volatility, and market reactions. In such a context, the significance of stock fundamentals is left behind in stock valuation. From the analysis, it is found that beliefs, perceptions other psychological factors, and behavioral factors determine the value of stocks rather than their true intrinsic value. The bottom line is that in contrast to a developed stock market like that of the U.S, South Asian stock markets specifically Pakistani and Bangladeshi stock markets are inefficient as the stock prices are stimulant to human psychology rather than the available information.

5.2 Policy Implications

As mentioned above, EMH assumes rationality for investors in their investment decision-making. The study at hand disconfirms the assumption in the form of evidence for the existence of various psychological and behavioral biases. The comprehension and scope of such biases for investors is highly significant as investors will better grasp their process of investment and the losses they incur due to the underlying irrationality. Moreover, these investors are provided a chance to rectify their bounded rationality in the process of evaluating investment opportunities.

It is evident from this study that market reactions, behavioral biases, market turnover, and market volatility are all dependent on each other in a cycle therefore, it also provides an opportunity for the investors to understand various aspects of prices estimation. Comprehending the role of market forces enables the investor to rectify their investment decisions on new lines involving the role of heuristics in addition to the opportunities provided for momentum strategies in south Asian stock markets. Which result into a dense and prolonged market overreaction but with future opportunity to gain from the market.

Investors in south Asia generally undergo various biases but they are not aware of them. So, this study will create awareness in investors about various biases which they commit unknowingly. Furthermore, investors can manage certain biases through the use of different strategies. As a matter of fact, these biases cannot be avoided but rather managed by less trading, with predefined trading principles and cut-offs and realistic and practical thinking about the existence of information. Moreover, taking services of financial consultants and analysts can also manage the risk of faulty financial decisions. In this vein a recent study by Hsu (2022) shows that investors more prone to behavioral and psychological biases are tend less to take the help of financial advisers. Moreover, the study also suggests that financial literacy and appropriate level of training can also help in managing the impact of biased financial decisions. Interestingly, even financial advisors are also prone to psychological or behavioral biases. Which points out that 'human factor' in financial decision making. In this context, the use of very powerful computer algorithms come in place, which can certainly add to efficient investment decision making especially in emerging markets.

Knowledge about the existence and impact of biases in financial markets will enable the policymakers to make and implement specific policies which will result in relatively efficient markets with minimum chances of mispricing, overreaction, and momentum effects. On the other hand, information asymmetry can be significantly curtailed by regulators if they focus on information disclosure in every segment. Through the existence of symmetric information, institutional investors and individual investors will behave indifferently to the available information and hence relative market efficiency can be achieved.

Financial intermediaries can benefit from this study who are more interested in introducing innovative strategies. Moreover, such intermediaries are expected to develop a deep understanding of financial markets, the underlying anomalies and the causes of momentums and bubbles, and the role of various macroeconomic variables. Which will help in the timely adjustment of investment strategies and financial instruments along with devising new more efficient strategies to cope with different variant economic and market conditions. Since financial markets demonstrate the economic prosperity of a country, stable financial markets would result in more strengthened economies resulting in high levels of trust made by foreign donors and investors in the local financial market. Financial managers including investment managers, mutual funds managers, and even professors may create awareness and educate investors and students regarding securities valuation and assist them in stock valuations through the use of available stock fundamentals rather than using instincts and emotions.

Fund managers may generally allow investors to use five to ten percent of investments at the investor’s discretion while the rest of the funds may be used by the fund’s manager for momentum trading and appropriate risk management. Such a strategy may delineate an investor’s irrationality to a restricted area hence not affecting the majority of investments and ultimately the majority of the market. Fund managers can also take into consideration these findings in order to make more profits for their clients through speculative investments.

5.3 Direction for Future Research

The study at hand, has taken only five biases namely self-attribution, anchoring, herding, limited attention bias, and disposition effect however, a number of other biases also exist which can come to influence an investor's investment decision-making. Most of such biases related to psychology are mentioned in the literature. These biases may also be studied in relation to an investor's investment decision-making. Consequently, this combination of two fields' i.e finance and psychology will add to the existing literature with absolutely new aspects which are never investigated earlier.

Secondary data has been used for the investigation of different biases under study. Different proxies have been used for these biases. However, the use of primary data for such biases may validate and improve the results of this study. The use of primary data is expected to provide a clearer insight into the behavioral dynamics of stock markets along with improving the statistical reliability of various tests. Moreover, using psychological theories, the use of primary data may also provide unique patterns which have not yet been reported before. Furthermore, the results of this study are based on available secondary data and standard econometric models. Robust checks can be used to improve the results of the study. Replicating the same methods in other stock markets including developed and developing markets and comparing their results will provide a reference point to make efficient strategies.

As investors are the core components of stock markets and their investment decision-making is translated into stock prices. Therefore, it will not be wrong to state that investor's decisions are not merely influenced by market returns, trading volumes, and market volatility but rather heuristic-driven decisions are also observed in the market. These behavioral factors in turn lead to market reactions. So, these reactions need to be studied on shorter and longer time horizons for a better understanding. Moreover, future research studies are also expected to include industry fixed effects, firm specific effects in their analysis.

Although the impact of various behavioral biases is well established, it is important to investigate the causes of such biases. In other words, for instance, it is generally understood that heuristics are originated by external factors while re-enforced by internal factors. For example, disposition effect is assumed to be of the same magnitude however some of the earlier studies suggest that disposition effect varies across professions, age, wealth, income, and ethnic background. Variations in country specific results also necessitates experimental research designs to investigate different behavioral and psychological biases especially in relation to financial decision making. Moreover, it is therefore very important for future researches to include various other factors like gender, age, educational background, geographic locations, individual personality traits, etc. as controlling moderators of the relationship between these biases and external factors. For this purpose, triangulated studies may be conducted to grasp individual factors in primary data and aggregate factors through secondary data in order to come up with more conclusive results generalizable to the aggregate markets.

Since the sampled countries faced various political and social turbulences. It is important to delineate the roles of these factors through separate event studies. Moreover, the sampled south Asian stock countries have a mutual history. Future research studies should therefore investigate the spillover effects including these countries.

Individual behavior is the most complex phenomenon which is quite difficult to predict or estimate. However, most of its foundations can be traced in the field of psychology. Behavioral finance is a thorough combination of psychology and finance, is a relatively new field. There is a lot of potentials to work within this field therefore plenty of new dimensions need to be investigated more rigorously in order to necessitate the significance of this field.

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Appendix 01

Unit root analysis for Trading volume, Returns, Dispersion, and Volatility (self-attribution bias)

	PSE		BSE		DSE		DJIA	
	Statistic	Prob.**	Statistic	Prob.**	Statistic	Prob.**	Statistic	Prob.**
Daily	364.932	0	248.693	0	305.653	0	218.075	0
	-16.7353	0	-14.0915	0	-15.5262	0	-13.0039	0

Method *ADF - Fisher Chi-square/ADF-choi z-stat*

Appendix- 02

Unit root analysis for Market returns, security returns, security volatility, and security turnover (Disposition effect)

	PSE		BSE		DSE		US	
	Statistic	Prob.**	Statistic	Prob.**	Statistic	Prob.**	Statistic	Prob.**
ADF - Fisher Chi	195.98	0.00	196.05	0.00	86.53	0.00	86.84	0.00
ADF - Choi Z-stat	-12.83	0.00	-12.69	0.00	-6.21	0.00	-5.47	0.00

Method *ADF - Fisher Chi-square/ADF-choi z-stat*