CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

# Behavioral Biases and Stock Market Reactions: A Study of Pakistani Market

by

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A thesis submitted in partial fulfillment for the degree of Doctor of Philosophy

in the

Faculty of Management and Social Sciences
Department of Management Sciences

2017

# Behavioral Biases and Stock Market Reactions: A Study of Pakistani Market

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**CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY**
**ISLAMABAD**
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*Dedicated to Dr. Tariq Javed (Late)*

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This is to certify that the research work presented in the thesis, entitled "**Behavioral Biases and Stock Market Reactions: A Study of Pakistani Market**" was conducted under the supervision of **Dr. Arshad Hassan**. No part of this thesis has been submitted anywhere else for any other degree. This thesis is submitted to the **Department of Management Sciences, Capital University of Science and Technology** in partial fulfillment of the requirements for the degree of Doctor in Philosophy in the field of **Management Sciences**. The open defence of the thesis was conducted on **14 September, 2017.**

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# *Acknowledgements*

First and foremost, thanks to the Almighty Allah, for giving me the opportunity to take on this task and giving me the strength, skills and determination to complete it.

This extensive work of research would not have been possible without the expertise and supervision of Dr. Arshad Hassan for whom I have nothing but tremendous respect, profound gratitude and immense appreciation. And yet I feel, no words of gratitude can do justice to his capabilities and the support he provided over the period of years that took me to accomplish this research. Thank you, Sir.

I am also deeply indebted to my peers who have always been there for me, be it for the academic solutions or moral support. Dr. Zulfiqar Shah who always showed confidence in me and was always there to lend a helping hand whenever it was most needed. Dr. Syeda Faiza Urooj and Dr. Sohail Amjad who has been with me through this journey, each and every step of the way, handled all the panics and taught me perseverance to never ever give up. Dr. Sumayya Chughtai who became the guiding light and supported in every possible way and finally Dr. Arif Khatak whose thoughtfulness got me through a number of times. All of you have been the beacons of the long route that achieved this research.

In the end, a big thankyou to my family and friends; my work colleagues and everyone who ever sent a single prayer, a heartening wish and a caring thought. My deepest gratitude to all of you.

**(Ms. Nousheen Zafar)**

# *List of Publications*

It is certified that following publication has been made out of the research work that has been carried out for this thesis:-

**Journal Papers**

1. Nousheen Zafar, Arshad Hassan. (2016). An Empirical investigation of Herding: Case of KSE100Index. Pakistan Journal of Life and Social Sciences, 14(2), 60-69.

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# *Abstract*

This study is an effort to answer the questions which traditional finance theories have failed to answer. Stock markets are run by human decisions which are the life blood for Behavioral Finance. The study also identifies the path through which behavioral biases affect the market where the investors over or under-react to upcoming news, leading to excess volatility and turnover patterns. Two heuristic driven biases from Behavioral Finance Micro that is, Self-attribution and Overconfidence and Anchoring, and two biases from Behavioral Finance Macro that is Herding and Disposition Effect has been selected for the purpose of study. Analyzing the daily return data for KSE-100 index for period of January 2000 to December 2014, it has been found that Pakistani investor is prone to overconfidence while making an investment decision giving more weightage to their own capabilities. When a 24-Week high was used as an anchor, investors showed underreaction to the sporadic news. On the contrary, when a historical high was used as an anchor, it leads to overreaction for prolonged news. Extreme market situation when defined at 5%, herding was found in down market situation, only implying that at times of low market returns investors tend to follow market trend. However, at extreme market defined at 10%, herding is significantly found in both up and down market conditions. Disposition effect is also found to be present in investors making them prone to realize paper gains as soon as possible. Existence of all the selected heuristic and behavioral biases makes the market highly vulnerable to irrational reactions. Using the methodology implied by Thaler (1975) tendency of overreaction has been found in KSE-100 index where $\text{ACAR}_L$ is always greater than $\text{ACAR}_W$ showing losers in one period outperformed in other testing period due to overreaction of investors. Examination of the contribution of market overreaction to the excess volatility in market has revealed that market over reaction has a significant effect over the excess volatility and thus, it can easily be predicted by assessing market behavior. Also trading volume/turnover driven by irrational behaviors and heuristics contribute to the excess volatility but in negative manner due to the momentum effect embedded in trading patterns.

**Key words: Overconfidence, Anchoring, Herding, Disposition effect, Over/under reaction, Excess volatility.**

# Contents

# List of Figures

# List of Tables

# Abbreviations

| | |
|---|---|
| ACAR | Average Cumulative Average Return |
| BE/ME | Book to Market Ratio |
| BFMI | Behavioral Finance Micro |
| BFMA | Behavioral Finance Macro |
| C/P | Cash flow to Price Ratio |
| CAPM | Capital Asset Pricing Model |
| CAR | Cumulative Average Returns |
| CSSD | Cross Sectional Standard Deviation |
| CSAD | Cross Sectional Absolute Deviation |
| EMH | Efficient Market Hypothesis |
| EPS | Earnings Per Share |
| HTSD | High Turnover Standard Deviation |
| HTAD | High Turnover Absolute Deviation |
| KSE | Karachi Stock Exchange |
| LTSD | Low Turnover Standard Deviation |
| LTAD | Low Turnover Absolute Deviation |
| OLS | Ordinary Least Square |
| P/E | Price Earnings Ratio |
| VAR | Vector Auto Regression |

# Chapter 1

# Introduction

In recent past it has widely been observed that equity markets are facing high volatility and fluctuation issues. Macro-economic conditions largely hit the markets on a global scale. This higher volatility has made investor uncertain or unpredictable about the market behavior as market conditions cannot always be forecasted by using standard financial measures.

Concept of market efficiency and rational investor behavior was introduced in early 1960's by Eugene Fama, who believed that investors make well informed and intelligent decisions. E. F. Fama in 1970 presented his famous Efficient Markets Hypothesis (EMH). According to him, markets were considered to be efficient and rational in determining financial prices. Individual stocks were regarded to be priced at the correct information known to all the investors in market. Any change in prices was supposed to be due to influx of new information.

Stock market cannot be perfectly efficient. There is a chance that price irregularity or predictable patterns in stock returns might occur over time and persist for short time period. The reason is that sometimes investors are not rational and their collective judgment can go wrong (Malkiel, 2003).

It was in late 70's, when efforts started to find out the ability of prices to reflect the available information. Then in 80's, direction changed and efforts to prove inefficiency of information started. The evidence in recent past is now increasing in favor of an Inefficient Market Hypothesis (IEMH), which is more closely in line with market reality. Much has been worked out on the volatility of stock prices with respect to the specific calendar time as they are considered a root cause for inefficiency of market. Hence, validity of the entire generally accepted asset pricing theories is now questionable. In order to explain why anomalies occur in market, new asset pricing theories rooted in human behavior may be worked on (Fama, 1998).

Investors are not always rational and consistently make perfect judgments, rather they are influenced by certain other psychological and social factors which provide them the basis to act in some particular way and thus result into market and calendar anomalies, widely been observed in past decades. There are models which describe this irrationality of investors based on their choices, preferences and mistaken beliefs. Such models and their justifications are the subject matter of Behavioral Finance. Where EMH implies that markets cannot foresee the future but can forecast future based on available information; Behavioral Finance believes that in some circumstances, financial markets may prove inefficient even if fully informed.

## 1.1 EMH to Behavioral Finance

It was in 1968 when Ball and Brown presented the findings of their research, showing that stock prices tend to rise (fall) with the unexpectedly high (low) reported earnings of the firms and this trend continues for many months. This was a clear contradiction with EMH but it was ignored for a long time.

Eugene. F. Fama in 1970 came up with his findings that all the available private and public information regarding value of the firm are incorporated in stock prices in no time. This reduces the chances of investor to find and exploit the mispricing of stocks to earn above market profits. Fama (1970) named this theory as well-known Efficient Markets Hypothesis (EMH). The theory implies that price movements are random and do not follow any pattern or trend that can be exploited rather, they react to that day's freshly arrived news whether that is any financial news or any information regarding some political, economic or social event. This makes the market informationally efficient.

Efficient Market Hypothesis is largely based on the set of assumptions such as investors are fully rational, they have the resources and computing capacity to analyze all the available information correctly and assume assets' true risk and return profile, asset markets are frictionless, without trading costs or taxes, and the information required to estimate the distribution of asset returns is costless and simultaneously available to all market participants. It is quite evident that all these conditions cannot hold at a time and are clearly unrealistic. However, if the model is capable of forecasting accurately, its assumptions are not assessed on the basis of realism (Friedman, 1953).

Since in efficient markets, information embeds in stock's value immediately, identification and exploitation of mispriced stocks that is stocks whose value does not match with its intrinsic value and thus their future price level can be predicted accurately; is not possible. But in case of inefficient market, stock prices either drops down more than required level (and then gradually moves up) or delays its response to new information and take few days to incorporate it. In both these cases market participants get the chance to earn above market profit by exploiting higher returns for the mispriced securities.

It has been found in literature that prices exhibit a positive serial correlation over the years (Lo and Mckinlay, 1988) and that the prices can be predicted by the publicly available information which does not constitute the fundamentals of assets. For example, Livnat and Mendenhall (2006) hold that prices can be predicted on the basis of earnings announcements made by the firms. Gleason and Lee (2003) finds prices to be predicted by analyst forecast. Lakonsihok, Shleifer and Vishny (1994) and Fama and French (1992) show that returns relate to book value to market value ratios. Though asset prices fully reflect the risk return profile of the asset, identification and exploitation of such phenomenon earns above market profits to the investors. This also implies that past returns can predict future returns. DeBondt and Thaler (1985) document 15 long horizons of two to five years where past losers consistently outperform past winners.

How rationally market behaves has been a topic of special interest. An examination of the volatility of share prices relative to the volatility of the fundamental variables affecting share prices, has been made to assess the rationality of market behavior. The magnitude of fluctuation in actual asset prices is found to be higher, than the fluctuation in fundamental variables affecting the stock prices. The reason being trends or waves of optimistic or pessimistic market psychology (Shiller,1981). Volatility tests have provided the evidence of movements in stock prices being not merely the result of rational expectations of investors rather an irrational component is also involved.

There exist two kinds of investors commonly found in market. Those who are rational speculators or arbitrageurs trading on the basis of available information and those who trade on the basis of imperfect information, termed as noise traders (Shleifer and Summers, 1990). Stock prices tend to deviate from their equilibrium fundamental value when noise trader starts trading based on imperfect information. Arbitragers, on the other hand, are put liable to stabilize the prices in market. However arbitrageurs, through their rational decisions, can only dilute the effect of such shifts in prices instead of eliminating them completely. This notion has made the assumption of perfect arbitrage (made under EMH) questionable and unrealistic. Theory of limited arbitrage implies that security prices are not determined merely by information but also by "changes in expectations or sentiments that are not fully justified by information" (Shleifer and Summers, 1990).

Stock Market is mainly constituted by human beings. Human decisions of buying and selling acts as a life blood to the market. Keeping this in view, any factor that helps explain the human and social psychology can also be vital to understand the behavior of stock market. Recent research is attempting to explain the anomalies persistent in market with help of the concepts and theories relating to the field of psychology. Literature in Psychology describes individuals with limited information processing capabilities, prone to systematic bias in processing information, tend to make mistakes, largely influenced by emotions, sentiments and perceptions and last but not the least has a tendency to base their decisions on the opinion of others.

To combat with the difficulties of traditional finance theories, Behavioral Finance has emerged as a tool in around past 20 years. It deals with how individual and collective attitudes are applied to financial decisions and their effects on financial activities, or more specifically how individuals behave with their money. Actually, Behavioral Finance is not too much interested when things run in a smooth and efficient way, this is the realm of standard Economics, but in cases when they turn wrong, in other words biases and anomalies, it turns into action. It mainly focuses on the cognitive and emotional biases of individuals (or group of individuals) that might affect their financial decisions and not only lead to suboptimal decisions but, also to financial market anomalies.

Behavioral Finance analyzes and explains what happens when we relax some of tenets that underlie individual rationality. Tools implied by Behavioral Finance, as highlighted by researchers are: susceptibility to frames and other cognitive errors, varying attitudes toward risk, aversion to regret, imperfect self-control, and preferences as to both utilitarian and value-expressive characteristics (Jo and Kim, 2008).

### 1.1.1 Branches of Behavioral Finance

Behavioral Finance combines two fields of study:

- Behavioral Finance Micro (BFMI)
- Behavioral Finance Macro (BFMA)

*Behavioral Finance Micro (BFMI)*, also known as Psychological Behavioral Finance or Financial Psychology, examines the behavioral biases (that is, the irrational behaviors) of individual investors. It explores the area how investors, borrowers or other individuals make choices and behave when money is at stake. Or practically, it is the study of individual decision making process and its consequences on financial decisions. It identifies the biases investors are faced with and help them overcoming these damaging investing biases. In BFMI irrational investors are compared with the rational investors, as envisioned in classical economic theory, also known as "Homo Economicus", or rational economic man.

*Behavioral Finance Macro (BFMA)*, also known as Quantitative Behavioral Finance, describes anomalies or irregularities in the overall market that contradict the Efficient Market Hypothesis. It mainly deals with the effects of collective attitudes, behaviors, choices, and reactions on the financial markets. It investigates the extent to which market deviates from the theoretical efficient prices and returns. It helps investors take advantage of and avoid pitfalls caused by biased market behaviors. In BFMA, we take markets as efficient but, abnormal market behaviors occur (such as the January effect) that demonstrates that human behavior influences security prices and therefore, markets.

Issues dealt in both these fields are quite different from each other. BFMI deals with: Are investors fully rational or their decisions are influenced by the emotional and cognitive errors? BFMA on other hand asks: Whether markets are fully efficient or they are affected by behavioral patterns? It is evident from this debate, that there is an ongoing debate between concepts of standard finance and Behavioral Finance.

### 1.1.2 Standard Finance Vs Behavioral Finance

Behavioral Finance tries to explain how and why actual market prices and returns differ from what "Standard Finance" predicts. Standard finance is characterized by rules that address how investors should behave rather than describing how they actually behave. Behavioral Finance, like standard finance, contains underlying assumptions, but standard finance grounds its assumptions in idealized financial behavior, while Behavioral Finance grounds its assumptions in observed financial behavior. Concept of EMH given by standard finance also contradicts with reality where fundamental, technical and calendar anomalies have been found and proven.

These anomalies found in market are explained by three schools of thought that are: revisionists, loyalists and heretics (Boudoukh et al, 1994). According to revisionists, markets are efficient. Loyalists believe that markets are efficient but there are problems due to measurement of data or shortcomings of standard models. Heretics are of the view that markets are not at all rational and their decision based on the psychological factors.

Wouters (2006) segregate investors into two groups: rationalists and behaviorists. Rationalists believe that markets are rational and abnormal returns are only the chance events. Behaviorists on the other hand are proponents of sentiment based decision making. According to them, sentiments of investors are the main cause of the securities' mispricing and thus the market anomalies.

Rationalists or proponents of standard finance oversimplify the reality by means of a set of assumptions for example concept of Homo Economicus that is, rational economic man making perfectly rational decisions all the time. Where standard finance explains how the investor "should" behave, Behavioral Finance deals with how an investor "actually" behaves. The assumptions of standard finance are governed by idealized financial behavior whereas roots of assumptions in Behavioral Finance are in the observed financial behavior.

Behaviorists believe that investors sometimes do not act rationally due to their bounded rationality and thus fail to maximize their utility of the outcome. People are neither perfectly rational nor perfectly irrational, but possess diverse combinations of rational and irrational characteristics. The decisions made in this state exhibits a gray area lying somewhere in between standard finance and Behavioral Finance. This school of thought has its roots in two building blocks: cognitive psychology and the limits to arbitrage. Cognitive refers to the process how people think, process information and make decisions or in other words it is the kind of distortion in human mind that cannot easily be eliminated and leads to wrong perceptions, erroneous judgment, and wishful interpretation without any logic. Financial decisions are largely effected by such factors in real world thus market reactions can also be defined in terms of investment decisions inspired by heuristic approach.

## 1.2 Reactions of Stock Market: Overreaction and Underreaction

Where Standard Finance takes individuals as fully informed, aware and rational, Behavioral Finance presents the individuals as normal people that are not always rational and are influenced by emotions, trends, perceptions, heuristics and biases (Statman,1999). Thus, it can be concluded that market is not always rational rather it may also react in irrational manner. Overreaction and Underreaction are the phenomenon which creates difference between Standard Finance and Behavioral Finance. Market efficiency has been accepted by finance scholars and professionals with respect to "beat-the-market" principle but as far as "rational-prices" are concerned, it faces a lot of criticism (Jo and Kim, 2008).

Assessing investor's cognitive psychology, two major reactions of market largely reported in literature are Overreaction and Underreaction of investors. Investor accepted as irrational in decisions, either under react or over react to every event or new information. Underreaction here refers to the response of investors to a news arrived in market less than what is expected from them. When market reacts to some news immediately after its release and continues to react even in subsequent period, the reaction is termed as Underreaction (Prast, 2004). Similarly reaction of investors to a series of news greater than what is expected is called overreaction. Case of overreaction is different from that of Underreaction, i.e. Reaction of market to recent news is offset by a change in opposite direction in subsequent periods.

DeBondt and Thaler (1985) are among those who formulated the idea of under and overreaction. By analyzing 3-5 year past monthly stock returns, they found that the winner tend to lose in future and vice versa. According to them, this long term return reversal basically shows investor overreaction; as they seldom give importance to the future mean reversion of returns rather, they heavily depend upon past performance of stock while making expectations.

Two more concepts attached with Underreaction and Overreaction is momentum and reversion. These are the strategies recommended to investors on the basis of market reaction. Nicholas, Shliefer and Vishny (1998) identify two regimes, i.e.

"mean reverting regime" and "trending regime" in which firm's returns move. It is more likely that firms earnings will stay in present regime therefore investors update their belief about which state they are in with every upcoming news. If good news followed by good news arrives in market investors believe they are in trending regime whereas if good news is followed by a bad news, they perceive they are in reverting regime. Continuation of a trend whether positive or negative for a short term, i.e. 1- 12 months refers to momentum. Momentum and reversions have often been associated with Over and Underreaction. In case of positive momentum, it is possible that investors are under reacting to negative, non-conforming news and in case of negative momentum investors may be overeating to negative circumstances and are ignoring positive signals (Spellman, 2009).

Momentum traders only focus on past prices whereas; news watchers rely upon any news about fundamentals of firm (earnings, etc). With any positive or negative news, newswatcher underreact (as fundamental information is spread slowly in market). Momentum trader accelerates this reaction and takes prices beyond equilibrium causing more sale or purchase of stocks and thus overreaction (Hong and Stein, 1999).

Most of the studies that tested market efficiency have confined their analysis to short term stock returns only assuming that there exist a short term lag between event and its adjustment in price. Recent studies are now focusing that market can be claimed inefficient only if long term returns are observed since prices take some time to adjust with the event. Only a long term analysis can help identifying inefficiency or long term underreaction or overreaction to information (Fama, 1998).

A review of literature regarding cognitive psychology provides a strong framework to analyze investors' behavior in the stock market. If the traditional assumption of investor being a rational creature is dropped, several disconfirming behaviors and anomalies persistent in market may need to be explained. For example, with the evidence of overreaction of investor it is believed that, in general, investors may tend to overreact to new information by ignoring base rates. Moreover the decisions of investors are highly driven by the irrelevant points of reference. This phenomenon is discussed in detail under "anchoring and adjustment".

Under and overreaction of investors helps the analysts to forecast the future stock returns by indicating the regime setting, i.e. a positive information such as earning announcement would be followed by the overreaction of investors and a series of positive returns (Michael, 2005). Reversion is the upward or downward adjustment to the early expected prices. After a series of negative revisions, probability of an upward revision is about one in four however, after the first upward revision probability becomes one in two. After two upward revisions (after a series of negative revisions) probability of next positive revision is positive become seven in ten Goldstein (1998). Investors anchor their future decisions with the past event, i.e. prior reversion.

Since investors are the most integral part of market, they might overreact to the same piece of information under different market conditions, at different levels. Market condition has been defined for research purposes by Cooper et al. (2004) by analyzing the performance of past 36 months. They described market in UP state when the lagged three-year market return is non-negative, and market is considered DOWN when the three-year lagged market return is negative. Chen, Jiang, Li (2010) has also defined "Up" market period as if there exist positive market returns for 3 consecutive months prior to portfolio holding period. Similarly, "Down" market is defined as negative returns for 3 successive months prior to portfolio holding. Investors, in different market conditions, over or under react to news which makes the prediction of future returns possible.

### 1.2.1 Biases, Market Behavior and Reaction

Presence of Over and Underreaction in financial market proves the anomalous behavior of investors. Investor's behavior in turn is formulated by the heuristics and biases. People employ imperfect rules of thumb (heuristics) to process data which induces biases in their beliefs and influence them to commit errors. Thus, the relationship between anomalous market reactions and heuristics can be put in a way that over and under-reaction observed in market is basically the outcome of heuristics and biases implied in information processing.

Since market may overreact to a piece of information and underreact to other piece of information, there is a need to highlight the biases, specifically heuristic driven biases, that causes same investor to underreact to some information or event and overreact to other (Fama, 1998).Three main themes of behavioral factors as classified by Shefrin (1998) are: heuristic driven biases, frame dependence, and inefficient markets. Heuristics driven biases and frame dependence are considered forms of biases whereas inefficient markets are the result of these two. The most reported heuristic driven biases and cognitive errors, widely discussed so far, that prejudice the investment decisions are:

- Representativeness and Conservatism
- Over confidence/Self-attribution
- Anchoring
- Confirmation Bias

Such biases observed at individual level formulate the anomalous behavior of market. Only a chunk of irrational investors may lead whole market to misprice the securities (Wouters, 2006). Since markets are made of heuristic driven individuals, and their decisions do not always follow the fundamentals, two widely observed anomalous behaviors of investors in market are:

- Herding
- Disposition Effect

These anomalous behaviors make the markets volatile and cause the investors to under or over react to the upcoming news. Thus efficiency of market can be challenged on behalf of these anomalous behaviors resulting from the biased decisions of investors.

## 1.3 Heuristic Driven Biases

DeBondt and Thaler (1995) establishes the idea that a good finance theory should cover the psychological aspect of actual behavior of individuals as well. This idea provides the basis for digging out the evidence of biases observed in behavior and the theory behind them with the help of Psychology literature. It is an important step to get to know how the behavioral biases arise and how they affect the reaction of market. Psychologists strongly support the evidence of too much attention of investors to extreme information, while analyzing and making investment decisions, without paying any attention to the validity of information (Griffin and Tversky 1992). Another trend observed is the assigning of weights or probabilities to uncertain outcomes following the cognitive heuristics. Despite the fact that following these heuristics the task of assigning weights become easy and manageable, this practice also leads to systematic biases (Kahneman and Tversky, 1986).

The corner stone of Behavioral Finance is the psychological or behavioral factors limiting the information reaching to investors or leading the investors to wrongly pick and interpret information which results in wrong decisions even if information is correct. There are certain behavioral and psychological models indicated by various studies that provide the basis for cognitive error. Heuristic driven biases such as representativeness, over confidence, anchoring, etc. helps understand the phenomenon of Over and Underreaction of investors to new information in market (Michael, 2005) and to predict the future returns on basis of anomalous behavior observed.

Lam, Liu and Wong (2010) states that investors attach wrong weights to the information rather than adopting a wrong model and this result into biases like representativeness and conservatism. Starting from Tversky and Kahneman (1974) who identified representativeness, anchoring and availability as the factors effecting human decision making, Famous BSV model of Barberis, Shliefer and

Vishny (1998) highlight representativeness and conservatism as the forces behind investor's Over or Underreaction. Similarly Daniel, Hirshleifer, and Subrahmanyam's (1998) model is based on the self-attribution and overconfidence biases. Amir and Ganzach's (1998), or "AG's", model present leniency, representativeness, and the anchoring and adjustment biases etc. The heuristic driven biases of investors are briefly explained below.

### 1.3.1 Representativeness

Various researches and psychological literature have found that major cause of investor over and underreaction is representativeness and conservatism bias, for instance; Barberis, Shliefer and Vishny (1998). Representativeness refers to the tendency of making judgment about the probability of an event in comparison to similar or nearly close past event assuming that probability of both events will be same.

It is a generally observed psychological phenomenon that people are reluctant to accept any new thing when they are following and going fine with their old beliefs. This behavior gives birth to the concept of conservatism. Conservatism refers to the approach where people do not update their minds and remain stuck to some old event.

Investors being overconfident about their analysis based on past performance of stocks, exhibits underreaction to recent information, i.e. slow updation of belief in respect of new evidence. This phenomenon is termed as conservatism (Grether, 1980). Investor's overconfidence about the recent information of stocks and ignoring or less emphasizing on past information leading to dramatic revision of their beliefs demonstrates representative heuristics (Tversky and Kahneman, 1974; Kahneman and Tversky, 1973).

### 1.3.2 Self-attribution and Over Confidence

Most important finding in the psychology of judgment is that people are overconfident (DeBondt and Thaler, 1995). Theory of over confidence states that investors are highly overconfident when valuing the stocks i.e. they rely on their own information and judgment more than any outside or publically available information. This is the reason that they usually ignore any chance of error in judgment.

Theory of self-attribution is based on the idea presented by Langer and Roth (1975), i.e. “Heads I win, Tails its chance”. It is investor’s overconfidence that when any of their strategy gets success or provide positive returns they attribute this success with their own analysis and judgment. On the other hand and if any strategy fails to give desired or expected results, investors attribute this failure with any outside factor affecting their strategy. Precisely, investors always credit themselves for the success and blame outside forces for failures (Taylor and Brown, 1988).

### 1.3.3 Adjustment and Anchoring

People have a general trend to decide by making certain adjustment to some initial point which comes to their mind (related to that particular situation). Sometimes adjustments might not be sufficient. Different starting points also have different results which may or may not be correct as they are clearly biased towards initial point. Forecast based on such biases contain systematic and predictable errors (Tversky and Kahneman, 1974).

The point to which adjustments is made in called “anchor” and this process of making adjustments is called “anchoring”. Accuracy and reliability of decision is based on how exact and related anchor is used as reference point. Selection of anchor depends upon the mental accounting process and what comes to the mind of investor instantly. More recently, Qu, Zhou, and Luo (2008) provide physiological evidence of the anchoring process based on event-related potential techniques (i.e., techniques that measure the brain responses stimulated by a thought or a perception).

Kahneman and Tversky’s (1974) present an example to explain anchoring. A wheel-of-fortune, producing a number between 0 and 100, is spun in front of the subjects and they are asked to estimate percentage of African nations in the United

Nations by observing the resultant quantity. Different groups of subjects get different quantities and thus difference in estimates is observed. For example, subjects who observed the number 10, their estimate is 25%. Similarly the estimate of subjects who observed the number 65 is 45%.

### 1.3.4 Confirmation Bias

Confirmation bias refers to a situation in which an individual unconsciously search for the information or proofs which confirm his existing beliefs or knowledge. Everyone has some prior beliefs, knowledge, judgment etc. People are generally biased to their prior beliefs (unlike Bayesians) and are reluctant to update their beliefs. They prefer to find such evidences which prove their existing body of knowledge.

Dave and Wolfe (2003) define confirmation bias as: *"Confirmation bias is defined as the tendency of agents to update their beliefs in light of new information in a manner more likely to confirm and less likely to disconfirm previously held beliefs relative to a Bayesian observer"*.

There are two basic reasons that can explain confirmation bias: First is that, decision makers tend to collect the information that confirms their previously formulated hypothesis than which can disconfirm. Secondly, decision maker may misinterpret the available signals mistakenly, so as to support his hypothesis (Dave and Wolfe, 2003).

Confirmation bias may also lead to escalation of commitment, i.e. people keep on engaging their resources to a failed venture while looking for some confirming events. Nickerson (1998) present different forms of confirmation bias. First an individual may give preference to the evidences supporting his existing hypothesis. Secondly an individual may try to look for only those cases which yield positive results. Thirdly an individual may over weight all the positive information and lastly an individual may find the patterns that they want to see (in others) and follow them.

Confirmation bias is a combination of two behaviors: searching and filtering. Human mind is either searching for confirming news only and it just filters all the confirming news from a bunch of upcoming information. However as a general rule, human mind is conservative and denies all the new realities in first instance. Dave and Wolfe (2003) construct their hypothesis on the basis of these two processes. According to them a decision maker may look only for the news confirming his belief or he may mistakenly interpret the evidence or news in favor of his hypothesis. Their results provide evidence of conservatism and confirmation bias in belief formation for pilot data.

Just like other heuristics, confirmation bias also negates the concept of Bayesian updating that is people receive and update their information in a rational manner. People tend to exhibit confirmation bias while assessing any upcoming news according to their beliefs, perceptions and knowledge i.e. when they are stuck to some information; they look for supporting information only (Fischer et al, 2008) and pays no attention to disconfirming information (Raghunathan and Corfman, 2006). Cognitive Dissonance theory explains the same phenomenon that individual investors distort the available information in favor of their desired option (Frey, 1986). When investors become prone to confirmation bias, they systematically affect stock prices and can bias the prices according to their beliefs. Shefrin (1999) also hold that investors assign more weight to the prior belief confirming evidences and vice versa. This provides us the evidence of underreaction of investors to new information.

## 1.4 Anomalous Behaviors of Market

### 1.4.1 Herding

Herding refers to the tendency of investors to follow what others are doing without analyzing the situation themselves. As defined by Hott (2006) *"If the decisions of a player are positively influenced by the decisions of the other players and this* *influence is stronger than the influence from her own signals, we call this herding behavior".*

Herding behavior cannot always be considered irrational as if someone is capable of making good analysis, it may prove good to follow him rather than relying on one's own judgment (Garber, 2000). Banerjee (1992) state a herd involves "everybody doing what everyone else is doing even when their private information suggests doing something else". Herding behavior proves to be a noise in financial markets and increases the risk that things will not go as suggested by fundamentals. This results into momentum returns and overreaction of investors. Thus it can be deduced that highly herded stocks yields significant overreaction of investors (Delong et al, 1990).

### 1.4.2 Disposition Effect

Disposition effect refers to the inclination of "selling winners and holding losers". Apparently it seems unreasonable and efforts are still on to discover the reasons for this tendency. A useful frame work in this regard may be the Prospect theory that provide an insight into disposition effect.

Kahneman and Tversky (1979) criticize expected utility theory on basis of two effects that is isolation effect and certainty effect. Certainty effect describes that people underweight the outcomes whose probability is very low, compared to the outcomes which are certain to occur. This trend shows that people are generally risk averse for the events having sure gains and for sure losses they seek more risk. Isolation effect develops that people discard all those components which are shared by all the scenarios under consideration. Then they present their own descriptive model known as prospect theory which states that people give importance to the losses and gains rather than the net wealth obtained. Also they replace probability of occurrence with the decision weights of people.

Prospect theory explains an asymmetric utility function. Kahneman and Tversky (1979) propose that the value function for changes of wealth is concave above the reference point (the domain of gains) and convex below the reference point (the domain of losses).

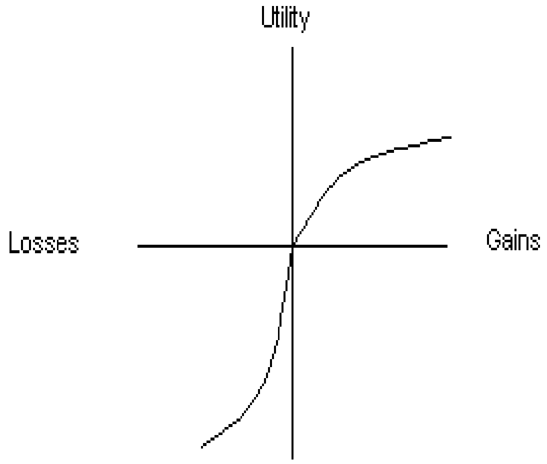


Figure 1.1: Prospect Theory Utility Function.

It can also be observed that Extra gains ("prospects") above a certain point are not valued as highly as initial gains; losses ("gambles") beyond a certain point do not create as much negative utility as initial losses. This reference point could include levels of current and past changes in performance. When conditions deteriorate below a reference point, individuals tend to be unhappy and escalate their original commitments by pouring more resources into the effort even if the likelihood of future success is low.

Escalation of efforts refers to the tendency where people keep on putting further resources to work knowing that it will not work anymore. Still based on optimism, they do not change their track.

The disposition effect put together the prospect value function presented by Kahneman and Tversky's (1979) and the focus of individuals on stock gains and losses. Prospect theory states that investors make their decisions based on gains and losses calculated from some reference point. At a certain point of time, selling of winner may be considered an optimal wealth-maximizing decision. If their reference point is the price they paid to acquire that stock, and if currently stock is selling at higher price, confirm gains can be realized instead of holding stock and having a chance to lose in future (in case value falls). This poses risk averse behavior of investor in case of gains and risk seeking behavior in case of losses.

Shefrin and Statman (1985) present another justification of disposition effect based on psychology of investors. According to them investor's decision to hold losers could be a cover to his regret (of bad investment) or his hesitation to admit the mistake. Selling winners, on the other hand, might add to his pride of making good/profitable investment.

## 1.5 Heuristic Biases and Excess Volatility

Theories have found extremely wide day-to-day changes in the stock prices quoted on stock exchanges. Many economists have tried to explain this phenomenon and find the elements behind these day-to-day price changes by concentrating on market details. Theorists have not yet agreed on whether or not it is economic or psychological realities which are the major cause of price fluctuations in the stock market.

Shiller (1990) is the biggest proponent of finding qualitative explanation of price fluctuations leading to stock market volatility. He proposes that investor reactions, due to psychological or sociological beliefs exert a greater influence on the market than good economic sense arguments. However, he does not totally ignore the work of economists advocating Efficient Market Hypothesis (EMH).

EMH assumes that prices in stock market fully reflect all the available information and thus no mispricing can be found. Also the investors are rational enough that prices exhibit the true present value of the stock's expected future cash flows. Although EMH can be backed by statistical data, investor attitudes are of great importance in determining price levels (Shiller, 1981). However, since not all investors are equally well informed and all the investors act differently to piece of information, excess volatility has been found in the stock market that cannot be justified by the EMH.

Stock market volatility in prices is five to thirteen times higher than the volatility which can be explained by the EMH and new information. Some efficient market theorists try to attribute this excess volatility to changes in expected real interest rates. Shiller (1981) claims though that the movements needed in expected real interest rates to explain this excess volatility are far larger than the movements in nominal interest rates over a sample period.

Excess volatility here refers to the level of volatility over and above that, which is predicted by efficient market theorists. This excess volatility can be attributed to a collective change of mind by the investing public which can only be explained by its thoughts and beliefs on future events, i.e. investors' psychological behavior (Shiller, 1979).

Volatile markets make it difficult for investors to assess and invest rationally. More fluctuation found in past returns, shakes the investor's belief on past strategies leaving them uncertain whether they will work out in future or not. This uncertainty leads them to be affected by the psychological factors. They act irrationally, faced with inertia, have limited cognitive abilities, highly feared by expected loss and try to avoid them. Such investors only take into account the short term perspectives and are overconfident in their own projections (Oster and Koesterich, 2013). As a result the stock market is completely ignored by the investors and they prefer to either trade in the trusted stocks or strictly hold the existing stocks/portfolios. Excessive trading or no trading in selected stocks contributes to the market volatility making it difficult to mitigate uncertainty.

Shefrin and Statman (1994) have found *overconfidence* as a source of increased volatility and decreased market efficiency. Odean (1998) has also reported overconfidence as a source of excess volatility. Shiller (1981) found stock prices too volatile to be explained by subsequent changes in dividends. According to him use of dividends in ex-post calculations is not justified since dividends are only a fraction of earnings and are not full representative of the value of a stock. He also took dividend as an arbitrary figure.

The other view point of looking into EMH is the momentum effect. Existence of Momentum effect in stock market also threatens the EMH since following momentum strategy investors get the chance to earn abnormal profits. Reasons that explain this phenomenon includes transaction costs, delayed stock reaction to market risk factors and underreaction, or even overreaction (Getsmansky and Jannette, 2002). Among all these, overreaction is the most documented by studies that it is due to overreaction of investors that makes the market inefficient. Thus Excess Volatility vis a vis Momentum violates the basics of EMH by making forecast possible.

Getsmansky and Jennette (2002) try to explain excess volatility in market by means of momentum. They classify investors into two groups: Fundamental investors who base their trades on the current prices relative to the intrinsic value of stock, and momentum traders who base their decisions on extrapolation of past stock performance into the future. They also report that fundamental investors failed to kick the momentum traders out of the market quickly to arrive at equilibrium. Thus "the excess of volatility is due to bounded rational behavior of the traders". If the arbitrageurs are also added to the model, it can better explain the excess volatility (Shliefer, 2000).

This study is an extension to the concept of bounded rationality. Excess volatility may be driven by the behavioral biases under study or may be explained through anomalous market behaviors. Volatility persists in inefficient markets and Pakistani market has been found semi strong or weak form efficient by many studies which provide the rationale to test this relationship. Efficiency of Pakistani market by means of irrational behaviors at micro and macro level and resultant volatility is the crux of this study.

## 1.6 Criticism on Behavioral Finance

Behavioral Finance deals with three types of issues: Heuristics that is; illogical decision making, framing that is; collection of evidences that supports mental emotional filters, and market inefficiency that is; mis-pricing and irrational decision making.

Behavioral Finance largely focuses on challenging the efficient market hypothesis stating that psychological factors along with fundamental factors plays vital role in investment decisions. However when it comes to forecasting, behavioral theories stays of no use since human psychology and behavior cannot be quantified and even if some pattern is identified, investor cannot generalize it for earning abnormal returns. Also it cannot forecast when bubbles will burst or when extended periods of irrationality will end.

Behavioral Finance is gaining interest day by day however there is a class that criticizes this field of finance on various grounds. Such critics do accept the presence of biases as a systematic error of judgment however, they believe that such biases have limited impact on people. Behavioral Finance is considered as a mere collection of anomalies, i.e. chance results occurring due to a shortcoming in methodology and as the measurement technique is changed reasonably, anomalies tend to disappear (Fama, 1998). Every individual is faced with behavioral biases time to time. Since market forces are always expected to act rationally to bring the prices back to fundamental value, irrational behavior of investors impact the market very negligibly (Lo, 2005).

Sarkar (2010) criticizing Behavioral Finance states: *"The efficient market hypothesis has proceeded from theory to empirics. Behavioral Finance on the other hand, is proceeding from empirics to theory. At the end perhaps the true model lies somewhere between a normative theory of human actions suitably modified by a descriptive theory of human rationality"*.

Behavioral Finance has its roots deep inside the disciplines of Psychology, Sociology, Anthropology, and Political science. However most of the literature on Behavioral Finance does not acknowledge any work done in these disciplines rather behavioral researchers keep on referring to either the work of each other or support from main stream finance and economics is obtained (Brooke, 2010). Also main focus of Behavioral Finance is the individual investor and his decisions whereas it has been proved by sociology and psychology that individual's investment decisions are mainly influenced by the social factors. Katona (1976) report that 35 years ago, most of the people were used to choose investments based on word of mouth recommendations from their friends and neighbors. Also the individuals do not always act by the rules and thus, any result obtained for an experiment cannot be generalized (Curtis, 2004).

Behavioral Finance focuses on the biases affecting decision making such as availability bias, herding, anchoring etc. However, so far it has not come up with some real and measurable contribution to improve or rectify the crisis identified.

Fama (1998) being the biggest proponent of efficient market hypothesis, does not accept the idea that Behavioral Finance will ever discard or replace the efficient market theory. Anomalies found in asset pricing may be the result of data mining techniques, whose significance can be challenged. He argues that the Behavioral Finance models itself contradict with each other and thus cannot be generalized. People weak in statistics who tend to accept anomalies without any logic or reason finds Behavioral Finance an interesting subject.

Researchers in Behavioral Finance also does not seem very sure about their findings and thus hesitate to take credit of the research. Shefrin (2000) states *"We don't have enough professionals who have been trained in both academic psychology and traditional finance, so the models they're putting together are ad hoc. They're only thinly veiled by psychology studies of how people think, and they're inconsistent with one another"*.

Despite of all this criticism, Behavioral Finance is still in picture and research is going on to prove its significance in decision making along with the fundamentals. With the passage of time, people are not only discussing this field of study but also getting convinced and shifting their attention to this new paradigm.

## 1.7 Behavioral Finance: A Future Perspective

Despite of all the criticism, importance of human behavior, emotions, and heuristics cannot be ignored for long. Stock market is run by the investors who are presumably rational enough in their decisions. However this is not a realistic view point since humans are always stimulated by their emotions, perceptions, and behaviors. Thaler (1999) predicts that in near future Behavioral Finance will no longer be a distant field of finance rather the economists and researchers will start accommodating as much "behavior" in their models as they will find around. "After all, to do otherwise would be irrational", Thaler (1999) states.

Bloomfield (2009) debates on traditional finance vs Behavioral Finance. Enlightening the future of Behavioral Finance in next twenty years, he states that along with traditionalists, three types of behaviorists will also exist. One, presenting behavioral modifications as a useful insight with increased predictive power. Second, who will emphasize the fundamental groundwork for highlighting the importance and usefulness of Behavioral Finance in distinct settings? Third and final group would be the one identifying finance settings where behavioral forces are weakly incorporated (for example decisions by individual managers in poorly functioning labor markets). These will be the researchers who will turn the focus of traditionalists to other fields as well, as they stop to resist to behavioral techniques and get convinced by new theory and evidence.

Now a days Behavioral Finance is no more an alien science rather most of the researchers are discussing and trying to explore new areas in this field. Most of the research is focusing on proving the presence of a particular bias and its effects on stock returns. Importance of emotions, perceptions, and behaviors has widely been accepted and efforts continue to relate these with any unusual move of stock market. To date most of the studies are focusing on stock market and its reactions only. Statman and Caldwell (1987) argue that not only the investors but the corporate managers are also faced with same biases in investment appraisal decisions. This paves new ways to the corporate Behavioral Finance. That is the models capturing investor irrationality should be extended to capture the managerial irrationality in corporate decisions as well (Fairchild, 2007). Overconfidence is the bias that has been discussed by many researchers in this regard.

In future, Behavioral Finance is expected to go beyond stock market. It's not only the investors that are affected by the biases rather corporate managers are also prone to same biases while making corporate decisions. Effects of heuristics and biases are expected to be analyzed in other financial decisions as well because wherever decision making involves humans, it is affected by same biases. Moreover in next 10-20 years behavioral factors will not be treated as something out of picture, rather they will be accepted and incorporated in the traditional finance models with same conviction and faith. So far Behavioral Finance is confined to developed markets only since sophisticated informed investors, excessive trading and large volume of business makes it easy to identify some pattern in decision making. However over the years this field of study would be found equally important and effective for the developed and under developed economies.

## 1.8 Gap Identification

Fama (1998) presented the idea that to challenge the most talked about efficient market hypothesis, a theory of Behavioral Finance is needed which must indicate behavioral biases which play their role in information processing and cause the same investors to under-react to some types of events and over-react to others. The expectation clock presented by Spellman (2009) is an effort in this regard in which he demonstrates the impact of environment on expectations and the market's under-reaction to negative stimuli in some situations and over-reaction to negative information in other. He relates the behavioral biases with the levels of inertia during different expectation phases of clock causing under and overreaction in market. So far it has not been segregated that whether over/underreaction of market is a consequence or it drives the investor to act in a biased manner giving birth to the volatility in market.

Anomalies found in market are basically the result of irrational behavior of the investors. This irrational behavior affects the market and leads to overreaction or underreaction of investors. Over and underreaction has now become a phenomenon much talked about. Similarly behavioral biases individually have been discussed and are still under lime light for research. These behavioral biases have not yet been prosecuted as the root cause or driver of the over/underreaction of market as a whole particularly in Pakistan's context. Existence of some biases has been tested in Pakistani Stock Exchange however, their relationship with under/overreaction on investors and market dynamics is still an area to be tested. Also there is room to question the given theoretical relationships between market reactions and underline biases.

There is a human tendency towards "overconfidence in ones beliefs". Moreover, people often rely on intuition when making investment decisions. The decision process is not based on carefully considered facts backed by numbers and evidence. Instead, investors make investment decisions based on the opinion of others. This stems from the need to conform. Do investors base their decision on "good stories" or stories that seem logical? All these aspects are yet unexposed and less attention has been paid to them. Thus insight is needed into the biases which not only governs the investor attitudes and decisions while making any financial decision but also discuss how these irrational behaviors affect behaviors of the market.

The fundamentals that constitute these biases vary in each environment. Support for these biases has been taken by the Psychology literature vastly in rest of the world. However, in an emerging market like Pakistan, where not only markets are volatile but also factors like religion, myths, culture, etc. play important role in decision making. Assessment of such fundamentals of behavioral biases needs to be highlighted to find out what role does these factors play in determining the market volume, volatility, and returns of market. Examination of the effects of biases on volatility returns and turnover in periods of over/underreaction can shed light on whether biases affect market in symmetric or asymmetric manner.

Most of the previous studies related to market efficiency discuss efficiency in context of rationality that is in which manner investors respond to any upcoming news in the market and how quickly information get reflected in stock prices. Many empirical studies have been found commenting on efficiency of equity market by analyzing impact of various events, financial health of firm, macroeconomic changes and much more on the stock returns. Studies are also found relating one bias at a time to the stock returns however, since a human is not necessarily hit by one bias at a time, paradigm relating more than one heuristic driven biases with not only returns but also with volume and volatility needs to be assessed. It is also yet to ascertain whether investors fail to outperform the market because of fundamental factors or due to the behavioral anomalies observed in the market.

Behavioral Finance allows the modelers to justify any new empirical result by relating it to any new bias supported by psychology. Since all the research so far is concerned with analysis of trading behavior in developed financial markets with fully aware sophisticated investors, there is a need to assess the investor behavior in emerging markets as well where some surprising evidences could be expected (Sarkar, 2010).

## 1.9 Scope of the Study

Behavioral Finance can be divided into two major attributes: Behavioral Finance Micro and Behavioral Finance Macro. Where Behavioral Finance Micro deals with the individuals effected by heuristics and their consequent irrational decision making, Behavioral Finance Macro focuses on the anomalous behaviors observed in the market due to irrational investors and how these market behaviors contribute to the under and over reaction of the market. This study covers both the branches of Behavioral Finance.

The study aims at highlighting the psychological factors that affect the thought process of the investors and lead them to make irrational decisions, leading to over and under reaction of investors and resultantly volatile market conditions. Market efficiency hypothesis can also then be challenged in Pakistan in light of the results obtained.

For this purpose, study takes into account the widely accepted heuristic driven biases that is anchoring and overconfidence bias and their impact over the market reaction leading to trading volume and volatility of the market. Since investor's reaction to any news is merely the result of existing market conditions as found by Docking and Koch (2005), the study also explores how market under or over reaction impact the existing state of returns, volume and volatility of market.

On the Macro side of Behavioral Finance, two widely observed market behaviors Herding and Disposition effect have been focused and their impact over the under/ over reaction of market have been analyzed. Thus the study combines the two phenomena that is Behavioral Finance micro and Behavioral Finance macro in one framework to assess their impact on the over/under reaction of market.

Behavioral Finance is an emerging field and all over the world. Focus of researchers is now shifting to the Behavioral Finance leaving other fields of finance aside. Behavioral Finance may be perceived as a blend of Classical Economics and Finance with Psychology and Decision Making Sciences. This study explores the criteria which investors follow to assign the weights to various factors before making an investment decision. Said criteria may differ with each other in similar situations which are also to be analyzed.

Whole economic system is based on the principal "Choice out of Scarcity". This principal applies to all the spheres of life including financial decisions. In making choice from these scarce resources, it is assumed that investors act rationally and also all the information necessary to make a decision are equally available to all. These two assumptions provide a framework to analyze the role one attribute over other by controlling for the concerned or impacting attribute which, despite being of vital importance, is in isolation till now and is getting perpetually ignored. This attribute is the investor and impact of his self-behavior on the investment process.

With the growing markets, anomalies are widely observed. Behavioral Finance tries to find the answers and reasons for these anomalies. This study relates to cognitive psychology of investors only which ultimately results in the over and underreaction of the investors and creates mispricing in markets. Thus we can deduce that various behavioral models described above (showing cognitive biases of investors) basically provides the basis; or more specifically, are the reasons for investor's irrational behavior in stock market. A detailed analysis is required whether these behavioral biases and heuristics provide the basis for irrational market reaction and what kind of reaction is observed for which bias.

## 1.10 Problem Statement

It is not only the fundamentals that governs the investment decisions rather human hopes, aspirations, perceptions, mental conditions, social factors, circumstances also have their impact on these decisions. The biases that affect Pakistani investor, the reaction it builds in market, and the way volatility and trading volume of market is affected needs to be ascertained.

## 1.11 Research Questions

This research will address the following questions.

- Whether Pakistani investors are rational in making investment decisions?
- Whether Pakistani stock markets manifest anomalous behavior?
- Whether heuristic driven biases contribute to the aggregate reaction of market?
- Whether market reaction drives the excess volatility in Pakistani financial market?
- Whether market reaction contributes to the trading volume of market?
- Whether Pakistani stock market can be declared efficient in light of heuristic biases, volatility, trading volume and market reactions?

## 1.12 Research Objectives

The major objectives of this research are:

- To test the rationality of Pakistani Investors in light of the heuristic biases.
- To explore the existence of anomalous market behavior in Pakistani markets.
- To investigate the role of heuristic driven biases towards the aggregate market reaction.
- To examine the relationship of market under/over reaction on excess volatility.

- To investigate the role of market reaction towards the Trading Volume of market.
- To test the efficiency of Pakistani market in light of heuristic biases, volatility, trading volume and market reactions.

## 1.13 Significance of the Study

There are various models in use that explains the determination of asset prices in stock market such as CAPM, market model, arbitrage pricing model etc. There is a view that anomalies whether calendar or financial observed in markets are basically the result of some shortcoming in these models and thus proves the market inefficient. Recent studies have found that human behavior also plays corner stone in the determination of asset prices. As all the participants are not rational enough to rely on information and cognitive approach of investors make them to take irrational decisions as well, it is ample to believe that behavioral biases can also serve as an anomaly to standard finance models. Humans are made up of emotions and this is the biggest factor that contributes to the increased probability of mistakes on the part of investor itself which results in false or biased expectations of returns to be earned in future by manipulating the actual picture today, leading to mispricing of securities in the market.

Thoughts, aspirations, perceptions, wishful thinking of investors plays a key role in decision to invest. The way investors think is replicated by all its strategies which may coincide with rest of the market. This study will add to existing literature by identifying the existence of behavioral anomalies in Pakistani Stock market and to highlight its relationship with returns, turnover and volatility by commenting on market efficiency.

It was in late 70's when efforts started to find out the ability of prices to reflect the available information. Then in 80's direction changed and efforts to prove inefficiency of information started. Much has been worked out on the volatility of stock prices with respect to the specific calendar time as they are considered a root cause for inefficiency of market. This study would be a new step in this regard i.e. to identify the psychological and behavioral reasons to explain the momentum and reversals in stock prices, especially in long run. Since asset prices are widely affected by all kind of anomalies, validity of the entire generally accepted asset pricing theories would be questionable if behavioral anomalies are found in Pakistani market.

Similarly market volatility has been discussed in light of change in prices with any upcoming news. Studies have also related the behavioral biases with the excess volatility in market. This study is an effort to identify the path which is being followed to the excess volatility in Pakistani market. The cycle identified in study establishes how an irrational decision taken at individual level may transform into the market phenomenon affecting not only the market but also whole economy.

This study will help not only to understand the efficiency of Pakistani market in light of behavioral biases but also to understand the behavior of these biases with respect t different measures of markets. It has been found that state of market contributes a lot to the momentum profits (Cooper et al, 2004). Pakistani market has not been analyzed in this respect so far.

The role of behavioral biases in stock market has widely been discussed and analyzed in developed economies however, for a developing nation like Pakistan it's a relatively new area. The direction and nature of these biases and their effect on stock returns and their volatility has not yet been confirmed in emerging markets like Pakistan. The main purpose of this study is to explain the nature of behavioral biases and risks that drive risk premiums and irrational reactions in Pakistani Stock Market.

Behavioral Finance being a relatively new field has not so far been applied to market in depth. Behavioral Finance micro and Behavioral Finance macro deals with same thing in two different dimensions that is it segregates between individual response and market response. This study is an effort to combine the two branches by analyzing their impact over the market over and under reaction simultaneously. It is an effort in this regard to investigate how both the market and individuals contribute to the market reactions simultaneously in a setting like

Pakistani market. Since Pakistani market is an emerging market and also the factors like religion, customs, myths, economy affects the investors, a different picture may be seen in this regard.

Pakistan has also been faced with the extreme conditions throughout the sample period. Incident of 9/11 in 2001 has shook the Pakistani economy to the large extent. Foreign pressures have been increased, foreign policies have been changed, war on terror has started, and military operations to counter this war are in progress. Analysis of how the investors have assumed and reacted to this uncertain conditions, whether rationally or irrationally, is going to contribute to the literature regarding effects of war on terror on Pakistani economy providing us the reasonable grounds to understand the resultant stock market behavior.

## 1.14 Contribution of the Study

This study contributes to the existing body of literature by developing a model of decision making against Bayesian approach, induced by investor's multiple heuristic driven biases, by combining both, the Behavioral Finance micro and macro factors in one model. Also the behavioral biases have been expressed quantitatively: Overconfidence and Anchoring at micro level and Herding and Disposition Effect at macro level. The study identifies the path of how heuristic driven irrational decisions provoke market reactions which in turn transforms into excess volatility in market. The study also highlights the nature of relationship that the behavioral biases contributing to market reaction and trading volume hold towards excess volatility.

Behavioral biases, market reaction, market volatility and market turnover all are interlinked and runs a whole cycle that provides a platform to the market participants for the future forecast. Figure 1.2 explains the elements, through which biases exercised at individual level, transform their effects into whole market and creates momentum in Pakistani Stock Market which in turn affects the investment decision and make the market reactions prolonged and dense. Trading volume in addition to volatility and returns have been tested in relation to the heuristic biases and resultant market reaction to provide the insight to Pakistani investors in the biases and behaviors that they follow but are not aware of. Also it makes investors capable of eliminating the effects of biased decisions by following rational decisions and helps the policy makers to devise the policies to beat the behavioral anomalies and keep the market efficient enough.

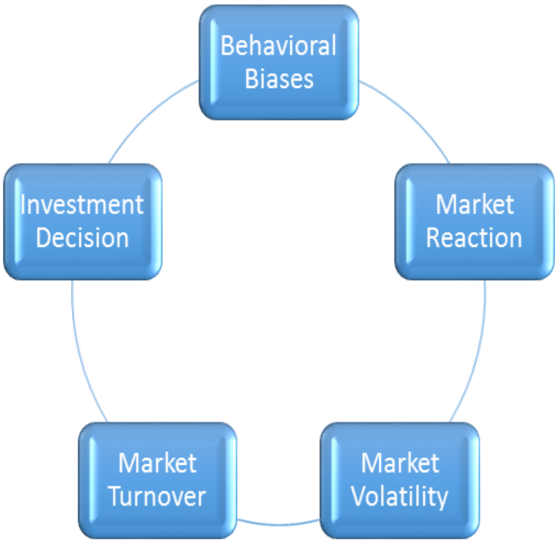


FIGURE 1.2: Market Force's Mechanism

## 1.15 Composition of the Study

Rest of the study has been composed as follows:

**Chapter II** reviews the literature regarding all the heuristic driven biases, market related biases, under/over reaction of investors, excess volatility and irrational behaviors and excess volatility and trading volume.

**Chapter III** provides the theoretical frame work for the study, develops testable hypothesis and describes the methodology to follow for testable implications.

**Chapter IV** discusses the results obtained after following documented methodology and accept/reject concerned null hypothesis.

**Chapter V** concludes the study by answering the research questions in light of results obtained.

# Chapter 2

# Literature Review

Concept of Market efficiency presented by Fama (1970) has been a point of interest for researchers for a long time. However, the discovery of certain anomalies doubted its validity in recent past. Research is now on to discover the behavioral reasons of anomalies. Whenever there occurs a mispricing in the market due to irrational behaviors and attitudes of investors, rational arbitrageurs are expected to push prices back to their intrinsic values, but this does not happen always. Limits to arbitrage prevailing in the market often make the arbitrage activity ineffective for putting market efficiency into effect. There are heavy transaction costs to arbitrage activity other than the risks involved. In case there are no sufficient investors to lend some specific security, extra borrowing costs also have to be borne by the arbitrager making it prohibitively expensive. Firm-specific risk cannot be completely and effectively hedged except some highly negatively covarying position is available.

Prices take time to revert back to their intrinsic value. This period may prolong for 3 to 7 years making arbitrage process ineffective in many cases (De Bondt and Thaler, 1985). When prices fail to revert to their intrinsic values in time, the supposedly rational arbitrageur with the decisions based on fundamental analysis, is found constrained and is forced to liquidate early sustaining forced losses. This unwanted liquidation in between the arbitrage process, compels the arbitrager to buy the already overvalued stock and sell the covarying position. This situation in turn worsens the anomaly.

## 2.1 Over/Under Reaction Hypothesis

### 2.1.1 Over Reaction Hypothesis

Two widely discussed and concentrated anomalies found in markets, related to investor behavior are overreaction and Underreaction of investors. One of the most initial works regarding market reaction is credited to De Bondt and Thaler (1985) who used monthly common stock returns data for NYSE from January 1962 to December 1982. They formed two portfolios of 35 stocks, one of past extreme winners in last three years and one of past extreme losers in past three years. Results showed that past losers happen to outperform winners in next 4 years. Returns to past losers were 19.6 percent high whereas returns to past winners were 5% down relative to the market in general that is asymmetric in nature (larger for losers as compared to winners). The study suggested that investors may cause market prices to deviate from fundamental values creating inefficient markets. Also a clear contradiction with Baye's rule was found as investors overreacted to unanticipated and dramatic news events. While making decisions, investors forget about mean returns reversion in long run which shows the overreaction of investors to past returns. Overreaction, on these grounds, can be justified as Behavioral Finance alternative to the traditional market efficiency (Fama, 1998).

Where De Bondt and Thaler (1985) supported the price-earnings ratio hypothesis confirming the overreaction of investors, De Bondt and Thaler (1987) re-examined winner - loser effect by implying firm size and differences in risk, measured by CAPM beta. Their findings were again consistent with the overreaction hypothesis. Seasonal patterns of return's investigation exhibited Excess returns in January as a function of short term and long term past performance and last year's market returns.

Alonso and Rubio (1990) investigated the behavior of the Spanish investor and his response to both very high and very low price levels. Following De Bondt and Thaler (1985, 1987) they also used the testing periods of twelve, twenty four and thirty six months. Their results were also in accordance with that of De

Bondt and Thaler (1985) that is portfolio of losers outperformed that of winners, confirming the overreaction hypothesis. However, the winners lost as much as the losers gained (Symmetric results). Similar pattern was found for earnings per share (EPS) and price earnings (P/E) ratio. Also no seasonal effect was found by them.

Lakonishok, Shliefer and Vishny (1994) provide another example of the overreaction of the investors. They took financial ratios as the indicator firm's performance. Stocks of the firms having high book to market ratio (BE/ME), earning to price ratio (E/P), and cash flow to price ratio (C/P) earns high profits. Some investors overreact to such stocks (that have done very well in the past). They perceive that these stocks will continue to earn good in future and thus they start buying them which make these "glamour" stocks overpriced. Similarly stocks of low BE/ME ratio, E/P ratio, C/P ratio firms earns low profits; investors expect their performance to be low in future and overreact to these value stocks. As a result they tend to oversell these stocks making them underpriced. Contrarian strategies succeed in outperforming the market because they invest disproportionately in underpriced stocks and under invest in overpriced stocks (De Bondt and Thaler, 1985).

In a psychological study, Kahneman and Tversky (1982) document individuals over-reacting to new information, whether good or bad. If over-reaction behavior occurs, profitable contrarian trading strategies, buying past losers and selling past winners can be formed. In this paper this strategy earned, on average, 25% abnormal returns over the period from 1980 to 1997.

Much has been worked on over reaction of investors in different markets all over the world. Evidences of overreaction have also extensively been found which has made it widely accepted phenomena. UK stock market has been studied in this regard by many researchers. Clare and Thomas (1995) studied UK stock market for the period 1955 to 1990 and found return's reversal over the two and three year period observing losers outperforming winners. They reported statistically significant but economically small overreaction effects in the UK equity market.

Campbell and Limmack (1997) also investigated the long-term reversals in the abnormal returns of UK companies during the period 1979 to 1990.

Evidence of overreaction has been confirmed for Canada, UK, Japan, Germany, France, and Italy (Baytas and Cakici, 1999), Brazilian equity market (Da Costa, 1994), Chinese stock market (He and Tan, 2009; Fang, 2013), Australian stock market (Leung and Li, 1998). Even for the emerging market such as Ukrain, overreaction of investors has been confirmed by analyzing short term price reactions in response to the one day abnormal price change (Mynhardt and Plastun, 2013). However, there are equity markets such as Australian equity market where no evidence of overreaction anomaly has been found (Beaver and Landsman, 1981). Also in US support for the overreaction hypothesis did not hold ((Baytas and Cakici, 1999).

Bowman, and Iverson (1998) confirmed the presence of short run overreaction in New Zealand market during the period 1976 to 1986. They tested the short term overreaction and its magnitude effect by using the weekly returns for all stocks listed on stock exchange. The results revealed overreaction for the losers with the evidence of greater initial price change followed by the greater return reversal confirming the magnitude effect as well.

### 2.1.2 Under Reaction Hypothesis

Cutler, Poterba and Summers (1991) reported positive autocorrelation in excess returns of stocks, bonds and foreign exchange in different markets over the period of 1960 to 1988. These autocorrelation evidences were consistent with the underreaction hypothesis, which states that information is gradually incorporated into stock prices.

Underreaction to returns can also be observed in market. Underreaction for a good news is stronger than that for the negative or bad news (Welfens and Weber, 2004). Jegadeesh and Titman (1993) for the first time documented strategies which buy stocks that have performed well in the past and sold stocks that have performed poorly in the past almost 3 to 12 months holding periods while using the data from 1965-1989. They found that stocks with higher returns in last one year tend to earn high returns in next six months also. They attributed this attitude to momentum effect. It means that stock prices react to high returns or earnings for about a year after they are being announced (Ball and Brown, 1968).

Schnusenberg, and Mdura (2001), investigated the short term over and under reaction of six US stock market indices (include Dow, S&P 500, NYSE, Sussell 3000, Wishire 5000, NASDAQ). They observed one day under reaction for winners and losers for all the six indexes. Extract of their study was an evidence of a sixty-day under reaction for winners. However, as the period is extended, abnormal returns for losers turned from negative to positive and showed significant reversals over the sixty-day period. Thus we may extract that market under reacts in short run and reverses its direction in long run.

Not only developed markets all over the world have been studied in search of underreaction evidence, but Asian stock markets have also been the area of interest for researchers. An extensive study of ten Asian markets that is Hong Kong, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Singapore, Taiwan, and Thailand has been conducted by Mazouz, Joseph, and Palliere (2009). Their examination of short term price behaviors following large price changes or "shocks" through OLS and GARCH methods for estimation of CARs found substantial discrepancies in the effects of shocks across the ten indexes indicating that the price reaction varies by country because investors process unexpected information in different ways. Their results supported return continuation in markets.

Rastogi et al (2009) analyzed adjusted monthly prices data for all NSE listed stocks on S&P CNX 500 index for the period of 1996 to 2008. By forming two portfolios of winners and losers based on average returns for prior "n" months, they found short term under reaction in Indian market, exhibiting momentum effect, and over reaction of investors in long run for mid-cap stocks only. Implying ANAR-TGARCH, Fang (2013) found that Chinese stock market underreact to good news and overreact to bad news, irrespective of the size.

Reversals have been associated with the market over reaction to information or contrarian strategy. Kelley (2004) analyzing weekly returns found that weekly winners outperformed losers for a full year in spite of the brief reversal. Since short run correctional reversals did not exist, it confirmed the evidence of under reaction in market. Evidence of systematic under reaction to both negative and positive information has been found by Stevens and Williams (2004) that is underreaction greater for positive information and lesser for negative information.

## 2.2 Biases Behind Under/Over Reaction

What makes the market to over or under react is the question of vital importance these days. Efforts are on to find the support for the reasons of market reactions. Investigating over reaction hypothesis for UK data, Clare and Thomas (1995) found that difference in performance among loser and winner portfolio was because of size effect since losers tend to be small cap companies that is small firms outperformed the big ones.

Barberis, Shliefer and Vishny (1998) presented "A model of investor sentiment" featuring mean reverting regime and trending regime for the formation of investor's expectations assuming that earnings follow a random walk. Investors believe that earnings would fall in any of two regimes and evaluate which regime they are in with every upcoming earning announcement. This cause them to either under react or overreact to the news. According to them investor's conservatism and representativeness bias makes them to under or overreact for news such as earnings announcement. Conservatism makes the Investor reluctant in updating their beliefs with every news (if it is in opposite direction to previous one) and causes underreaction in the market. Similarly if there is a series of good or bad news investors being victim of representativeness bias overreacts. Since investor sentiment has been the driving force behind all type of reactions, there is a need to investigate the sentiment driven extent to which investors can over or underreact (Gregaliuniene, 2013).

Reason for investor's over and underreaction has also been worked out by the researchers. Daniel, Hirshleifer, and Subrahmanyam, (1998) found that investor's over and underreaction is basically due to their self-attribution and overconfidence.

According to them Overconfidence refers to the negative long-lag autocorrelations, excess volatility, and public-event-based return predictability (if managerial decisions are correlated with stock mispricing). Biased self-attribution reflects positive short-lag autocorrelation, i.e. momentum and short-run earnings drift. Also the negative correlation between future returns and long-term past stock market and accounting performance have been found by them.

Whether overreaction or underreaction are conditioned on the extreme stock price variations had been declared as "informed event" or "uninformed event" in the Wall Street Journal (WSJ) has been investigated by Larson and Madura (2003). They observed that uninformed winners experience overreaction and informed winners do not because the release of public information reduces uncertainty. Daniel et al. (1998) also put forward that "stock prices overreact to private information but underreact to subsequent public information". These results for winners are also in accordance to the theory of overconfidence and self-attribution bias.

Momentum has also been presented as the root cause of under reaction (Chan et al, 1996). Momentum is observed due to slow updation of beliefs which causes the investor to under react since it takes a long way for asset prices to reach to its true value. Hong and Stein (1999) by analyzing two groups that is news watchers and momentum traders held that there is single type of shock that drives everything in the model and that is slow diffusion of news about future fundamentals. News watchers observe their private information whereas momentum traders follow past price changes. Their model shows that when only news watchers are into the picture, there is underreaction but when momentum traders are also added to model, overreaction is found. This implies that if there is any short run underreaction to this type of shock, it will ultimately result into long run over reaction of investors. Investor's overreaction in long run is explained by the over confidence bias where over confident investors tend to extrapolate a series of good or bad news.

Du (2002) presented their model based on different confidence levels of heterogeneous investors. According to them the investors with higher confidence level treats every news/earning announcement as permanent and start buying the stocks leading to increase in trading volume and returns. This in turn increases the confidence level of low confidence group of investors and they also start buying the stocks. Thus slow updation of news leads to short term positive autocorrelation of returns and thus under reaction in market. The news arrived may only be transitory but investors with different confidence level considers it permanent. Prices over shoot and then after corrections revert back to fundamental value. This provides the evidence of overreaction. Underlying behavioral/psychological attributes for this phenomenon is biased self-attribution and confirmation bias that is looking for confirming evidence only and attributing all the success with self-decisions. Both leads to increased confidence level which results into overreaction. This also supports the market behavior influenced by herding that is low confident investors following trend of market and leading to overreaction in long run.

Frazzini (2006) investigated the underreaction phenomena in order to find possible explanations for the post earnings announcement drift. His study presented disposition effect as the main course for explaining underreaction. The tendency of investors to carry forward the losses and realizing gains at the moment contributes to the post earnings announcement drift as well as underreaction of investors. Investors more desperate to attain gains, delay the information dissemination and thus makes the adjustment process of prices slow.

Aguiar, Sales and Sousa (2006) proposed a model based on fuzzy sets which they believed is closest to Behavioral Finance. Two separate portfolios were formed for the petrol/petrochemical sector and textile sector. Stocks from petrochemical sector exhibit overreaction for Brazilian stock market whereas Textile sector stocks exhibit underreaction.As described by behavioral fuzzy model, the reason behind these two reactions is representativeness and anchoring bias.

Other studies have pointed towards other factors like self-attribution self-deceptions, emotion-based judgments, framing effects, and mental accounting (Daniel et.al. (2002) which affects the investor psychologically while making decisions and plays their roles in asset pricing.

## 2.3 Heuristic Driven Biases

### 2.3.1 Self-attribution and Over Confidence

Psychology literature supports the idea that people tend to overestimate their own capabilities and wrongly attribute the success period with their own strategies. Mark Alicke, a professor of Psychology, Ohio university while describing human psychology stated that tendency of assuming oneself better than the other average people is very common. They called it the "staple finding of Social Psychology" Alicke et al (2001). There is a fine line defined between confidence and overconfidence. Confidence implies realistically trusting in one's abilities, while overconfidence usually implies an overly optimistic assessment of one's knowledge or control over a situation.

Werner De Bondt and Richard Thaler are among those academicians who formulated the concept of Behavioral Finance. This tendency of feeling privileged than others has strongly been supported by De Bondt and Thaler (1995) declaring overconfidence as "the strongest finding in the psychology of judgment". It is the investor's overconfidence that makes them believe that they can control the outcomes. Langer (1975) first time introduced this phenomenon as "illusion of control", i.e. a case when expected probability of personal success exceeds the probability of objective outcomes.

Daniel, Hirshleifer, and Subrahmanyam (1998) formulated the idea that investors are not perfectly rational. They combined two behavioral regularities to explain the pricing anomalies, i.e. overconfidence and self-attribution. Biased self-attribution leads to the overconfidence and consequently to the under reaction for public information whereas overreaction to the private information. These over and underreactions, followed by the corrections to fundamentals, leads to the excess volatility in market. According to their overconfidence theory, Investors over estimate their own abilities and stock valuation and under estimate their forecast error variance. This implies that Investor's attribute any profit to their own stock picking ability and any loss to their bad luck. Biased self-attribution says that

Investor confidence grows when public information confirms his private information, sustaining overreaction in market, but conversely this confidence does not fall when public information contradicts its private information. The reason being investors always blame the external factors for their failures and credit themselves for all the successes (Langer and Roth, 1975; Taylor and Brown, 1988; Miller and Ross, 1975).

Findings of Daniel Hirshliefer and Subrahmanyam (1998) were also tested by Cremers and Pareek (2011) by implying two novel proxies for overconfidence and self-attribution of investors. Since trading behavior has a strong relationship with overconfidence (Odean, 1999; Barber and Odean, 2000) proxy for overconfidence taken by Cremers and Pareek (2011) is Stock Duration (that is institutional holding duration based on their quarterly portfolio holdings) and that for self-attribution, the proxy is the superior performance of institutional investors which cannot be explained by market, size, value or momentum. Their findings supported the existence of momentum returns, return reversals and share issue anomalies for the stocks traded by short horizon traders with good performance history.

Self-attribution is generally associated with overconfidence of investor. It is the overconfidence of investor in his strategies which makes him to relate all the successes with personal efforts and all the failures with some external factors (Weary-Bradley, 1978; Miller and Ross, 1975). It is merely the overestimation of self-abilities or biased estimation of themselves. Bem (1965) presented attribution theory stating that individuals tend to strongly attribute events that authenticate the strength of their actions to their own high abilities and events that disconfirm their decisions are attributed to external noise.

Self-attribution makes the investor overconfident due to consistent success in trading (Statman et al, 2004). "$\cdots$ it is successful traders, who are the most overconfident. Overconfidence does not make traders wealthy, but the process of becoming wealthy can make traders overconfident" (Gervais and Odean, 2001).The overconfident investor relies too much on its own information and do not rightly judge the precision of this information (Soll and Klayman, 2004). This phenomenon is termed as "miscalibration" since the probabilities assigned by investors are hardly in line with the actual probabilities. Where miscalibration leads to the unjustified excessive trading which may lead to the reduced profitability (Barber and Odean, 2001), overconfident investors may also outperform rational investors since they assume higher risk with higher expected returns.

Any public information found confirming the private information, creates overreaction in market. Continued overreaction generates momentum in security prices. However in long run, as further public information arises, prices tend to revert. Thus biased self-attribution can lead to short term momentum and long term price reversals (Daniel, Hirshleifer, and Subrahmanyam, 1998).

When an investor receives some information that confirms his actions or decisions, his confidence rises and belief on personal abilities strengthens. This results in increased trading volume. Statman, Thorley and Vorkink (2004) found that as the stock returns grows; Level of investor's overconfidence also grows with the stock returns. Investor attributes this increase to its stock picking ability which induces him to further trade. Thus overconfidence leads to increase in trading volume (Barber and Odean, 2001) along with the stock returns. Here it is also noteworthy that people who has great knowledge and are considered experts of their field are more overconfident than the relatively inexperienced man (Griffin and Tversky, 1992).

The increased confidence leads to the momentum in the market. Also due to confirming public information, investor overreacts to his personal information. Wang (1998) and Odean (1998) without identifying the nature of information i.e. whether it is private or public, found overconfidence a result of information precision. Since overconfident investors generally conduct more trades than their less-confident counterparts, this excessive trading due to overconfidence leads to overreaction in markets in form of excess volatility and negative return autocorrelation (Odean, 1998).

Bertella et al (2017) investigated overconfidence bias by analyzing fluctuations in stock prices and their rates of return in an artificial stock market composed of fundamentalists and chartists. Their study found that confident chartists created more fluctuations in stock prices as compared to those who were not confident.

The study concluded on a self-drawn confidence index that stock prices effects confidence index but confidence index is not affected by the stock prices.

Garcia et al (2007) studied effects of behavioral biases in financial markets by assessing the response of rational traders on the overconfidence of irrational traders by joining two main characteristics of market, i.e. coexistence of rational and overconfident traders and endogenous information acquisition by agents. Their results revealed that in response to overreaction of irrational traders (due to their overconfidence), rational traders cut down their own demand for information, in order to balance out the effect of overconfidence on the rational agents' expected profits and welfare. It means that overconfidence of few investors has negative impact on the number of rational investors. However, trading volume, market depth and price informativeness always positively increases in case of overconfidence of investors (Barber and Odean, 2001; Benos, 1998; Odean, 1998; Kyle and Wang, 1997).

Abbes, Boujelbene and Bouri (2009) investigated four inter related phenomena of over confidence using French stock market data. Using a VAR model they found that overconfident investors tend to overreact to private information and underreact to public information. Granger-causality test found that investors, realizing gains, trade more aggressively and thus increases trading volume. A two GARCH model implied provided the evidence of self-attribution bias leading to increased investor over confidence and trading volume. And finally the analysis of relationship between return, volatility and trading volume found excessive volatility as an outcome of excessive trading of over confident investors.

Odean (1998), and Gervais and Odean (2001) hypothesized that high returns leads to high trading volume. The reason they pointed out is overconfidence of investors. However, their theories did not explain lead lag relationship between stock returns and trading volume. The lead lag relationship has been examined by Harris and Raviv (1993). He examined the lead lag relationship of concurrent return volatility and trading volume. Relationship between trading volume and returns has also been found by Karpoff (1987), Bessembinder, Chan and Seguin (1996), Chordia, Roll, and Subrahmanyam (2000), and Lo and Wang (2000). Lee and Swaminathan

(2000), Llorente et al (2002) also focused on trading volume as a tool to forecast future returns.

Investors prone to biases tend to underreact for any new information and keeps on following the prior signals. This biased information processing, in turn generates momentum in returns (Daniel, Hirshleifer, and Subrahmanyam, 1998; Hong and Stein, 1999; and Barberis, Shleifer, and Vishny, 1998). Different biases have been highlighted in this regard. Daniel, Hershliefer and Subrahmanyam (1998) associated biased self-attribution with the momentum returns which is considered to be a form of confirmation bias (Rabin and Schrag, 1999; Hirshliefer, 2001). Self-attribution leads to overconfidence which combined with anchoring and adjustment, makes an investor to exhibit conservatism and thus generates momentum in market by underreacting to upcoming information.

Park et al (2010) discussed confirmation bias and overconfidence simultaneously. The hypothesized that confirmation bias would make the investors over confident about their decisions and thus trading volume and investor's expectations would rise whereas realized returns would be low. After analyzing 502 investor reactions on largest message board, they confirmed the presence of confirmation bias and resulting over confidence in South Korea. Overconfident investors make more judgment and investment errors (Barber and Odean, 2001). While discussing role of confirmation bias in belief formation, Rabin and Schrag (1999) also found that confirmation bias can lead to overconfidence of investor which is reluctant to learn about the state of nature even if enormous amount of information is available.

Evidence of Over confidence bias has also en confirmed by the Metwally and Darwish (2015) in Egyptian Stock Market concluding that there is a significantly positive impact of overconfidence bias on trading activity that is trading activity increases with investor's overconfidence. Jlassi et al (2014) examined overconfidence as a main driver behind prolonged global financial crisis in eleven advanced markets, Four Latin American markets and seven Asian markets from all over the world. The study provided the evidence of the strong overconfidence in advanced markets as compared to the emerging markets under study, in both up and down states of the market. The evidence could not hold for some Asian and

Latin American markets though. By analyzing the daily return and turnover data of twenty seven companies, overconfidence bias has also been found important for the analysis and understanding of Tunisian financial market (Adel and Mariem, 2013).

### 2.3.2 Anchoring/Adjustment

Daniel Kahenman and Amol Tversky are the two Israeli non economists, who defined anchoring for the first time in their paper "Judgment under Certainty: Heuristics and Biases" in 1974 in following words: *"In many situations, people make estimates by starting from an initial value that is adjusted to yield the final answer. The initial value, or starting point, may be suggested by the formulation of the problem, or it may be the result of a partial computation. In either case, adjustments are typically insufficient That is, different starting points yield different estimates, which are biased toward the initial values. We call this phenomenon anchoring"*.

In order to use anchoring while making financial decisions, anchor used must be accurate and relevant otherwise whole judgment will go in wrong direction. Decisions base largely upon the point from where individual has started and thus it may be biased towards initial point (Tversky and Kahneman, 1974). Adjustments are then made to this initial point and final decision is made but adjustments are always insufficient (Lichtenstein & Slovic, 1971).

Different studies have found evidences of anchoring in different parts of the world by implying different proxies to explain the most valid and appropriate anchor. For example Campbell and Sharpe (2009) found that forecast of macro-economic variables such as CPI depends upon their previous values. Survey data of Meredith et al (2007) developed that long run inflation expectations are significantly anchored in Euro area and U.S. However for U.S data, great dispersion was found among long run forecast.

Kaustia, Alho, Puttonen (2008) conducted a controlled experiment with 300 Scandinavian financial market professionals and 213 university students by manipulating background information. Their results found a large anchoring effect in students for the long term stock returns expectations whereas a small but significant anchoring effect in professionals. They held that professionals are not much affected by historical values while making forecast. Evidence of anchoring bias in Pakistani as well as Malaysian Stock market has been found on the basis of primary data collected from investors by Khan et al (2017). Investors most commonly use historical average of firm as an anchor while assessing the future performance of the firm (Cen et al, 2013).

Rationality hypothesis states that investors give less importance to new information and stick to the old one. Nordhaus (1987) found for macroeconomic variables that one-step-ahead professional forecasts were anchored to the previous month's two step ahead forecast. When forecast moves around the previous month forecast and the trend continues month to month, investors may use long run average value of data release as anchor (Campbell and Sharpe, 2006).

When it comes to the estimation of future performance of the firms, anchoring again plays its role. Cen et al (2010) while investigated impact of anchoring bias on efficiency of financial markets stated that analysts uses industry median EPS as anchor to forecast firm's future profitability. Their results found that for firms with low forecasted EPS, relative to industry median EPS, earning forecast is more optimistic as compared to the similar firms having high forecasted EPS than industry median EPS. Also the stock returns for high forecasted EPS were high. They further added that these high returns are not due to risk factors, or momentum effect, or book to market ratio etc. rather they are the result of high forecasted EPS by firms relative to the industry median EPS.

Campbell and Sharpe (2009) found significant evidence of anchoring hypothesis for monthly economic releases from Money Market Services surveys for period 1990-2006. Their results revealed biased expert consensus forecasts towards the value of previous months' data releases. Also they found strong evidence of the reaction of bond yields to the unpredictable component of the information only which means that bond yields are not affected by the forecast error provoked by anchoring.

Given the markets over or under reacting to new information, Anchoring bias has also been associated with market reaction along with other behavioral biases. Anchoring and adjustment leads to the underreaction of market. However, the predictions made in this case are excessively moderate. The extent to which anchoring and adjustment influences the prediction made, depends upon the importance of anchor (Amir and Ganzach, 1998).

When it comes to investing, 52-Week high and 52-Week low for a stock is largely used as an anchor since people assume a stock will go back to its 52-Week high and will not go beyond its 52-Week low (Ben, 2009). Literature has identified historical high as the frequently used anchor for future predictions (Li and Yu, 2009) as well as 52-Weeks-high has also been supported as an important anchor (George and Hwang, 2004; Li and Yu, 2009; Kartano, 2013). Future month forecasts largely depend upon the previous month figures since that are the only information currently available for future decisions. If any such tendency is found, previous month figures can comfortably be used as anchor (Campbell and Sharpe, 2006). However, prediction power of nearness to 52-Week high for future returns has been found much larger than the past returns by George and Hwang (2004). Also they held that future return forecast using 52-Week high does not revert in long run which implies that 52-Week high is more closely related to underreaction to information. Since investors in this way react slowly to new information, 52-Week high can reasonable be used as an anchor for evaluation of stock price increments.

Anchoring and over confidence are the two biases that provide basis to investors to underreact to new information (Fuller, 2000). In the absence of any new and reliable, relevant information, past stock prices is considered as anchors to determine today's prices. The stock market underreacts to the fundamental information whether it is dividend omission, initiation or an earnings report (Montier, 2002). "If the analysts are overconfident and also anchored to their most recent estimate, they may be reluctant to give as much weight as they should to the information in the current earnings announcement and not raise their estimate" (Fuller, 2000).

George and Hwang (2004) found that nearness to the 52-week high is a better predictor of future returns than are past returns as the price level itself can better explain the momentum effect as compared to price changes. Explaining the behavioral implications of theory they stated that 52-Weeks high prices of a stock serves as an anchor or reference point to make adjustments to forecast the future returns. Any stock found near its 52-Week high means that good news has already been arrived in market. For such stocks investors are not likely to bid even if upcoming information confirms future increase in prices. Eventually the information spreads and the prices go up. Similarly for a stock price near 52-Week low, investors are more likely to buy the stocks rather than selling the stock at low price. However, with the spread of news in market, the prices tend to fall. Same are the findings by Grinblatt and Keloharju (2001) and Kartano (2013) for OMX Helsinki stock exchange.

Stocks close to their 52-Week highs tend to outperform because investors use the 52- week high as an “anchor” against which they assign the value to the stocks. Thus they tend to be reluctant to buy a stock as it nears this point regardless of new positive information. As a result, investors underreact when stock prices approach the 52-week high and thus, contrary to most investors’ expectations, stocks near their 52-week highs are found to be systematically undervalued.

Li and Yu (2009) further added that nearness to the 52-week high as proxy for underreaction, positively predicts future returns whereas nearness to the historical high being proxy for overreaction, negatively predicts future market returns in short horizon of about 1 - 12 months. These two proxies when combined with macro-economic variables predict 46% of market returns, reason being stock market’s underreaction to discontinuous news, and overreaction to a series of news. Current price of a stock near to the 52-Week high depicts under reaction of the market to some good news whereas current price far from 52-Week high predicts under reaction to a bad news. On the other hand stock prices near/far to historical high depict overreaction to some prolonged good/bad news.

In different market settings the biases may act differently. Same piece of information in the context of two different biases may give different results. A positive earnings announcement or any information regarding value of the stock may cause over reaction in the market as per representativeness theory but at the same time it may act as a driver of underreaction of market influenced by anchoring such as persistent trading at a low price for an extended period might lead to an underreaction to the announcement due to anchoring at the lower price that has been established during the trading period (Caginalp et'al, 2010).

## 2.4 Market Anomalous Behaviors

### 2.4.1 Herding

According to Bikhchandani and Sharma (2000) herding behavior is the intention of investors to replicate the behavior of other investors. Herding can provoke a mispricing of securities because of biased opinion / expectation of expected risk and return and causes trouble for rational decision making (Chang, Cheng and Khorana, 2000). Herding normally emerges in the period of huge price movement or market stress. Institutional investors have a major impact on the price movement, it is surprising to notice that the institutional investors also herd, although they are considered to be the most sophisticated and well equipped with their personal information as compared to the individuals. Christie and Huang (1995) argue that investors are more likely to suppress their private beliefs in favor of consensus during periods of unusual market movement. The intensity of herding increases with the information risk (Boortz et al. 2013).

Bikhchandani and Sharma (2000) identified three reasons for why institutions herd? First, other market participants may have information about the returns on a particular investment and their trading strategies may also expose this information. Secondly the incentives plan and terms of employment under which money managers (particularly those who invest on behalf of other investors) are paid, may encourage and reward the replication. And finally, investors may have an inherent desire to conform their actions.

Different researches have given different theories why investors herd? It is held that investor's attraction for similar securities with similar attributes like historical returns, size and liquidity may be just a coincidence (Gompers and Metrick, 2001; Falkenstein, 1996). Another important element explaining herding behavior is the fashion (Barberis and Shleifer, 2003). Herding behavior is most common in investors, managers, portfolio managers, analysts etc. because normally their compensation depends upon their performance (Trueman, 1994; Scharfstein and Stein, 1990). In order to show high performance or accurate forecast, they have a feeling not to differ from other's opinion. Especially when analysts feel themselves less capable of making forecast, they prefer to copy what highly capable analysts have judged even if their available information fails to confirm that forecast (Trueman, 1994). If investors are short of time to collect and analyze information, especially in financial panic periods, or if the cost of acquiring information is high investors feel like herding as observing and following the predecessor's actions is almost free, in extreme market conditions (Kultti and Miettinen, 2006).Another reason behind herding documented by Subash (2004) is the increased confidence of investors on the collective judgment. They perceive it unlikely that a decision by masses can go wrong.

Another factor contributing towards herding is that investors or analysts tend to believe on the consensus forecast i.e. what is agreed by most of the analysts as true (Gallo, Granger, and Jeon, 2002; Lamont, 2002; Clement and Tse, 2005). However, as analysts use almost same time frame and same set of information for making forecast, there are greater chances that they make same forecast generating consensus in market. Thus having consensus cannot necessarily show herding behavior (Zitzewitz, 2001).

According to the Prechter and Parker (2007) herding may be because of uncertainty about valuation. The investors who have financial crises may not have sufficient time to collect and analyze information from raw data; hence investors may go for herding during financial panic. Also if the information required for valuations is not freely available, people will prefer to rely on their own signals.

Every agent in the market has to pay some price to acquire the information about their predecessor's actions however, observing other agent's action is absolutely free. When no price is associated to observing, investors are likely to herd. Nevertheless with the introduction of small observation cost, herding gets discontinued (Kultti and Miettinen, 2006). During extreme market situations information disseminates in its due time but investor's do not have much time to acquire information first and then decide. Thus they tend to herd in extreme market situations where there is either no information is available or it is costly.

Jegadeesh et al. (2004) argue that the normally analysts gave high value to those stocks which have positive momentum, higher growth and volume which also contribute in making the stocks expensive. It can be argued that herding is an irrational behavior which is strengthens by low information. Low turnover stocks have highly been associated with the lack of information available. Since there is no cost to be paid for observing market, low turnover stocks yields more evidence for herding as compared to high turnover stocks (Fu and Lin, 2010; Gregroriou and Ioannidis, 2006).

Jegadeesh and Kim (2006) investigated whether sell-side analysts herd around the consensus when they make stock recommendations. Their results showed that when the new recommendation is different from the consensus, stock price reaction to that recommendation revision is greater than when recommendation is closer to consensus. This shows that market has the ability to recognize herding behavior. Same results were found by Clement and Tse (2005) and Gleason and Lee (2003).

Hachicha et'al (2008) tested international herding as a reason of "home bias" phenomenon by adjusting ICAPM. Holding all the domestic assets being aware of the benefits of international diversification is known as "home bias equity". He developed a new tool "international dynamic herding" and evaluated its impact on euro zone financial markets. Results found strong relationship between market return and herding behavior. Also ICAPM improved drastically when adjusted for herding and herding as psychological bias provided the justification for home bias phenomenon for euro zone countries.

Chang, Cheng and Khorana (2000) investigated the behaviors of market participants, specifically herd behavior, in international markets. They developed a measure CSAD, i.e. Cross sectional absolute deviation to find out the relationship of level of equity return dispersion and market returns. In case of presence of herd behavior, CSAD has to decrease or increase at decreasing rate. Their results found no evidence of herding by market participants in the U.S. and Hong Kong. Partial evidence of herding was found in Japan. South Korea and Taiwan are the markets where investors were found to be significantly involved in herd behavior. They also held that macroeconomic information had more influence on investor's behavior and tend them to herd rather than firm specific information.

Herding behavior has been found in china's A and B share markets (Zhou, 2007) and a little evidence for market wide herding in Australian equity market (Henker et al, 2003). By using the CSAD measure, some evidence of herding has been found by Demirer et al (2007) in Asia and Middle East but no evidence has been found in Africa, Western Europe, Eastern and Central Europe, and Latin America. Evidence of herding has also been found in Shanghai and Shenzhen stock exchanges by Demirer and Kutan (2006) however, results of herding behavior tested for same stock exchanges by Tan et al (2007) failed to find any such evidence. National stock exchange of India has been declared efficient by Prosad, Kapoor and Sengupta (2012) since no evidence of herding has been found there. However, herding test for periods of market stress found some evidence for bull phase. Ahsan and Sarkar (2013) also did not find herding in Dhaka stock exchange for daily and monthly returns for the period 2005 to 2011 inferring that investors in Dhaka are rational enough to make investment decisions based on available information rather than following market consensus.

Lao and Singh (2011) tested for herding behavior in Chinese and Indian Stock market. Their findings were that although both, Indian and Chinese stock markets are considered inefficient and have low information disclosure standards, herding behavior found in Chinese market is greater than the herding behavior in Indian market. However in both the markets, herding behavior is stronger in large market movements. Asymmetry test revealed Chinese stock market have more profound herding behavior when market is low and trading volume is high. On the other hand, herding behavior in Indian market is observed when market is high. Also herding behavior in Indian market had no relationship with trading volume. Reasons for herd behavior existing in Chinese stock market, in both up and down states, are analyst recommendation, short-term investor horizon, and risk involved in decision making (Chong et al, 2016).

Javed, Zafar, and Hafeez (2013) recently investigated herding behavior in Pakistani market. Stocks in KSE 100 index were analyzed for their monthly returns. The results found that there exist no support for herding behavior in Karachi stock exchange. Usually the studies found no evidence of herding posits that investors are rational. But for a country like Pakistan it is difficult to assume therefore it was suggested by the study that a more deep and comprehensive study should be conducted. Also herding is a short term phenomena and so should be examined at short intervals.

Christie and Huang (1995) tested herding by analyzing CSSD, i.e. cross-sectional standard deviation of returns. According to him if investors do not rely on their own market judgments during period of high volatility and follows the market trend, value of CSSD will be low as individual security returns will not much deviate from rest of the market. Same model of Christie and Huang (1995) based on cross sectional volatility of returns was implied by Kapusuzoglu (2011) to Istanbul Stock Exchange, National 100 index and found increase in cross -sectional absolute deviation with the increase in index returns. The results found that index return rises in the rising days of market and thus cross sectional volatility increased both in up and down markets however, the response is non-linear.

Noise in financial markets makes the stock prices deviate from their fundamentals. One source of noise in financial markets is herding (Delong et'al, 1990). Filip et al (2015) held herding behavior responsible for the speculative bubble deviating from the fundamentals. Herding beyond fundamentals explains the probable reason for momentum strategies and ultimately results in investor's overreaction. Intensity of herding is positively related to momentum returns. A firm-quarter-specific measure of speculative intensity (SPEC) used to measure herding implies that higher the value of SPEC, greater is the chance that investors will expect more participation of investors in same directions and thus are motivated to trade actively. This provides the chances to earn profit due to short term momentum. Low value of SPEC cannot generate such rounds of buying and selling and thus no momentum is created (Delong et al, 1990).

Brown, Wei, Wermers (2007) investigated two major issues that is whether mutual funds herd or simultaneously trade in the direction similar to the analyst recommendation revisions even when new revisions are released and second, what impact does such revision-induced mutual fund herding have on stock prices. Examining U.S equity mutual funds for period 1994-2003 it is revealed that mutual funds herd on analyst recommendation changes and the resultant trading impacts stock prices by generating overreaction in market. Fund managers overreact to the information embedded in the consensus signals of analysts. This revision induced herding implies that fund managers herd for some reasons other than the "information".

Hoitash and Krishnan (2008) investigated impact of noise on market returns where noise refers to herding (acting beyond what is justified by information) by investors. They also used firm-quarter-specific measure of speculative intensity (SPEC) based on autocorrelation in daily trading volume adjusted for the amount of available information as a proxy of herding. By finding significantly positive relationship between returns and speculative intensity, it was established that high-SPEC firms yield high returns to momentum trading strategies and also investors overreact significantly to high SPEC firms.

Fu and Lin (2010) investigated whether turnover rate have any effect on herd behavior or not. Their results found the significant turnover effect for low turnover stocks as compared to high turnover stocks. Low turnover stocks are not very attractive for the investors and thus no or less information about these stocks arrive at the market. Due to lack of information, investors find it reliable to herd whereas this is not the case with high turnover stocks (Gregroriou and Ioannidis, 2006). Influence of Low trading volume has also been tested on herding behavior by Kallinterakis and Lodetti (2009) for Montenegro new securities exchange for the period 2003-2008. However, their results found no such relationship.

Moreover herding drives the stock prices away from their fundamental values, creating momentum in the market that is winners keep on earning good and vice versa unless some correcting information arrives in the market or mean reversion starts. While investigating joint effect of herding and momentum effect, it was found by Yan et al (2012) that low level herding in investors, at industry level, magnifies the momentum effect. Existence of this momentum not only challenges the validity of EMH but also highlights the overreaction of investors to the public signals. Cooper et al (2004) associated stronger momentum effect in up market conditions with the overreaction of investors and stated that momentum effect will ultimately reverse in the long-run since the market eventually corrects its mispricing.

### 2.4.2 Disposition Effect

Buying and selling decision of investors usually depend upon the future price expectations of the stock rather than past price performance. However, behavioral theories imply that investor's decision to sell and buy depends upon past performance of stock, compared with some reference point. Prospect theory presented by Kahneman and Tversky (1979) states that people prefer gains over losses, i.e. they tend to choose the options which either does not have chance of loss or very minimal losses, calculated from some reference point, are there. The logic behind this risk averse behavior is people assign less weights (with reference to the context) to the outcomes with uncertainty which is something against the basic expected utility theory (depending on probability).

Traditionally, the stocks which are expected to fall in value in future are sold and stocks whose value is expected to rise in future are bought by the investors. When it comes to Behavioral Finance, as stated by prospect theory, people calculate their actual losses and gains from the point they have acquired that stock. The stock appreciated in value, from its time of purchase, is sold by investors to realize actual gains. Those who depreciated in value are considered as losses and thus retained until they convert into actual gains. This tendency was named as disposition effect by Shefrin and Statman (1985).

This trend is observed in many stock markets of the world. Grinblatt and Keloharju (2001) examined five investor categories i.e. households, non-financial corporations, financial and insurance companies, government and non-profit institutions and foreign investors in Finland. Leaving foreign investors at a side (due to shorter time period, and low turnover) for rest of the categories they found that Finnish investors do not tend to sell a stock realizing capital loss. Odean (1998) found a strong evidence of disposition effect by analyzing 10,000 accounts from 1987 to 1993 in USA. Jackson (2004) also reported that in Australia, stocks with positive returns are more likely to be sold by individual investors which confirm the presence of disposition effect. Choe and Eom (2009) found disposition effect in Korean stock index futures for all individuals, institutions and foreign investors. Cekauskas et al (2011) analyzed Estonian Stock market and found the evidence of Disposition effect. Li et'al (2014) formulated a multi agent model, classifying agents into chartist, fundamentalist and inactive traders on the basis of trading strategies, to investigate investor behavior with respect to the Chinese financial market. The results found disposition effect revealing asymmetric volatility in Chinese mainland market that is volatility is more affected by bad news as compared to good news.

Barber et al (2006) analyzed all trading activity (over one billion) by about four million traders, on the Taiwan Stock Exchange (TSE) for the period of five years ending in 1999. According to their study, Eighty-four percent of all Taiwanese investors sell winners at a faster rate than losers. An analysis of different investor classes further explained that Individuals, corporations, and dealers in Taiwan are generally hesitant to realize losses as compared to mutual funds and foreigners which do not show this tendency. However, this group forms only less than 5% of total trades. Overall investors in Taiwan are about twice as likely to sell a stock if they are holding that stock for a gain rather than as loss.

In order to test disposition effect Weber and Camerer (1998) conducted experiment by analyzing subjects in fourteen periods. Subjects were allowed to buy and sell in six risky assets before the beginning of each period. Prices of these stocks were then fluctuated in each period without having any concern with the sale and purchase activity. The objective behind was to isolate disposition effect from price formation process. The experiment showed that subjects had tendency to sell winners and to retain losers as disposition effect holds.

Stocks trading at higher prices as compared to the reference point are traded frequently by the investors to realize gains. Thus positive stock returns increases the security turnover (based on trading volume). Overconfidence bias also states that investors tend to trade more frequently when they feel overconfident about their stock picking ability. Although both biases are directly related to security turnover, Disposition effect deals with one sided trade only that is selling of a stock to some rational investor to realize gains whereas overconfidence is a two sided trade need not any other rational investor. Also the disposition effect related to specific security and overconfidence is a market wide phenomena in general (Statman, 2004).

Zhao, Su and Hooper (2011) investigated effect of accounting conservatism on disposition effect. In order to measure disposition effect used capital gain as a function of passed returns and turnover. They defined capital gain as the difference of closing price and reference price divided by the closing price of stock. Their model used independent variables as cumulative return that has passed one month, cumulative return from passed one month to passed one year, cumulative return from post one year to the post three years, corresponding period's turnover, and natural logarithm of market capitalization. Disposition effect to be present, all the independent variables should have significantly negative values. Results found that conservatism offsets the overestimation and underestimation caused by disposition effect.

Several studies have investigated probable explanations for this trend of investors. Following are some factors which affect disposition effect:

#### 2.4.2.1 Individual Characteristics

It has been established that individual investor's characteristics determine his decisions to hold or sell the stocks. Differences in investor literacy about financial markets and trading frequency also determine the variation in individual's buy and sell decision (Dhar and Zhu, 2006). Disposition effect is less exercised by Individual investors with strong financial background and investors employed in professional occupations. Also the trading frequency affects the disposition effect (Dhar and Zhu, 2006).

Women are considered to be more risk averse as compared to men. This gender based difference of attitudes has been postulated by Hibbert et al (2008) who has explained gender risk aversion as a function of age, income, wealth, marital status, race, ethnicity and no of children at home below age of eighteen. Their findings suggested that individual having same level of education, not specifically related to finance, exhibits same level of risk taking. Inherent characteristic of investors such that age and gender also affects the disposition effect. Women are usually more eager to realize gains and are impatient by nature. Therefore women are more intended to sell winners soon and hold losers (Feng and Seasholes, 2005). Females specially aged female investors are more prone to asymmetrically deal with their gains than losses (Shu et al, 2005). However, results found by Richards (2011) are contrary to this as they found women more prone to realize losses.

Another valuable finding of Richards (2011) while looking for factors disposition effect for a sample of UK is that old age people are more prone to realize losses as compared to gain realization which is contradictory with findings of Feng and Seasholes (2005) however, the two studies has defined age in different manner. Similarly the investors following stop losses experienced less disposition effect than those who did not. Two stop losses have been used ordinary and tracking. With ordinary stop loss, when price drops to a predetermined level, sale is automatically activated. With tracking stop loss, when a price drops from a recorded peak by a certain amount, sale is triggered. "Both can be used to sell gains and losses" Richards (2011) claims.

Cultural diversity is another factor that explains disposition effect. Strong disposition effect has been observed in Taiwan as compared to USA. Reason being Taiwani investors have stronger beliefs in mean reversion than the U.S. investors (Shu et el, 2005).

Another argument established is that it is level of sophistication that determines the disposition effect (Grinblatt and Keloharju, 2001; Brown et al, 2006; Dhar and Zhu, 2006). Different variables have been used to explain sophistication. Whether it is investor's income and job experience (Dhar and Ahu, 2006), gender, age, portfolio diversification and trading rights (Feng and Seasholes, 2005) type of investor (Brown et al, 2006; Grinblatt and Keloharju, 2001) or knowledge and experience of managing complicated financial products (Richards, 2011).

#### 2.4.2.2 Tax Loss Selling Hypothesis

Tax loss-selling hypothesis also provides some justification for disposition effect especially in month of December. It has been established that investors tend to sell their loosing investment around the end of the year to get maximum benefit of tax loss (Lakonishok and Smidt, 1986; Badrinath and Lewellen, 1991).

Investors throughout the year sells profitable or winner investments and saves losers in their hands to sell them at year end and take advantage. Around the end of December, investors start selling their losing investments to record heavy losses in their books and to save tax on their net profits (Shefrin and Statman, 1985).

Constantinides (1984) also supported the idea that investors should continue with tax motivated selling all over the year and in month of December this should be at its peak that is selling losers at end of year and re-buying them at beginning of next year to get back to previous portfolio composition. Holding losers throughout the year to sell at end of year to save taxes may serve as a major motivation behind disposition effect.

Dyl (1977) analyzed monthly trading volume of one hundred stocks for the period of ten years, i.e. 1960-1969. His results supported tax loss selling hypothesis by providing evidence that the stocks whose value has been depreciated more than twenty percent experienced abnormally high trading volume in December while the stocks with twenty percent or more appreciation in their value observed abnormally low trading volume. However, no significantly abnormal trading volume was observed for month of January, even for stocks with capital appreciation.

Brown et al (2006) found evidence of disposition effect all over the year from July to May. June being the last month of Australian financial year demonstrates disposition effect tempered by tax loss selling for all the investors except for foreign traders and tax exempted government departments.

Disposition effect has also been associated with window dressing and momentum effects. Strong evidence of disposition effect in last month of the financial year can be viewed merely as an effort to window dress the actual performance by showing realized losses. Similarly disposition effect can be the result of momentum generated due to continued selling of winners for whole year. However, whatever is the rationale behind, actual motive remains the tax loss selling (Brown et al, 2006).

#### 2.4.2.3 Future Expectations

Prospect theory value function is (S-shaped) happens to be concave to gains and convex to losses. It means that even high level gains are achieved; it will not add a tremendous increase in overall joy as compared to a little gain earned. Similarly a huge loss will not imply much more increase in pain as compared to small loss and resultant pain (Kahneman and Tversky, 1979). This theory implies that investors in general are not very much eager to earn profits since it does not considerably add to their overall joy and vice versa. This decreased sensitivity to future returns can help explaining the potential reason behind disposition effect.

Prospect theory value function implies that pain of loss is always greater than the joy of gain even if the magnitude of gain and loss is same. This tendency declares the investor as risk averse in nature affecting all its future decisions. Also the investor's decisions based upon the prior outcomes of the investments. If positive returns have been earned in past, investor tend to be more risk averse for future investments. Similarly negative returns in prior investments reduce the risk averse behavior of investor. Risk aversion makes an investor believe in unjustified mean reversion that is today's winner will be loser in future and vice versa, giving birth to disposition effect (Zuchel, 2001; Odean, 1998; Shefrin and Statman, 1985; Weber and Camerer, 1998).

Investors tend to retain losing investments because they believe that today's losers will be future's winners. And the future performance of stocks will outperform today's loss. This approach is only justified when future expected return of today's loser is higher than today's winners. Otherwise it shows irrationality of investor. There is a possibility that investor is deceiving himself by posing that he believes today's loser will experience mean reversion, just not to admit that he is scared of experiencing loss (Odean, 1998).

It is not always fundamentals on whose behalf investors take decision to sell or hold a stock. It can also be some psychological factor or anything not be explained traditionally. Losing investments may bring regrets to the investor in form of an error of judgment, making them feel bad about their abilities and performance. Thus to avoid said regret, investors tend to sale winners only and keep losers with them building an expectation that they will outperform in future. Selling winners and realizing gains give them pride whereas selling losers will bring regrets to them (Shefrin and Statman, 1985; Zuchel, 2001).

Mean reversion theory refers to the stocks earning above average profits, expected to have fall in prices ahead that is negative autocorrelation between stock prices. When this theory is falsely believed or considered, it leads to disposition effect in market (Weber and Camerer, 1998). Investor's being overconfident rely too much on their stock picking ability. As a general rule they prefer to buy undervalued stocks which they expect to appreciate in value in future with an objective of taking advantage of this mispricing. As soon as they find the stock appreciated in value, they tend to sell that stock which apparently is earning profits for them. Thus the overconfidence of investor's may serve as a root cause for disposition effect (Zuchel, 2001).

## 2.5 Excess Market Volatility and Irrational Behaviors

Much has been worked on finding out behavioral or psychological reasons for this excess volatility of market. Literature in Behavioral Finance found over and under reaction of investors behind excess volatility in market which are further postulated as the function of heuristic biases. Thus there exist a relationship between behavioral biases and excess volatility prevalent in market.

Volatility in returns, higher than the volatility in fundamentals of a firm, may be explained with the help of overreaction of investors to any news (De Bondt and Thaler, 1985) leaving the market informational inefficient. In fact during past two decades the most talked about and most researched anomalies have been identified as excess volatility, overreaction and underreaction (Lam and Liu, Wong, 2010). Behaviorists have associated various behavioral/psychological biases with these anomalies to find out justification behind. Barberis, Shleifer and Vishny (1998) highlighted representativeness and conservatism biases working out behind overreaction and underreaction of investors however, no evidence of their existence behind excess volatility was found.

Too much over confident investors change their mind too often sometimes too optimistic and sometimes too pessimistic (Dumas, Kurshev, Uppal, 2005). This attitude may also make the markets more volatile. This effect of overconfidence of investors cannot even be written off by the presence of few rational investors since overconfident investors adds to the sentiment risk due to which rational investors feel deterrent to invest unless they are extremely positive about future (Dumas, Kurshev, Uppal, 2007).

Although overconfidence has been reported as the most robust finding in psychology literature (De Bondt and Thaler, 1995), other behavioral factors may also contribute to the decision making and affect the trading patterns and thus create volatility in market. Lam, Liu and Wong (2007) through their model of investor sentiment based on assignment of weights to the earning shocks of stocks under representativeness and conservatism established that excess market volatility is the outcome of investors' biased heuristics. They elaborated that representative heuristic, rather than the conservative heuristic, is the main source of excess volatility in the market. Abbes (2011) found loss aversion and capital loss of disposition investors explaining a large part of asymmetric Volatility that is lagged returns negatively correlated with volatility. He documented that disposition investors prefer to hold their position for loser stocks to avoid losses in this case which increases conditional volatility.

Pouget and Villeneuve (2012) stated that markets exhibit volatility due to the overreaction of biased investors to some news. Investors in receipt of some information inconsistent with their prior beliefs are prone to underreaction to that information. Thus difference of opinion due to confirmation bias may lead to excess volatility in market.

Investors are prone to irrationality and often make decisions with excessive optimism. This optimism make them believe that the existing scenario will continue in future and thus with each private signal received, price volatility increases. Abbes (2012) tested for overconfidence bias as a contributor to excess volatility observed during global financial crisis in developed and emerging equity markets. Also the relationship between excess trading volume and excess trading volatility was examined. The equity markets examined includes developed markets of US, Canada, France, UK, Swiss, Australia, Hong Kong and Japan. Emerging Markets include: Brazil, Mexico, Korea, Malaysia, Singapore, India, and Kuwait. Using EGARCH estimation model based on two components of trading volume. One component that is "Due to past stock prices" related to investor's over confidence and the other one was unrelated to investor's overconfidence. Their results revealed asymmetric volatility for all equity markets and conditional volatility positively related to trading volume caused by over confidence bias.

Anchoring bias or the adjustment to some reference point is widely observed in volatile markets. Since noisy markets generally inherit cognitive errors anchoring bias can also serve to increased volatility due to irrational decisions. The other way round, while discussing IPOs partial adjustment phenomena, Dolvin (2005) states "increased market volatility at time of final offer price selection in addition to increasing price uncertainty may increase the anchoring bias".

Volatility prevailing in market affects the investor's reaction to the upcoming information. Psychology literature postulates "frame reference" that is no information is processed without its due context and is affected by the circumstances in which it is presented. Shefrin (2000) termed this as "frame dependence" where risk and return of a security depends upon how the decision problem is framed. Difference in framing cause the market price deviate from fundamental values. Thus any news coming to the market, receives the reaction according to the state of market and volatility/uncertainty at that time. Establishing a link between investor responsiveness, market direction and volatility, Docking and Koch (2005) found that a dividend change announcement, when market is up with high uncertainty, receives a reaction different from that which is received in bad market times with low uncertainty.

## 2.6 Excess Market Volatility and Turnover

Turnover may also be considered an indicator of the dispersion in beliefs of the investors and trading opportunities in market leading to stock market uncertainty. Turnover is an important piece of information which directly affects the price movements in market (Wang, 2002). Looking at trading volume it can be assessed that what volatility level is likely to exist. When information driven trading persist in market, negative correlation between lagged trading volume and current volatility is expected. Wang and Huang (2012) examined volume-volatility relationship using volatility de-composition approach. The results revealed positive correlation between continuous component of volatility and trading volume whereas negative correlation was found between trading volume and jump component of volatility. This effect was associated by them with the public information available in market. Campbell et al. (1993) reported a positive correlation between current volatility and lagged trading volume with liquidity trading in market.

Volatility in market is the result of imbalance in trade orders. If the stock's traded volume is high, but balance of orders is not disturbed, the volatility remains low. De Bondt and Thaler (1994) has explained excessive trading as the most embarrassing fact to the standard finance. Behavioral Finance has attempted to explain this phenomenon in light of human behaviors. Gervias and Odean (2001) and Statman et al (2006) has presented that high returns increases investor's over confidence and they tend to trade more aggressively which increases the trading volume. Vliet (2015) presented excessive trading as a result of investor over confidence and misalignment of interests of asset managers and asset owners. According to him there exist a concave relationship between turnover and achieved risk reduction. In order to reduce portfolio volatility by 25%, 30% annualized turnover shall be enough.

High trading volume/turnover has generally been associated with the high volatility in market. Zhang (2010) established that high-frequency trading is positively correlated with stock price volatility after controlling for firm fundamental volatility and other exogenous determinants of volatility where high frequency trading refers to fully automated trading strategies with very high trading volume and extremely short holding periods ranging from milliseconds to minutes and possibly hours.

Summers and Summers (1989) attributed the growth in daily turnover with the noise trading in security market. Since noise trading is based on incorrect information, it induces excess volatility in market. Mulherin (1990) analyzed daily turnover data of NYSE and found variation in share turnover directly relates to the trading cost. However, any increase in trading cost, in anticipation of low trading volume, may not fully explain the decrease in volatility in that period.

Karpoff (1987) provided a model establishing asymmetric association between trading volume and price change based on information flow however the evidence found was very weak. Nevertheless a scientific model directly relating trading volume and stock returns still lacks. Brailsford (1994) found irrespective of the direction, price changes significantly for the daily trading volume of aggregate market and individual stock. Bessembinder and Seguin (1993) documented an asymmetric volatility response to unexpected shocks in trading volume. Unexpected positive shocks to trading volume induced, on average, an increase of 76% in volatility whereas negative shocks induced a smaller response in volatility.

Price changes induced by trading volume prove to be an important input for the trading strategies (Schewart, 1990). An anticipation of price persistence leads the investors herd in same direction. This increased trading when incorporates in price change, make more investors trade in same direction limiting the volatility level in market.

Studies have also found that either there is negative relationship between volatility and volume or no relation at all. It depends upon the measures of volume that may give the conflicting results. Abnormally high trading volume, measured by number of transactions, has been observed in response of price decline with new equity issue (Barclay and Litzenberger, 1988). Bad news earning announcement resulted in lesser transactions however, average volume of transactions remain higher than trades in response of good news earning announcement (Woodruff and Senchack, 1988). Trading volume is found un-affected by the macro economic news for example money supply, consumer price index, industrial production and unemployment whereas 500 S&P index returns were directly affected by these (Jain, 1988).

# Chapter 3

# Methodology

This chapter presents the theoretical frame work on which whole study is based along with the testable hypotheses for each behavioral bias, market reaction and its relationship with excess volatility and trading volume. Methodology in detail to test each bias and excess volatility has also been discussed.

## 3.1 Development of Hypotheses

The study aims at finding out the evidence of behavioral biases that is over-confidence and self-attribution, anchoring, herding and disposition effect and to ascertain whether or not any association exists between the irrational behaviors of investors leading them to over or under react and the prevailing level of volatility and volume or not. For this purpose, initially existence of irrational biases has been assessed and then said relationship is to be reported.

### 3.1.1 Self-attribution and Over Confidence

Self-attribution has been found by the researchers as the root cause for overconfidence of investors. Hirshliefer (2001) explains the relationship between two in following words: "overconfidence and self-attribution are static and dynamic counterparts, self-attribution cause individuals to learn to be over confident rather than converging to an accurate self-assessment".

Measuring overconfidence of investor has been a debate for long. Cesarini, Sandewall, Johannesson (2006) state that overconfidence depends upon the response function of investors and thus can be measured in terms of response format. The items selected to measure the overconfidence bias may also create difference in results (Juslin, 1994). Overconfidence of investor directly affects its trading pattern and resultant stock returns. Thus the analysis of trading pattern, stock returns and its effect on trading volume can be taken as most robust technique. Over confidence of investors can reliably be traced by analyzing the changes in trading volume (Odean, 1998; Gervais and Odean, 2001).

Lo and Wang (2000) measure trading volume by turnover defined as shares traded divided by outstanding shares. Similarly, market turnover is defined on value weighted basis as the dollar value of all shares traded divided by the total dollar value of the market. Statman et al, (2004) test the market trading volume to find out the overconfidence of investor and report positive relation between turnover and lagged returns for months and perhaps years, even after controlling for turnover trend and contemporaneous volume-volatility relationships.

Investors are more confident or overconfident when they realize high returns even if rest of the market is also enjoying same high returns (Gervias and Odean, 2001). Investors attribute the high stock prices and returns with their own art of picking up the stocks and thus they trade more frequently. This excessive trading leads to the excess volatility in market (Odean, 1998). Since overconfident investors have a strong illusion of their own success, with excessive trading they not only assume high risks (De long et al, 1990) but also reap benefits from the available trading opportunities (Taylor and Brown, 1988).

As developed by Statman et al (2004), market turnover as well as individual security turnover positively related to market lagged returns provides the evidence for overconfidence bias. To test for the evidence of overconfidence bias in Pakistani market, assessment of the trends prevailing in trading volume and lagged market returns may be conducted to have a true picture whether any such relation between returns and trading volume exist or not. Thus for finding out overconfidence bias the study hypothesizes:

***H1: Trading turnover increases directly with the lagged market returns.***

### 3.1.2 Anchoring/Adjustment

Anchoring is an easy-to-demonstrate, hard-to-eradicate behavioral bias that has all sorts of nasty implications for investors, many of them not obvious. While taking a decision to invest, although the fundamentals are available, human tend to opt for some value they have in their mind. This could be past performance, past rating, past portfolio value or most commonly the price paid for a security (although the fair value of a stock has nothing to do with the price one pays for it). The forecasts or assessments made by investor depend a lot on the anchor since it can drive the forecast either way.

A common behavior observed in investors is that they process the information widely available in market with more confidence as compared to the firm specific information (Peng and Xiong, 2006). Investors may have an appeal for the stocks whose prices have fallen considerably from their previous or all-time highs for example a 52-Week high. The reason being investor is anchoring to the high prices that the stock has reached and now believes this provides an investment opportunity. If the fall in prices is observed due to overall market sentiment and not due to any deterioration in business fundamentals, then the investor has made a right decision. However, if it is otherwise, the investor is most likely to lose in future. Investors may also anchor their estimates to a price only below which they will buy the stock. This way they might miss the opportunity to invest. Similarly, investors may hold on to a price for selling that is they want to sell a stock only if it reaches a certain price or a target.

Also a number of studies such as George and Hwang (2004), Li and Yu (2009), Kartano (2013) have found the 52-Week high and 52-Week low to be used as the anchor to assess the uplift in stock prices or fall in stock prices. Also this can be used for the forecast reasons that whether prices are likely to revert in long run and will continue for some time. Any stock found near its 52-Week high means some positive information about stock has just arrived and underreaction of investors is at its peak this moment (Li and Yu, 2009). Thus one can expect positive future returns for a stock near its 52-Week high. Griffin and Tversky (1992). Li and Yu (2009), George and Hwang (2004) have also established use of Dow historical high as anchor. If current price is found far from the historical high, it means investors are overreacting to some bad information and thus returns in future are expected to revert or improve.

Investors tend to underreact to random news as compared to a series of news to whom they overreact (Griffin and Tversky, 1992). When a stock is found at or near its 52-Week high, it means that some good news has recently been arrived about the stock and investors are currently underreacting to that news. On the other hand, when Dow historical high is used as anchor, Li and Yu (2009) has found that the moment when stock price is far from its historical high, it points out the investor's overreaction presumably in response to a series of good or bad news. Thus nearness to the 52-Week high may be taken as a measure of investor's underreaction with a positive forecast of expected returns whereas nearness to historical high may measure the extent of investor's overreaction possessing a negative relationship with future expected returns.

George and Hwang (2004) suggested 52-Week high as an anchor for predicting impact of upcoming news on the future returns. As the stock's price reach near its 52-Week high due to some good news, investor's prone to underreaction does not bid high for the stock initially. With the passage of time information spreads in the market and prices in general go up. Similarly, for price far from 52-Week high, due to underreaction to bad news, investors do not sale stock unless the news prevails in market and prices in general drops down.

Li and Yu (2009) assume the historical high an anchor to evaluate information with same effectiveness. In response to a series of bad news, investors overreact and stock price may drop down more than the new would imply and bring the stock price far from its historical high. However, as the news prevail in market prices automatically go up and generates positive returns.

Whole discussion above establishes two variables as the proxies of under and over reaction in market and that can most reliably be used as anchors for the future forecast. Nearness to Historical high has been established as a proxy of investor overreaction and thus predicts negative returns in future. Nearness to 52-week high has been established as proxy of underreaction and predicts positive future returns. Based on data set and Pakistani investor trends, this study has moderated 52-week high anchor as a 24-Week high that covers period of 6 months. Thus the hypothesis to measure anchoring in Pakistani market by constructing two distinct anchors is:

***H2: Nearness to Historical high predicts negative future returns.***

***H3: Nearness to 24-Week high predicts positive future returns.***

### 3.1.3 Herding

Herding refers to the tendency of following what people around are doing or believe to be right. Investor's aptitude of relying on other's forecasts and judgments rather than being confident about their own valuations based on fundamentals shows their irrationality and may induce investors to herd (Prechter and Parker, 2007).

Herding is an irrational behavior and does not follow the traditional thinking that the people are rational, it is information dissemination, in the extreme market situation the traders do not know the value of upcoming new information they need to make decision in the short period of time then they go for herding. According to Kultti and Miettinen (2006), it is quite easy and not expensive to observe the change in market return. Investors go for herding in this extreme market situation. Existence of herding leads to a momentum in market whether in upward direction or downward direction, depending upon the market movement, and explains the investor's overreaction to the public information and underreaction to private signals. Since investors in market does not tend to act rationally, market cannot be declared efficient as explained by Fama (1970). Thus the existence of herding behavior is a key factor to be tested for the market.

Investors are found to herd in extreme market situations (Chang, 2000; Christie and Huang, 1995) where either information is costly or investors do not have time for valuations and thus they follow consensus decision. When herd behavior exists, dispersion among individual stock returns and market returns minimizes or increase at a diminishing rate.

Most of the scholars use cross sectional standard deviation (CSSD) or cross sectional absolute (CSAD) deviation to measure the herding. According to Chang et al. (2000) herding measure is higher when market is declining than when it is advancing. This study hypothesizes that herding exists in the period of high market volatility. If herding exists in the market the return of an individual stock converges towards the market index. Therefore, there will be small difference between the return on individual stock and market return.

In efficient markets, investors are perceived to respond to the information immediately, reflected in stock prices as well as stock market index. However, in times of extreme market conditions when markets are found to be highly volatile, investors tend to rely on movement of market rather than depending upon their own information. The returns earned during this period by an investor cannot be expected to be significantly different from that of whole market. Thus the analysis of dispersion between individual security returns and market returns can provide a reliable evidence of herding. In order to find whether herd behavior exists in Pakistani market or not, hypothesis has been formulated as follows:

***H4: Dispersion between individual stock returns and market returns decrease in extreme market conditions.***

Fu and Lin (2010) examine Chinese stock markets and report that the stocks with low turnover rate have higher tendency to herd market. For high turnover stocks generally investors rely on their own calculations and do not follow the trends in market. This trend has been termed as Turnover Effect in Herding. According to the Avery and Zemsky (1998) investors may not have sufficient information; they may observe and follow the other investors' action. Since for low turnover stocks usually much information is not available thus herding is more expected for such stocks. In this case dispersion between market returns and low turnover stock returns is expected to be found very low. Since an examination of turnover effect can also help founding the evidence of herding, hypothesis for turnover effect is as follows:

***H5: Dispersion between low turnover stock returns and market returns decrease in extreme market conditions.***

### 3.1.4 Disposition Effect

Investors due to their risk adversity have a tendency to sell the stocks appreciated in value to realize gains or they might think that today's losers will be winners tomorrow. Grinblatt and Keluharju (2001) using logit regression and controlling for investor characteristics as well as market conditions report the presence of disposition effect in Finland. They use dependent variable of one for sales and zero for paper sales. Along with control variables such as past returns and market returns, disposition effect has been demonstrated by using a dummy variable, one for realized paper losses and zero otherwise. Results reveal that investor's response to past returns varies along with investor class. Institutional investors prefer to buy the stocks with good past performance (creating momentum) and others prefer to buy stocks classified as losers.

In order to measure disposition effect, Odean (1998) analyzed trading pattern and found losers are held longer than winners. He hypothesized that disposition effect occurs when proportion of realized gains is higher than the proportion of realized losses where proportion of realized gains is equal to realized gains divided by realized plus paper gains. Same applies to the proportion of realized losses.

Zhao, Su and Hooper (2011) while measuring the effect of accounting conservatism on disposition effect for Chinese stock market measured disposition effect and conservatism separately. For the existence of disposition effect, they found that capital gains are negatively correlated with returns and turnover.

Disposition effect is very similar to overconfidence of investor and has its roots there. A slight difference between two is that overconfidence theory talks in general (Gervais and Odean, 2001) and disposition effect only deals with individual securities i.e. investor attitude varies on security to security basis (Shefrin and Statman, 1985). The investor's selling and buying decisions, even for individual security, determines the trading and pricing behavior of whole market.

For testing the overconfidence bias in KSE-100 index, association between market returns and trading pattern in terms of turnover are analyzed and significantly positive relationship between two has been hypothesized as the evidence of overconfidence. Similarly, significantly positive relationship of security turnover and security returns is hypothesized as evidence of disposition effect.

Most of the studies have focused on the past returns and turnovers to be analyzed for testing presence of disposition effect. As stated by theory of disposition effect, if the security is earning high profits, an investor with a belief on mean reversion theory tend to sell that stock to realize gains which in turn increases the trading volume and turnover of the security. Thus we have the hypothesis for disposition effect as:

***H6: There exist positive relationship between a security's lagged returns and its turnover.***

### 3.1.5 Market Reaction

Rational as well as irrational investors are the part of the stock market. Where rational investors base their decisions on facts, numbers, and calculations, irrational investors are found to be largely influenced by their own emotions, perceptions, circumstances, resources, previous experiences, myths, norms, culture etc. with a news in market both type of investors start playing their roles. However, it has been found that irrational investors usually supersede the rational which disturbs the market equilibrium conditions. Two widely reported phenomena found in this state are the short term underreaction and the long term overreaction.

While underreaction defines a slow adjustment of prices to corporate events or announcements, overreaction deals with extreme stock price reactions to previous information or past performance. Or we can say that when investors underreact, prices reflect the new information, such as earning announcement, gradually whereas in case of overreaction future prices show a negative autocorrelation with the past prices.

Whenever any unexpected or dramatic news arrive in the market, investors tend to over react. Investors are largely found simultaneously exhibiting short-term Underreaction to earnings announcements and long-term overreaction to past highly unexpected earnings (Kaestner, 2006). De Bondt and Thaler (1985) found the evidence of investor overreaction by analyzing two portfolios of past winners and past losers. According to them investors tend to overreact to a series of good news until the share prices fall due to mean reversion. This makes past winners lose in subsequent periods. Pakistani market is an emerging market dominated by few large players. Also the investors are not sophisticated enough to keep market in equilibrium. Thus in order to investigate whether investors in Pakistani market also tend to under or overreact in long run, the study hypothesize:

***H7: Investors tend to overreact to a series of good news in long run.***

In order to declare the stock market as to whether it underreacts or overreacts in extreme market conditions, it is to be analyzed what are the underlying biases that influence the thought process and decision making of investors, generally termed as noise traders. Existence of heuristic biases and their nature in Pakistani market is the key factor to assess since it provides the basis for onward testing and analysis of market dynamics with references to these biases. Separate hypothesis is formed for each bias as to whether they exist in market or not. Similarly, anomalous market behaviors have to be investigated first before moving on.

### 3.1.6 Excess Volatility, Market Reaction and Turnover

Investors overreacting to upcoming information shows excessive optimism for good news and thus makes the prices drift from their fundamental value. This state enables the market participants to forecast future movement in prices by following mean reversion theory that is price revert to its true value in long run. On the other hand, if more weight is assigned to prior information and new information is very slowly incorporated in prices, investors are found exhibiting underreaction with a short term momentum, again making it easy for market forces to forecast future moves. Market over or under reaction directly affects the trading volume of the market. An overreaction creates a momentum in market which stimulate the drift in trading volume unless it becomes negative and vice versa.

Chui, Titman, and Wei (2000) tested the relationship of momentum and trading turnover in eight Asian countries. Their results revealed that among five out of eight countries, momentum profits are higher in stocks with high turnover ratios. Glaser and Weber (2001) reported same momentum effect for high turnover stocks by analyzing German stock market. Momentum and trading volume has been found positively related to each other (Chan, Hameed, Tong, 2000).

As the market overreacts creating a short term momentum for high turnover stocks, stock returns tend to fall due to excessive trading. This study assesses the relationship of market reaction and subsequent market turnover for making a forecast about the market. The testable hypothesis is:

***H8: There exist significantly positive relationship between market reaction and market turnover.***

Where EMH theory is based on the rational expectations of investors to the pricing of assets utilizing all the available information, Bubble theory suggests that stocks may go through periods of under- and overvaluation. These bubbles may reflect investors' reactions to the factors other than fundamental, economic and business conditions which leads to volatility in market. Psychology justifies the existence of these bubbles as a result of certain heuristic and behavioral biases at micro and macro level which makes the investor over or under react to certain news.

Both the phenomena, underreaction and overreaction, drifts the stock prices away from their intrinsic value making them more volatile as rational investors at the same time may also be taking positions according to the fundamental values. Getsmansky and Papastaikoudi (2002) term this scenario as excess volatility that is variation in stock returns which cannot be explained by the changes in fundamentals or efficient market hypothesis. They further establish that trading of fundamental as well as momentum traders makes the stock prices swing to and fro creating volatility in market. Since this volatile behavior cannot be justified by efficient market hypothesis, it is believed that bounded rationality of investors is the major contributor towards volatility.

Bounded rationality on investors makes them behave in a biased manner, not only at individual level but also at macro level directly affecting the stock prices, and giving birth to short term momentum (underreaction) or long term reversal of prices (overreaction). Also, all the heuristics followed by investors create dispersion in market leaving rationality far behind and making the markets highly uncertain. Uncertainty in turn increases volatility in market. This study presents excess volatility as a function of over/underreaction in market and thus the testable hypothesis has been formulated as:

***H9: Excess volatility in market is driven by irrational market reactions.***

Since inefficient markets are not rationally priced, there exist bubbles in stock market. Investors consider this short term mispricing a chance to earn abnormal profits and start trading frequently. As per mean reversion theory, in case an overpriced stock is identified, investors start selling it to earn maximum profit. Similarly, in case of underpriced securities investors tend to purchase the stock to sell in future at high price. Both the situations lead to increased trading volume with a momentum in trading which depicts an element of certainty in investors. Volatility has been defined as a function of uncertainty. Thus the increased trading volume in stock market may have a negative impact over the excess volatility found in market. To test this implication of momentum trading and resultant turnover of market over excess volatility, testable hypothesis has been formulated as:

***H10: There exist significant relationship between turnover and excess volatility.***

## 3.2 Sample

In order to test the entire hypotheses formulated in above section for Pakistani market, 100 companies' representative of 86% of Karachi Stock Exchange (KSE) has been analyzed. KSE is considered a small, opaque and highly volatile emerging market of Asia and is declared as the "Best Performing Stock Market of the World" by Business Week. Since KSE is an active market as compared to other markets of this size, returns earned by investors in KSE are usually high as well as highly volatile (Sheikh and Riaz, 2012). Turnover ratio for KSE ranks good in world stock markets. Major chunk of the Karachi stock exchange has been occupied by some large investors which can determine the behavior of whole market through their pattern of trading. To test for all the biases, market under or overreaction, volatility and for all the corresponding calculations, companies with less frequent trading or incomplete data for study period have been excluded from the sample.

## 3.3 Data Description and Source

In order to meet the objectives of study, secondary data of daily closing share prices and daily turnover of KSE-100 index companies, financial and non-financial, have been collected from the official web site of Karachi stock Exchange, Pakistan and business recorder. In addition to stock related data, market data for index and turnover has also been gathered through the website of Karachi stock Exchange and business recorder. Data required for analysis has been collected for the time period of January 2000-December 2014 which covers a span of fifteen years. The study employees the analysis of daily returns for stocks as well as market since more frequent data gives more reliable results. Ball and Brown (1989) prefer monthly returns over annual returns to have a stronger support for the Overreaction Hypothesis. Daily returns for the study have been calculated from share prices as follows:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.1}$$

where

$R_t$ = Daily continuously compounded return for stock $i$

$P_t$ = Closing share price of the stock at day $t$

$P_{t-1}$ = Closing share price of the stock at day $t-1$

Similarly, to obtain daily market returns from uninterrupted series of Market index, same formula has been modified as follows:

$$R_{m,t} = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.2}$$

where

$R_{m,t}$ = Daily continuously compounded return for market

## 3.4 Methodology

### 3.4.1 Self-attribution and Over Confidence

Having inappropriate estimates of future returns due to very tight error bound, investors keep on trading until they start realizing losses which ultimately results into reduced trading volume by investors. Reduction in trading volume in turn leads to the lower stock returns and high market returns leads to the high trading volume. Thus the analysis of changes in trading volume can provide the basis to test for existence of overconfidence (Odean, 1998; Gervais and Odean, 2001). Also trading activity can be measured by turnover since value weighted turnover is the money value of the shares traded (volume) divided by the money value of market (Lo and Wang, 2000). Investors deem to be overconfident in general not particularly for a specific security that is they believe in their stock picking ability to make profit out of any investment thus studying market behavior is appropriate enough to find evidence of overconfidence of investors.

Statman (2004) present an unrestricted vector autoregressive (VAR) model to test the time series data of securities as well as market to ascertain the relationship of turnover and returns. The model is based on two main endogenous variables, i.e. market return and market turnover. The endogenous variables are ones which are explained by the relationships between functions within the model. Endogenous variables are important in econometrics and economic modeling because they show whether a variable causes a particular effect or not. Causal modeling has widely been employed to examine the outcomes based on a number of independent variables and to find out whether these outcomes are a result of endogenous or exogenous variables and to which extent.

Market returns (Return) have been calculated same as described in data description section above. For the purpose of this study, daily data of variables has been used to form the monthly values of variables. However, market returns have been calculated by utilizing month end index values. Market turnover (Turn) has largely been defined as daily market trading value by daily contemporaneous total market capitalization and cumulated to form monthly turnover. The amount of daily trade volume/turnover tends to fluctuate on any given day with the any new information available in market whether this be an earnings surprise or may be a third party communication such as any new regulation etc. in either case, this is perhaps the most robust correlation found and thus depicts the market in full.

Exogenous variables are the factors or variables, part of a causal model, whose value is independent from the states of other variables in the model, especially by changes in the endogenous variables. Their value is determined independently by the factors outside the causal system under study. Two exogenous variables used for this study are Market Volatility (Mvol) and Dispersion (Disp) as employed by Statman (2004). Market Volatility (Mvol) is the monthly temporal volatility of market returns. Daily market returns have been used to arrive at monthly volatility figures by applying methodology suggested by French, Schwert and Stambaugh (1987) as follows:

$$\delta^2_{m,t} = \sum_{i=1}^{N_t} r^2_{i,t} + 2 \sum_{i=1}^{N_t - 1} r_{i,t}(r_{i+1,t}) \tag{3.3}$$

where

$\delta^2_{m,t}$ = Volatility during the month

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

$N_t$ = Number of trading days in a month

Monthly variance between market returns has been presented as a sum of squared returns plus twice the sum of the product of adjacent returns unlike the Mean Absolute Deviation (MAD) measure used by Abbes, Boujalbene and Bouri (2009) and Ross (1989) based on volume volatility relationship that is there exist positive autocorrelation between trading volume and price volatility (Karpoff, 1987). However, the adjustment in variance due to MAD is very small (French, Schwert, Stambaugh, 1987).

Dispersion has generally been defined as the difference between the actual value and the average value. The larger this dispersion or variability is, the higher the standard deviation. Control variable "Dispersion" (DISP) in this study is depicting the same state and has been defined as monthly cross sectional standard deviation among the returns. Basic purpose to add dispersion as a exogenous variable is to capture the effect of portfolio rebalancing on the potential trading activity (Statman, 2004). Calculations for dispersion (DISP) are made as follows:

$$S_t = \sqrt{\sum_{i=1}^{N} \left[ \frac{(X-\mu)^2}{N_t} \right]} \tag{3.4}$$

where

$S_t$ = Standard Deviation for the month $t$

$\mu$ = Sample mean for the month $t$

$X$ = Daily return for month $t$

$N_t$ = Number of days in month $t$

With the above mentioned endogenous variables that is market return (Returns) and Market turnover (Turn) and exogenous variables volatility (Mvol) and Dispersion (Disp),Vector Auto Regression model (VAR) has been used to measure the relationship of market turnover and return time series.

In order to make analysis of time series data, it is of vital importance that data must be stationary or de-trended to avoid the chances of biased and spurious results. A simple technique to identify any trend is series may be a simple plotting of series. Different techniques can then be used to remove the trend. In order to check stationary of data, unit root test has been employed through augmented dickey fuller test (ADF) and Phillips Perron test (PP). The augmented Dickey-Fuller (ADF) statistic, used in the test, is a negative number. The more negative it is, the stronger the rejection of the hypothesis that there is a unit root at some level of confidence. ADF test has a basic autoregressive AR(1) model as:

$$Y_t = \beta Y_{t-1} + \varepsilon_t \tag{3.5}$$

where

$Y_t$ = Variable under study

$\beta$ = Coefficient of lagged value of $Y_t$

$\varepsilon_t$ = Error term

This equation can also be written as:

$$\Delta Y_t = (\beta - 1)Y_{t-1} + \varepsilon_t \tag{3.6}$$

or

$$\Delta Y_t = \delta Y_{t-1} + \varepsilon_t \;\cdots\; \text{if } (\beta - 1) = \delta \tag{3.7}$$

Unit root test has a null hypothesis as: H0 = unit root exists and time series is not stationary. For above mentioned ADF AR (1) model, unit root is present (model is non stationary) if value of ? is found 1. If a variable is found having unit root it means the series is not stationary and mean and variance are changing overtime. The ADF test is based on the assumption of statistically independent error term with a constant variance. Since this assumption in reality may not be fulfilled, Phillip Perron test may be used which allows the error term to be disturbed.

There are different ways that may be used to convert a non-stationary series into stationary one. This includes taking logs, calculating ratios, taking first difference, second difference, third or higher order difference, cointegration, error correction etc. unit root test may be adopted to check which method to adopt for stationary series.

It has been a practice to conduct the pre-tests for unit root and cointegration before applying the VAR model to find out the appropriate transformations that causes the data stationarity. Incorporation of cointegration information in VAR model reduces the uncertainty of estimation and degree of small sample bias of impulse response functions. However, these pre-tests are prone to the lack of robustness for small deviation from unit root and cointegration (Gospodenov, Herrera, Pesavento, 2013). Basic equation for VAR model is:

$$Y_t = \alpha + \sum_{k=1}^{K} A_k Y_{t-k} + \sum_{l=0}^{L} B_l X_{t-l} + e_t \tag{3.8}$$

where

$Y_t$ = $n\times 1$ vector for endogenous variables (Market Returns and Turnover in this case)

$X_t$ = $n\times 1$ vector of exogenous variables (volatility and dispersion in this case)

$e_t$ = $n\times 1$ vector of residuals

$A_k$ = Coefficient of endogenous variable vector

$B_l$ = Coefficient of exogenous variable vector

In this generalized model, $k$ and $l$ used in subscript with coefficients of endogenous variable vector and exogenous variable vector respectively are the number of lags to be used in model. Lag length estimates if values in the past are still affecting today's values of the variable under study. To determine appropriate lag length (that is how far in past the values are affecting today's value) different selection criteria can be employed. Two most commonly used criteria are: Akaike Information Criterion (AIC) and Schwartz Bayesian Information Criterion (SIC). Akaike Information Criteria (AIC) was introduced by Hirotugu Akaike in 1970's establishing a relationship between maximum likelihood (an estimation tool) and

Kullback-Laibler Information (a measure to minimize the loss of information, established earlier by Kullback and Leibler). AIC has been defined as:

$$\text{AIC} = 2K - 2\log(L) \tag{3.9}$$

where $K$ is the number of predictors and $L$ is the maximized likelihood value. However, value of AIC itself does not have any meaning but the model with the lowest AIC value is the preferred one and lag length is determined at point where first minimum for AIC is achieved. Same clich is followed for Schwartz Information Criteria (SIC). SIC is a criterion for model selection among a finite set of models. It is based, in part, on the likelihood function and it is closely related to the Akaike information criterion (AIC).Although both the criteria depicts same thing, use of AIC has been recommended for the estimation of autoregressive lag lengths as it minimize the chances of under estimation of model and maximizes the chance of recovering the true lag length (Liew, 2004). For the purpose of this study, based on AIC, lag lengths are determined as $k = 3$ for endogenous variables and $l = 2$ for exogenous variables so that exogenous variable with its two lags help to explain relationship of endogenous variable.

The VAR model presents one equation for each dependent variable. Each equation has lagged values of all the included variables as dependent variables, including the dependent variable itself. It is one of the most successful and reliable measure used for analysis of multivariate time series. VAR model formulated for this study is as follows:

$$\begin{bmatrix} Turn_t \\ Return_t \end{bmatrix} = \begin{bmatrix} \alpha_{Turn} \\ \alpha_{Return} \end{bmatrix} + \sum_{k=1}^{3} A_k \begin{bmatrix} Turn_{t-k} \\ Return_{t-k} \end{bmatrix} + \sum_{l=0}^{2} B_l \begin{bmatrix} Mvol_{t-l} \\ Disp_{t-l} \end{bmatrix} + \begin{bmatrix} e_{Turn,t} \\ e_{Return,t} \end{bmatrix} \tag{3.10}$$

where

$Turn_t$ = Market Turnover for month $t$

$Return_t$ = Market Returns for month $t$

$Mvol_t$ = Cross sectional standard deviation of daily returns for month $t$

$Disp_t$ = Dispersion of returns from the mean for month $t$

$k$ = Lag length for endogenous variables

$l$ = Lag length for exogenous variables

The positive and highly significant association between market turnover and lagged market returns provides the evidence of overconfidence of investors. T-values obtained explain the significance of causal relationship.

The VAR methodology allows for a covariance structure to exist in the residual vector, $e_t$, that captures the contemporaneous correlation between endogenous variables. Changes in residual immediately changes the current value of variable and also affects the future values of itself as well as other variables. The reason being lagged values of one variable appears in both equations through the coefficient matrix $A_k$.

Individual VAR coefficient estimates do not capture the full impact of an exogenous variable observation. It is often of interest to know the response of one variable to an impulse in another variable. Impulse response relationship between two variables is investigated for this purpose. A reaction of one variable to an impulse in another variable declares the latter causal for the former. Impulse response function uses all the VAR coefficient estimates to trace the full impact of a residual shock that is one sample standard deviation from zero. This study also employs the impulse response function to find out how the one standard deviation shock in residuals will affect the current and future values of endogenous variables that is turnover and market returns.

### 3.4.2 Anchoring/Adjustment

Two anchors have been used as a proxy of under/overreaction to measure the Anchoring effect in Karachi Stock Exchange. In order to calculate these proxies, Daily index points for 100-index in Karachi stock exchange has been obtained for the period 2000 to 2014. 24-Week high has been calculated each day by identifying the maximum highest value is last six months. For the 24-Week high value on 01.01.2000, period of previous six months 01.07.1999 to 31.12.1999 has been utilized. Similarly, in order to find out Historical high returns, maximum highest value of returns since 01.01.1999 to date has been utilized. No computerized data for Karachi stock exchange exist before January 1999 and thus cannot be used for the calculation of historical high.

Based on these two variables that is 24-Week high and historical high, our proxies to measure anchoring have been calculated that is Nearness to 24-Week high and Nearness to historical high using following formula:

$$X_{(24w)} = \frac{P_t}{P_{24,t}} \quad \text{and} \quad X_{(HH)} = \frac{P_t}{P_{max,t}} \tag{3.11}$$

where

$X_{(24w)}$ = Nearness to 24-Week high

$X_{(HH)}$ = Nearness to Historical high

$P_t$ = Index point at day $t$

$P_{24,t}$ = 24-Week high value

$P_{max,t}$ = Historical high index value

In addition to Nearness to 24-Week high and Historical high, two dummy variables are also to be computed to measure high and low points of stock exchange each day as compared to the proxies calculated above. The two dummies calculated are as under:

$D_t$ = 1 when stock exchange reaches a record high at day $t$, zero otherwise

$I_t$ = 1 when historical high at day $t$ equals the 24-Week high at day $t$, zero otherwise.

Daily returns have been calculated from stock index as:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.12}$$

where

$R_t$ = Daily Return on day $t$

$P_t$ = Closing price at day $t$

$P_{t-1}$ = Closing price at last trading day

Standard correlation and OLS regression analysis have been used to test the relationship between nearness to 24-Week high, historical high, and future returns. At first instance, predictive power of lagged returns has been assessed to predict future returns by implying following equation:

$$R_t = \alpha + \beta R_{t-1} + \mu \tag{3.13}$$

where

$R_t$ = Returns at day $t$

$R_{t-1}$ = Return at day $t-1$

$\beta$ = Coefficient of variable

$\mu$ = Error term

At second step, Nearness to Historical high has been added to the regression equation to determine the predictive power of both that is lagged returns and Nearness to Historical high as follows:

$$R_t = \alpha + \beta_1 R_{t-1} + +\beta_2 X_{(HH)} + \mu \tag{3.14}$$

where

$R_t$ = Returns at day $t$

$R_{t-1}$ = Return at day $t-1$

$X_{(HH)}$ = Nearness to Historical High

$\beta$ = Coefficient of variables

$\mu$ = Error term

At final step, Nearness to 24-Week high is added to the lagged returns and Nearness to Historical high along with the two dummies created. $D_t$ as a measure of historical high, and It as measure of situation where historical high becomes equal to 24-Week high. The regression equation so used is as under:

$$R_t = \alpha + \beta_1 R_{t-1} + \beta_2 X_{(HH)} + \beta_3 X_{(24w)} + \beta_4 D_t + \beta_5 I_t + \mu \tag{3.15}$$

where

$R_t$ = Returns at day $t$

$R_{t-1}$ = Return at day $t-1$

$X_{(HH)}$ = Nearness to Historical High

$X_{(24w)}$ = Nearness to 24-Week high

$D_t$ = Dummy for indicator of historical high

$I_t$ = Dummy for historical high equals 24-week high

$\beta$ = Coefficient of variables

$\mu$ = Error term

When traders tend to underreact to current good news, with current price level is close to its 24-Week high, $X_{(24w)}$ is expected to predict future returns positively. Similarly when investors overreact to some bad news, current price level is far below its historical high, $X_{(HH)}$ is expected to predict negative future returns. Special attention is to be paid at the situation when historical high becomes equal to 24-Week high since that is the point where investors will rely on only one anchor and more likely to underreact to good news (Li and Yu, 2009).

### 3.4.3 Herding

In efficient markets, investors are perceived to respond to the information immediately, reflected in stock prices as well as stock market index. However, in times of extreme market conditions when markets are found to be highly volatile, investors tend to rely on movement of market rather than depending upon their own information. The returns earned during this period by an investor cannot be expected to be significantly different from that of whole market. Thus the analysis of dispersion between individual security returns and market returns can provide a reliable evidence of herding.

Cross sectional standard deviations (CSSD) and cross-sectional absolute standard deviations (CSAD) are the two measures used to measure the difference between individual security returns and market returns. CSSD was initially proposed by Christie and Huang (1995) for testing of herd behavior which is further refined by Chang et al (2000) adding cross sectional absolute deviation CSAD to the initial CSSD as a measure of dispersion between stock and market returns. A reduced CSSD or CSAD in extreme market conditions provides the evidence of herding implying that investors are earning returns closer to the market returns. CSSD and CSAD has been analyzed by Gleason et'al (2004), Demirer et al (2007), Chang, Cheng and Khorana (2000), Ahsan and Sarkar (2013), Kapusuzoglu (2011) Fu and Lin (2010) and a number of other studies as most robust measure of herding. When market is facing extreme situation or is earning extreme returns as compared to bench mark market, herd behavior has more chances to exist.

CSSD measure used by Christie and Huang (1995) and by number of other studies to test herding has been defined as:

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N_t}(R_{i,t} - R_{m,t})^2}{N_t - 1}} \tag{3.16}$$

where

$R_{i,t}$ = Stock return at time $t$

$R_{m,t}$ = Stock market index returns at time $t$

$N_t$ = Number of stock listed in equity market during time period $t$

**Model I** to test Herd behavior would be estimated as:

$$CSSD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t \tag{3.17}$$

where

$D_t^U = 1$ 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. $D_t^L = 1$ 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.

Different studies have used different measures to define up and down market. Demirer et al (2007) while analyzing daily returns for 1998-2004 applies two strategies to define extreme market that is at 5% and at 1%. Lao and Singh (2011) defined extreme market at 1%, 5% and 10%. Henker et al (2003) defined extreme markets for India and China at 1%, 2% and 5%. Fu and Lin (2010) used 5% of returns for upper and lower tail of return distribution. This study is analyzing daily returns for the period 2000 to 2014that is 4910 observations which is a reasonable large data set to analyze. Since 1% or 2% are too small percentages to investigate the effect of herding, this study has implied at 5% and 10% of return distribution to define extreme market conditions. When return distribution has been arranged in descending order, upper 5% and 10% observations indicate extreme upper tail of return distribution and lower 5% and 10% observations indicate the extreme lower tail of return distribution.

Since for herding to exist dispersion between individual return and market returns should be minimum, a small value of CSSD in extreme market situations support the evidence of herding. Thus to have an evidence of herd behavior in KSE, values of regression coefficients that is $\beta_1$ and $\beta_2$ should be significantly negative.

#### 3.4.3.1 Non Linearity of Herding

Christie and Huang (1995) held that herd behavior contradicts with the traditional asset pricing theories which states that dispersion increases with the absolute market returns because of differing sensitivity of stocks to market returns. It is not necessary that a change in returns always bring about same magnitude of change in spread between stock returns and market returns. Based on this idea, Chang et al (2000), negating linear relationship of dispersion and market returns proposed by rational asset price models used cross sectional absolute deviation (CSAD) to capture dispersion and propose a new model covering all possibilities of nonlinear relationships between returns and dispersion. CSAD has been defined as:

$$CSAD_t = \frac{1}{N_t} \sum_{i=1}^{N_t} |R_{i,t} - R_{m,t}| \tag{3.18}$$

**Model II** to test herding based on measure of CSAD has been implied as:

$$CSAD_t = \theta + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{3.19}$$

where

$CSAD_t$ is the average cross-sectional absolute deviation of each stock with respect to the equally-weighted market return, $R_{m,t}$ in period $t$. According to this model, in case herd behavior exists, a nonlinear relationship would be indicated by significantly negative value of $\gamma_2$.

#### 3.4.3.2 Swap of Dependent Variable

Fu and Lin (2010) test herding by swapping both the dependent variables in model I and Model II.

Same methodology has been implied to see whether results change or remain the same. After swapping dependent variables, the equations are changed as follows:

$$CSAD_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t \tag{3.20}$$

$$CSSD_t = \theta + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{3.21}$$

#### 3.4.3.3 Turnover effect on Herding

Turnover effect has its roots in the notion that low turnover stocks are more prone to herding as compared to high turnover stocks due to lack of information (Fu and Lin, 2010; Gregroriou and Ioannidis, 2006). In order to test turnover effect on herding, stocks have been divided into two groups that is high turnover stocks and low turnover stocks on the basis of average turnover for the period. Median of the average turnover has been used to segregate between high turnover and low turnover stocks. Stocks above median average turnover are classified as high turnover stocks and below median stocks are classified as low turnover stocks.

Based on the concept of standard deviation (SD) and absolute deviation (AD), four measures of dispersion from market (two each for high and low turnover stocks) have been established following Fu and Lin (2010) as under:

$$HTSD_t = \sqrt{\frac{\sum_{h=1}^{N_t/2}(R_{h,t} - R_{m,t})^2}{N_t/2}} \tag{3.22}$$

$$LTSD_t = \sqrt{\frac{\sum_{l=1}^{N_t/2}(R_{l,t} - R_{m,t})^2}{N_t/2}} \tag{3.23}$$

$$HTAD_t = \frac{1}{2N_t}\sum_{h=1}^{N_t/2}|R_{h,t} - R_{m,t}| \tag{3.24}$$

$$LlTAD_t = \frac{1}{2N_t}\sum_{l=1}^{N_t/2}|R_{l,t} - R_{m,t}| \tag{3.25}$$

where

$t =$ Time period, $R_{m,t} =$ Daily market returns, $R_{h,t} =$ Daily return of high turnover stocks, $R_{l,t} =$ Daily returns of low turnover stocks, $N_t =$ Number of stocks at time period $t$.

Low dispersion from market returns implies the existence of herding. Since low turnover stocks are more likely to herd due to lack of sufficient information, turnover effect to exist needs significantly higher mean values for HTSD and HTAD than the LTSD and LTAD. All the four measures of dispersion calculated for turnover effect will be tested for Model I and Model II (specified above) with the exception that HTSD, HTAD, LTSD, and LTAD will be used as dependent variable ($Y_t$) respectively. The generic models will thus take the shape as under:

$$Y_t = \alpha + \beta_1 D_t^U + \beta_2 D_t^L + \varepsilon_t \tag{3.26}$$

$$Y_t = \theta + \gamma_1|R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \tag{3.27}$$

Significantly negative values of $\beta_1$, $\beta_2$, $\gamma_2$ for LTSD and LTAD being dependent variables implies turnover effect in extreme market situations. Extreme market has been defined at 5% and 10% on same pattern as defined above. However, for HTSD and HTAD as dependent variables, $\beta_1$, $\beta_2$, and $\gamma_2$ does not need to be significantly negative.

#### 3.4.3.4 Asymmetry Test

Since markets behave differently to good and bad news, same behavior cannot be expected for whole sample. Thus a further bifurcation of herding model can be made for up and down markets. Variance between the up market returns and down market returns will show the asymmetry between responses to news. Basic model for CSAD has been modified by Fu and Lin (2010) as follows to test asymmetry in herding behavior:

$$Y_t = \alpha + \gamma_{1,up}|R_{m,t}| + \gamma_{2,up}(R_{m,t})^2 + \varepsilon_t \tag{3.28}$$

$$Y_t = \alpha + \gamma_{1,down}|R_{m,t}| + \gamma_{2,down}(R_{m,t})^2 + \varepsilon_t \tag{3.29}$$

CSSD, CSAD, HTSD, HTAD, LTSD, and LTAD have been used one by one as dependent variable Yt. In order to test asymmetry in reactions, market returns are first ranked into ascending order. Market has been defined as down market up to the point where market returns are zero. Beyond this point, when returns turn positive, market has been defined as up market. To have an evidence of asymmetric herding behavior in up and down markets, not only $\gamma_2$ has to be negative but also value of $\gamma_{2,up} - \gamma_{2,down}$ should be significantly different than zero or $H_0$: $\gamma_{2,up} - \gamma_{2,down} = 0$ should be rejected.

### 3.4.4 Disposition Effect

Investors evaluate each security, with reference to the associated gains and losses, individually rather than evaluating the performance of whole portfolio (Thaler, 1980). Since investors are always interested in multiplying their invested capital, stocks are appraising in value happen to be delightful for investors in an anticipation of realizing allied gain by selling the stock at higher price. As the investor finds a stock at perceived high of a value, they tend to sale that stock to immediately realize the gain. This tendency, being irrational, is termed as disposition effect by behavioral economists. Kahneman and Tversky's (1979) prospect theory also explains this behavior in light of human psychology that people prefer gains over losses. They identified it as risk adverse behavior for gains and consequently risk seeking behavior for losses as losing stocks are held in anticipation of rise in value in future. Behavioral aspect of this tendency has been explained by Shefrin and Statman (1985) as the realization of gain by selling a winner stock validated the strength of investment decision of investor which makes him proud and confident about his evaluations. Similarly holding a loser stock is a deliberate effort of investor to refrain from the feeling of regret of making wrong investment decision. Thus the security with higher returns is more prone to be traded frequently and resultant increase in turnover. Thus Disposition effect can sufficiently be traced through interaction of individual security's return as well as market return with the security turnover (Shefrin and Statman, 1985).

As for testing the association between market returns and turnover in Karachi Stock Exchange, Vector Auto Regressive (VAR) model has been implied, same can be used to test the relationship between security returns and security turnover. Statman et al (2004) segregated between investor over confidence and disposition effect by attributing the positive relationship of individual security turnover with its own lagged returns to the presence of disposition effect by analyzing Vector Autoregressive (VAR) estimates.

In order to test for the Disposition effect in KSE 100 index during 2000 to 2012, based on Statman (2004), vector autoregressive model has been formulated with three endogenous and one exogenous variable. For any model, endogenous variables are those in whose terms dependent variables are explained that is they are confirmed part of a model whereas exogenous variables are those whose relation with dependent variable is determined outside the model and are added to model to account for the random external conditions. Where endogenous variables can be influenced by the variables of economic model, exogenous variables are generally uncontrollable. Endogenous variables used by this study to find out the evidence of disposition effect are security turnover, security return and market return. The only variable used as exogenous one is volatility. Security returns (SRET) have been calculated same as the market returns were calculated. For the purpose of this study, closing share prices of firms at month end has been used to calculate the corresponding returns using formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.30}$$

where

$R_t$ = Return of a security on month $t$

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

$P_{t-1}$ = Closing price of the stock at last trading day of previous month

Security returns for each security, so obtained, are then averaged out for each month to generate a series of SRET to be utilized for the purpose of analysis.

Security Turnover (STURN) has largely been defined as value of monthly trading volume of security. Since the study is employing monthly data to be tested, daily figures have to be converted into monthly values. Monthly turnover of the security refers to the sum of the value of daily trading volume at last trading day of the month. Although daily trade volume is highly prone to fluctuations due to any new information available in market (for example earning surprise, introduction of any new policy by government, etc), sum of the daily trading volume fully accommodates these factors and reflects an aggregated figure, most suitable to be tested.

Disposition effect has already been discussed as closely related to overconfidence bias. Overconfidence bias states positive market returns makes an investor feel "I am the best" and thus he trades more frequently which increases the trading volume of market. Overconfident investors, in such conditions, tend to sale winning stocks and holding loser stocks to validate their belief in themselves giving birth to disposition effect. Thus it may also be tested whether disposition effect has its roots in overall positive returns of the market or not. For this purpose, third endogenous variable, market return (MRET) has been introduced in the model. Market return has been calculated with the help of market index at last trading day of the month on the same pattern as security returns have been calculated above.

Exogenous variables, as stated, are determined independently by the factors outside the causal system under study. Only exogenous variable used for this study is the volatility in security returns (SVOL) and defined as monthly temporal volatility of Security returns. Daily security returns have been used to arrive at monthly volatility figures by applying methodology suggested by French, Schwert and Stambaugh (1987) as is done for measuring market volatility. The formula is specified as follows:

$$\delta_{m,t}^2 = \sum_{i=1}^{N_t} r_{i,t}^2 + 2 \sum_{i=1}^{N_t - 1} r_{i,t}(r_{i+1,r}) \tag{3.31}$$

where

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

$r_{i,t}$ = Daily return of security at day $t$

$N_t$ = Number of trading days in a month

After the variables being defined as endogenous and exogenous variables, stationarity of variables is to be tested in first instance. Return series, both for market and securities, is generated after taking natural log of the share prices and market index. Natural log or first difference is widely considered a tool to remove non-stationary properties from the series. Non stationary series contain some trend in it with mean and variance not constant over the series which results in spurious regression results and other biases. Thus in order to analyze true behavior of a series, data has to be stationary any way. For disposition effect, market returns and security returns are already been logged and stationarized. Since volatility has been calculated for series of security returns, it contains all the qualities of a stationary series. The only variable taken at its face value is security turnover which needs to be checked for stationarity. Whether a series contain unit root or not has been analyzed for all the four variables under study using the two famous statistical tests that is Augmented Dickey Fuller (ADF) test and Phillip-Perron (PP) test.

To test the time series data of securities and market to ascertain the relationship of turnover and returns, Vector auto regressions (VAR) and associated impulse response functions has been implied to capture the full impact of an exogenous variable observation. The model is formulated as:

$$\begin{aligned}\begin{bmatrix} STURN_t \\ SRET_t \\ MRET_t \end{bmatrix} &= \begin{bmatrix} \alpha_{STURN} \\ \alpha_{SRET} \\ \alpha_{MRET} \end{bmatrix} + \sum_{k=1}^{3} A_k \begin{bmatrix} STURN_{t-k} \\ SRET_{t-k} \\ MRET_{t-k} \end{bmatrix} \\ &+ \sum_{l=0}^{2} B_l \begin{bmatrix} SVOL_{t-l} \\ SVOL_{t-l} \\ SVOL_{t-l} \end{bmatrix} + \begin{bmatrix} e_{STURN,t} \\ e_{SRET,t} \\ e_{MRET,t} \end{bmatrix}\end{aligned} \tag{3.32}$$

where

$STURN_t$ = Security Turnover for month $t$

$SRET_t$ = Security Returns for month $t$

$MRET_t$ = Market Returns for month $t$

$SVOL_t$ = Cross sectional standard deviation of daily stock returns for month $t$

$k$ = Lag length for endogenous variables

$l$ = Lag length for exogenous variables

$A_k$ = Coefficient for endogenous variables

$B_l$ = Coefficient for exogenous variables

STURN, SRET and MRET are endogenous variables for the period t whereas volatility, SVOL, is the only exogenous variable in the model. Since only one security cannot determine the market return, MRET can also be taken as exogenous variable (Statman, 2004) however this study is utilizing only one exogenous variable that is volatility. The regression coefficients, $A_k$, and $B_l$, estimate the time-series relationships between the endogenous and exogenous variables with their lagged values. The positive and highly significant association (based on p-values) between security turnover and lagged security returns would provide us the evidence of disposition effect and will prove our hypothesis.

### 3.4.5 Overreaction of Market

Whenever any unexpected or dramatic news arrive in the market, people tend to over react (De Bondt and Thaler, 1985). To measure this reaction of investors in Pakistani market, autocorrelation between monthly stock returns has been analyzed. A negative autocorrelation in the long run between returns indicate overreaction to investors to specific news. Similarly, positive autocorrelation of returns in short run represents underreaction. In order to test autocorrelation, in first instance, excess residual returns have been calculated from the monthly returns of market as well as stocks in following manner:

$$\mu_{i,t} = R_{i,t} - R_{m,t} \tag{3.33}$$

where

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

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

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

Following DeBondt and Thaler (1985), this study is also using a strategy of non-overlapping 3/3 years that is three year holding period and three year formation period. For the data period of this study, three such periods have been defined with portfolio formation dates of December 2005, December 2008, and December 20011. On each portfolio formation date, Cumulative excess residual returns are calculated for non-overlapping three year as follows:

$$CAR_i = \sum_{t=0}^{n} \mu_{it} \tag{3.34}$$

where

$CAR_i$ = Cumulative Excess Residual Returns for stock $i$

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

On each of the portfolio formation date, stocks are ranked on the basis of cumulative excess returns (CARs). Different studies documented different thresholds for identification of winners and losers such as extreme 5% stocks performing (Chopra et al, 1992), best and worst 35 performing stocks (DeBondt and Thaler, 1985), top and bottom deciles (Jegadeesh, (1990); DeBondt and Thaler, (1985)) etc. Since our sample includes 100 companies, it is reasonable enough to use a ratio of 10% to identify winners and losers. First ten extremely good performers with highest CARs are assigned to winner's portfolio whereas bottom ten stocks that is extremely low performers with lowest CARs are assigned to loser portfolio.

In order to test the performance of each portfolio, cumulative excess returns (CARs) of each stock have been taken for a testing period of next 36 months ($t$ = 1,2,3,4·36) starting next to the portfolio formation date ($t = 0$) for winner as well as loser portfolio. Cumulative Average Returns ($CAR_{w,n,t}$ and $CAR_{l,n,t}$) for both the portfolios are then calculated as follows:

$$CAR_{p,z,t} = \sum_{t} \left[ \left( \frac{1}{N} \right) \sum_{i=1}^{N} \mu_{it} \right] \tag{3.35}$$

where

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

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

$N$ = Number of stocks in portfolio

Using CARs from all test periods, average CARs are calculated from both portfolios and denoted as $ACAR_{W,t}$ and $ACAR_{L,t}$ as follows:

$$ACAR_{p,t} = \sum_{z=1}^{Z} CAR_{p,z,t} \div z \tag{3.36}$$

where

$ACAR_{p,t}$ = Average Cumulative Abnormal Returns of portfolio at time $t$
$CAR_{p,z,t}$ = Cumulative Average Abnormal Return for test period $z$ at month $t$
$Z$ = Test periods that is 3

The Overreaction Hypothesis predicts that for any $t > 0$:

$$\begin{aligned} ACAR_{W,t} &< 0 \\ ACAR_{L,t} &> 0 \quad \text{and} \\ (ACAR_{L,t} - ACAR_{W,t}) &> 0 \end{aligned} \tag{3.37}$$

In order to assess the statistical significance of difference in portfolio performance, and to find out whether for any month $t$, the average residual return makes a contribution to either $ACAR_{W,t}$ and $ACAR_{L,t}$, T-stat has been calculated as:

$$T_{p,t} = \frac{AR_{p,t}}{S_p/\sqrt{N}} \tag{3.38}$$

where

$T_p$ = $t$-value of the month $t$ in portfolio
$AR_{p,t}$ = Average cumulative abnormal return of the portfolio at time $t$
$N$ = Number of observations
$S_p$ = Standard deviation of average returns of portfolio and has been defined as:

$$S_p = \sqrt{\frac{\sum_{n=1}^{N}(CAR_{p,z,t} - AR_{p,t})^2}{N-1}} \tag{3.39}$$

Also for the study, a pooled estimate of population variance in $CAR_t$ will be required which is estimated as:

$$S_t^2 = \frac{\sum_{n=1}^{N}(CAR_{W,n,t} - ACAR_{W,t})^2 - \sum_{n=1}^{N}(CAR_{L,n,t} - ACAR_{L,t})^2}{2(N-1)} \tag{3.40}$$

where

$ACAR_{W,t}$ = Average Cumulative Abnormal Returns of winner portfolio at time $t$
$CAR_{W,n,t}$ = Cumulative Average Abnormal Return for winner portfolio at month

$t$

$N$ = Number of observations

With two samples of equal size $N$, the variance of the difference of sample means equals $2S_t^2/N$ and T-stat is:

$$T_t = \frac{[ACAR_{L,t} - ACAR_{W,t}]}{\sqrt{2S_t^2/N}} \tag{3.41}$$

where

$ACAR_{W,t}$ = Average Cumulative Abnormal Returns of winner portfolio at time $t$
$ACAR_{L,t}$ = Average Cumulative Abnormal Returns of Loser portfolio at time $t$
$S_t^2$ = Population Variance
$N$ = Number of observations

Similar procedure applies to the portfolio of Loser for the formation period of 36 months ($t$ = 1,2,3,·36).

### 3.4.6 Market Reaction, Excess Volatility and Market Turnover

After testing for all the heuristic and behavioral biases and market under/over-reaction so formed, there is a need to assess whether the presence of behavioral biases giving birth to market under/ overreaction are contributing towards the market volatility or not. In order to calculate excess volatility, in first instance, standard deviation among daily market returns has been calculated as follows:

$$\sigma_t = \sqrt{\frac{\sum_{t=1}^{n}(X_t - \overline{X})^2}{n-1}} \tag{3.42}$$

where

$\sigma$ = Standard deviation of daily returns at time $t$
$X_t$ =Market return at day $t$
$X$ = Mean of daily market returns
$n$ = No of observations

In order to calculate moving average, testing period has been defined from January 2000 to December 2002. Moving average for the standard deviation obtained has been calculated as follows:

$$MA_t = \frac{\sum_{t=1}^{n} A_t}{n} \tag{3.43}$$

where

$MA_t$ = Moving Average at time $t$

$A$ = Average of standard deviation for the selected period at time $t$

$n$ = No of observations

Excess volatility in market implying the moving average method has been calculated as:

$$Vol_t = \sigma_t - MA_t \tag{3.44}$$

where

$Vol_t$ = Excess volatility at time $t$

$\sigma$ = Standard deviation of daily returns at time $t$

$MA_t$ = Moving Average at time $t$

Market reactions has been defined in section 3.5 as the market tend to over react when $ACAR_w < 0$, $ACAR_L > 0$ and by implication $ACAR_L - ACAR_w > 0$. Thus to find out whether investors have over reacted or under reacted to any upcoming news, $ACAR_L - ACAR_w$ has been used where $ACAR_L - ACAR_w > 0$ shows over reaction of investors and $ACAR_L - ACAR_w \leq 0$ shows the under reaction of investors.

Volatility in market has been defined as a function of Market reaction. However, it is not only the market reaction that constitutes the volatility in market but several other factors may also apply. This study hypothesizes that market turnover also has an impact over the excess volatility. Market Turnover here refers to the total value of shares traded during the period divided by the average market capitalization for the period.As to test this implication, along with the market reaction, market turnover (Turn) has also been added to the excess volatility function that is volatility = $f$ (market reaction, turnover).

In order to find out the nature of relationship between excess volatility, market reaction and market turnover, regression equation has been applied as under:

$$Turn_t = \alpha + \beta_1 MR_t + \mu \tag{3.45}$$

$$Vol_t = \alpha + \beta_1 MR_t + \beta_2 Turn_t + \mu \tag{3.46}$$

where

Vol = Excess volatility at time $t$

MR = Market reaction at time $t$

Turn = Market Turnover at time $t$

# Chapter 4

# Data Analysis

A challenge to the efficient market hypothesis is that individuals often over- or under-react to news. It is held that investors tend to over react to the unanticipated news which results in exaggerated stock prices. This attitude of investors may be associated with the overweighing of recent information as compared to under weighing of fundamental information by irrational investors. Since fundamental do not change in long run, stock prices tend to correct in long run. This implies that current winners appear as losers in long run and current losers win in future. Based on this mean reversion theory contrarian strategy may be the best option to get optimal benefit.

## 4.1 Overconfidence and Self-Attribution

Irrational investors while making a decision tend to rely on their own judgment and overweight any personal information as compared to information available to market. The reason being, investors overestimate their ability to assess the value of stock and are confident enough about their skills (Odean, 1998). Such overconfident investors tend to trade more frequently until they start earning losses. Two basic testable implications for overconfidence theory are that overconfident traders show high trading activity following high observed market returns, i.e. Past returns are positively correlated with current turnover. Second, aggressive trading in securities by overconfident traders contributes to observed excessive returns volatility. Relationship between trading volume and lagged returns has more pronouncedly been found in developing, opaque, corrupt and volatile markets (Griffin and Tversky, 1992). Safely said, all these conditions apply to Pakistani markets thus the stronger findings for this relationship from analysis of KSE 100 index for period 2000 to 2014 may provide more robust and interesting results.

### 4.1.1 Unit Root Test

In order to identify whether a series is stationary or not, plotting of series is the simplest way. Turnover series so obtained for period under study when plotted shows the persistence of trend which makes a series non stationary which can lead to bias in coefficient of error term of VAR model. Figure 4.1 below exhibits the same.

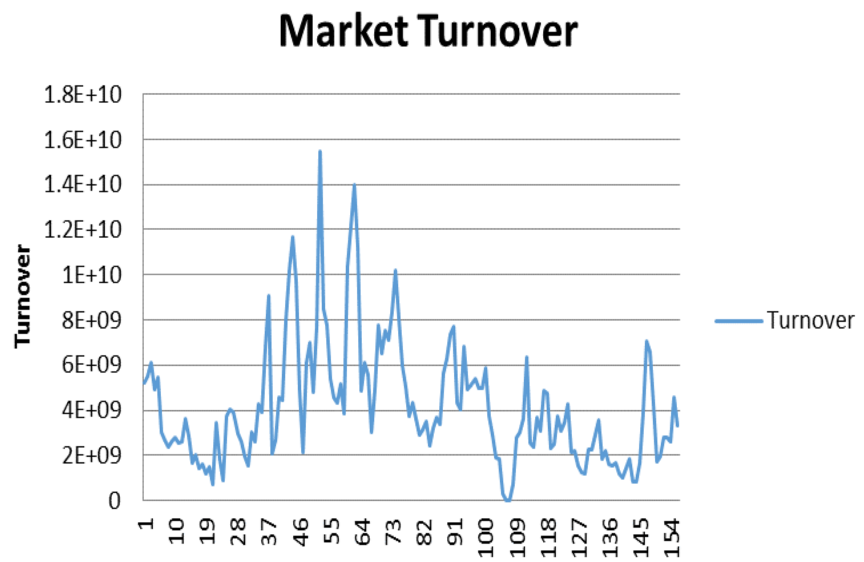


FIGURE 4.1: Trend in monthly Turnover of KSE 100 index during period 2000 to 2014.

Figure 4.1 has plotted the values of monthly turnover over sample period that is from 2000 to 2014, as shown by solid fluctuating lines. A trend line has been fitted to the observations to depict movements in turnover more precisely. Trend line shows that turnover has undergone changes, ups and downs, over the period which implies that mean and standard deviation of series overtime is not constant.

Thus series is considered non stationary. In order to de-trend the given series or to make the series stationary, taking natural log may be an appropriate solution since turnover cannot assume any negative value. However, there is a possibility of nonlinear secular trend in logged turnover series as well, thus it is reasonable enough to test the unit root for logged series. Variable "Turn" thus depicts the de-trended logged turnover series.

Unit root test with a null hypothesis $H_0$: *series has a unit root*, has been applied to the variables under study. Results found are described as under:

TABLE 4.1: Unit Root Analysis of variables for testing Overconfidence Bias.

| Description | ADF I(0) | PP I(0) |
|---|---|---|
| **Turn** | -5.5692 | -4.7245 |
| **Ret** | -11.3079 | -11.3129 |
| **Mvol** | -9.0234 | -9.0126 |
| **Disp** | -8.4852 | -8.4931 |
| **Critical Values** | | |
| **1%** | -3.4728 | -3.4728 |
| **5%** | -2.8801 | -2.8801 |
| **10%** | -2.5767 | -2.5767 |

Table 4.1 above shows the results for unit root test for the variables under study for the period 2000 to 2014. Augmented Dicky Fuller test (ADF) and Phillip Perron test (PP) test have been used for this purpose. Results shows that values for all the variables are significantly higher than the critical values mentioned in lower part of the table. P-values of the obtained coefficients has not been reported however conclusion achieved at by analyzing coefficient values remains the same even if verdict is given on behalf of p-values.

Results reveal that none of the variable under study has unit root and thus null hypothesis is rejected at 1% level of significance. Even with other levels of significance that is 5% and 10%, null hypothesis is rejected. Since series for all the variables has significantly high coefficients than critical values, it means that series are stationary at level (without taking first difference). When series is found integrated at a lower order than I(1), Ordinary Least Square (OLS) may be employed, since long term relationship of turnover and lagged returns is to be analyzed, cointegration has an advantage over the OLS to be used.

### 4.1.2 Descriptive Statistics

Descriptive statistics of the variables under study are presented below to better understand the behavior of variables in long run.

TABLE 4.2: Descriptive Statistics of Variables for Testing Overconfidence Bias.

| | **Turn** | **Ret** | **Mvol** | **Disp** |
|---|---|---|---|---|
| **Mean** | 21.8862 | 0.0144 | 0.0626 | 0.0002 |
| **Median** | 22.0018 | 0.0193 | 0.0543 | 0.0001 |
| **Maximum** | 23.4602 | 0.2411 | 0.22 | 0.0011 |
| **Minimum** | 14.8421 | -0.4488 | 0.0001 | 0 |
| **Std. Dev.** | 0.9743 | 0.0845 | 0.0391 | 0.0002 |
| **Skewness** | -3.5868 | -1.1524 | 1.6766 | 2.1885 |
| **Kurtosis** | 24.6837 | 8.421 | 6.4442 | 7.8535 |

*Turn = Market Turnover, Ret = Market Return, Mvol = Market Volatility, Disp = Dispersion*

Table 4.2 above shows the results for descriptive statistics for market turnover, market returns, market volatility and dispersion. The results for de-trended turnover series reveal that KSE 100 index has a mean value of 21.8862 on average for a month. Minimum value for the turnover is 14.8421 and maximum value achieved is 23.4602. This gives margin for a standard deviation of 0.9743 to exist. This shows that time series for de-trended turnover is highly volatile and moves between two extremes. Skewness and Kurtosis both are the measure of normality of distribution of series. Value of skewness for turnover series is -3.5868that is skewness is ¡0 which implies that most of the extreme values of turnover series lies at left side of the mean and thus distribution has a long tail at left side. Kurtosis for turnover series is 24.6837 which is greater than 3 means that data curve is peaked from center and falls down quickly with heavy tails. This shows that most of the values of turnover series are concentrated around mean.

Time series for returns shows a mean value of 0.0144 which means that on average monthly return for KSE 100 index is 1.44% which is reasonable enough. Maximum return to Karachi stock exchange for a month is 24.11% whereas minimum return may be a figure of loss that is 44.88% loss on average for one month may be earned. Standard deviation between the returns series is 8.45% which is sufficiently high to make a market volatile. Skewness for returns is again a negative number that is $-1.1524 < 0$ showing that most of the values of return series lies at the left side of the mean and distribution is negatively skewed to the left. Kurtosis figure that is 8.42 is again greater than 3 adding peak to the distribution and showing the concentration of values around mean value.

Series of market volatility shows a monthly volatility of 6.26% on average in the market return series. Maximum volatility observed in market during a month is 22.00% and a minimum volatility observed is equivalent to 0.01%. Standard deviation between the volatility series is 3.91% that is values of volatility at different points of time has a wide spread to move. Skewness observed is 1.6766 which is greater than "0" means that data is not normally distributed and is skewed towards right side. It depicts that maximum values lies at the right side of the mean elongating the right side tail of distribution. Kurtosis observed is 6.444 which is greater than 3 thus the data is leptokurtic distribution.

Dispersion series shows an average dispersion of 0.02% which is very low. The dispersion in returns from mean value is not high enough which can also be seen from the spread between maximum value of 0.11% and minimum value of 0. Standard deviation of dispersion series is again very low that is 0.02%. Skewness and Kurtosis are both positive values where skewness $>0$ and kurtosis $>3$. This implies that data is positively skewed with a leptokurtic distribution.

### 4.1.3 Correlation Analysis

In order to test the mutual relationship of variables under study, correlation analysis has been conducted. Also it is necessary to have correlation analysis so that if there exist any multicollinearity among variables, it may be detected and removed before applying further analytical model.

TABLE 4.3: Correlation Analysis of the variables.

| | **Turn** | **Ret** | **Mvol** | **Disp** |
|---|---|---|---|---|
| **Turn** | 1 | | | |
| **Return** | 0.23891 | 1 | | |
| **Mvol** | 0.206842 | -0.35576 | 1 | |
| **Disp** | 0.174246 | -0.29319 | 0.86904 | 1 |

*Turn = Market Turnover, Ret = Market Return, Mvol = Market Volatility, Disp = Dispersion*

Table 4.3 shows the correlation matrix for the variables under study that is market return, market turnover, volatility and dispersion. The matrix shows that there exists very weak relationship between turnover and returns that is only 23.89%. This is the weakest relationship observed as compared to the return's relationship with market volatility and dispersion. Comparatively strongest relationship exist for market returns and volatility however it has appeared as a negative relationship. As far as turnover is concerned, the relationship it has with returns is strongest as compared to turnover related to volatility and dispersion.

Strongest relationship in whole matrix exists for market volatility and dispersion that is 86.90%. Whenever such a high correlation is found between two variables it is feared that multicollinearity may exist. It means that inclusion of both the variables are not adding any information to the model and thus one variable may be dropped. In order to identify whether multicolinearity exist or not, auxiliary regression may be employed. Auxiliary regression is this regresses the squared residuals from the original regression model onto a set of regressors that contain the original regressors, the cross-products of the regressors and the squared regressors. One then inspects the $R^2$.

For this study auxiliary Mvol has been regressed upon dispersion (Disp). The regression results show the value of $R^2$ as 0.7552. As a result of auxiliary regression, if value of $R^2$ is less than 0.90, both the variables can stay in model. Another measure is to calculate Variance Inflation Factor (VIF) as follows:

$$\text{VIF} = \frac{1}{1 - R^2} \tag{4.1}$$

With a $R^2$ of 0.7552, value of VIF has been calculated as 4.08. As a rule of thumb, value of VIF lesser than 10 is acceptable and implies that multicollinearity does not exist. Thus there results of regression cannot be disturbed by inclusion of both the variables in model.

### 4.1.4 Vector Auto Regression (VAR) Model

VAR model has been accepted as most flexible, successful and easy to use to describe the linear interdependencies of multiple time series. Variables in VAR are treated symmetrically in a structural sense where each variable has its own equation to explain its development over time depending on its own lagged values as well as the lags of other variables. VAR model employed to find out the long term relationship of market return, market turnover, volatility and dispersion. Out of these variables, prior two are taken as endogenous variables, whereas later two are the exogenous variables. VAR estimation for two classes of variables has been presented separately in Table 4.4.

Panel A and Panel B of Table 4.4 shows the results of Vector Autoregressive Model (VAR) to estimate long term relationship of market returns and turnover. Independent variables in the table are the lagged values of market turnover and returns which are placed in columns. Dependent variable that is market ret and turnover are placed in rows and their corresponding values of independent variables appear in front of them. For each variable, coefficient, standard error and t-value of the test has been presented.

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

| | | | Panel A Lagged Values of Turnover | | | Panel B Lagged Values of Return | | | Panel C Lagged Values of Volatility | | | Panel D Lagged Values of Dispersion | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **C** | **Turn(-1)** | **Turn(-2)** | **Turn(-3)** | **Ret(-1)** | **Ret(-2)** | **Ret(-3)** | **Mvol** | **Mvol(-1)** | **Mvol(-2)** | **Disp** | **Disp(-1)** | **Disp(-2)** | $R^2$ | F |
| | Coefficient | 5.173 | 0.913 | -0.222 | 0.044 | 1.119 | 0.648 | 0.943 | 6.412 | 0.646 | -5.7 | -1.977 | -2.698 | 2.931 | | |
| Turn | Std Error | -1.412 | -0.073 | -0.094 | -0.071 | -0.567 | -0.348 | -0.56 | -2.47 | -3.4 | -2.973 | -1.107 | -0.681 | -0.216 | 0.699 | 4.88* |
| | t-value | (3.66)* | (12.486)* | (-2.36)** | -0.616 | (1.97)*** | (1.86)*** | (1.68)*** | (6.644)* | -0.19 | (-1.917)* | (-4.89)* | (-0.03) | (-0.976) | | |
| | Coefficient | -0.405 | 0.017 | 0.018 | -0.014 | -0.023 | -0.122 | -0.075 | -0.507 | -0.048 | 0.155 | -1.004 | -1.37 | -2.294 | | |
| Ret | Std Error | -0.2 | -0.01 | -0.013 | -0.01 | -0.08 | -0.077 | -0.079 | -0.348 | -0.445 | -0.389 | -0.517 | -0.069 | -0.777 | 0.208 | 4.74* |
| | t-value | (-2.03)** | (1.639)*** | (1.640)*** | (-1.349) | (-0.29) | (-1.585) | (-0.949) | (-1.75)*** | (-0.107) | (-0.397) | (-0.818) | (-0.149) | (-0.992) | | |

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

Table 4.4 Panel A shows that there exist a significantly positive relationship between turnover and lagged turnover. Especially current turnover is very strongly dependent on the first lag where t-value = 12.4866 that is highly significant with 99% confidence interval. Second lag of turnover, Turn (-2), also have a significant relationship with turnover however; confidence level at second lag is minimized to 95% confidence interval. At third lag, relationship between Turn (-3) and turnover disappears as t = 0.6163 which is an insignificant value. When come to returns, there exist a significantly positive relationship between Return and Turn (-1) and Turn (-2) as evident by the t-values of 1.6395 and 1.6406 for first and second lag of turnover respectively. At third lag, again the relationship between returns and Turn (-3) is found insignificant that means turnover of the third month prior to time t does not have any impact on the current market returns. Lee and Swaminathan (2000) found that previous trading volume can be used to predict the future returns; the finding was for individual stocks though. Results for this study endorse these findings when applied to market instead of individual stocks.

Second endogenous variable for study has been Returns whose lagged values have been associated with dependent variables: Market turnover and Market return in Table 4.4 Panel B. The results reveal that turnover has a significantly positive relationship with the lagged returns. This effect can be traced for all the three lags employed in this study. T-values obtained for the coefficients of lagged returns are t-value = 1.9727, 1.86, and 1.6837 respectively for first, second and third lagged returns, which are significant with 90% confidence interval. Thus it can be deduced that lagged returns play their role in determining the current turnover of market.

As hypothesized by the overconfidence theory that higher returns earned by investors are associated by themselves to their own art of picking stocks which makes them overconfident and they start trading more aggressively. This aggression of investors results into the increased trading volume and turnover. Same relationship has been confirmed by our results and thus we can accept our hypothesis for overconfidence bias which states that there exists positive relationship between trading turnover and market returns. An investigation of association between returns and lagged returns has revealed that no such relationship exists at least for three lags as the results obtained are highly insignificant and does not provide any such evidence.

Table 4.4 Panel C shows that coefficient for relationship of Mvol and returns is 6.4121 with a t-value of 6.6447 which is highly significant at 1% level of significance. The relationship implies any increase in market volatility increases the market turnover as well. These results are in accordance with the volume-volatility relationship of Karpoff (1987) and French, Schwert, Stambaugh (1987). Coefficient for the first lag of volatility (Mvol(-1)) is found insignificant (coeff = 0.6464, t-value = 0.1901) which means that volatility of previous month does not affect turnover at time t any way. However, coefficient for second lag of volatility is again found significant (Mvol(-2) = -5.7004, t-value = -1.9175) but the nature of relationship is negative which implies that market volatility in prior two months affect the current turnover negatively that is inverse relationship exist. Increase in prior two volatility reduces the turnover.

When come to returns, it is found that coefficient of Mvol is -0.5069 with t-value of -1.7577 that is significant at 10% level of significance. Inverse nature of relationship implies that as the volatility in market increases, returns tend to fall since increases volatility generates uncertainty and thus investors prefer to trade less which decreases the turnover. However, this relationship does not hold for lagged values of Mvol as shown by insignificant coefficients and t- stats of -0.1079 and 0.3979 for variables. Mvol(-1) is also depicting a negative relationship between two but since the value of coefficient is insignificant, no evidence of lagged volatility causing reduced returns can be found.

Investigation of relationship between dispersion (Disp) and turnover in Table 4.1.4 Panel D reveals that both variables share a highly significant negative relationship that is as the dispersion between stock returns increases, market turnover tend to fall. However, this relationship has not been proved as lead lag relationship since any lagged value of dispersion do not affect the value of turnover. Coefficient for relationship between dispersion and return is -2.0044 with a t-value of -0.8187 depicting a negative relationship between both the variables. However, since t-value is highly insignificant, and t-values found for Disp(-1) and Disp(-2) are also found insignificant, no relationship between dispersion and returns can be advocated, neither for today nor for prior month's dispersion.

Summing up the relationship of exogenous variables and endogenous variables (turnover and returns) we may find that both cross sectional standard deviation in market prices (Mvol) and the cross sectional variation in stock returns (Disp) have a very strong impact on trading pattern and returns although nature of relations found for both the exogenous variables is different from each other. The pronounced variation in market and stock returns may be due to the effects of any upcoming information in the market that every investor has perceived in its own way that is effected by the investor's own beliefs and perception.

### 4.1.5 VAR Granger Causality

The VAR can be considered as a means of conducting causality tests, or more specifically Granger causality tests. Granger causality involves the correlation between the current value of one variable and the past values of others. However, it does not mean that changes in one variable cause changes in another. A variable is said to be a granger cause of other variable if its lagged values are helpful in predicting the values of other variable. VAR model has a null hypothesis as $H_0$*: Variable A does not granger cause variable B.* A Wald test is commonly used for granger causality. VAR granger causality results for endogenous variables are given in Table 4.5.

The results for VAR granger causality with Wald test shows that when turnover is the dependent variable, p-value obtained is 0.0432 that is lesser than 0.05. P-value lower than the critical value shows that the coefficients of the lagged values of returns are not jointly zero in the equation for turnover. Thus we may reject null hypothesis and conclude that Returns granger cause Turnover. These are the results in confirmation of VAR model results which showed significantly positive relationship between turnover and returns for all three lags.

For the equation of Returns, having turnover and its lagged values as independent variable p-value obtained is 0.0061 that is significant at 5% of level of significance.

Table 4.5: VAR Granger Causality/Block Exogeneity Wald Test.

| **Dependent variable: TURNOVER** | | | |
|---|---|---|---|
| **Excluded** | **Chi-sq** | **Df** | **Prob.** |
| **RETURNS** | 7.2897 | 3 | 0.0432** |
| **All** | 7.2897 | 3 | 0.0432** |
| **Dependent variable: RETURNS** | | | |
| **Excluded** | **Chi-sq** | **Df** | **Prob.** |
| **TURNOVER** | 12.41294 | 3 | 0.0061* |
| **All** | 12.41294 | 3 | 0.0061* |

**significant at 1% level of significance, **Significant at 5% level of significance*

It means that null hypothesis is rejected and it is established that Turnover granger causes Returns. This result is in accordance with the results of VAR estimation which found significant relationship between lagged values of turnover and Returns except for third lag which showed an inverse relationship however the evidence was weak enough to rely upon.

### 4.1.6 Impulse Response Function

Granger-causality may not give us the complete picture about the interactions between the variables in a model. Response of one variable to an impulse in another variable of the system (that involves a number of further variables as well) may be analyzed to get the period wise information of responses which is not evident in other estimations. The "impulse" refers to a short-duration time-domain signal which allows us to predict what the system's output will look like in the time domain. Impulse response functions use the VAR coefficient estimates to find out the impact of a residual shock that is one sample standard deviation from zero.

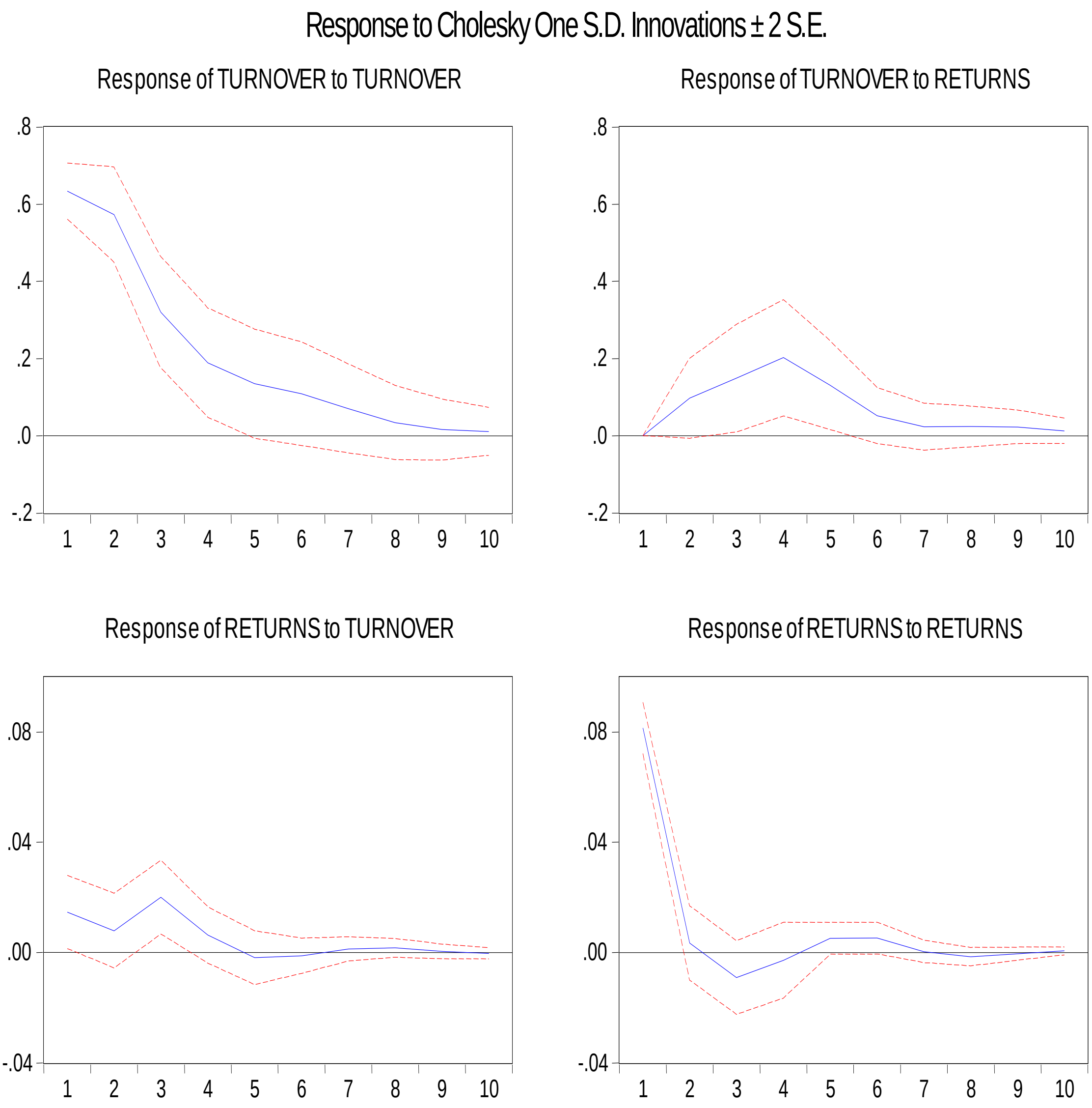


FIGURE 4.2: Impulse Response Analysis for Overconfidence Bias.

Figure 4.2 above shows the impulse response function of turnover and returns in four different scenarios that is response of turnover to one standard deviation shock in turnover, response of turnover to one standard deviation shock in returns, response of returns to one standard deviation shock in turnover and response of returns to one standard deviation shock in returns.

Panel A and Panel B of Figure 4.2 presents the response of turnover to turnover and response of turnover to returns, respectively. For both the panels, along vertical axis, turnover in form of percentages has been presented whereas along horizontal axis months bearing shocks have been taken. Panel A shows a gradual downward trend over time in turnover for every shock received. An impulse response in period 1 shows that one standard deviation shock to market turnover has bring about the change of almost 6.1% in the turnover of next month/period. Similarly, a one standard deviation shock in second period generated an impulse response of approximately 5.9% in next month's turnover. The trend continues and with each additional period, impulse response tends to fall for each one standard deviation shock in turnover. Although the impulse response of turnover has a declining trend, impact of shocks remains positive all over the period and around 8th period impulse response has become almost equal to zero. This may be due to the reason that turnover series under study was initially been de-trended. However, Panel A also proves the serial dependence of turnover over time.

Panel B depicts the response of turnover to a shock in returns. A one standard deviation shock in returns does not generated any impulse response in turnover and remain equal to Zero. However, from next month onwards, the impulse response of turnover to each one standard deviation shock starts increasing and ranges to 2% increase in next month's turnover in period 4. This is the highest response achieved. Beyond this point impulse response of turnover starts declining but remains positive for all periods. Impulse response of turnover to shock in returns, observed for period seven, is around 0.05% showing next month's turnover to be increased with this percentage in response to one standard deviation shock in returns.

Figure 4.2 Panel C and Panel D shows the responses of returns to returns as well as to turnover. For Panel C and Panel D we take difference in market return as compared to average returns along vertical axis and periods in which change is observed along horizontal axis. Panel C shows the response of returns to one standard deviation shock to turnover. It is evident that a one standard deviation shock in period one has brought about a 2% impulse response in returns of next period. For period two, this response declined to 1% for one standard deviation shock in turnover but again in third period it rose to 3% response in returns of next month. Beyond this point response of returns gradually declined at became zero in period 5 which continued till end. VAR estimates showed that returns increase with the increase in turnover up to two lags whereas in third lag the relationship turns negative but remain insignificant. It is may be due to this reason that response of returns to one standard deviation shock declines with time and remain around zero throughout later period under study.

Panel D shows the response of returns to the one standard deviation shock in returns. The results show that one standard deviation shock in returns generated an impulse response of 8% in returns of next month. This response for next month's returns, to one standard deviation shock, drastically dropped to approximately 0.03% in period 2 and even turns negative in period 3. In period five impulse response of returns again turns positive and after a declining trend remain equal to zero for rest of the periods.

Impulse response function tested for response of turnover to a shock in returns in panel B has presented a persistent positive response of turnover to the shocks in returns. This finding is in accordance to the results obtained through VAR estimations and thus confirms that investors are prone to overconfidence bias which states that continuously high returns make the investors overconfident about their information precision and they trade more aggressively which ultimately results in increase in turnover.

## 4.2 Anchoring

All of the individuals have their own experiences which help them to form an opinion or belief. Anchoring can only take place when individual or investor has some particular point available with him to use as anchor. However, individuals may also base their decisions on the result of some incomplete computation blended together with the adjustments to anchor. Since anchoring does not allow any investor to act rationally, there are very high chances that efficient markets may not be achieved.

A very commonly used anchor may be the past returns, having very low predictive power though. This study is analyzing the anchoring effect by constructing two anchors named nearness to Historical High (HH) and nearness to 24-Week

High where the former represents overreaction and later represents underreaction of investors. The anchors have been constructed on the basis of stock market's underreaction to intermittent news and overreaction to prolonged series of news (Li and Yu, 2009).

### 4.2.1 Graphic Presentation

Figure 4.3 shows that KSE 100 index has a general upward trend over the period 2000 to 2014. Although the periods of depression also hit the market during this period but due to the overall upward trend in economy, 100 index also tend to increase over the years. Value of Historical high keeps on increasing until it reaches the level of 14841 in May 2005 and then gets stagnant showing that market has not outperformed its own performance after this period. Market 6 month or 24 week high depicts the same pattern over the years as KSE 100 index. Although periods of depression are also seen, on the whole market has an upward trend. However, market 24 week high remains slightly above the KSE 100 index at all the times being the highest value is last 6 months of market performance.

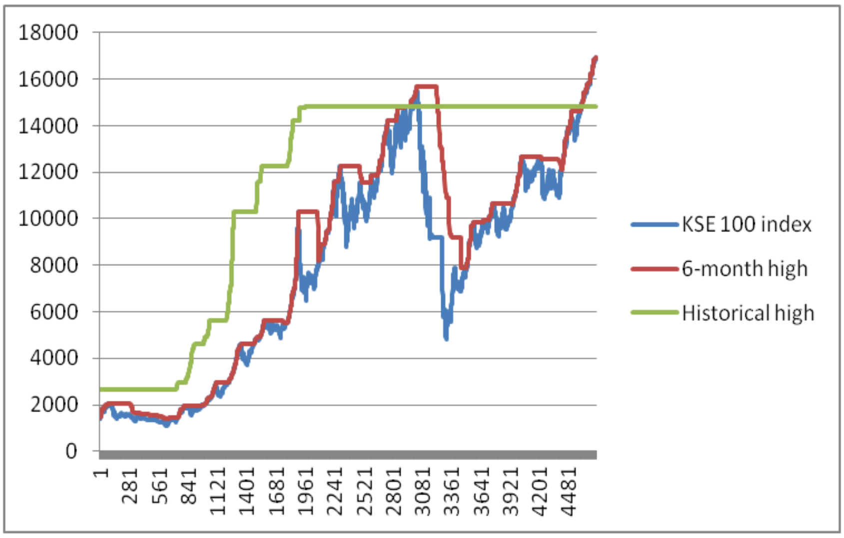


FIGURE 4.3: KSE 100 Index, 24 Week High and Historical High.

Based on the values obtained for 24 week high and historical high, two variables, Nearness to Historical High ($X_{(HH)}$) and Nearness to 24 Week High ($X_{(24W)}$) have been constructed to depict how near the existing value of index is to the historical high and 24 week high. Both these measures have been hypothesized as an indicator of investor's over and under reaction in market. Also it is held that said variables are being used as anchors while making the investment decisions.

Trends in Nearness to historical high ($X_{(HH)}$) and nearness to 24 Week high ($X_{(24W)}$) have been presented as graphic illustration in Figure 4.4 below. Whole chart depicted under Figure 4.4 can be divided into three parts. In first part, it is seen that as the nearness to historical high increases, nearness to 24 week high decreases. Gap between the movements of both the variables reflects this situation. In second part of the chart, it is seen that gap between both the trend lines has been minimized and they are perceived as moving in same direction, till the point where both the trend lines become equal to each other. However, in third part, the gap between two variables also increases and most of the time moves in opposite direction.

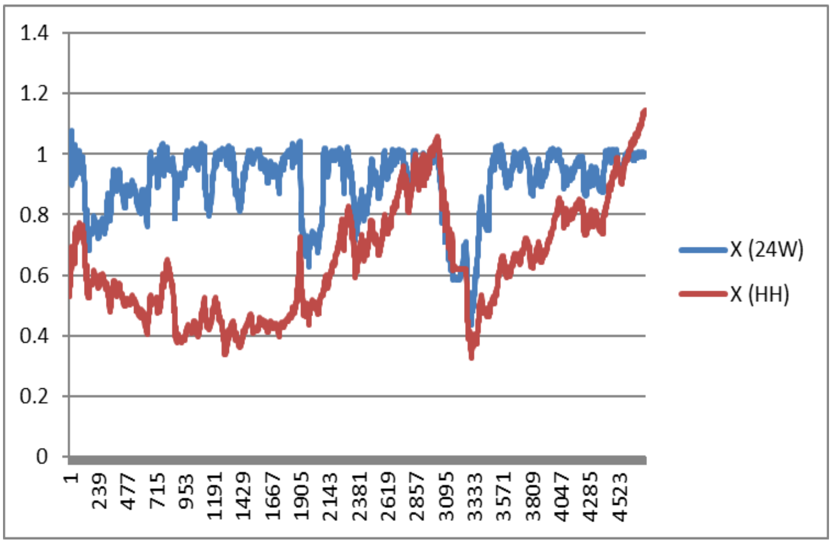


FIGURE 4.4: Nearness to Historical high and Nearness to 24 Week High.

It has also been supported by the literature that as both, nearness to historical high and nearness to 24 week high, are used as anchors while making an investment decision, both the variables predicts market in opposite direction. Nearness to 24 week high depicts the under reaction of investors to some sporadic news and nearness to historical high indicates the overreaction of investors to some prolonged good news. Also it is held that when nearness to historical high becomes equal to nearness to 24 week high, investors have only one anchor in mind that is nearness to 24 week high, however, this phenomenon is further investigated statistically.

### 4.2.2 Descriptive Statistics

Table 4.6 below shows the mean, standard error, standard deviation, and other descriptive statistics in respect of the two dummy variables created $I_t$ and $D_t$, Two anchors used in study $X_{(24W)}$ and $X_{(HH)}$, and the lagged returns $R_{t-1}$.

TABLE 4.6: Descriptive Statistics for Anchoring Effect.

| | $I_t$ | $D_t$ | $X_{(24w)}$ | $X_{(HH)}$ | $R_{t-1}$ |
|---|---|---|---|---|---|
| **Mean** | 0.0118 | 0.0453 | 0.9093 | 0.6427 | 0.0005 |
| **Standard Error** | 0.0016 | 0.0030 | 0.0016 | 0.0027 | 0.0002 |
| **Minimum** | 0.0000 | 0.0000 | 0.4365 | 0.3250 | -0.0774 |
| **Maximum** | 1.0000 | 1.0000 | 1.0776 | 1.1437 | 0.0851 |
| **Standard Deviation** | 0.1080 | 0.2079 | 0.1096 | 0.1872 | 0.0121 |
| **Kurtosis** | 79.9009 | 17.1551 | 2.2987 | -0.6090 | 6.0825 |
| **Skewness** | 9.0481 | 4.3758 | -1.5934 | 0.5316 | -0.2340 |
| **Observations** | 4749 | 4749 | 4749 | 4749 | 4749 |

*$I_t$ = Dummy variable to show Historical high is equal to 24 week high, $D_t$ = Dummy variable to show KSE 100 index touches its record high, $X_{(24W)}$ = Nearness to 24 week high, $X_{(HH)}$ = Nearness to historical high, $R_{t-1}$ = Lagged returns*

Series depicted by Dummy variable $I_t$ represents the times when historical high has become equal to the last 24 week high. These are the points where investors have only one anchor in mind, mostly historical high only. Mean value for $I_t$ (dummy variable for historical high equals 24 week high) is 0.0118 with a standard deviation of 0.1080 which does not show much variation in the values obtained for the series. Values for skewness and kurtosis show that the data is positively skewed towards right side of normal distribution and also it is highly peaked showing extreme values in the series of data. Dummy variable Dt represents the series for the times when KSE 100 index has touched its record high. This series has a mean value of 0.0453 with a standard deviation of 0.2079. Also the data series is positively skewed and peaked with extreme values.

$X_{(24W)}$ has a mean value of 0.9093 that is on average index value is 90.93% of its last 24 week high with a standard deviation of 10.96%. Value of kurtosis is 2.2987 and skeweness is -1.5934 which shows that data is not highly peaked and also has a tail that is negatively skewed. Both the values rejects the assumptions of normal distribution. Data series for $X_{(HH)}$ shows that on average index value is 64.27% of its historical high (Mean value = 0.6427). Value of kurtosis shows that data series is platykurtic with low peak and light tails. Value of skewness is positive and slightly different from zero however, the data still cannot be considered normally distributed. Lagged Returns, $R_{t-1}$ shows the minimum standard deviation of 0.01% approximately with a very low mean value of 0.0005. Also the data series has found laptokurtic with high peak, heavy tails and negatively skewed.

### 4.2.3 Correlation Analysis

Table 4.7 below presents the correlation between the nearness to historical high, nearness to 24 week high and lagged returns. Also the dummy variables for the incidents where historical high is equal to 24 week high and when 100 index touched its record high is included in the matrix.

TABLE 4.7: Correlation matrix for Anchoring Effect.

| | $I_t$ | $D_t$ | $X_{(24w)}$ | $X_{(HH)}$ | $R_{t-1}$ |
|---|---|---|---|---|---|
| $I_t$ | 1 | | | | |
| $D_t$ | -0.0144 | 1 | | | |
| $X_{(24w)}$ | 0.0410 | 0.1726 | 1 | | |
| $X_{(HH)}$ | 0.1796 | 0.4828 | 0.2910 | 1 | |
| $R_{t-1}$ | -0.0046 | 0.0064 | 0.1344 | 0.0018 | 1 |

*$I_t$ = Dummy variable to show Historical high is equal to 24 week high, $D_t$ = Dummy variable to show KSE 100 index touches its record high, $X_{(24W)}$ = Nearness to 24 week high, $X_{(HH)}$ = Nearness to historical high, $R_{t-1}$ = Lagged returns*

Results show that highest correlation exist between nearness to historical high and Dt that is 48% however, it is yet not that high that two variables are called strongly correlated. Correlation between Nearness to historical high ($X_{(HH)}$) and lagged returns is found to be very weak with $r = 0.0018$. Similarly nearness to 24 week high is weakly correlated to lagged returns that is $r = 0.1344$. Two variables used as the anchors by the investors, nearness to historical high and nearness to 24 week high, bears $r = 0.2910$ which implies that the two anchors used for study are not strongly correlated that tend to plague each other's effect. Both have their own predictive ability for future market returns.

### 4.2.4 Regression Analysis

Regression analysis has been done with different sets of variables. Initially predictive power of only lagged returns has been assessed towards future market returns. Nearness to historical high and Nearness to 24 week high are then added to lagged returns and their impact has been assessed with respect to future returns. Collective impact of all the variables has been figured out at final stage. Table 4.8 presents the regression analysis for the future returns and lagged returns.

TABLE 4.8: Regression Analysis for lagged returns.

| | **Returns** |
|---|---|
| **Intercept** | 0.0005 |
| | (2.8382)* |
| $R_{t-1}$ | 0.0438 |
| | (3.0206)* |
| $R^2$ | 0.0019 |
| **Adj** $R^2$ | 0.0017 |
| **F-value** | 9.1237* |

**Significant at 01% level of significance, $R_{t-1}$ = lagged returns, t-values in parenthesis*

As evident from the literature, nearness to historical high when added to the lagged returns gives an opposite effect towards the future returns. Table 4.9 below shows the results for the two variables that is nearness to historical high and lagged returns as under:

Table 4.9: Regression Analysis for Lagged Returns and Nearness to Historical High.

| | Returns |
|---|---|
| **Intercept** | 0.0005 |
| | (0.7979) |
| $R_{t-1}$ | 0.0438 |
| | (3.0202)* |
| $X_{(HH)}$ | -0.0003 |
| | (-0.0037) |
| $R^2$ | 0.0019 |
| **Adj** $R^2$ | 0.0015 |
| **F-value** | 4.5609** |

**Significant at 01% level of significance, **Significant at 05% level of significance, $R_{t-1}$ = Lagged returns, $X_{(HH)}$ = Nearness to Historical high, t-values in parenthesis*

The results shows the same that nearness to historical high, when added to lagged returns, gives an opposite effect. Coefficient for nearness to historical high has been found insignificantly negative ($\beta_2$ = -0.0003, t-value= -0.0037) implying that there exist negative relationship between nearness to historical high and future returns however, the relationship remains insignificant. As the nearness to historical high is added to equation, relationship of lagged returns and future returns remains positively significant with $\beta_2$ = 0.0438, t-value = 3.0202. $R^2$ remains very low with a significant F-value that is 4.5609.

Nearness to historical high and nearness to 24 week high have been hypothesized as two main anchors depicting under and over reaction of the investors. However, both the variables have opposite direction. Table 4.10 presents the results for nearness to historical high and nearness to 24 week high as under:

TABLE 4.10: Regression Analysis for Lagged Returns, Nearness to Historical High, and Nearness to 24 Week High.

| | **Returns** |
|---|---|
| **Intercept** | -0.0129 |
| | (-8.7312)* |
| $R_{t-1}$ | 0.0235 |
| | (1.629)*** |
| $X_{(HH)}$ | -0.0029 |
| | (-2.9385)* |
| $X_{(24W)}$ | 0.0168 |
| | (10.0016)* |
| $R^2$ | 0.0225 |
| **Adj** $R^2$ | 0.0219 |
| **F-value** | 36.4477* |

**Significant at 01% level of significance, **Significant at 05% level of significance, $R_{t-1}$ = Lagged returns, $X_{(HH)}$ = Nearness to Historical high, $X_{(24W)}$ = Nearness to 24 Week High, t-values in parenthesis*

Nearness to 24 Week high when added with nearness to historical high and lagged returns gives the sign opposite to Nearness to historical high. Relationship found between nearness to 24 week high and future returns has been found as significantly positive ($\beta_1$ = 0.0168, t-value = 10.0016). Nearness to historical high also has a significantly negative relationship with future returns with $\beta_2$ = -0.0029 and t-value = -2.9385. Lagged returns show the same predictive pattern as before. $R^2$ of the model has been improved to 2.25%.

Table 4.11 below regress the market returns onto corresponding lagged returns, nearness to historical high, nearness to 24 week high, KSE 100 index historical high indicator, $D_t$ and KSE 24 week high equal historical high indicator, $I_t$.

$I_t$ has been used as a dummy variable which assumes a value of 1 when KSE 100 index historical high equals its 24 week high and zero otherwise. $D_t$ is another dummy variable with a value of 1 when 100 index reaches its record high at day

TABLE 4.11: Regression Analysis for Lagged Returns, Nearness to Historical High, and Nearness to 24 Week High.

| **Returns** | |
|---|---|
| **Intercept** | -0.0129 |
| | (-8.4982)* |
| $R_{t-1}$ | 0.0235 |
| | (1.6208)*** |
| $X_{(HH)}$ | -0.0028 |
| | (-2.5185)** |
| $X_{(24W)}$ | 0.0168 |
| | (9.9903)* |
| $D_t$ | -0.0010 |
| | (-0.0100) |
| $I_t$ | -0.0003 |
| | (-0.1932) |
| $R^2$ | 0.0225 |
| **Adj** $R^2$ | 0.0215 |
| **F-value** | 21.867* |

**Significant at 01% level of significance, **Significant at 5% level of significance, ***Significant at 10% level of significance, $\beta$ = Coefficients for $I_t$, $D_t$, $X_{(24W)}$, $X_{(HH)}$ and $R_{t-1}$, t-values in parenthesis*

$t$ and zero otherwise. As the $I_t$ and $D_t$ have been added to the nearness to 24 week high, nearness to historical high and lagged returns, predictive value of past performance has significantly lowered and remain statistically insignificant. When nearness to 24 week high increases, expected return also increases as evident by statistically significant relationship between the two. Whereas the magnitude of nearness to historical high is different, having statistically significant relationship with expected returns. In the same time when KSE 100 index reaches its record high, next day's return is likely to be lower as evident with the significantly negative $\beta_2$ = -0.0028 with t-value = -2.5185.

Li and Yu (2009) associates this result with the selling pressure after having a positive good news. Keeping this psyche of market in mind, market may be expected to go up each time 100 index is close to its 24 week high. The trend so found in market may be attributed to the investors under reaction to recent good news and a prolonged overreaction to the past bad news. However, this phenomenon may revert in long run.

Since market has an upward trend in stock prices, reaching a record high may not be a good proxy for the prolonged good news (Li and Yu, 2009). It indicator examines the situation where historical high is equal to the 24 week high. Results reveal when historical high is equal to its 24 week high, future returns turn negative however the results remain insignificant. This is not consistent with the notion that as the 24 week high achieved becomes equal to historical high; investors tend to under react to the recent good news.

$X_{(24W)}$ and $X_{(HH)}$ have been used as proxies to the degree to which investors have underreacted and overreacted, respectively. The investors tend to underreact to sporadic news while overreact to prolonged news. Same has been revealed by the results that investors underreact when use 24 week high as reference point in their mind and overreacts to the prolonged good news when having historical high in their mind as reference point.

## 4.3 Herding

In extreme market situations, investors tend to follow the trends of market instead of relying on their own signals. This tendency, termed as herding, has been tested for KSE-100 Index companies for the period 2000 to 2014 by measuring Cross Sectional Standard Deviation (CSSD) and Cross Sectional Absolute Deviation (CSAD) between market and individual stock returns. Also the turnover effect on herding has been measured through High Turnover Standard Deviation (HTSD), High Turnover Absolute Deviation (HTAD), Low Turnover Standard Deviation (LTSD), and Low Turnover Absolute Deviation (LTAD). The results so obtained have been discussed below.

### 4.3.1 Descriptive Statistics

Mean, Median, Skewness, Kurtosis, Standard deviation and Standard error for the data series of CSSD, CSAD, HTSD, HTAD, LTSD, LTAD and market returns for the period 2000 to 2014 has been presented in Table 4.12 below.

Descriptive stats show that mean value for KSE 100 index returns is 0.0005 or 0.05% with a standard deviation of 0.0121 or 1.21% showing the volatility among the returns earned by the market during sample period. Value of standard error is very low that is 0.0002 authenticating the results obtained for series of market returns.

TABLE 4.12: Descriptive Statistics for KSE-100 index.

| | **Mkt Ret** | **CSSD** | **CSAD** | **LTSD** | **LTAD** | **HTSD** | **HTAD** |
|---|---|---|---|---|---|---|---|
| **Mean** | 0.0005 | 0.0173 | 0.0115 | 0.0226 | 0.0056 | 0.0238 | 0.0057 |
| **Median** | 0 | 0.0188 | 0.0129 | 0.0233 | 0.0059 | 0.0255 | 0.0062 |
| **Maximum** | 0.0851 | 0.4667 | 0.2051 | 0.5594 | 0.128 | 0.3584 | 0.0831 |
| **Minimum** | -0.0774 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Std. Dev.** | 0.0121 | 0.0212 | 0.0115 | 0.0282 | 0.0062 | 0.0254 | 0.0056 |
| **Skewness** | -0.2338 | 8.141 | 4.4846 | 8.015 | 6.8439 | 4.1028 | 3.5009 |
| **Kurtosis** | 9.0746 | 132.0003 | 62.5277 | 124.9693 | 111.4856 | 43.2205 | 41.6336 |
| **Std error** | 0.0002 | 0.0003 | 0.0002 | 0.0004 | 0.0001 | 0.0004 | 0.0001 |
| **Observations** | 4749 | 4749 | 4749 | 4749 | 4749 | 4749 | 4749 |

**Paired Mean Test**

| | **HTSD and LTSD** | **HTAD and LTAD** |
|---|---|---|
| **Mean** | | |
| **Difference** | 0.0013 | 0.0001 |
| **T-value** | 2.2781** | 1.1635 |

***significant at 5% level of significance*

Skewness and kurtosis are important because few investment returns are normally distributed. Investors often predict future returns based on standard deviation, but such predictions assume a normal distribution. An investment's skewness and kurtosis measure how its distribution differs from a normal distribution and therefore provide an indication of the reliability of predictions based on the standard deviation. Skewness being a measure of asymmetry indicates how much the series deviates from the normal distribution. A value of -0.2338 (skewness $< 0$) shows data is negatively skewed towards left side of normal distribution. This implies that most of the values of market returns lies on the right side of mean however, extreme values lies at the left side of mean distribution and are negative. Value of kurtosis is 9.0746 (kurtosis $> 3$) displaying the data series as a leptokurtic distribution or a distribution with the values concentrated around mean value. This shows that there are very strong chances for extreme values to occur and also there is rapid decay in distribution with heavier tails.

Mean value of CSSD has been found as 0.0173 which is higher than the mean value of CSAD that is 0.0115 however, the standard deviation of CSSD 0.0212 or 2.12% is higher than the standard deviation of CSAD that is 0.0115 or 1.15%. Thus the cross sectional standard deviation (CSSD) contains more volatility as compared to cross sectional absolute deviation (CSAD). Standard error for CSSD is also higher than that of CSAD ($0.0003 > 0.0002$) making inferences from CSAD more reliable. Values of skewness are positive and greater than zero for both the distributions. This implies that most of the values of distribution may lie on left side of mean value but extreme values lies at the right side of the mean making both the series abnormally distributed towards right. Similarly values of kurtosis for both the series are way greater than 3, the standard value of kurtosis, which means that both CSSD and CSAD are peaked distributions and the variation from mean is basically due to few extreme values.

Low turnover standard deviation (LTSD) when compared with Low turnover absolute deviation (LTAD) mean value for LTSD is found higher than the LTAD that is a value of 0.0226 against the mean value of 0.0056 for LTAD. Standard deviation for both the series is 0.0282 and 0.0062 (2.82% and 0.06%), respectively. Similarly, standard error for LTSD is higher than LTAD. Thus the LTSD data series is more volatile and less reliable as compared to LTAD. Analysis of skewness shows that both the series are positively skewed that is extreme values lies at the right side of the mean and there are less negative values deviating from mean. Values of kurtosis is very high for both LTSD and LTAD it shows that few values in both series are responsible for peak in data series and two series are not at all normally distributed.

Series of HTSD and HTAD shows mean values of 0.0238 and 0.0057 that is 2.38% and 0.05% respectively portraying higher values for HTSD series. Standard deviation is 0.0254 and 0.0026 or 2.54% and 0.02% respectively. Dispersion among the observations of HTSD is way higher than the HTAD which has a very low standard deviation. Thus the characteristics of both the series seems to be very different till this point. Skewness and kurtosis values for both the series are lowest among all the other data series variables making them nearly normally distributed as compared to other variables. Skewness for both the series is 4.1028 and 3.5009 respectively showing positively skewed data series with heaviest observations lying at right side of mean implying all extreme values are also positive. Kurtosis implies that data is peaked or leptokurtic but not as much peaked as other variable series are such as LTSD and LTAD.

In order to have basis to test turnover effect on herding, it is necessary to test whether there exists any significant difference in means of two measures or not. If mean value of HTSD and HTAD is significantly higher than the LTSD and LTAD, turnover effect will be found. Paired mean test for HTSD and LTSD shows the mean difference of 0.0013 with a t value of 2.2781 which is significant at 5% level of confidence. Results for paired mean test for HTAD and LTAD found a mean difference of 0.0001 and a t-value of 1.1635 that is positive but insignificant. Significantly, high mean value of HTSD shows that low turnover stocks have less dispersion from market and thus are tenderer for herding. However, this cannot be generalized for HTAD and LTAD since t-value remain insignificant.

### 4.3.2 Test of Herding

In order to find evidence of herding in KSE-100 index during the period 2000 to 2014, basic test of herding has been implied through two different models with two different dependent variables. Results for Model I are shown in Table 4.13.

Table 4.13 explains the regression results for model I of herding measuring cross sectional standard deviation (CSSD) in extreme market conditions. Extreme market has been defined at 5% and 10% respectively. $\beta_1$ and $\beta_2$ are the coefficients for dummy variables used to explain up market and down market states, respectively. Results reveal a significantly positive value for $\beta_1$ that is 0.0201 (t-value = 4.9392) when extreme market is defined a stop and bottom 5% values of return distribution. Coefficient for down market $\beta_2$ is -0.0026 (t-value = -1.9402) which is significant at 90% confidence interval.

TABLE 4.13: Model I: Test of Herding in KSE-100 Index.

| **Cross Sectional Standard Deviation (CSSD)** | | |
|---|---|---|
| | **5% extreme market** | **10% extreme market** |
| **Intercept** | 0.0163 | 0.0324 |
| | (5.8406)* | (5.1404)* |
| $D_t^u$ | 0.0201 | -0.0101 |
| | (14.9392)* | (-16.7942)* |
| $D_t^L$ | -0.0026 | -0.0157 |
| | (-1.9402)** | (-16.9664)* |
| $R^2$ | 0.0449 | 0.1428 |
| **Adj** $R^2$ | 0.0445 | 0.1424 |
| **F-value** | 15.3132* | 18.3482* |

**Significant at 01% level of significance, **Significant at 05% level of significance, $\beta_1$, $\beta_2$ are the coefficients for $D_t^u$ and $D_t^L$ respectively, t-values in parenthesis*

These results show that there exists a positive relationship between CSSD and up market. When market is enjoying high returns, cross sectional standard deviation between stock returns and market return increases which is against the norms of herding. Thus no evidence of herding can be proved for up market when defined at 5%. Significantly negative value of $\beta_2$ proves the negative relationship between CSSD and down market state. When market on the whole is earning low returns, standard deviation between stock returns and market returns decreases that is investors rely more on the market behavior rather than on their own signals in down market conditions.

Extreme market when defined at 10% shows the values of $\beta_1$ and $\beta_2$ as -0.0101 and -0.0157 with the t-values of -16.7942 and -16.9664 that is significant at 99% confidence interval. This shows that there exist significantly negative relationship between CSSD and extreme market returns. Standard deviation between market returns and stock returns decreases in extreme market which provides the evidence of herding in both up and down market conditions.R2of model is 14.28% for 10% extreme market and 4.45% for 5% extreme market.

#### 4.3.2.1 Model II: Non Linearity of Herding

Herding measured by CSAD accommodating nonlinear relationship of dispersion and returns has been presented in model II. Results for Model II are given as under:

Table 4.14: Model II: Test of Non Linearity of Herding in KSE 100 Index.

| **Cross Sectional Absolute Deviation (CSAD)** | |
|---|---|
| **Intercept** | 0.0051 |
| | (13.1877)* |
| $R_{m,t}$ | 1.206 |
| | (14.8870)* |
| $R^2_{m,t}$ | -1.1401 |
| | (-12.4326)* |
| $R^2$ | 0.4347 |
| **Adj** $R^2$ 0.4345 | |
| **F-value** | 19.956* |

**significant at 01% level of significance, $\gamma_1$, $\gamma_2$ are the coefficients for $R_{m,t}$ and $R^2_{m,t}$ respectively, t-values in parenthesis*

Table 4.14 depicts the regression results for cross sectional absolute deviation and market returns. Results shows significantly positive value for $R_{m,t}$ that is 1.2060 (t-value = 14.8870) and significantly negative value for $R^2_{m,t}$ = -1.1401 (t-value

= -12.4326). There exists positive relationship between absolute market returns and cross sectional absolute deviation (CSAD) that is increase in market returns increases the deviation between stock and market returns. However, relationship between CSAD and squared market returns is significantly negative depicting the nonlinear negative relationship between CSAD and market returns. As the market returns increases at double rate, dispersion between stock returns and market returns decreases by magnitude of one half. This is exactly the same as document by theory of herding. $R^2$ of the model is 43.47% which is reasonable enough to rely on evidence of herding.

#### 4.3.2.2 Swap of Dependent Variables

As we swap the dependent variables in Model I and Model II, the results obtained are as follows:

TABLE 4.15: Swap of CSSD and CSAD in Model I and Model II.

| **Swap Model I** | | **Swap Model II** | |
|---|---|---|---|
| **Dependent Variable: CSAD** | | **Dependent Variable: CSSD** | |
| **Intercept** | 0.0099 | **Intercept** | 0.0086 |
| | (6.3649)* | | (4.3560)* |
| $D_t^u$ | 0.0159 | $R_{m,t}$ | 1.6497 |
| | (13.3364)* | | (18.6843)* |
| $D_t^L$ | 0.0158 | $R_{m,t}^2$ | -1.7819 |
| | (11.1175)* | | (-13.6152)* |
| $R^2$ | 0.1729 | $R^2$ | 0.2321 |
| **Adj** $R^2$ | 0.1726 | **Adj** $R^2$ | 0.2318 |
| **F-value** | 15.5674* | **F-value** | 24.1873* |

**significant at 01% level of significance, $\beta_1$, $\beta_2$ are the coefficients for $D_t^u$ and $D_t^L$ respectively, $\gamma_1$, $\gamma_2$ are the coefficients for $R_{m,t}$ and $R_{m,t}^2$ respectively, t-values in parenthesis*

Table 4.15 above shows the result for swap of dependent variables in basic Model I and Model II. $D_t^u$ and $D_t^L$ are the coefficients of up and down market respectively, defined as top and bottom 5% returns of a series of market returns. $R_{m,t}$ and

$R^2_{m,t}$ are the coefficients for market returns and squared market returns respectively. When CSAD is put to the model I as dependent variable, results reveal significantly positive coefficients for $D^u_t$ and $D^L_t$($D^u_t$ = 0.0159, t-value = 13.3364 and $D^L_t$ = 0.0158,t-value = 11.1175) which shows when there is an upward trend in market, cross sectional absolute deviation (CSAD) also increases means in up market investors do not give much weightage to the buy and sell decisions of other market participants and act on their own signals. Same trend has been found when market on the whole has a downward trend. $R^2$ of this model is 17.29%. These are the results contrary to the results of model I testing existence of herding with CSSD being dependent variable which indicates a tendency of herding in Pakistani investors in down market conditions.

When CSSD is put to the Model II as dependent variable in place of CSAD, results shows significantly positive value as coefficient of $R_{m,t}$ = 1.6497 (t-value = 18.6843) and significantly negative coefficient for $R^2_{m,t}$ = -1.7819 (t-value = -13.6152). Negative value of $R^2_{m,t}(\gamma_2)$ proves the nonlinear relationship of cross sectional standard deviation (CSSD) with market returns. These results are exactly the same as found by Model II with CSAD being dependent variable. Thus we may conclude that herding exists in Pakistani market in a nonlinear manner. $R^2$ for this model is higher than that of Model I with CSAD being dependent variable that is 23.21%.

### 4.3.3 Turnover Effect

Once the evidence of herding has been discovered partly for model I and in full for Model II, its relationship with turnover is to be investigated. To measure Turnover Effect KSE-100 index has first been divided into high turnover stocks and low turnover stocks. Based on standard deviation and Absolute deviation four different measures have been calculated. Basic Model I and model II have been estimated with high turnover standard deviation (HTSD), Low turnover standard deviation (LTSD), high turnover standard deviation (HTAD) and low turnover absolute deviation (LTAD) being dependent variables respectively. Results for market model I are given below.

Table 4.16: Model I: Turnover Effect in KSE 100 Index.

| | 5% Extreme Market | | 10% Extreme Market | |
|---|---|---|---|---|
| | **HTSD** | **LTSD** | **HTSD** | **LTSD** |
| **Intercept** | 0.02 | 0.021 | 0.0179 | 0.0222 |
| | (14.1606* | (5.3907)* | (14.4329)* | (4.3724)* |
| $D_t^u$ | 0.0241 | 0.0279 | 0.0241 | 0.0099 |
| | (13.4090)* | (17.5937)* | (12.6259)* | (8.1289)* |
| $D_t^L$ | 0.0269 | -0.0282 | 0.0227 | -0.0065 |
| | (13.9018)* | (-17.7196)* | (13.5436)* | (-5.3399)* |
| $R^2$ | 0.0744 | 0.1109 | 0.1104 | 0.0178 |
| **Adj** $R^2$ | 0.074 | 0.1105 | 0.1101 | 0.0174 |
| **F-value** | 19.8371* | 29.0061* | 12.6061* | 42.9939* |

**significant at 01% level of significance, $\beta_1$, $\beta_2$ are the coefficients for $D_t^u$ and $D_t^L$ respectively, t-values in parenthesis*

Table 4.16 shows the results for turnover effect on herding using the basic model I based on extreme market situation with HTSD and LTSD being dependent variables. Extreme market has been defined at 5% as well as at 10% of return series to have a more comprehensive view of herding. $D_t^u$ shows the coefficient for the dummy variable depicting up market (top 5% and 10% of market return series) and $D_t^L$ depicts the coefficient for dummy variable used to depict down market or bottom 5% and 10% of market return series. Results for HTSD shows positively significant values of $\beta_1$ and $\beta_2$ ($\beta_1 = 0.0241$, t-value = 13.4090 and $\beta_2 = 0.0269$, t-value = 14.9018) when extreme market is defined at 5%. $R^2$ of the model is 7.44%. These results reveal that as the market moves up standard deviation between high turnover stock returns and market return increases. Similarly when market has a downturn and earnings are lowest, dispersion between high turnover stock returns and market returns increases or remains the same implying no herding for high turnover stocks.

Results for low turnover standard deviation (LTSD) shows positive value of $\beta_1$ ($\beta_1 = 0.0279$, t-value = 17.5937) which is significant at 99% confidence interval. This shows that dispersion between low turnover stock returns and market returns does not reduce in up market condition. However, significantly negative value of $\beta_2$ ($\beta_2$ = -0.0282, t-value = -17.7196) implies that in down market, dispersion between low turnover stock returns and market returns decreases. This gives us the evidence of herding in down market situation for low turnover stocks. $R^2$ of the model is 11.09%.

When extreme market is defined at 10% of return series, the results remain the same. Highly significant positive values are obtained for $\beta_1$ and $\beta_2$ when HTSD is used as dependent variable. Thus for high turnover stocks dispersion between stock returns and market returns does not reduce in up and down markets which implies no herding exist. However, for LTSD as dependent variable, regression results show significantly positive coefficient for $\beta_1$ but significantly negative coefficient for $\beta_2$ implying reduction in dispersion between low turnover stock returns and market returns in down market which is exactly in accordance to herding theory.

Table 4.17: Model II: Turnover Effect for KSE 100 Index.

| | **5% Extreme Market** | | **10% Extreme Market** | |
|---|---|---|---|---|
| | **HTAD** | **LTAD** | **HTAD** | **LTAD** |
| **Intercept** | 0.0048 | 0.0049 | 0.0043 | 0.0043 |
| | (14.2835)* | (23.1019)* | (24.6529)* ( | 14.5512)* |
| $D_t^u$ | 0.0069 | 0.0079 | 0.0066 | 0.0073 |
| | (17.7723)* | (12.5740)* | (13.8245)* | (12.1773)* |
| $D_t^L$ | 0.0071 | 0.0079 | 0.0061 | 0.0067 |
| | (18.4062)* | (13.4627)* | (12.0363)* | (10.3753)* |
| $R^2$ | 0.1158 | 0.1812 | 0.1665 | 0.2521 |
| **Adj** $R^2$ | 0.1154 | 0.1809 | 0.1661 | 0.2518 |
| **F-value** | 23.7889* | 15.164* | 31.999* | 19.9683* |

**significant at 01% level of significance, $\beta_1$, $\beta_2$ are the coefficients for $D_t^u$ and $D_t^L$ respectively, t-values in parenthesis*

Table 4.17 explains the turnover effect on herding with HTAD and LTAD as dependent variable when market is defined as extreme market at 5% and 10% of market return series respectively. The results reveal values of $D_t^u$ and $D_t^L$ are significantly positive for High turnover absolute deviation (HTAD) and low turnover absolute deviation (LTAD). This implies that dispersion between stock returns and market returns does not reduce for high turnover stocks as well as for low turnover stocks in extreme market situations. Results remain the same when extreme market is defined at 10% of market return series.

In order to have a turnover effect on herding, values of $\beta_1$ and $\beta_2$ has to be negatively significant for LTSD and LTAD as dependent variable. However, for HTSD and HTAD no such condition applies for high turnover stocks, whether market is up or down. Since high turnover stocks are generally considered as favorites (or winners) they do not lack relative information which is available to all. Investors on the basis of freely available information can make their own judgments easily and thus no herding behavior arises for high turnover stocks. As far as low turnover stocks are concerned, information is either less available or it is costly thus investors prefer to rely on the overall trend of market which gives birth to herding. Results of regression reveals partial existence of turnover effect (with significantly negative $\beta_2$) only for down market (both at 5% and 10% extreme market) only when LTSD is estimated by Model I. However, as far as high turnover stocks are concerned, they exhibit turnover effect as documented.

#### 4.3.3.1 Turnover Effect: Model II

Table 4.18 below shows the regression results for model II based on nonlinear nature of herding. In order to test turnover effect, HTSD, HTAD, LTSD and LTAD have been regressed with market returns and the results are as under:

Results in Table 4.18 shows values of $R_{m,t} = 0.0991$, t-value = 3.0959 and $R^2_{m,t} = 0.4347$, t-value = 12.0734) are significantly positive when HTSD is regressed with market returns. Similarly, positive and significant values of $\gamma_1$ and $\gamma_2$ have been found for HTAD and LTAD regressed with market returns. However, the results for LTSD are different with $\gamma_1 = 0.0443$ and corresponding t-value = 1.4665 which shows a positive but insignificant relationship between LTSD and market returns. $\gamma_2$ has obtained a value of -0.3545 and corresponding t-value is -6.1002 which is negative and significant with 99% confidence interval. $R^2$ of the model is extremely low that is only 0.81%.

Table 4.18: Model II: Turnover Effect for HTSD, LTSD, HTAD, LTAD.

| | **HTSD** | **LTSD** | **HTAD** | **LTAD** |
|---|---|---|---|---|
| **Intercept** | 0.0194 | 0.023 | 0.0047 | 0.0048 |
| | (4.9674)* | (5.1002)* | (3.2454)* | (6.2327)* |
| $R_{m,t}$ | 0.0991 | 0.0443 | 0.0274 | 0.0283 |
| | (3.0959)* | (1.4665) | (3.9872)* | (4.7862)* |
| $R^2_{m,t}$ | 0.4347 | -0.3545 | 0.5226 | 0.2633 |
| | (12.0734)* | (-6.1002)* | (7.6486)* | (3.6464)* |
| $R^2$ | 0.1015 | 0.0081 | 0.1397 | 0.2199 |
| **Adj** $R^2$ | 0.1011 | 0.0076 | 0.1394 | 0.2195 |
| **F-value** | 17.9916* | 9.0253* | 5.4779* | 8.9817* |

**significant at 01% level of significance, $\gamma_1$, $\gamma_2$ are the coefficients for $R_{m,t}$ and $R^2_{m,t}$ respectively, t-values in parenthesis*

In order to have a turnover effect, negative value of $\gamma_2$ is required for LTSD as well as LTAD. However, only a partial evidence of turnover effect (that is only for LTSD) has been found by results obtained. Results for turnover effect measured by Model II are somewhat same as the results of model I where only for LTSD evidence of turnover effect is found for down market situation.

### 4.3.4 Asymmetry Test

Since investors as well as market do not react to good and bad news in same manner, it is hypothesized that there exist asymmetric responses of market participants for up and down markets. This tendency has been tested for the measures of herding and turnover effect. Results for asymmetry test are as under:

Table 4.19 Panel A shows the results of regression with CSSD and CSAD were up market has been defined as one where returns are positive. All the zero and negative returns are included in down market. For asymmetric reaction to exist, difference between $\gamma_{2(up)}$ and $\gamma_{2(Down)}$ has to be significantly other than zero. Value of $\gamma_1$ for CSSD in up as well as down market is positively significant with 99% confidence interval. $\gamma_2$ for CSSD in up market is 0.4445 with a t-value of 0.1855

Table 4.19: Asymmetry Test for Herding using CSAD and CSSD.

| | **5% Up Market** | | **10% Down Market** | |
|---|---|---|---|---|
| | **CSSD** | **CSAD** | **CSSD** | **CSAD** |
| **Intercept** | 0.0211 | 0.0128 | 0.0051 | 0.003 |
| | (2.5592)** | (3.1897)* | (5.6380)* | (3.3299)* |
| $R_{m,t}$ | 0.4905 | 0.4842 | 1.9409 | 1.4091 |
| | (4.2468)* | (9.5750)* | (8.0515)* | (4.3832)* |
| $R^2_{m,t}$ | 0.4445 | -0.6398 | -1.0495 | -1.0846 |
| | (0.1855) | (-0.6096) | (-14.2328)* | (-12.8895)* |
| $R^2$ | 0.0488 | 0.1773 | 0.3419 | 0.5559 |
| **Adj** $R^2$ | 0.0478 | 0.1764 | 0.3414 | 0.5556 |
| **F-value** | 8.1510* | 9.467* | 17.3377* | 18.287* |

**significant at 01% level of significance, **significant at 05% level of significance, $\gamma_1$, $\gamma_2$ are the coefficients for $R_{m,t}$ and $R^2_{m,t}$ in up and down market respectively, t-values in parenthesis*

which is positive and insignificant. $\gamma_2$ for CSSD in down market is -1.0495 with a t-value of -14.2328 that is significant at 99% confidence interval.

$\gamma_1$ for CSAD is again positive and significant at 99% confidence interval for both up and down market. Value of $\gamma_2$ for CSAD for up market is negative that is -0.6398 with a t-value of -0.6096 which is an insignificant value. $\gamma_2$ for CSAD in down market is also negative that is -1.0846 but significant (t-value = -12.8895). Difference between $\gamma_{2(up)}$ and $\gamma_{2(Down)}$ for CSSD is 1.494 that is >0 and that for CSAD is 0.4448 which is again greater than zero showing asymmetry between the reactions of investors.

### 4.3.5 Asymmetric Turnover Effect

Since market responds differently to good and bad news, turn over effect is also expected to appear asymmetrically for given sample. Results for Table 4.20 shows significantly positive values of $\gamma_1$ for all the dependent variables that is HTSD, HTAD, LTSD, and LTAD in both up and down market conditions.

When comes to $\gamma_2$, insignificant positive value has been obtained ($\gamma_2$ = 0.2777, t-value = 0.0814) for HTSD in up market. $\gamma_2$ for LTSD is negatively significant with a coefficient of -1.1263 and t-value of -2.943 in up market. Rest LTAD and HTAD both have significantly negative value for $\gamma_2$.

Result for down market shows significantly negative values for all the four measures of turnover effect in herding that is HTSD, LTSD, HTAD and LTAD. However, the level of significance in down market is higher as compared to that of up market.

Table 4.20: Asymmetry Test for Turnover Effect in Up and Down Market.

| | **Up Market** | | | |
|---|---|---|---|---|
| | **HSTD** | **LSTD** | **HTAD** | **LTAD** |
| **Intercept** | 0.0285 | 0.024 | 0.0065 | 0.0063 |
| | (2.3912)** | (2.2861)** | (5.5081)* | (3.3305)* |
| $R_{m,t}$ | 0.604 | 0.5386 | 0.2048 | 0.2368 |
| | (3.6747)* | (4.0486)* | (6.5308)* | (10.1857)* |
| $R^2_{m,t}$ | 0.2777 | -1.1263 | -0.4322 | -0.2352 |
| | (-0.0814) | (-2.943)* | (-1.664)*** | (-1.78)*** |
| $R^2$ | 0.0357 | 0.0103 | 0.0854 | 0.2007 |
| **Adj** $R^2$ | 0.0346 | 0.0092 | 0.0844 | 0.1998 |
| **F-value** | 32.553* | 9.1523* | 8.1044* | 20.714* |

| | **Down Market** | | | |
|---|---|---|---|---|
| | **HSTD** | **LSTD** | **HTAD** | **LTAD** |
| **Intercept** | 0.0065 | 0.0185 | 0.0015 | 0.0015 |
| | (6.4033)* | (4.3569)* | (6.5662)* | (9.5039)* |
| $R_{m,t}$ | 2.5001 | 0.8927 | 0.6725 | 0.6881 |
| | (13.1165)* | (7.8618)* | (11.6504)* | (2.6187)* |
| $R^2_{m,t}$ | -1.07397 | -1.36448 | -0.978 | -0.6376 |
| | (-14.716)* | (-4.626)* | (-18.711)* | (-2.032)** |
| $R^2$ | 0.3853 | 0.0325 | 0.4457 | 0.5536 |
| **Adj** $R^2$ | 0.3849 | 0.0318 | 0.4453 | 0.5533 |
| **F-value** | 5.4199* | 5.0709* | 12.117* | 18.262* |

**significant at 01% level of significance, **significant at 05% level of significance, ***Significant at 10% level of Significance, $\gamma_1$, $\gamma_2$ are the coefficients for $R_{m,t}$ and $R^2_{m,t}$ in up and down market respectively, t-values in parenthesis*

## 4.4 Disposition Effect

Disposition effect refers to a tendency of investors to sell winners early and to hold loser stocks for a long time. Whereas the most logical action, as perceived, to be taken would be to hold winning stocks with an intention of having further gain and to sell loser stock to avoid the escalating losses. Two possible reasons behind investors this irrational attitude could be the Kahneman and Tversky (1979) study in which they held that people prefer to go for confirm gains rather than to take riskier options even if the realized gain is lesser than what is offered with some risk factor. This phenomenon is purely based on risk adversity of investors. On the other hand, investors tend to hold losing stocks in an anticipation of losses converting into gains. However, it seldom happens that a stock recovers in future and thus losses keep on mounting.

Kahneman and Tversky's (1979) prospect theory is based on these factors that people base their decisions on perceived gains rather than losses. If a person is given two equal choices, one expressed in terms of possible gains and the other in possible losses, people would choose the former-even when they achieve the same economic end result.

Disposition effect refers to a tendency of investors to sell winners early and to hold loser stocks for a long time. This tendency has been tested for Pakistan by analyzing KSE 100 Index for the period 2000 to 2014. Results based on the methodology explained earlier are presented as under.

### 4.4.1 Unit Root Test

A time series data being stationary or non-stationary can influence the overall results and behavior of series in a considerable manner. Thus to conduct any further test, stationarity of the data needs to be checked in first instance. There are different means by which data can be turn stationary for example by taking log, or by taking first difference, second difference etc. Our variables under study that is Security Return (SRet), Market Return (MRet), and Security Volatility

(SVol) has already been obtained by taking first difference of share prices and market index. Thus, there series are expected to be stationary already. The only series that is taken into as original is that of Security Turnover (STurn) which needs to be tested for stationarity. Plotting series of Security Turnover in this regard gives a picture as follows:

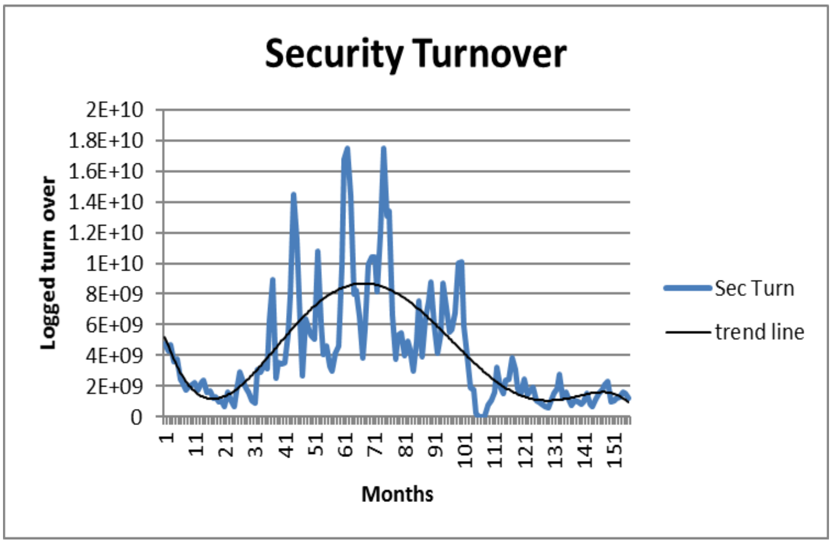


FIGURE 4.5: Plot of Security Turnover.

Figure 4.5 shows the values of the monthly turnover of the securities related to KSE 100 Index . Along horizontal axis sample period in form of months is taken and vertical axis shows value of the corresponding security turnover for each month. A trend has been fitted to the series to identify where series is stationary or not. The trend line shows fluctuations in security turnover series which implies that mean and variance of series is not constant over time, making the series non stationary. Thus in order to make series stationary, natural log of security turnover is taken.

Figure 4.6 presents the logged series of security turnover. It is evident that after taking natural log, when plotted again, security turnover series showed the reduced correlation between the trend line and the volatility around trend line. Which means that mean and variances of the series has now turned constant and series is declared as stationary.

From this point onwards, wherever security turnover has been used, it refers to the de trended security turnover series. Although all the variables under study are

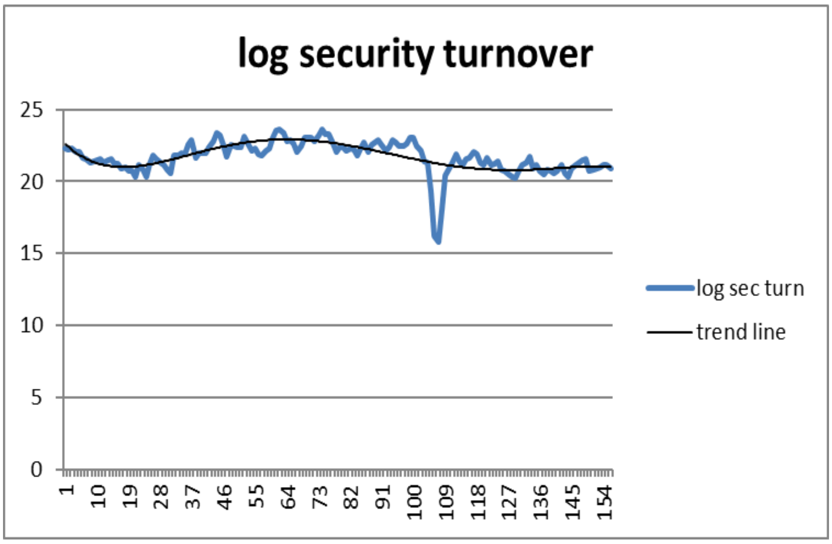


FIGURE 4.6: De-trended Series of Security Turnover.

now expected to be stationary, Unit root test has further been applied to confirm their status. Results for the unit root test have been presented in Table 4.21.

TABLE 4.21: Unit root Test for Testing Disposition Effect.

| **Description** | **ADF** | | **PP** | |
|---|---|---|---|---|
| | **t-Statistic** | **P value** | **Adj. t-Stat** | **P value** |
| **S.Turn** | -4.3225 | 0.0006 | -3.42 | 0.0117 |
| **S.Ret** | -10.5151 | 0 | -10.5151 | 0 |
| **M.Ret** | -11.2356 | 0 | -11.2375 | 0 |
| **S.Vol** | -8.2564 | 0 | -7.9842 | 0 |
| | | **Critical Values** | | |
| **1%** | | | | -3.4728 |
| **5%** | | | | -2.8801 |
| **10%** | | | | -2.5767 |

Table 4.21 above shows the results of unit root test applied to test stationarity of the variables under study to test disposition effect. Augmented Dicky Fuller (ADF) test and Phillip Perron (PP) test has been used for this purpose. Results show that t-stats for both the tests are significant at 1% level of significance except for security turnover (Sturn) series whose t-value -3.4200 is significant at 5% level

of significance. Even if P-values are examined, results remain the same since all the p-values obtained are less than 5% enabling us to reject the null hypothesis of unit root test that is $H_0$ = *Unit root exists in series*. Thus all the four series that is security turnover (S.turn), security Return (S.Ret), market Return (M.Ret) and security volatility (S.Vol) are found stationary at level or in other words are integrated at level that is I(0). Since all the variables are integrated at level, co-integration needs not to be checked.

### 4.4.2 Descriptive Statistics

For all the four series under study Security turnover (S.Turn), security return (S.Ret), market return (M.Ret) and volatility (S.Vol), descriptive statistics have been calculated and are presented as under:

TABLE 4.22: Descriptive Statistics for Disposition Effect.

| | **S.Turn** | **S.Ret** | **M.Ret** | **S.Vol** |
|---|---|---|---|---|
| **Mean** | 0.0064 | 0.0123 | 0.015 | 0.0543 |
| **Median** | 0.0044 | 0.0099 | 0.0196 | 0.0473 |
| **Maximum** | 0.0275 | 0.2345 | 0.2411 | 0.1961 |
| **Minimum** | 0.0001 | -0.3488 | -0.4488 | 0.001 |
| **Std. Dev.** | 0.0057 | 0.0773 | 0.0845 | 0.031 |
| **Skewness** | 1.61 | -0.8586 | -1.1696 | 1.813 |
| **Kurtosis** | 2.5185 | 5.845 | 8.4337 | 7.1046 |

Table 4.22 shows the mean, median, maximum, minimum values standard deviation, and skewness kurtosis for the variables under study. It is found that mean value of security turnover (S.Turn) is 0.0064 where whole series range from 0.0001 to 0.0275. Standard deviation is found as 0.57% which is less than one percent not making the series highly volatile over the months without a chance to forecast the future movement. Skewness is1.61 which means that whole series is positively skewed and the null hypothesis of skewness $H_0$*: Skewness of series is zero* is rejected and data is not found normally distributed. Kurtosis of 2.5185does not shows excess kurtosis as it has not exceeded the normal range of kurtosis = 3.

Security return (S.Ret) shows the mean value of 0.0123 that is 1.23% return for the securities per month. This implies that on average securities earn an annual return of 11.76% which is a good ratio. Standard deviation in return series is found as 7.73% which does not show much variation in monthly returns realized by individual stocks. Skewness is -0.8586 that shows maximum values lying on left side of mean and thus data is negatively skewed rather than normally distributed. Kurtosis being 5.8450 does not imply much peak is data as normal value of kurtosis is assumed as 3.

Market return assumes the mean value of 0.0150 that is 1.5% per month, slightly higher than the average security returns. This implies that market on the whole earns 18% return per annum. Standard deviation in series is found as 8.45% which is also higher than that of security returns where market returns range from -44% to 24% approximately. Skewness is found as -1.16 which shows that data is negatively skewed towards left side of the mean. Value of kurtosis 8.4337 shows that data is distributed in wider fashion where only few observations lie near mean and rest of the values lie either far above or far below the average.

Mean volatility found in returns is the 5.42% with a maximum of 19.6% and a minimum value of 0.10% volatility series itself has a standard deviation of 3.10%. Skewness shows maximum values lies on right side of the mean and kurtosis shows that more observations lies at the extremes rather than lying at the tails of the normal distribution.

### 4.4.3 Correlation Analysis

Correlation among the variables has also been tested to know how one variable moves in response of the movement in other variable. Results for correlation are given as under:

Table 4.23 shows the correlation matrix for the variables under study Security turnover, security returns, market turnover, and volatility. Value of correlation coefficient r ranges from -1 to +1 where -1 means perfect negative correlation and

Table 4.23: Correlation matrix for Disposition Effect.

| | **S.Turn** | **S.Ret** | **M.Ret** | **S.Vol** |
|---|---|---|---|---|
| **S.Turn** | 1 | | | |
| **S.Ret** | 0.2561 | 1 | | |
| **M.Ret** | 0.2481 | 0.9219 | 1 | |
| **S.Vol** | 0.0963 | -0.3240 | -0.3173 | 1 |

+1 mean perfect positive correlation. A value of "0" assumes no correlation. Correlation between security turnover and security return is found as 0.2561 means both the variables are weakly correlated with each other however moves in same direction as the correlation coefficient is found positive. Security turnover and market return have the same weak relation evident with the value of 0.2481. Volatility is also weakly correlated to each variable especially with security turnover which has a value of 0.0963. Volatility has also been found negatively correlated with market return and security return which implies that an increase in volatility leads to lower returns for both, individual stocks and market. Highest correlation that is near to one exist between security return and market return that is 0.9219. It shows that any change in security return can bring a change of about 92% in market returns.

When two variables are so closely there arising a fear of multicollinearity between the variables. Once the collinear variables are identified, it may be helpful to study whether there is a causal link between the variables. For this purpose, auxiliary regression is best way. Our results for auxiliary regression suggest that although change in security turnover significantly affects the market returns, the value of $R^2$ is 0.061 which gives the Variance inflation factor (VIF) as 1.066. Since, by rule, value of VIF up to 10 is acceptable for any model, two variables although are closely related does not create the problem of multicollinearity and can be included in one model.

### 4.4.4 VAR Estimation

Disposition effect is all about the tendency of investors to sell a particular security that is earning good returns and to hold a security that is losing value over time. Since disposition effect relates to the specific individual securities in the portfolio and their trading pattern (Shefrin and Statman, 1985), individual security turnover, returns and volatility has been analyzed to find whether any such trend exist in Pakistan or not. Market returns are also added to the suggested model to investigate whether any role is played by market on the whole in determining individual security volume. Presence of any such relationship will help deducing investor's overconfidence relates to the disposition effect in a way that when market is earning good or in a bearish mode, high returns earned by investors are attributed by them to their own stock picking skills and thus to realize more gains in pursuit of confirmation of their perception, they start selling winners giving birth to disposition effect (Statman et al, 2004).

Results of VAR estimation with three endogenous variables (Security turnover, security return, and market return) and one exogenous variable security volatility for KSE 100 index has been presented in Table 4.24.

VAR estimation presented in Table 4.24 shows three dependent variables security turnover (Sturn), security return (Sret), and market return (Mret). Lagged values of these variables are taken as independent variable. Based on Akaike Information Criteria (AIC) number of lags are set as (1, 3) for endogenous variables.

Security turnover (Sturn) in Panel A when regressed with its own lagged values shows that there exists a significantly positive relationship between security turnover and its lagged value which means that security turnover heavily depends upon its turnover in previous period and moves in same direction. However, this relationship changes its direction in second lag and is found as negatively significant. In third lag again the relationship turns positive and significant. After being negative in second lag, although relationship again turns positive in third lag but the evidence found remain very weak due to its lower level of significance.

Security return (Sret) when regressed with lagged values of security turnover (Sturn) does not provide the evidence of any significant relationship between these two variables. For lag one (Sturn (-1)) and lag two (Sturn(-2)) results remain positive but insignificant. When reached Sturn (-3), the relationship found is negative and significant (coefficient= -0.0225, t-value = -2.0008) which implies that there exists inverse relationship between third lag of security turnover and current security return. This may imply investors do not take immediate past values of turnover while making decisions but anticipates that current situation will go in opposite direction to the turnover 3 months ago.

Regression results for market return and lagged values of security turnover in Panel A of Table 4.24 shows that market return does not move along the security turnover in immediate past since t-value of 0.2243 for Sturn (-1) shows the insignificant relationship between two variables. However, this relationship is found significantly positive for Sturn (-2) and significantly negative for Sturn (-3). It is noticed that as we move along the lagged values of security turnover, behavior of market return changes from being indifferent to being negatively associated to security turn over.

Panel B of Table 4.24 shows the regression results for the Sturn, Sret and Mret as dependent variable and lagged values of security return Sret as independent variables. Results show that security turnover (Sturn) has a significantly positive relationship with the security returns in all three lags. Value of coefficient of Sret(-1) is 1.9099 with a t-value of 1.5931 which is pretty close to the critical value. Since the coefficients of Sret(-2) and Sret(-3) are sufficiently significant at 5% and 10% level of significance (t-value = 2.2902 and 1.8287 respectively), results for first lag are also considered significant. It is thus concluded that security turnover is highly determined by the past security returns. If a particular security is earning high returns for past three months, investors rank it as winner and tend to sell that security which increases the trading volume/ turnover of that security.

TABLE 4.24: VAR estimation of Endogenous and Exogenous Variables for Disposition Effect.

| | | | Panel A | | | Panel B | | | Panel C | | | Panel D | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Lagged values of Security Turnover | | | Lagged values of Security Return | | | Lagged values of Market Return | | | Lagged values of Security Volatility | | | | |
| | | **C** | **Sturn(-1)** | **Sturn(-2)** | **Sturn(-3)** | **Sret(-1)** | **Sret(-2)** | **Sret(-3)** | **Mret(-1)** | **Mret(-2)** | **Mret(-3)** | **Svol** | **Svol(-1)** | **Svol(-2)** | $R^2$ | **F** |
| | **Coefficient** | 3.777 | 1.108 | -0.430 | 0.137 | 1.910 | 3.204 | 2.537 | -1.127 | -2.200 | -1.967 | 3.964 | 0.759 | -3.085 | | |
| **Sturn** | **Std Error** | -0.946 | -0.084 | -0.121 | -0.080 | -1.133 | -1.399 | -1.387 | -1.295 | -1.277 | -1.262 | -1.477 | -1.885 | -1.811 | 0.816 | 5.73* |
| | **t-value** | (3.99)* | (3.167)* | (-3.542)* | (1.714)*** | (1.69)*** | (2.290)** | (1.83)*** | (-0.870) | (-1.722)*** | (-1.558) | (2.68)** | -0.402 | (-1.7)*** | | |
| | **Coefficient** | -0.056 | 0.002 | 0.026 | -0.023 | 0.039 | 0.348 | 0.101 | 0.018 | -0.344 | -0.131 | -1.024 | 0.115 | -0.417 | | |
| **Sret** | **Std Error** | -0.134 | -0.012 | -0.017 | -0.011 | -0.203 | -0.198 | -0.196 | -0.183 | -0.181 | -0.178 | -0.209 | -0.283 | -0.272 | 0.234 | 3.50 |
| | **t-value** | (-0.421) | (-0.177) | (-1.522) | (-2.000)** | -0.1919 | (1.75)*** | -0.515 | -0.098 | (-1.904)*** | (-0.732) | (-4.90)* | -0.406 | (-1.533) | | |
| | **Coefficient** | -0.039 | 0.003 | 0.041 | -0.038 | 0.130 | 0.334 | 0.086 | -0.110 | -0.422 | -0.126 | -1.108 | 0.243 | -0.527 | | |
| **Mret** | **Std Error** | -0.145 | -0.013 | -0.019 | -0.012 | -0.219 | -0.214 | -0.212 | -0.198 | -0.195 | -0.193 | -0.226 | -0.305 | -0.293 | 0.251 | 3.84 |
| | **t-value** | (-0.266) | -0.224 | (2.204)** | (-3.160)* | -0.594 | -1.561 | -0.406 | (-0.557) | (-2.162)** | (-0.654) | (-4.91)* | -0.798 | (-1.80)*** | | |

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

Similarly, if security is earning negative returns in past three months, investors rank it as loser stock and hold it into the bucket in an anticipation of revision of share prices or to avoid realizing losses. Since this is exactly what disposition effect holds, on the basis of these results we may reject our null hypothesis for disposition effect that there exists no positive relationship between security turnover and its lagged returns.

Security return (Sret) does not found to be significantly associated with its lagged values for lag 1 and lag 3. However, for Sret(-2) the coefficient of 0.3478 is found significant with a t-value of 1.758 at 10% level of significance. It is surprising that data does not provide the evidence of most pronounced relationship of returns and lagged returns. The reason may be the fact that along with lagged returns, many other factors also contribute to the security's current returns which are not covered in this model. Results for Market return being dependent variable shows all the three insignificant relationship with lagged values of security returns in previous three periods.

Panel C of Table 4.24 presents the security return (Sret), security turnover (Sturn), and market return (Mret) as dependent variables with lagged values of market return being independent ones. Regression analysis of (Sturn) shows although the nature of relationship between security turnover and lagged market return is negative, the relationship is insignificant for Mret(-1) and Mret(-3). However, for Mret(-2) the result is found negatively significant. This implies that as the market return increases, turnover of individual security falls down and vice versa. Absence of a significant relationship between market returns and security turnover segregates overconfidence of investor with disposition effect. As stated earlier, with a high market earning high returns, investors attribute positive returns to their own capabilities and start trading more aggressively. Here comes the proposition that investors with this mental state sell particularly the winner stocks to realize immediate gains for confirmation of their belief and hold on losers to avoid losses. The results of this study negates this phenomenon by finding there exist no relationship between market return and security turnover. And a weak evidence found for Mret(-2) also implies with an increase in market return, security turnover tends to fall which shows no exuberant trading happening due to overconfidence of investor. On the basis of results it may be concluded that overconfidence bias is not inter mingled with the disposition effect and it has its own reasons and justifications to exist in market.

Security return (Sret) and market return (Mret) both have insignificant relationship with Mret(-1) and Mret(-3) and both the relationships are found significant in Mret(-2) with t-values of -1.9048 and -2.1626 respectively. Negative sign with coefficients shows the inverse relationship of security return (Sret) and market return (Mret) with its own lagged values. This means that any increase in market return in past decreases the current security return and market return. VAR analysis with exogenous variable has also been performed and reported as under:

Based on Akaike Information Criteria (AIC) number of lags for exogenous variable cross sectional volatility in stock returns (Svol) is set as (1,2). Values for the constant term used in the model are also reported.

Results reveal that security turnover (Sturn) has a significantly positive relationship with security volatility. This shows that as the cross sectional volatility of returns increase, security turnover also tend to increase. This result found is in accordance to the volume volatility relation documented by Karpoff (1987) and Lo and Wang (2000). High volatility provides more chances to earn profits and so investors tend to trade excessively increasing the trading volume. However, although volatility and volume have a strong positive correlation, their behavior in long run may differ (Rangau, 2008). As shown by results that security turnover does not have any significant relationship with lagged volatility despite having very strong correlation with volatility. Going to further lag, their relationship turns negative and the values obtained for Svol(-2) are statistically significant showing inverse relationship of two variables. Confirming the findings of Rangau (2008) a further investing may change the nature of relationship in long run.

Security return is also found positively related with volatility as an increase in volatility provides the investors an opportunity to find mispricing and earn higher profits. However, no relationship is found between security returns and lagged values of volatility. Although security returns increase with volatility, it does not take into account the previous values of volatility because mispricing occurs in volatile markets for a particular point of time and investors interested in exploiting this opportunity has to take decisions quickly. Since no trend emerges in volatile markets, previous period figures cannot be of much help to investors.

Market return is found significantly dependent upon the security's cross sectional volatility but the relationship disappears in lagged period and then reappear in second lag in form of an inverse relationship. Trading volume/turnover exhibits how the investors in market are forming or changing their future expectations and thus is considered the most vital indicator of market (Harris and Raviv, 1993). Since change in investor's perceptions, moods, emotions make the market volatile, strong relationship between two is in accordance to the documented theory in this regard.

### 4.4.5 VAR Granger Causality/Block Exogeneity Wald Tests

In order to find out the evidence of Granger Causality in VAR environment, Wald test has been applied to VAR estimates. Unlike ordinary granger causality test, VAR Granger Causality or Wald Test measures whether the lagged values of a variable jointly cause the dependent variable or not. Decision is based on the p-values and all the variables are assumed as endogenous. Results for VAR Granger Causality are presented in Table 4.25.

Table 4.25 above shows the VAR Granger Causality results for security turnover (Sturn), security return (Sret) and market return (Mret) as dependent variable. Since the model assumes lagged values of independent variable jointly cause the dependent variable, Null hypothesis for relationship of Sret and Sturn would be $H_0 : Sret(lg1+lag2+lag3)$ does not jointly cause the Sturn. Panel A of table 4.25 presents that p-value for Sret and Sturn occur as 0.0190 which is significant at 5% level of significance. This result allows to reject the null hypothesis and to held that lag1, lag2 and lag3 of Sret jointly cause the security turnover (Sturn). This is also in accordance to the VAR estimates obtained. Similarly, null hypothesis for independent variable in Panel A, Mret is tested as $H_0 : Mret(lag1 + lag2 + lag3)$

Table 4.25: VAR Granger Causality for Disposition Effect.

| **Dependent variable: Sturn** | | | |
|---|---|---|---|
| **Excluded** | **Chi-sq** | **Df** | **Prob.** |
| **S.Ret** | 9.9486 | 3 | 0.0190* |
| **M.Ret** | 5.2969 | 3 | 0.1513 |
| **All** | 13.2292 | 6 | 0.0395 |
| **Dependent variable: Sret** | | | |
| **Excluded** | **Chi-sq** | **Df** | **Prob.** |
| **S.Turn** | 6.8208 | 3 | 0.0778 |
| **M.Ret** | 4.0182 | 3 | 0.2595 |
| **All** | 10.6465 | 6 | 0.0999 |
| **Dependent variable: Mret** | | | |
| **Excluded** | **Chi-sq** | **Df** | **Prob.** |
| **S.Turn** | 14.1543 | 3 | 0.0027** |
| **S.Ret** | 2.8364 | 3 | 0.4175 |
| **All** | 17.5758 | 6 | 0.0074 |

***significant at 05% level of significance*

does not jointly cause the Sturn. P-value obtained in this case is 15.13% which does not allow us to reject null hypothesis at 5% level of significance and thus it is concluded that lagged values of Mret does not jointly cause the security turnover (Sturn).

Panel B of Table 4.25 presents Sret as dependent variable and security turnover, Sturn, and market return Mret are the independent variables. In order to test relationship of two independent variables with dependent variable, null hypothesis is tested as $H_0 : Sturn(lag1 + lag2 + lag3)$ does not jointly cause the Sret and $H_0 : Mret(lag1+lag2+lag3)$ does not jointly cause Mret. Results obtained show the p-values of 7.78% and 25.95% for Sturn and Mret respectively. Since both the values are above the threshold of 5% level of significance, null hypothesis may be accepted and it is concluded that lagged values of security turnover and lagged values of market return does not cause security return.

Panel C of Table 4.25 presents market return Mret as a variable dependent upon security turnover Sturn and security return (Sret). Null hypothesis for Sturn is formulated as $H_0$ : $Sturn(lag1 + lag2 + lag3)$ jointly does not cause Mret. Results show the p-value of 0.0027 that is 0.27% which is significant at 5% level of significance. Since the result allows rejecting null hypothesis, Sturn can be considered as a cause of Mret. Second relationship presented in Panel C is for Sret which has a null hypothesis as $H_0 : Sret(lag1 + lag2 + lag3)$ jointly does not cause Mret. With a p-value of 41.75%, null hypothesis is sufficiently rejected and no evidence of any such relationship is found.

### 4.4.6 Impulse Response Function

Impulse response function is considered to be a shock to whole VAR system. It measures the responsiveness of dependent variables to a shock in error term (or impulse). Thus in order to test this responsiveness a unit shock that is one standard deviation shock is applied to all the variables, through the shock to error term, and how variables react to each other is analyzed.

Figure 4.7 presents all the possibilities of when one standard deviation shock is provided to one variable how the other two variables reacted. Along vertical axis response of variables has been measured and along horizontal axis periods to which their impact is analyzed are taken.

First diagram (from left) shows the response of security turnover to security turnover that is when one standard deviation shock is provided to the residuals of S.Turn, how does the series of S.Turn reacted in next ten periods. It is evident that as the impulse is introduced, response of S.Turn increases from 5% in first period to 6% in second period. However, a declining trend is observed in responsiveness all over rest of the eight periods which means response to the impulse is decreasing with each shock but remain positive and above zero.

Second diagram provides the analysis of response of security turnover to one standard deviation shock in residuals of security return. It shows as the shock is introduced, security turnover responded in an increasing manner. It ranges from

0% to approximately 2% response in 4th and 5th period and then start declining but remain positive and non-zero till end of test periods. Similarly, if the one standard deviation shock is given to market return M.Ret, security turn over will first decrease up to a level of -2% in period 4 and then start rising at a decreasing rate. However, the response of S.Turn to an impulse in M.Ret remains negative till end of test periods.

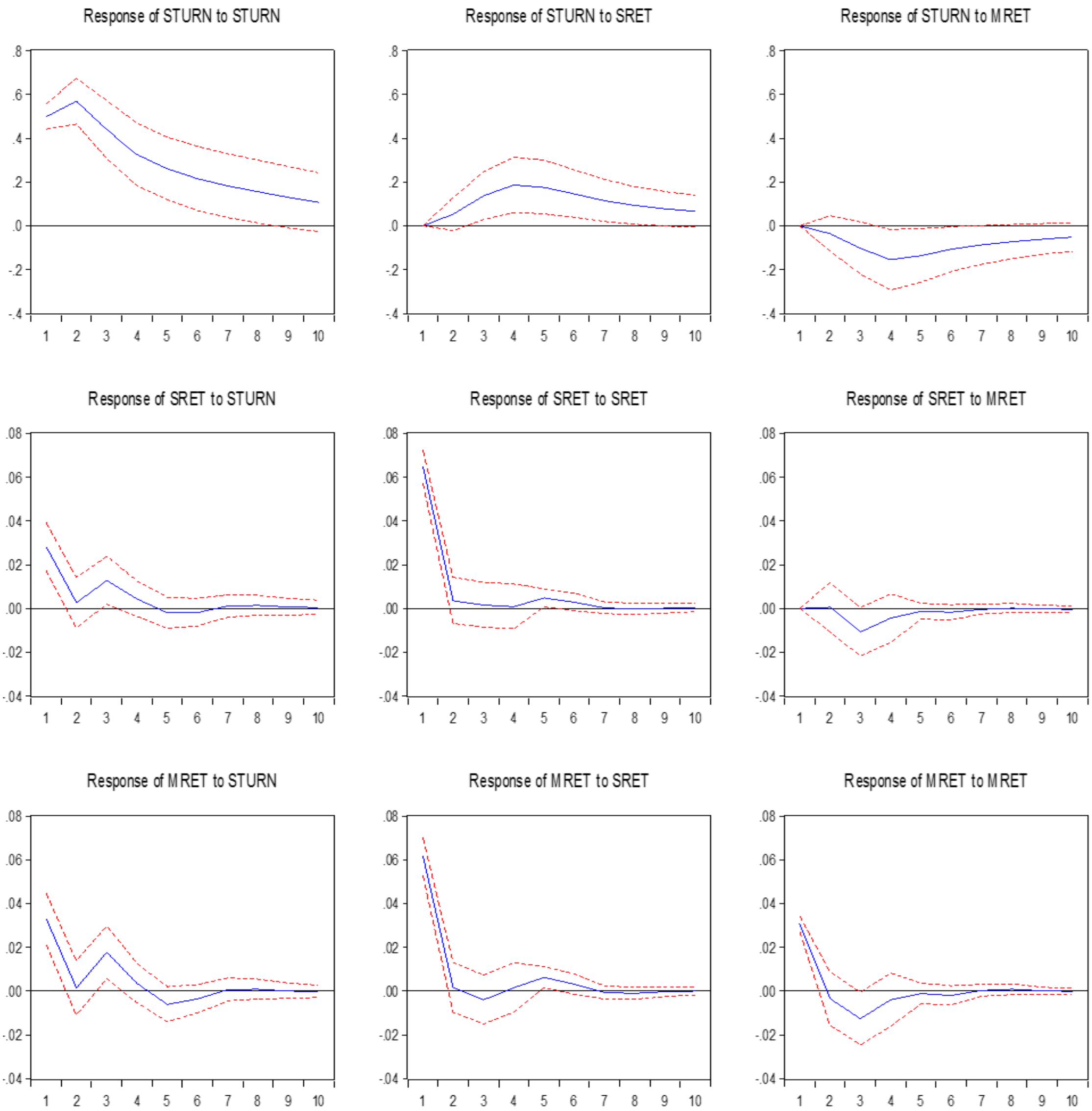


FIGURE 4.7: Impulse Response Function for Disposition Effect.

Analysis of response of security return S.Ret to security turnover shows that as the one standard deviation shock is introduced to security turnover, the security returns responded in a negative manner and declined in period 2 near zero. In period 3, the security returns rises up to 2% and then again immediately declined to zero. With minor un-noticeable fluctuations, the response of security returns remains zero till end. Analyzing the response of S.Ret to S.Ret reveals that as the impulse is received by the S.Ret, it responded immediately and response dropped from 7% to zero in second period. For all the rest of the period it will remain around zero. Similarly when a shock is introduced to market return M.Ret it generates negative response in S.Ret becomes negative in period 3. Afterwards it will recover and reach zero and will stay there till end at 10th period.

When comes to market, M.Ret responsiveness has been plotted to check how it has responded to one standard deviation shock in each other variable. Response of M.Ret to the one standard deviation shock to security turnover S.Turn shows rapid fluctuations in first 5 months. That is initially there is a decrease in response then it increases in 3rd period and again fall down up to a negative in 5th period. From period 7 onwards the response remain zero that is it stopped responding shocks to S.Turn. Response of M.Ret to a shock in the residuals of security return (S.Ret), exhibits a downward trend initially and then with minor fluctuations remain around zero for rest of the period means the responsiveness remain very low throughout the period. Response of market return to a shock in market returns starts from an appropriate positive response and drops down to negative in second period. It remains negative up to period 4 and then stop responding becoming equal to zero for rest of the periods.

For most of the diagrams, especially those pertaining to response of security return and market return, it is noticed that after initial few movements, S.Ret and M.Ret stop responding to the any shock in residuals or the response becomes too low that it almost equals zero. However, a response over whole test periods can be seen for security turnover. Also the response of S.Turn to S.Ret is just a reciprocal of the response of S.Turn to one standard deviation shock in M.Ret. It can be concluded that security turnover responds to the changes in other variables for a long period whereas security return and market return are not long run phenomena and their response does not last for long in future.

## 4.5 Market Under/Over Reaction

All the tests conducted above has shown that investors in Karachi Stock Exchange does not act rationally and are prone to the behavioral biases that is overconfidence and self-attribution, Anchoring, Herding and Disposition Effect. Presence of these biases not only confirms the irrationality of investors but also declares the market as inefficient. It is further to investigate whether presence of these biases leads to under or over reaction of investors as a whole in market.

### 4.5.1 Under/Over Reaction of Market

Implying the methodology of Thaler (1985), monthly stock returns and excess returns for the period 2000 - 2014 have been analyzed for non-overlapping three year formation period by identifying winners and losers in the market at a threshold of 10%. The results obtained are presented as under:

TABLE 4.26: Average Cumulative Excess Returns for Winner and Loser Portfolio.

| Period | $ACAR_W$ | $ACAR_L$ | $ACAR_L$-$ACAR_W$ |
|---|---|---|---|
| **2006-2008** | -0.0455 | -0.0231 | 0.0225 |
| **2009-2011** | -0.0077 | 0.0255 | 0.0332 |
| **2012-2014** | -0.0058 | -0.0013 | 0.0045 |

*$ACAR_W$ is the Average Cumulative excess returns for portfolio of winners, $ACAR_L$ is the Average Cumulative excess returns for portfolio of losers*

Table 4.26 shows the values of Average cumulative excess returns for each portfolio of winners and losers for three distinct formation periods in sample that is from 2006 to 2008, 2009 to 2011 and 2012 to 2014. As suggested by the theory, evidence of overreaction can be obtained when $ACAR_W < 0$, $ACAR_L > 0$ and thus by implication $ACAR_L\text{-}ACAR_W > 0$. Results have revealed that ACARs for winner portfolio have constantly been negative for the three formation period that is less than zero which is consistent with overreaction hypothesis. ACARs for loser portfolio have shown a controversial trend where ACARs of loser portfolio for the formation period of 2006-2008 and 2012-2014 are negative (-0.0231 and -0.0013 respectively). However, for the formation period 2009-2011, $ACAR_L = 0.0255$ which is greater than zero. Analysis of $ACAR_L$-$ACAR_W$ also shows overreaction of investors in all three testing periods 2006-2008, 2009-2011 and 2012-2014 with the positive values.

The analysis of cumulative average excess returns of the winner and loser portfolios of three distinct formation periods 2006-2008, 2009-2011 and 2012-2014, based on the holding period of previous three year's excess returns, reveals that winners of holding periods tend to lose in all three formation periods as depicted by negative cumulative average excess returns in each period. This condition is exactly what overreaction hypothesis states that is $ACAR_W < 0$. Losers of holding period, on the other hand, kept on losing in formation periods 2006-2008 and 2012-2014 as well which is contrary to overreaction hypothesis. However, losers of holding period 2006-2008 turned out to be the winners in formation period 2009-2011 as shown by positive value of average cumulative excess returns. This position is in accordance to the condition of overreaction. Positive value for the difference between $ACAR_L$ and $ACAR_W$ confirms that magnitude of winning is higher than the magnitude of losing in formation period. Same is the position in period 2006-2008 and 2012-2014 winners outperformed the losers as shown by value of $ACAR_L$-$ACAR_W > 0$. The results imply that overreaction of investors is strongly observed in case of winner portfolios.

### 4.5.2 Analysis of ACARs

Average Cumulative excess returns for all the three portfolios of winners and losers, each, have been calculated and statistical significance has been tested. Aggregate results for the portfolio average cumulative excess returns and their T-values has been given in Table 4.27.

TABLE 4.27: ACARs of Winners, Losers and Their Difference.

| **Period** | **ACAR$_W$** | | **ACAR$_L$** | | **ACAR$_L$-ACAR$_W$** | |
|---|---|---|---|---|---|---|
| | **mean** | **t-value** | **mean** | **t-value** | **mean** | **t-value** |
| 1 | -0.0372 | -0.6347 | 0.0765 | 1.6491*** | 0.1137 | 2.1509** |
| 2 | -0.0602 | -0.9884 | 0.0563 | 1.5124 | 0.1165 | 2.3077** |
| 3 | -0.1333 | -1.4161 | 0.0522 | 1.1918 | 0.1855 | 2.5267** |
| 4 | -0.1633 | -2.3590** | 0.0326 | 0.6105 | 0.1960 | 3.1682* |
| 5 | -0.2499 | -2.7097* | -0.0119 | -0.1325 | 0.2380 | 2.6176* |
| 6 | -0.2617 | -2.9148* | -0.0235 | -0.2672 | 0.2381 | 2.6772* |
| 7 | -0.2282 | -3.3434* | 0.0204 | 0.2147 | 0.2486 | 3.0011* |
| 8 | -0.2429 | -2.2300** | 0.0029 | 0.0242 | 0.2458 | 2.1392** |
| 9 | -0.2515 | -2.4408** | 0.0174 | 0.1381 | 0.2689 | 2.3333** |
| 10 | -0.2897 | -2.4500** | 0.0359 | 0.2687 | 0.3256 | 2.5807* |
| 11 | -0.3273 | -2.2725** | 0.0310 | 0.1973 | 0.3583 | 2.3768** |
| 12 | -0.3484 | -2.0164** | 0.0035 | 0.0199 | 0.3519 | 2.0190** |
| 13 | -0.3584 | -2.1209** | 0.0410 | 0.2503 | 0.3995 | 2.3996** |
| 14 | -0.3666 | -2.0919** | 0.0405 | 0.2331 | 0.4071 | 2.3339** |
| 15 | -0.3927 | -2.1914** | 0.0542 | 0.3022 | 0.4468 | 2.4931** |
| 16 | -0.3643 | -2.3456** | 0.0774 | 0.4584 | 0.4417 | 2.7233* |
| 17 | -0.3454 | -2.5126** | 0.0928 | 0.6410 | 0.4382 | 3.1043* |
| 18 | -0.3059 | -2.4192** | 0.1429 | 1.0329 | 0.4488 | 3.3866* |
| 19 | -0.2953 | -2.6493* | 0.1662 | 1.1252 | 0.4615 | 3.5272* |
| 20 | -0.3345 | -2.9242* | 0.1393 | 0.7019 | 0.4738 | 2.9250* |
| 21 | -0.3476 | -3.1785* | 0.1569 | 0.7979 | 0.5045 | 3.1711* |
| 22 | -0.3285 | -3.3775* | 0.1838 | 0.9070 | 0.5123 | 3.2234* |
| 23 | -0.3369 | -3.2352* | 0.2194 | 1.0552 | 0.5563 | 3.3833* |
| 24 | -0.3231 | -3.3833* | 0.1875 | 0.7370 | 0.5106 | 2.6577* |
| 25 | -0.3145 | -3.2974* | 0.2373 | 1.0238 | 0.5519 | 3.1135* |
| 26 | -0.3494 | -3.0638* | 0.2582 | 1.0589 | 0.6076 | 3.1919* |
| 27 | -0.3619 | -3.1763* | 0.2490 | 0.9504 | 0.6109 | 3.0242* |
| 28 | -0.3516 | -3.3674* | 0.2603 | 0.9648 | 0.6119 | 2.9910* |

| | | | | | | |
|---|---|---|---|---|---|---|
| 29 | -0.4291 | -2.6352* | 0.2099 | 0.6797 | 0.6390 | 2.5886* |
| 30 | -0.4130 | -2.6448* | 0.1974 | 0.6202 | 0.6104 | 2.4350** |
| 31 | -0.4651 | -2.1198** | 0.1369 | 0.3743 | 0.6020 | 1.9960** |
| 32 | -0.5097 | -1.8636*** | 0.0977 | 0.2397 | 0.6074 | 1.7499*** |
| 33 | -0.5243 | -1.8553*** | 0.1014 | 0.2432 | 0.6258 | 1.7565*** |
| 34 | -0.5850 | -1.7518*** | 0.1085 | 0.2517 | 0.6936 | 1.7983*** |
| 35 | -0.5991 | -1.6827*** | 0.1130 | 0.2594 | 0.7122 | 1.7897*** |
| 36 | -0.7090 | -1.5232 | 0.0133 | 0.0264 | 0.7224 | 1.4861 |

**significant at 01% level of significance, **significant at 05% level of significance, ***Significant at 10% level of significance, Period represents each month over 3 years, $ACAR_W$, $ACAR_L$ are the Average Cumulative Excess Returns of winner and loser portfolio, t-values in parenthesis*

Table 4.27 above shows the Average Cumulative Excess Returns for the winner ($ACAR_W$) and loser portfolio ($ACAR_L$) at time t = 1,2,3,4,·,36 along with their respective t-values to test their statistical significance. Difference of $ACAR_L$ and $ACAR_W$ has also been presented with their t-values. Results shows ACAR of winner portfolios remain negative throughout the 36 months depicting negative mean returns for the winners in formation period. To test the statistical significance, confidence interval has been defined at three different levels to indicate the strength of significance at 90%, 95% and 99%. The mean values obtained for the portfolios of winners are found to be statistically significant after month 2 and remain significant till month 35. Value obtained for month 36 turned to be statistically insignificant (mean =-0.7090, t-value= -1.5232). Significantly negative returns in the months following the holding period of winner stocks is exactly what is brought forward by overreaction hypothesis that past winners tend to lose in future due to mean reversion. Investors in this state thus prefer to follow contrarian strategy to get maximum benefits.

Results for the $ACAR_L$ shows Average cumulative excess returns for the portfolio of losers. Results revealed that average excess returns for the portfolio for past losers performed better in formation period and earned positive profits throughout 36 months except for month 5 and 6. Since t-values for all the periods are statistically insignificant no statistical importance can be assigned to these results except for the first month with $ACAR_L$ mean= 0.0765 and t-value = 1.6491 that is significant with 90% confidence interval. This trend of average cumulative excess returns for the portfolio of past losers has been supported by overreaction hypothesis but since results are found statistically insignificant, these cannot be generally accepted.

Results for the $ACAR_L$-$ACAR_W$ shows positive excess returns for period 1 to period 36 and the values obtained have also been supported by statistical significance except for the month 36 that's is last period where mean value obtained is 0.7224 and t-value is found as 1.4861. These findings are in accordance with the overreaction hypothesis which states $ACAR_L$-$ACAR_W > 0$.

### 4.5.3 Graphical Presentation

Same results can more easily be understood by having a graphical presentation rather than messing up with a lot of numbers. Chart depicting comparative movement of ACARs of winner and loser portfolios for all the non over lapping three-year formation period has been presented in Fig. 4.8.

Months of formation period referring to t =1, 2,3·,36 have been taken along X-axis and along Y-axis Cumulative excess returns of the portfolios for the next 36 months after the portfolio formation date have been presented. It is clearly evident that movement in the ACARs of winners and losers is absolutely in opposite direction. Winners tend to lose over time whereas Losers tend to improve.

$ACAR_W$ started with the negative average excess returns in t = 1 and remain negative till t = 36. This continuous trend of declining average cumulative excess returns of winner's portfolio in each period, as plotted above, shows how investors overreact to unanticipated news in long run and drift the stock prices in an anomalous manner. Irrationally increased stock prices ultimately correct to

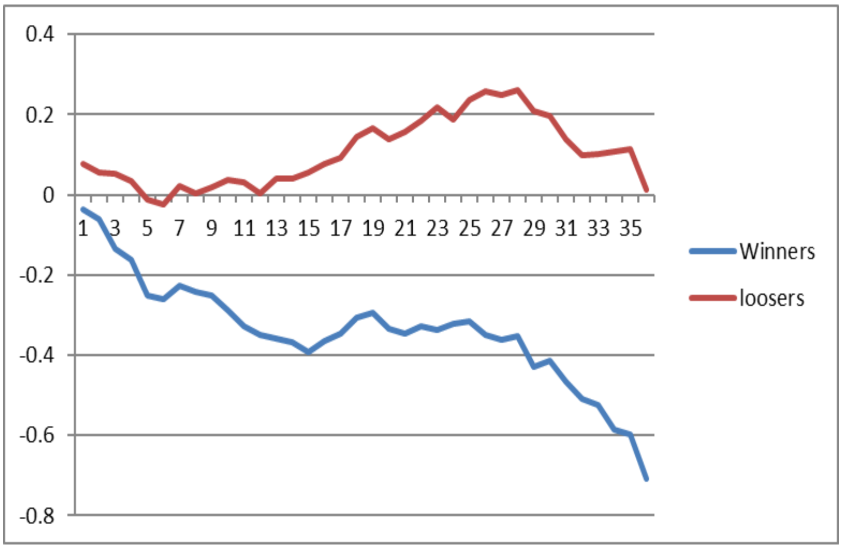


FIGURE 4.8: Average Cumulative Excess Returns for the Winner and Loser Portfolio with non over lapping three-year formation period.

its fundamental value in long run and apparent decreased returns transforms a winning stock into a loser stock.

Series of $ACAR_L$, when plotted, shows that average cumulative excess returns for loser portfolio starts from 0.0764 in t = 1 that is greater than "Zero" and remain positive till t = 4. In t = 5 and t = 6, a downward movement is observed in average cumulative returns as evident by negative values. The condition improved in t = 7 but again in t = 8 the mean value becomes equal to zero. After another hype in returns, average cumulative returns again found equal to zero in t = 12. However, t = 13 onwards, the excess returns remain positive for the loser portfolio. It is observed that despite the ups and downs in excess returns of loser value, it remains positive for most of the period and the curve depicting excess returns for losers remain above that for past winners. This trend is in accordance to what overreaction hypothesis suggest that past losers tend to win in future in long run.

Overreaction phenomenon implies loser stocks in long run adjust their prices and earns higher profits which transform them into a winning stock. This is the pattern observed in average excess returns for past losers with minor ups and downs all over the formation period. Winner portfolio also shows a strong evidence of overreaction of investors with a mean reversion effect as to which continuous negative excess return in formation period are earned. Thus the study confirms the overreaction of investors for the past loser stocks of KSE-100 index during the sample period of 2000 to 2014 by rejecting our null hypothesis that in extreme market conditions, investors does not tend to react irrationally.

## 4.6 Excess Volatility, Market Reaction and Turnover

Shiller (1990) propose that investor's psychological and sociological behaviors have great influence over the price level in market. He statistically proves that excess volatility always exists in stock market and therefore volatility cannot be totally explained by the EMH. Excess volatility is the level of volatility over and above that level which is predicted by efficient market theorists. Also it is hypothesized that behavioral biases makes the market react irrationally leading to under or over reaction.

This section focuses on investigating what is proposed by Shiller (1990) that is how investor's over or under reaction may affect the level of excess volatility in market. Moreover, market reaction not being the only element to govern excess volatility, relationship of market turnover with excess volatility is also to be analyzed.

### 4.6.1 Graphical Presentation

Excess volatility (referred as volatility hereafter) in KSE-100 index during the period 2000-2014 has been plotted below to find whether presence of behavioral biases during all this period and resultant overreaction of investors has have any impact on market volatility or not.

Overreaction has been defined as $\text{ACAR}_L$-$\text{ACAR}_W$ and market turnover has been defined as total value of shares traded. Market volatility during sample period gives following picture:

Figure 4.9 above presents the level of volatility in KSE-100 Index during the sample period. It is evident that volatility during all this period remains significant enough

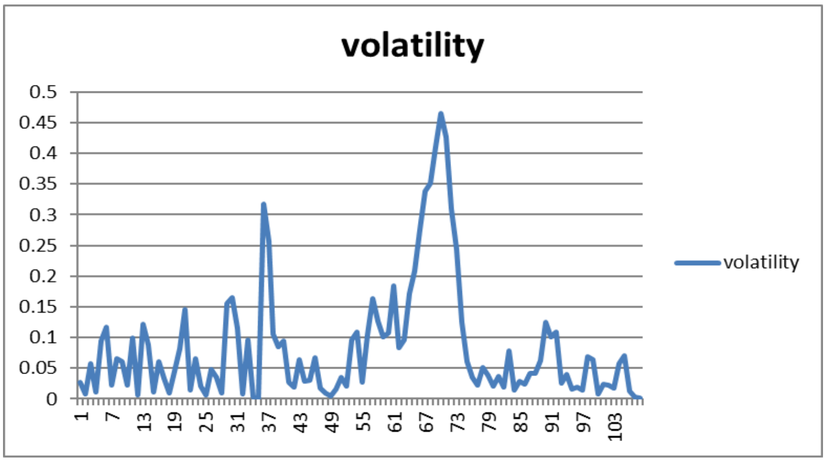


FIGURE 4.9: Volatility in KSE-100 Index during 2000 to 2014.

ranging from 0.05 to 0.15 except for two points where exuberantly high volatility has been observed. Volatility at these two points has been found as high as 0.3 and 0.45 showing record highs during this period.

Figure 4.10 presents the market turnover over three formation periods in sample. It is evident that in first month turnover was at its highest level which gradually dropped until 15th month and then again started rising till 21st month. Lowest turnover has been observed in 35th month where market turnover has become even below 2,000,000,000. For rest of the period turnover keeps on moving between the limits of 2,000,000,000 to 8,000,000,000.

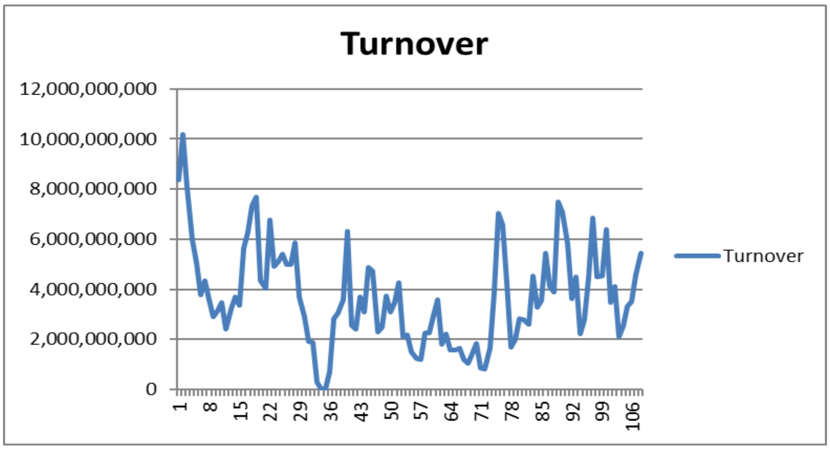


FIGURE 4.10: Market Turnover for KSE 100 index.

It has been hypothesized that irrational attitudes of investors, motivated by their psychological and sociological behaviors, creates excess volatility in market. Figure

4.11 presents the relationship between irrational attitudes and excess volatility:

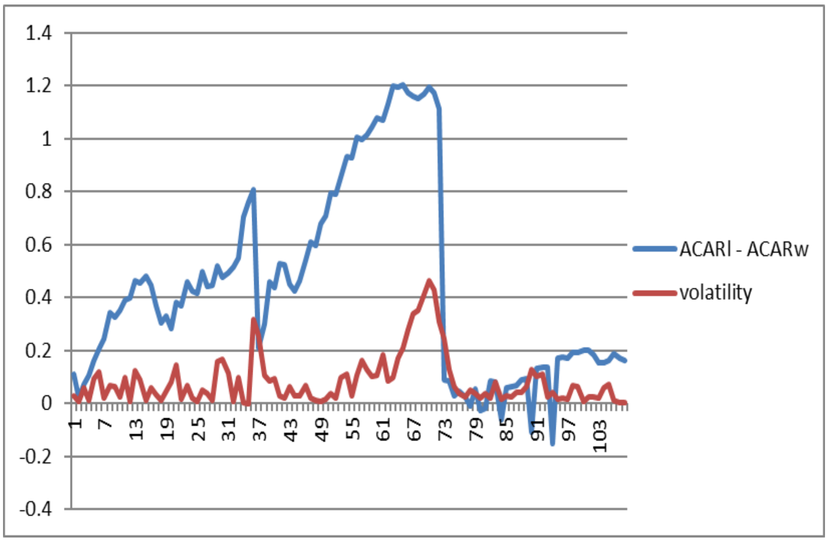


FIGURE 4.11: Volatility and Investor Reaction.

Figure 4.11 shows the association between excess volatility in market and investor irrational behavior. Just like volatility, two peak points are also observed in market reaction. In the initial period, investor's reaction remains high and increasing till it reached its first record high at 0.8. This is the same point where volatility touched its first high peak at 0.3 implying that both the variables move in same direction. Covariance tested between the two variables till first high point gives the value of 0.0034 implying that both the variables move in same direction.

Second high point in market reaction is observed when difference between the ACARs of Loser and Winner portfolios reached at 1.2. Again it is almost the point where record high volatility has been observed at 0.45. Value of Covariance = 0.0193 also proves as the market overreaction increases, volatility in market also increases. Volatility beyond this point remain low and at same time $ACAR_L$-$ACAR_W$ remain significantly low that in some months it went even lesser than zero. However, in general, over reaction of investors continued. Covariance tested shows the same results with the value of 0.0162.

### 4.6.2 Descriptive Statistics

Table 4.28 below presents the descriptive statistics for three variables, Market Reaction, Volatility and Turnover where market reaction has been defined as $ACAR_L$-$ACAR_W$. Positive values of $ACAR_L$-$ACAR_W$ implies over reaction of investors whereas zero and less values implies under reaction of investors. Significantly positive values have been found for the KSE-100 Index during sample period in section 4.2 depicting over reaction of investors.

TABLE 4.28: Descriptive Statistics for Market Reaction, Volatility and Turnover.

| | **MR** | **Vol** | **Turn** |
|---|---|---|---|
| **Mean** | 0.4418 | 0.0835 | 0.0092 |
| **Standard Error** | 0.0359 | 0.0093 | 0.0002 |
| **Minimum** | -0.1537 | 0.0001 | 0.0000 |
| **Maximum** | 1.2010 | 0.4644 | 0.0134 |
| **Standard Deviation** | 0.3734 | 0.0965 | 0.0026 |
| **Kurtosis** | -0.5780 | 4.4129 | 0.3641 |
| **Skewness** | 0.7149 | 2.0997 | 0.6468 |

*MR = Market Reaction during sample period, Vol = Volatility during sample period, Turn = Turnover during sample period*

Table 4.28 shows mean value obtained for market reaction is 0.4418. Since it is hypothesized that investors tend to over react to a news if $ACAR_L$- $ACAR_W$ $> 0$, mean value of 0.4418 over a period of 2000 to 2014 provides an evidence of investor's overreaction to any sporadic news arrived in Karachi Stock market. Standard error so obtained is as low as 3.59% making the results sufficiently reliable. Standard deviation has been found as 37.34% which shows variation in responses within sample and is highest among the three data series. Value of kurtosis (-0.5780) being $k < 0$ demonstrates the data as platykurtic distribution with a tail towards right side of normal distribution as shown by the value of skewness, 0.7149.

Mean excess volatility is 0.0835 with the very low standard error of 0.0093 keeping the result more reliable. Standard deviation found during the sample period is also very low as 9.65%. With k > 0, kurtosis of 4.4129 demonstrates the data as leptokurtic with a heavy positively skewed tail. Mean Turnover found is the 0.0092 (0.92%) with the minimum standard error of 0.0002. Value of kurtosis and skewness is positive and slightly greater than zero making data almost normally distributed.

### 4.6.3 Correlation Analysis

Graphical presentation of volatility and market reaction has shown some association between the two variables. However, in order to define the nature of relationship Pearson correlation coefficient has been calculated as follows:

TABLE 4.29: Descriptive Statistics for Market Reaction, Volatility and Turnover.

| | **MR$_t$** | **Vol$_t$** | **Turn$_t$** |
|---|---|---|---|
| **MR$_t$** | 1 | | |
| **Vol$_t$** | 0.5696 | 1 | |
| **Turn$_t$** | -0.5471 | -0.4190 | 1 |

*MR = Market Reaction during sample period, Vol = Volatility during sample period, Turn = Turnover during sample period*

Table 4.29 above shows the correlation matrix defining the association between market reactions, turnover and excess volatility during the sample period. Results show that value of r found for market reaction and volatility is 0.5696, almost 57%, which shows a strong correlation exists between these two variables. This is a confirmatory result for what is found through graphical presentation. Turnover and market reaction is also found strongly correlated with a value of r = -0.5471 however, the nature of association remains negative that is both the variables move in opposite direction. Same is the result that holds for turnover and volatility however, value of correlation coefficient for these two variables is as low as 42% approximately.

### 4.6.4 Regression Analysis

Regression analysis has been made to find what effect does market reaction hold on excess volatility and Turnover. Table 4.30 below explains the relationship of market over reaction and turnover:

TABLE 4.30: Regression Analysis for Market Overreaction and Turnover.

| | **Market Turnover** |
|---|---|
| **Intercept** | 0.0124 |
| | (2.053)** |
| **MR**$_t$ | -0.0072 |
| | (-6.729)* |
| $R^2$ | 0.2993 |
| **Adj** $R^2$ | 0.2927 |
| **F-value** | 45.2797* |

**Significant at 01% level of significance, **Significant at 05% level of significance, MR = Coefficients for Market Reaction, t-values in parenthesis*

Market over reaction has been measured as the positive difference between ACAR$_L$ and ACAR$_W$. While measuring market over reaction it was found that winners of formation period turned out to be the losers of testing period and losers of formation period transformed into winners of testing period. This tendency of market has depicted in the significantly negative relationship between market turnover and market overreaction as shown in Table 4.30. Coefficient of market over reaction being significantly negative ($\beta$ = -0.0072, t-value = 6.7290) shows that as the market over reaction increases, trading volume of winner stocks start decreasing and ultimately results into negative returns in future period and vice versa. Thus analyzing turnover, investors can predict future move of the market and can base their investment decisions upon them.

Results for correlation indicate the positive relationship between excess volatility and market over reaction however, significance of this relationship is yet to be tested for which regression analysis has been used in Table 4.31.

TABLE 4.31: Regression Analysis for Market Reaction, Volatility and Turnover.

| Volatility | |
|---|---|
| **Intercept** | 0.0557 |
| | (2.152)** |
| **MR**$_t$ | 0.1256 |
| | (5.1334)* |
| **Turn**$_t$ | -2.9903 |
| | (-1.618)*** |
| $R^2$ | 0.3409 |
| **Adj** $R^2$ | 0.3284 |
| **F-value** | 27.1579* |

**Significant at 01% level of significance, **Significant at 05% level of significance, ***Significant at 10% level of significance, MR = Coefficients for Market Reaction, Turn = Coefficients for Market Turnover, t-values in parenthesis*

Table 4.31 above shows the regression results, Excess volatility is dependent variable and market over reaction and Turnover are independent variables. Results have revealed that there exists a significantly positive relationship between market reaction and volatility ($\beta_1$ = 0.1256, t-value = 5.1334). A 1% change in market reaction contributes towards a 12.56% increase in market volatility. Movement of excess market volatility and reaction of market in same direction also corroborates the results of graphical presentation of excess volatility and market reaction in figure 3 that when market showed an exuberant over reaction, market volatility touched its record high in that month.

Relationship found between turnover and volatility is negative and significant at 90% level of confidence implying an inverse movement in both the variables that is increase in Turnover significantly reduces the market volatility. $R^2$ found for the model is almost 34% which is good enough to believe that 34% of volatility in market is characterized by reactions of investors and market turnover. F-value has also been found significant and positive.

Excess volatility here refers to the volatility of stock returns that cannot be explained through the variation in fundamentals, more specifically earnings. LeRoy and Porter (1981) and Shiller (1981) for the first time claim that prices move too much to be the rational forecasts of future earnings, discounted at a constant rate. Shiller (1981) propose that there are number of psychological and behavioral biases that contribute towards this irrationality by affecting the decision making of investors making them to either overreact or underreact to the news. Thaler (1975) define overreaction of investors as $\text{ACAR}_W < 0$, $\text{ACAR}_L > 0$ and by implication $\text{ACAR}_L$-$\text{ACAR}_W > 0$. Our data analysis of KSE-100 index over the period 2000 - 2014 has revealed that Karachi stock market does not hold Efficient Market Hypothesis since difference between ACARs of Loser Portfolio and ACARs of Winner portfolios has been found significantly greater than zero during sample period implying that investors of KSE-100 index tend to over react.

Results of regression model confirm that any increase in market reaction brings a significant direct increase in excess volatility. This relationship may be associated with the overreaction of investor as found in section 5.5 that is investor over reaction directly contributes to the excess volatility in market. As the investor overreaction increases, volatility in market also increases. Based on this statistically significant evidence of direct relationship between excess volatility and market reaction, this study rejects the null hypothesis that market volatility is not driven by market reactions.

Hong (1997) established a unified model where both under and overreaction are obtained with one primitive shock: gradual diffusion of news about fundamentals. Where one group of investor under react to private information, the other group tries to arbitrage away this mispricing and creates a momentum in prices resulting into overreaction. Herding, self-attribution and over confidence, confirmation bias and many other biases have also been discussed as reason for momentum which are also the drivers of over/ under reaction. Lee and Swaminathan (2000) reports that momentum is stronger in high turnover stocks and turnover predicts the magnitude and persistence of momentum. Momentum strategy can only work in low volatility era. Thus an observed pattern in turnover can predict the level of volatility in market.

Results reported in Table 4.30 have found the inverse relationship between turnover and excess volatility that any increase in turnover, reduces the volatility in market. Reason being existence of momentum in trading (Lee and Swaminathan, 2000). Since turnover based on trading pattern of investors does have a significant impact over volatility level in market, this study rejects its null hypothesis which states that there exists no relationship between volatility and market turnover.

Another possible explanation for the excess volatility and overreaction of investors in market could be the uncertainty. Pakistan over the sample period has been faced with the extreme terrorism and political instability along with the poor economic conditions and foreign power interventions. Post 9/11 war on terror, changing foreign policies, deteriorated law and order, ongoing Military operations are some of the factors which has left no niche of the society untouched. Resultant increased foreign borrowings, low economic growth and less capital formation have been the factors which created an environment of overall uncertainty in the country restraining the foreign as well local investor to invest in Pakistani stock market. Also these macro-economic conditions have affected the humans psychologically causing traumas, stress, and mental disturbance (Khan, 2013). It is hard for the investor in this scenario to make fundamental and technical analysis while taking the investment decisions rather most of their decisions have been influenced by their own perceptions, level of fear, assumption of uncertainty and speculations. This tendency of investors provides sufficient room for the existence of heuristic and behavioral biases to which they are prone to while reacting to the market conditions or any upcoming news giving birth to the momentums and bubbles. Overreaction of investors, excess volatility found in stock market and turnover observed in the sample period may be associated to the same uncertain economic, social, political and psychological conditions.

# Chapter 5

# Conclusion and Future Directions

How rationally market behaves has been a topic of special interest since long. Theories presented by traditional finance base on set of assumptions such as the concept of "Homo Economicus": the rational economic man making perfectly rational decisions all the time. Where standard finance explains how the investor "should" behave, Behavioral Finance deals with how an investor "actually" behaves. The assumptions of standard finance are governed by idealized financial behavior whereas roots of assumptions in Behavioral Finance are in the observed financial behavior. Theory of limited arbitrage, presented as a counter agreement for efficient market hypothesis, also implies that security prices are not determined merely by information but also by changes in expectations or sentiments that are not fully justified by information. Investor being accepted as irrational in decisions either under reacts or over reacts to every event or new information. Market reaction to some news immediately after its release when continues even in subsequent period, the reaction is termed as Underreaction. Case of overreaction is different from that of Underreaction that is reaction of market to recent news is offset by a change in opposite direction in subsequent periods. People employ imperfect rules of thumb (heuristics) to process data which induces biases in their beliefs and influence them to commit errors. Thus the relationship between anomalous market reactions and heuristics can be put in a way that over and underreaction observed in market is basically the outcome of heuristics and biases implied in information processing.

This study aims at highlighting the psychological heuristic biases that affect the thought process of the investors and lead them to make irrational decisions, leading to over and underreaction of investors and resultantly volatile market conditions. This implies that investor is not always rational enough to base his decision on fundamentals rather human perception, moods, psychology and fears also plays their role in this regard. Two heuristic driven biases, Anchoring and Overconfidence & Self-Attribution, and two widely discussed market behaviors Herding and Disposition effect constitutes the scope of this study. This selection has enriched that scope of our model as individual and market, both factors, have been combined for the first time to investigate their effect on collective market behavior. KSE 100 index being representative of 86% Karachi Stock Exchange has been studied as sample during the period 2000 to 2014 to investigate the presence of these heuristics and biases and the resultant market reaction. Relation between market reaction, biases, excess volatility and turnover has also been investigated.

In order to test Overconfidence and self-attribution Vector Autoregressive (VAR) model has been employed to find out the long term relationship between endogenous variables: market return and market turnover and exogenous variables: volatility and dispersion. Results revealed that there exist a strongly positive relationship between market returns and trading turnover. Also cross sectional standard deviation in market prices that is volatility and the cross sectional variation in stock returns that is dispersion has a very strong impact on trading pattern and returns. These results confirms that Pakistani investors are prone to overconfidence and self-attribution bias where they tend to each positive return to their own stock picking art and tend to trade more aggressively which results in increased turnover depicting overreaction of market.

Anchoring bias has been tested by constructing two anchors named nearness to Historical High ($X_{(HH)}$) and nearness to 24-Week High ($X_{(24W)}$) where the former represents extent of overreaction and later represents extent of underreaction of investors. Regression analysis made for KSE 100 Index Historical High Indicator, 24 Week High Equal Historical High Indicator, Nearness to Historical High, Nearness to 24-Week High and Lagged Returns, confirms the Pakistani investor prone to Anchoring bias by establishing investors underreact to sporadic news when use 24-Week high as reference point in their mind and overreacts to the prolonged good news while having historical high in their mind as reference point.

Evidence of overconfidence and self-attribution bias and Anchoring has established individual Pakistani investor as irrational. He has found to be the one who is not a "Homo Economicus" rather is prone to bounded rationality due to his own emotions, aspirations, and perceptions. Since investment decisions made by Pakistani investor largely depend upon psychological factors, ignoring all the fundamentals, the trading pattern exhibited may collectively tend the market behave in irrational manner.

Coming to Behavioral Finance Macro, tendency to Herd has been tested herding, has been tested for KSE-100 Index companies by measuring Cross Sectional Standard Deviation (CSSD) and Cross Sectional Absolute Deviation (CSAD) between market and individual stock returns. Also the turnover effect on herding has been measured through High Turnover Standard Deviation (HTSD), High Turnover Absolute Deviation (HTAD), Low Turnover Standard Deviation (LTSD), and Low Turnover Absolute Deviation (LTAD). It is hypothesized that investors tend to herd in extreme market situations where extreme market has been defined at 5% and 10% respectively. Results revealed that when extreme market is defined at 5%, CSSD measured between market returns and stock returns has been lowered in down market situation. This implies that investors rely more on the market behavior rather than on their own signals in down market conditions only whereas no such evidence is found for up market condition. However, extreme market when defined at 10% provides the evidence of herding in both up and down market conditions depicted by negative relationship of CSSD and extreme markets. Also the nonlinear and asymmetric relation remains the same when CSAD is used as dependent variable. This makes study reject its null hypothesis for herding. As for the turnover effect in herding, for high turnover stocks dispersion between stock returns and market returns does not reduce in up and down markets which implies no herding exist. However, for LTSD as dependent variable, results show reduction in dispersion between low turnover stock returns and market returns in down market which is exactly in accordance to herding theory. The way investors deem to follow market trend instead of making personal judgments, also reflected by pattern of trading turnover, demonstrates the investor overreaction to bad news arriving in market.

Disposition effect refers to a tendency of investors to sell winners early and to hold loser stocks for a long time. Positive returns make an investor trade more aggressively in those stocks which in turn increases its turnover. VAR estimation has provided the evidence of strong positive association between security lagged returns and its turnover and thus the study rejected its null hypothesis which states that there does not exist any positive relationship between security turnover and its lagged returns. Tendency of investors to sell winners instead of holding them as profitable venture depicts the underreaction of investors to the positive news in market.

An evidence of herding behavior and disposition effect in Pakistani stock market has provided the basis for existence of anomalies in market. Karachi stock exchange is largely run by the few major institutions that can shake the market any time. Any irrational wave or information coming from them may be considered by individual investors as reliable and they tend to follow the market trends. Such anomalous behaviors of market make the investor over or underreact to a particular incident depending upon the prevailing market conditions.

An investigation of market reaction has been made by forming three testing periods 2006-2008, 2009-2011, and 2012-2014. It has been found that past winners turned out to be losers in next testing period and vice versa except for period 2012-2014 which depicted underreaction of investors in market. An examination of ACAR or loser portfolios and ACAR of winner portfolios provided the evidence that $\text{ACAR}_L$ -$\text{ACAR}_{W>0}$ for all 36 periods depicting market overreaction during sample period. Also this market over reaction has been found significantly correlated with market turnover and excess volatility building an argument that part of volatility which cannot be explained through efficient market hypothesis basically exist due to behavioral biases embedded in investors while making investment decisions leading them to overreact to a particular event. Also the relationship of turnover and volatility has been found significantly negative deducing that high turnover leads to a momentum in market which negatively affects the excess volatility.

Not only the existence of behavioral biases affecting investment decisions has been proved by the study but they have also proved as a source of overreaction embedded in Pakistani stock market. Overreaction of investors has been defined as $\text{ACAR}_{W<0}$, $\text{ACAR}_{L>0}$ and by implication $\text{ACAR}_{L}\text{-ACAR}_{W>0}$. Our data analysis of KSE-100 index over the period 2000-2014 has revealed that difference between ACARs of Loser Portfolio and ACARs of Winner portfolios is significantly greater than zero during sample period implying that investors of KSE-100 index overreact to every news. The reason behind this overreaction being heuristics and behavioral biases: overconfidence, anchoring, herding and disposition effect are affecting investment decisions. Such decisions in turn have a direct impact over the market price and resultant returns. Since most of the investment decisions are based on the expected returns, it adds to the existing overreaction and behavioral biases continues to multiply their effect.

This study has also found significantly positive association between investor over reaction and excess volatility implying that bounded rational behavior of investor is basically the reason behind excess volatility which was the part of volatility not justified by EMH. Thus we may conclude where role of traditional finance end and it fails to answer the questions raised, Behavioral Finance start playing its role. Stock market may be considered a blend of traditional and Behavioral Finance. Where traditional finance theories helps in forecasting the expected returns and other dynamics of market, bounded rational behavior of investors make it more volatile and difficult to predict.

The roots for the observed overreaction and excess volatility in stock market could be found in political and economic conditions of Pakistan. War on terror, foreign policies and ongoing military operations have contributed to the uncertainty making the investor overreact to the existing situation. Herding, Disposition effect, Anchoring and Self-attribution have been the factors played their role in investor's overreaction in response to the prevailing uncertainty about market.

Market under/overreaction leads to short term momentum in stock prices and momentum trading helps the investor predict future move of the market. Pakistani investor has been found prone to overreaction for a long period which implies existence of an upward momentum till the point is reached where excessive trading start reducing the returns and resulting turnover. Regression analysis for market overreaction and Turnover has also shown the negative relationship between two. As the market overreaction increases, turnover start decreasing in market in long run. Investigating the excess volatility in more detail, results of this study finds as the volume of trading or turnover increases as a result of momentum, it reduces the level of excess volatility in market whereas continued overreaction of market leads to increase in excess volatility. Since market overreaction has been associated with the heuristic driven behavioral biases, we may conclude on the basis of relationship between market reaction, Turnover and Excess volatility that in a market setting like Karachi Stock Exchange, excess volatility found is merely the result of bounded rational behavior of investors and momentum guided trading volume.

The study has provided insight into the market forces that is market reactions, excess volatility and turnover that how these forces play their role in market. Behavioral biases tested in study have shown their relationship with trading turnover. Overconfidence and self-attribution, Disposition effect and Herding are measured directly through trading turnover. Behavioral biases transforms into overreaction of investors which directly results into excess volatility in market. Excess market volatility as well as market over reaction are found significantly correlated with market turnover. Investors in market study the trading pattern and base their decisions on this trading turnover which are again prone to the behavioral biases. The market forces cycle for overreaction and volatility keeps on working this way making the market over reaction more dense and prolonged. This may be the reason that Karachi Stock Exchange has shown overreaction over the years 2000 to 2014.

Behavioral Finance may be perceived as a blend of Classical Economics and Finance with Psychology and Decision Making Sciences. The study has combined two branches of Behavioral Finance that is Behavioral Finance micro and Behavioral Finance macro in one model establishing that not only individuals affected by heuristics but also the anomalous behaviors observed in the market contributes to the irrational decision making by investors which constitutes the market under and overreaction. This study has also explored the criterion which is followed by investors while assigning the weights to various factors before making an investment decision that is own perceptions, overconfidence, previous reference in mind, market trend, hurry to realize paper gains etc. Since these attributes vary from person to person and no uniform policy can be formulated, stock prices also widely vary in market. This condition is contrary to Efficient Market Hypothesis which states investors are fully informed about fundamentals which are fully incorporated in stock prices and thus no mispriced stock can be identified. All the investors earn identical returns.

The study has also found returns earned by investors vary too much since decisions based on heuristics are like a gamble and can go either way: a success or a failure, due to which identical returns does not hold in reality. A paradigm with varying investor response to news is a more practical approach to observe and believe. The evidences found for the overconfidence and self-attribution bias, anchoring bias, herding and disposition effect has confirmed the presence of heuristic driven investment atmosphere in market. Overconfidence and self-attribution makes an investor overreact to the news in market, anchoring bias leads to the underreaction to a sporadic news, herding again contributes to the overreaction of market by following the same trend, and disposition effect makes an investor underreact by selling his winner stocks and retaining losers. All these heuristics are closest to nature and can be observed in reality unlike the assumption of EMH, investor being fully rational which sounds idealistic holds. Also the excess volatility found in market and its relationship with irrational market over/underreaction negates the Efficient Market Hypothesis to be hold in Pakistani market.

Since the Pakistani stock market has shown anomalous behavior to a great extent due to irrational individual investors constituting the market and the excess volatility, trading volume, and market reactions have also been found as the outcome of heuristic driven biases, fundamental analysis has left far behind while making an investment decision. Stock prices have found to be determined by the emotions, hopes, perceptions and other psychological factors rather than exhibiting their true intrinsic value. This phenomenon has proved the Pakistani stock market inefficient where stock prices do not reflect the available information but the human psychology.

## 5.1 Practical Implications

Efficient market hypothesis assumes that all the investors in market are rational. This study negates this basic assumption of efficient market hypothesis by providing the evidence of behavioral biases to which Pakistani investors are prone to. Quantification of these behavioral biases may help investors to better understand the pattern followed by them while making investment decisions providing them the chance to correct their bounded rational behavior while assessing an investment opportunity.

Behavioral biases, market reaction, market volatility and market turnover all are interlinked and constitutes a whole cycle that provides a platform to the market participants for the future forecast. An understanding of market forces may facilitate the investor not only to correct the effects of heuristic driven investment decisions, transforming into whole market and creating momentum in Pakistani Stock Market making the market overreaction prolonged and dense, but also to forecast the future trading pattern in market with an opportunity to outperform the market.

Relationships between trading volume, volatility and returns with the heuristic biases and resultant market reaction have provided the insight to Pakistani investors in the biases and behaviors that they follow but are not aware of. Also it makes investors capable of eliminating the effects of biased decisions by following certain strategies. Behavioral biases can't be avoided rather can just be managed by trading less and investing more, having fix trading rules with thresholds, and by resisting the urge to believe they have better information.

An understanding of behavioral biases prevailing and being exercised by investors in market may help the policy makers to devise such policies which may make the stock market efficient enough minimizing the overreaction, mispricing and momentum effect. Regulators in this regard shall focus on the disclosure of information to each and every segment of market so that asymmetry of information could be reduced significantly. Having symmetric information, individual investor as well as institutional investors will be on same page and the chances of biased decision making will be minimized.

The study also provides some useful insights for financial intermediaries who are keen to introduce innovation in their strategies. A thorough understanding of financial market forces at work, the anomalies it face, and the reasons for bubbles and momentums along with macro-economic factors will not only ensure the fast adjustment of new financial instruments and investment strategies to the market but also will help devising better strategies to work under varying market and economic conditions. Since stock market has widely been considered indicator of the economic activities in the country, stable stock market would impact the economy in a positive manner helping foreign investors and donor agencies to believe that Pakistan is a safe option to invest.

The financial advisors being aware of the anomalous behavior of the investors may arrange to educate investors about the pricing mechanisms and help them to calculate actual worth of the stocks based on fundamental analysis instead of recent price history providing them the basis for better decision. Also fund managers can carve out the space in the portfolios for their clients to make speculative investing. A manager may allow investor to play with 5-10% of investment as per their desire and rest 95% of portfolio may be managed nicely for risks and momentum trading. This arrangement can allow investor practicing bias without inculcating its effect in overall market to a great extent.

## 5.2 Direction for Future Research

The study identified only four behavioral biases overconfidence bias, anchoring, herding and disposition effect however, there are number of behavioral and psychological biases to which investors may prone to. Number of such behavioral biases has been reported by literature, particularly in field of psychology, which may be tested in the stock market setting to identify more biases that may affect the investment decisions of investors. A blend of two distinct fields of study that is psychology and finance may enrich the existing literature with some new dimension of study that is not yet highlighted.

The study has used secondary data by creating certain proxies for the behavioral biases. An improvement to the research may be to use primary data, collected directly from the investors. This will not only provide a better insight into the investor behavior but also will improve the reliability of the statistical tests implied. Also the data so collected may help in identifying a distinct pattern in human behavior which is not yet reported in literature.

The results reported in study are based on the available data and standard econometric methods. Reliability of results can be improved by with robustness checks and measures. Applying same methods in different scenarios of market and comparing them with the results obtained for advanced markets may provide a platform to devise better strategies on the grounds how advanced markets managed the rationality issues faced by them.

Investors are the primary constituents of the stock markets and any decision made by them is reflected in stock prices. Thus it is not only the volatility, volume and returns that are affected by the human decisions rather there are number of other market forces as well which may be tested for heuristic driven investment decisions and market over reactions. Also market over reaction may be tested for shorter or longer horizons to better understand market reactions.

Human behavior is a vast field of study that no one can completely understand or predict. Most of its roots are found in literature from psychology. Behavioral Finance is a blend of psychology and finance and is an emerging field of study.

However, not much has been done in this regard so far and it is still considered as a gray area. In this scenario there are number of other dimensions as well in which research can be carried out to authenticate the findings.

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