THE EFFECT OF PAST RETURNS ON THE CURRENT TRADING AT THE NAIROBI SECURITIES EXCHANGE

BY MAINA PHILIP MWAURA

REG NO: D61/76831/2012

A RESEARCH PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT OF THE AWARD OF DEGREE IN MASTER OF BUSINESS ADMNISTRATION, UNIVERSITY OF NAIROBI.

NOVEMBER, 2013

DECLARATION

I hereby declare that this research project is my original work and has not been presented for a degree by myself or any other person from any other institution known and unknown to me.

SIGNED………………………………… DATE…………………………………

MAINA PHILIP MWAURA

Supervisor Declaration:

This research project has been submitted for examination with my approval as University supervisor.

SIGNED………………………………… DATE…………………………………

DR. LISIOLO LISHENGA

ACKNOWLEDGEMENT

I take this opportunity to thank God, for giving me the strength, commitment, dedication and morale to work this project through to completion even when it seemed impossible.

I also acknowledge my supervisor Dr. Lisiolo Lishenga for his professional guidance, support and encouragement throughout this project.

DEDICATION

I dedicate this research to the Almighty God and my sponsors Mr. & Mrs. Enzo Soderini

ABSTRACT

Investor overconfidence has been proposed to explain various anomalous findings in security markets. The theory of investor overconfidence provides testable implication assuming investor overestimation of their abilities and private information and biased self-attribution. High (low) trading activity following market gains (losses) present on of the testable implication among others. The study sought to find out whether past returns have an effect on the trading volume at the NSE.

The objective of the study was to find out how past returns influence trading activity. The population of the study was the 62 companies listed in the NSE. The companies in the 20 share index were considered as an appropriate sample for the study due to their representativeness. The weekly index and volume was obtained from the Nairobi Securities Exchange (NSE) official website and was analyzed through simple linear regression.

Inconsistent with overconfidence hypothesis prediction, the findings indicated an insignificant relationship between past returns and trading volume. Based on the findings the study recommends that future studies use a longer period of time for analysis and also to analyze different sectors and indices separately. The major limitation of the study was in the method of analysis since some other variable(s)is (are) causing the variation on the dependent variable.

TABLE OF CONTENTS

LIST OF TABLES

ABBREVIATIONS

NSE	Nairobi Securities Exchange
FTSE	Financial Times Stock Exchange
NASI	NSE All-Share Index
PEV	Post ElectionViolence
KSE	Karachi stock exchange

CHAPTER ONE

1.1 Background of the study

The volume of transaction is a variable whose movement depends on many factors. Several researchers tried to determine the reasons of its variation in the time. Smidt, (1990) attributes the increase of the transaction volume to the reduction of the transaction costs and to the big institutional investor influence on the operations of purchase and sale of the stocks. Glaser and Weber, (2006) show that transactions carried out with the motive of liquidity are not necessarily irrational and not satisfactory to explain why the volumes of exchange rose. This raises red flag and invites the inclusion of human psychology in the determination of the variation of the transaction volume.

It has been argued that trading volume in speculative markets is too large to be justified on rational grounds. Trading motivated from hedging and liquidity purposes seems to explain only a small fraction of the observed trading activity and fails to support a substantial amount of trade in the real world. Overconfidence has been advanced as an explanation for the observed excessive trading volume. Gervais and Odean (2001) develop a model predicting that investors mistakenly attribute market gains to their ability to pick up winner stocks, and the process of wealth accumulation makes them overconfident. Because of rising overconfidence investors trade more aggressively subsequent to the up state of the market. De Long et. al, (1991), Kyle and Wang, (1997), Benos (1998), Odean (1998), Wang (1998, 2001), Daniel, Hirshleifer, Subrahmanyan(2001) argue that greater overconfidence leads to greater trading. De

Bondt and Thaler (1995, p.393) state,”… the key behavioral factor needed to understand the trading puzzle is overconfidence.

1.1.1 Past Returns

Practitioners claim and anecdotal evidence suggests that past returns affect market trading volume. For example, a report from Deutsche Bank Research on the crisis of the German online brokerage market argues that the “declines in the equity markets have severely curbed the trading activities of these investors, eroding the online brokers’ chief source of income.” Similarly, Deloitte &Touche’s 2001 survey of online securities trading writes that “the decline in stock prices between Spring 2000 and spring 2001 has led to slower growth of new online accounts and reduced trading volumes.”

In a bid to answer the question why past stock returns affect trading volume, recent theories have been proposed: High returns make investors overconfident and, as a consequence, these investors trade more subsequently. Gervais and Odean (2001) while analyzing the link between past returns and trading volume, develop a multi-period model in which traders learn about their ability. This process is affected by self-attribution bias. The investors in the model attribute past success to their own abilities which make them overconfident. Accordingly, the degree of overconfidence is higher after market gains and lower after market losses. Gervais and Odean (2001) show that “greater overconfidence leads to higher trading volume” and that “this suggests that trading volume will be greater after market gains and lower after market losses”

Barber and Odean (2002) analyze a data set from a U.S. discount broker. They argue and find that high past portfolio returns induce individual investors to switch from phone based to online trading. As a consequence, investors trade more subsequently.

1.1.2 Current Trading Volume

Foreign investor participation at the Nairobi Securities Exchange (NSE) has hit the highest level in the past six months, even as stock prices cooled off. The latest stock market trading data shows that foreign investor participation accounted for 56.14 per cent of turnover in June, up ten per cent points from 46.46 per cent in January. The last time that foreign trades hit the June level was in December, when international investors accounted for 59.54 per cent of turnover.

Participation of foreign investors in June was also higher than a similar month last year, even though total trade volumes at the NSE have decelerated. The NSE-20 share index has increased by 14 percent to 4,720.53 points from 4,140.3, a per cent increase but in the six-month period it has touched an all-year high of 5,030 in April. The June to August period is also characterized by “summer doldrums,” reflected in a drop in foreign driven sales as fund and investment managers take holidays. Mr. Nderi, Suntra’s investment bank head of research however points out that this time round the NSE is benefiting from the general tide that has lifted global markets. Traders said there are signs of foreign traders being bullish on the NSE this month.

“Unlike most Fridays, the market is upbeat today on enhanced foreign participation. About 43.6 million shares valued at 438 million have been traded so far. Foreign investors have continued to dominate with about 75 per cent of the traded value being attributable to their trades," said a mid-morning report by NIC securities on Friday.

The market rallied after the peaceful conclusion of the March General Election, which saw the NSE cross the 5,000-point psychological mark in April and resume a positive trade from foreign investors. February, a month before the general election, was the only one this year where foreign sales were greater than purchases at shs. 10.21 billion, against shs. 6.23 billion. The NSE has also maintained top position among global stock exchanges as measured by the Merrill Lynch global frontier markets index.

By April the Nairobi bourse had gained, in dollar times, 31.2 per cent over a 12-month period against the United Arab Emirates which rose by 30 per cent and Nigeria by 18.8 per cent. The NSE has however ceded the position to the United Arab Emirates and has been overtaken by Bulgaria, which have made 51.4 per cent and 51.3 per cent gains respectively against the NSE's 45 per cent. (Business Daily)

1.1.3 Relationship between the Returns and Volume traded

The stock return-volume relation in both developed and emerging financial markets has been subject to extensive research. Empirical studies on the return-volume relation in developed financial markets began in the 1960's. For example, Granger and Morgenstern (1963) use weekly data to examine the relation between price changes and volume and find price changes follow a random walk. In the 1970's, Crouch (1970) found a positive correlation between daily volume and absolute values of daily price changes for both market indexes and individual stocks. Morgan (1976), Epps and Epps (1976), found a positive correlation between volume and price changes for individual stocks by employing daily or monthly data. In the late 80's Smirlock and Starks (1988), found a strong lagged relationship between volume and absolute price changes using individual stock data.

A number of studies in the emerging financial markets have also been carried out. Basci et al., (1996) use weekly data on 29 individual stocks in Turkey and found that price level and volume are correlated. Saatcioglu and Starks (1998) use monthly data from six Latin American stock markets to test the relation between price changes and volume, where they found a positive price volume relation and a causal relationship from volume to stock price changes but not vice versa. Silvapulle and Choi (1999) use daily Korean composite stock index data to study the linear and non-linear Granger causality between stock price and trading volume, where they found a significant bi-directional linear and non-linear causality between the two series.

1.1.4 Nairobi Securities Exchange

Stock markets in the world individually and collectively play a very critical role in their economies. They provide an avenue for raising funds, for trading in securities including futures, options and other derivatives which provide opportunities for investors to generate returns. (Lee, 1998).

In Kenya, dealing in shares and stocks started in the 1920's when the country was still a British colony. However the market was not formal as there did not exist any rules and regulations to govern stock broking activities. Trading took place on a 'gentleman's agreement.' Standard commissions were charged with clients being obligated to honor their contractual commitments of making good delivery, and settling relevant costs. At that time, stock broking was a sideline business conducted by accountants, auctioneers, estate agents and lawyers who met to exchange prices over a cup of coffee. Because these firms were engaged in other areas of specialization, the need for association did not arise.

In 1954 the Nairobi Stock Exchange was then constituted as a voluntary association of stockbrokers registered under the Societies Act. Since Africans and Asians were not permitted to trade in securities, until after the attainment of independence in 1963, the business of dealing in shares was confined to the resident European community. At the dawn of independence, stock market activity slumped, due to uncertainty about the future of independent Kenya.

Since then the equity market has developed steadily with the most notable developments being; the change of name to Nairobi Securities Exchange Limited reflecting the strategic plan to evolve into a full service securities exchange which supports trading, clearing and settlement of equities, debts derivatives and other associated instruments, the movement of equity settlement cycle from the previous T+4 settlement cycle to the T+3 settlement cycle allowing investors who sell their shares to get their money three (3) days after the sale of their shares and crediting of the shares bought immediately to the investors CDS accounts, establishment of back broker office which facilitates internet trading, enrolling as a member of the financial information services Division (FISD) and more recently the introduction of the FTSE NSE Kenya 15 and FTSE NSE Kenya 25 index which were made available to the NSE website giving investors the opportunity to access current information of the Kenyan Equity market performance during trading hours. (www.nse.co.ke)

1.2 Research Problem

The stylized facts in security markets such as high turnover rates observed nowadays have captured financial economists' interests since long. Many researchers have developed theoretical models assuming investor overconfidence to justify these stylized facts.

Gervais & Odean, (2001), contend that the people overestimating their trading and investment skills may be more likely to choose their career as traders or they may trade actively on their own. Moreover, these overconfident traders survive and dominate the markets in the longer horizon (Benos, 1998; Daniel, Hirshleifer & Subrahmanyan, 1998, Gervais&Odean, 2001, Hirshleifer &Luo, 2001; Kyle & Wang, 1997; Mubark & Javed, 2009). Therefore, if most investors suffer from overconfidence and if overconfidence is a systematic cognitive bias, it is possible to trace investor overconfidence by analyzing the market level trading behavior. (Investors' aggregated trading behavior).

While analyzing individual investors' portfolio, Chou & Wang, (2011) (see also, Glaser & Weber, 2009) posit that only high portfolio returns can lead investors to buy high risky stocks, therefore, dynamic changes in investor confidence can only be triggered from their past portfolio returns rather than from prior market returns. However, models of overconfident investors (Gervais & Odean, 2001; Odean, 1998) tell that the overconfident investors trade aggressively following market gains especially in bull market. A recent study tested the predictions of overconfidence models and finds that both individual and institutional investors trade more aggressively following market gains. The findings of this study by (Chuang & Susmel, 2011) also indicate the investors' tend to trade more in riskier securities following market gains.

The models of overconfidence (Gervais& Weber, 2001; Statman, Thorley &Vorkink, 2006) argue that overconfidence is a market wide phenomenon and can be traced at market level, while other studies (Chou& Wang, 2011, Glaser & Weber, 2009) argue that level of overconfidence varies with individual portfolio returns rather than market returns. Therefore, implications of investor overconfidence should be tested at both levels i.e. at market levels and at individual portfolio level. However owing to the difficulties of obtaining individual investor trading accounts this study tests the implications of overconfidence at market level data.

Several researchers in the local market have found evidence of overconfidence at the NSE. A study that was carried out by Kimani, (2009) revealed a strong impact of overconfidence on investors' decision making. Using the Friedman's ranking, Mustwenje, (2006), found out that past performance of a stock was a major factor influencing investor's decision making. Other studies such those by Werah, (2006), Mbaluka, (2008) and more recently Aduda, Oduor and Onwonga (2012) found that investors in the Kenyan market were both rational and irrational in their decision making. Some of the behavioral biases that were identified include Herding behavior, regret aversion, anchoring and overconfidence.

This study considers the Nairobi stock exchange (NSE) to test overconfidence hypothesis due to the activities taking place at the moment. According to a report by MCSI a global market information vendor, investors at the NSE emerged among the biggest gainers globally as the stock market outperformed other asset classes in 2012, driven mostly by blue chip companies and foreign capital inflows. The bourse hit an all-time high trading level in the past 6 months (from January to June) with a turnover of $852 million which according to stock analyst is the highest ever to be recorded. (Business daily).

There have been an increasing number of studies on Kenyan equity market in recent years. Many issues have been investigated such as establishing whether investors at the NSE are affected the various behavioral biases but no studies have directly examined the relationship between past returns and volume in the Kenyan stock market. This study fills this gap by investigating the implications of overconfidence hypothesis related to past returns and trading volume in the Nairobi Stock Exchange (NSE), the only equity market in Kenya.

The study sought to answer the following research question

Do past market returns have an effect on the current trading volume?

1.3 Objective of the Study

To establish the effect of past returns on current trading activity

1.4 Value of the Study

The research is valuable in several important ways. First, the new evidence would allow re-evaluating the soundness of the EMH propositions on which the theory rests on. Second, it contributes to the evidence found at the NSE by previous researchers especially by establishing how the behavioral biases in this case, overconfidence, affects market performance more so its impact on trade volume. Third, such study indicates the level of investor sophistication and the potential need to improve it. Fourth, it sheds some light on whether market facilitators and the regulators should take any actions to improve arbitrage, which could minimize the negative impact of behavioral biases. Answers to these questions are important step in determining the path to improve the quality of our financial markets.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter will review studies done by various scholars and theories that address both the conventional and behavioral finance. Theoretical review on market efficiency, random walk theory and several heuristic biases are discussed in this section.

2.2 Theoretical framework

The theoretical framework helps to make logical sense of the relationship of the variables and the factors that have been deemed relevant to the problem. It provides definitions of the relationship between all the variables so that the theorized relationship between them can be understood. The theoretical framework will therefore guide the research, determining what factors will be measured and what statistical relationship the research will look for.

2.2.1 Efficient Market Hypothesis

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

The efficient market hypothesis (EMH) in conventional finance asserts that financial markets are "informationally efficient", or that prices on traded assets, e.g stocks, bonds, or property, reflect all known information and change immediately to reflect new information. According to theory, the market cannot be consistently outperformed using any information the market already knows, except through luck.

There are three forms of EMH.

Fama (1965) distinguishes three forms of the EMH (i) the "weak" form efficiency where all the past market prices, returns and other information are fully incorporated in prices, which makes it impossible to earn credible risk adjusted profits based on historical data. This renders technical analysis useless (ii) the "semi- strong" form states that it is impossible for investors to earn superior returns using publicly available information since they would already be incorporated in the prices. This renders fundamental analysis useless and (iii) the "strong form" EMH that states that all information, public and private, are fully reflected in securities prices. This implies that even insider information would not help an investor earn superior returns. Much of the evaluations have been based on the weak and semi-strong form efficiency since it was difficult to accept the strong form, and there was also evidence that insiders did in fact earn abnormal returns even while trading legally (Seyhun, 1998).

2.2.2 Random Walk Hypothesis

Proponents of the random walk theory posit that the current market price of a given stock is independent of and unrelated to previous market price patterns. This theory implies that a series of stock-price changes has no memory- that one cannot predict future market prices on the basis of the past history of price behavior. It implies also that at any moment in time the actual market price of a stock represents the market's best estimate of the "intrinsic" value of that stock based upon all available information. This intrinsic value is determined by a fundamental analysis of the expected future earnings of the company. As new information becomes available, investors may revise their estimates of expected future earnings; and these revisions, in turn, will affect their estimate of the intrinsic value of the stock. As a result, the actual price of the stock may change in response to new information. However, these changes in price are a reflection of a change in the market's estimate of intrinsic value and are unrelated to past price trends.

The random-walk theory implies that the market assimilates new information in a manner that any deviations about intrinsic value will be random. If for, some reason, these deviations were to become systematic, proponents of the theory would argue that there are a number of market participants who would recognize the recurring pattern of deviations and buy or sell to profit them. The arbitrage actions of these market participants would tend to drive out any profit that was based upon non-random fluctuations about intrinsic value. Thus, the random walk implies an efficient market where there are no systematic over-valuations or under-valuations of stocks. There are simply too many rational market participants with sufficient resources who are able to take advantage of such profit opportunities. With information about past prices freely available, these participants are said to compete against each other until all non-random fluctuations about intrinsic value become so small that they cannot be exploited for a profit.

2.2.3 Behavioral Finance Theories

Behavioral finance is a branch of finance that studies how the behavior of agents in the financial market can be influenced by psychological factors and the resulting influence on decisions made while buying or selling the market financial securities, thus affecting the prices. (Rahul, 2011).

There are several behavioral biases that have been identified over time namely: overconfidence, representativeness, herding, anchoring, cognitive dissonance, regret aversion, gamblers fallacy, mental accounting and hindsight bias.

The science aims to explain the reasons why it's reasonable to believe that markets are inefficient. According to Sewell (2007), "behavioral finance is the study of the influence of psychology on the behavior of financial practitioners and the subsequent effect on markets." Fama, (1998) suggests that the field proposes explanation of stock market anomalies using identified psychological biases, rather than dismissing them as "*chance results consistent with the market efficiency hypothesis.*" It is assumed that individual investors and market outcomes are influenced by information structure, and various characteristics of market participants (Barnerjee, 2011).

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

2.2.3.1 Prospect Theory

The theory distinguishes two phases in the choice process; the early phase of framing (or editing) and the subsequent phase of evaluation. In essence it explains how people manage risk under uncertainty. It portends that human beings are not consistently risk-averse; rather they are risk averse in gains but risk takers in losses. People place more weight on the outcomes that are perceived more certain than those that are considered mere probable, a feature known as "*certainty effect*". (Kahneman and Tversky, 1979). People's choices are also affected by the 'Framing effect'. Framing refers to the way in which the same problem is worded in different ways and presented to decision makers and the effect deals with how framing can influence the decisions in a way that the contradicts the classical axioms of rationality. (Tversky and Kahneman, 1981).

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

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

2.2.3.2 Heuristics

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

People often use heuristics (or shortcuts) that reduce complex problem solving to more simple judgmental operations (Tversky and Kahneman, 1981). In heuristic decision making process investors find out things for themselves usually through trial and error leading to the development of rules of thumb.

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

2.2.3.4 Overconfidence Bias

The term "overconfidence" has been widely used in psychology starting from the 1960's. As researchers in other fields, including economics have stretched its meaning beyond its original definition. Overconfidence in psychology is most closely related to the calibration and probability judgment research and the term itself is frequently equaled with one of the forms of miscalibration. The most important extensions to this definition scope, usually applied by economists, are studies of overconfidence in the context of positive illusions, i.e. the better than average effect, illusion of control and unrealistic optimism. In behavioral finance models, overconfidence is often interpreted as: (i) investors overestimating the precision of their information (sometimes more specifically: overestimating private and underestimating the public ones) and (ii) investors underestimating risk, which makes them e.g. hold riskier portfolios. (Dorota, 2008).

2.2.3.5 Better than Average Effect

Psychological research has established that, in general, people tend to have an unrealistically positive view of themselves. Most of us when comparing ourselves to group, (co-students, co-workers, random participants), believe to be superior to an average representative of that group in various fields. (Dorota, 2008).

The better than average effect, as studied by Taylor and Brown (1988), consists of various factors, such as a belief that positive traits describe us more accurately than average person, an assessment of others from the perspective of our own positive traits, and a form of self-serving bias in self-assessment. The self-serving bias analyzed by Taylor and Brown (1988) makes people assign more responsibility for success and less failure to themselves, while others are not given the same credit. The only exception to the rule, are relatives or close friends, who are also, granted the same favorable treatment. Miller and Ross, (1975) found out that people tend to attribute own success largely to internal reasons (such as knowledge, preparation) rather than external ones (such as luck).

2.2.3.6 Unrealistic Optimism

Unrealistic optimism towards the future can be seen as an error in evaluating future events, either in the sense of the better- than-average effect (e.g when all or most people believe their chances of achieving financial success are higher than the “average” person’s) or in absolute terms (when people believe their chance of winning a lottery are higher than true probability). Some definitions from findings in the area could be “The future will be great for me” (Taylor, Brown, 1988, p. 197). Weinstein,(1980) while analyzing different aspects of people’s optimism towards the future, with participants comparing their chances of a potential fortune or misfortune to an average’ person, he found that people believe that positive events are more likely to happen to them than others, with the opposite valid for negative events. This effect increases for especially desired occurrences, events with objectively higher probabilities and events perceived to be controllable (such as e.g. passing an exam). People believe that negative experiences would rather affect a subjectively formed (and often wrong) stereotypical “representative”, which obviously they do not resemble. These comparisons clearly overlap with the better than average research, with the qualification that they refer to future events.

2.2.3.7 Illusion of Control

Psychological research and common observation demonstrate that people tend to believe they are able to influence events which in fact are governed mainly, purely, by chance (Taylor, Brown 1988). An extreme example of this illusion is an insistence on throwing a dice personally as if it could show a more favorable result. Moreover, if people expect certain outcomes and these outcomes do occur, the participants are prone to assign them to their doing rather than luck, and re-affirm their belief in control over a situation where the only factor is probability.

The existence of illusion of control in purely chance driven tasks has repeatedly been proven experimentally, with the participants convinced that their skill or past experience can influence the outcome of predicting the result of the task. (Langer & Roth, 1975). After some result manipulations in a coin-tossing task, Langer and Roth, (1975) led rational participants to believe they are able to better predict the outcome of coin-tossing than others and were convinced that their success in predictions was not pure chance, but that they were able to ‘control’ the outcome. If certain factors usually involved in situations depending on skill, such as competition, choice, familiarity or involvement, are introduced into purely chance driven tasks, individuals will believe they control the tasks more than the probability itself indicates (Langer, 1975).

2.2.4 Overconfidence in Finance

Economists started implementing psychological findings into economic models starting in the 1970's but most rapid development of that trend began in the 1990's. Since then, overconfidence has also become a field of interest for economists, mainly in the context of behavior on financial markets. Overconfidence is defined here usually as an overestimation of one's knowledge or precision of private information, or the interpretation thereof. (Dorota, 2008).

Some puzzles found on the financial markets, which previously could not be solved using the standard economic theory, were successfully accounted for once overconfidence was assumed. These issues include primarily continuing securities misvaluations, excessive trading volumes and the disposition effect, i.e. the tendency to sell well performing stocks and to hold on to losing ones. The potential presence of overconfidence on the markets stimulated an ongoing discussion on the well-established idea of efficient markets and economic agent rationality. Despite some skepticism among economist on the existence and effect of overconfidence as such, its prevalence on financial markets has been proven repeatedly, through methods ranging from experimental and questionnaire studies to formal models and financial market data. (Dorota, 2008).

Other heuristic biases are discussed below:-

2.2.4.1 Representativeness Bias

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

2.2.4.2 Anchoring

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

2.2.4.3 Cognitive Dissonance Bias

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

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

2.2.4.4 Regret Aversion

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

2.2.4.5 Gamblers' Fallacy

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

2.2.4.6 Hindsight Bias

Shiller (2000) describes Hindsight bias as the tendency to think that one would have known actual events were coming before they happened, had one been present then or had reason to pay attention.Monti and Legrenzi (2009) investigated the relationship between investment decision making and hindsight bias and found a strong evidence for the consequences that hindsight bias can have on the investor's portfolio decisions: the portfolio allocation perception and therefore, the risk exposure.

2.2.4.7Mental Accounting Bias

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

They can also be referred to as codes people use when evaluating an investment decision. (Rahul, 2011)

2.3 Empirical Evidence

There has been a lot of analysis of financial markets that has marked a turning point in overconfidence research in finance. (Odean, 1999; Barber, Odean, 2000; 2001), analyzing trading data of individual investors taken from a large US brokerage firm, allowed overconfidence to evolve from a neglected psychological side effect to a widely accepted factor influencing financial markets and investor behavior.

Although in fact psychology does not unanimously link gender to overconfidence, Barber and Odean (2001) confirm that overconfident traders (men) in their sample trade more than women. As a result, the performance of men is more hurt by excessive trading.

Chuang and Lee (2006) use data of listed companies in the period of 1963-2001, to prove a variety of effects of overconfidence on financial markets. They find evidence for overreactions to private and under reactions to public signals, as well as the existence of the short-term momentum and long-term reversal, such as those suggested by Daniel et al., (1998). The assumptions of Gervais and Odean (2001), that trading profits induce overconfident investors to trade more frequently, are also confirmed empirically, both by Chuang and Lee (2006) and by Statman et al., (2003). In addition, Chuang and Lee (2006) provide support for investors displaying a self-attribution bias (putting more weight on their forecasts that prove to be correct, and less on those that turn to be wrong), for high market volatility being due to the presence of investor overconfidence, and for overconfident investors being prone to trade more in relatively riskier securities, after experiencing market gains.

Based on a survey data of financial market participants in Germany and using their confidence interval assessments of the stock exchange index DAX six months in advance, Deaves et al. (2005) study overconfidence of financial experts, defined here as miscalibration. Market participants are not clearly miscalibrated, but their past success leads to higher overconfidence, both on the individual level and equally on the market as a whole. These findings are complemented by Hilary and Menzly (2006) on a large 1980-1997 sample of financial analyst predictions of corporate quarterly results. These empirical findings are in line with the model of overconfidence as dynamic process rather than a stable trait (Gervais, Odean, 2001)

Friesen and Weller (2006) estimate their theoretical model of overconfidence and cognitive dissonance, defined as a "psychological discomfort that accompanies evidence that contradicts one's prior beliefs or world view" (p.342), which lies close to the confirmatory bias phenomenon (i.e. a tendency to seek evidence confirming our already formed hypothesis and disregard evidence contrary to our beliefs). Friensen and Weller, (2006) formally prove overconfidence of financial analysts, seen as an overestimation of private information value, and verify it empirically using earnings forecasts. It is interesting to note that analysts seem to accommodate for the cognitive bias in the behavior of other analysts, but do not apply it to their own forecasts.

Psychologist Jarome D. Frank (1935) showed that most people are generally overconfident about their abilities. Scholars investigating subjective probabilities find that people tend to overestimate the precision of their knowledge (Alpert and Raiffa, 1982; Fischhof, Slovic, and Lichtenstein, (1997). Such overconfidence applies to many professional fields, not only economics (Barber and Odean, 2001). It is greatest for difficult tasks, and stock selection is an example of such a task.

Odean (1998b) develops overconfidence model in financial securities market. Investors overestimate their ability to assess value of security more precisely than others. Individuals believe in their own valuation, which in turn causes differences in opinion that motivate trading (Varian, 1989; Harris and Raviv, 1993). However, individuals should only trade if doing so increases their expected utility (Grossman and Stiglitz, 1980). Odean (1998b) finds that the more investor is overconfident the more he trades, and the lower his expected utility is. This is because investorspossess unrealistic beliefs about how precise the returns can be estimated and spend too many resources on gathering information. Overconfident investors also hold riskier portfolios than rational investors. However there are exceptions to the rule as noted by Annaert, Heyman, Vanmaele, and Van Osselaer (2008) who find that trades of mutual funds do not erode performance, thus do not exhibit overconfidence.

Other researchers, Biais, Hilton, and Mazurier (2005) perform an experiment with 245 participants and find that investors are overconfident in the precision of their information and that investors are overconfident in the precision of their information and that such overconfidence reduces trading performance. Daeves, Luders, and Luo (2009) perform another experiment and analyze whether overconfidence induce more trading and find it to be true at the level of individuals and at the market level. Using Barber and Odean (2000) method, they find that men trade 45% more than women and trading educes men's net returns by 2.65 percentage points as compared to 1.72 percentage points for women.

Barber and Odean (2002) investigate individual investors who switch to the internet trading. They hypothesize that because of access to more information and higher degree of control over their account investor should become more overconfident. They find that after switching to internet trading investors' trade more actively and perform worse. Hsu and Shiu (2010) investigate the investment performance of 6993 investors in IPO auctions in Taiwan stock market. They find that frequent bidders have lower returns and conclude that investors suffer overconfidence.

Several reasons for overconfidence have been put forward to explain overconfidence in the financial markets. Some of these reasons include (i) trading for liquidity needs in order to move less or more risky investments, (ii) to realize tax losses and (iii) to rebalance. Odean, (1999) controls for these and still finds statistically significant effect of investors' overconfidence. Investors perform even worse-buys underperforming securities by 5.8% over one year's horizon. Barber and Odean (2000) also check whether trading is caused by rational expectations, and find that liquidity, risk based rebalancing, and taxes can only explain some trading activity, but are unable to explain the annual turnover of 250% for the most frequently trading households.

2.4 Summary of Literature Review

Stemming from research on calibration and probability, overconfidence has become an important interdisciplinary concept. Its structure and development are currently studied from both a psychological and an economic perspective. Some discussions, as to the origins of overconfidence, its dynamic or stable on the study context, continue in both fields.

The economic effect of overconfidence on individuals and markets, be it in the context of miscalibration or positive illusions, has been established through both theoretical models and financial data analysis. Puzzles such as excessive trading volumes or security misvaluations on financial markets can be explained at least partly with reference to overconfidence. Even if the degree and direction of effect of overconfidence on some variables, such as trading profits, are not agreed upon, the phenomenon itself has been helpful in explaining a significant range of financial market phenomena.

CHAPTER THREE

STUDY METHODOLOGY

3.1 Introduction

This chapter looks at the procedures and methods that were employed in conducting the study in order to answer the research question and achieve the objective. It entails the research design, target population, sampling, data collection and data analysis.

3.2 Research Design

This study adopted a descriptive research design. It is a type of non-experimental research design for collecting and analyzing data in order to describe the problem in its current status. The design allows researchers to gather information, summarize, and present it for the purpose of clarification (Orodho, 2004). This method is appropriate due to its capacity to establish whether past returns may influence current trading volume, in the NSE.

3.3 Population of the Study

The target population of this study was all the 62companies listed at the NSE as at the end of July, 2013. This was used because of the availability of the relevant information on the quoted companies.

3.4 The Sampling Procedure and Sample Size

After an appropriate research design has been developed the next process is to select those elements from which the information will be collected. One possibility is to collect information from each member of the population. Another way is to collect information from a portion of the population by taking a sample of elements from the larger group and, on this basis, infer something about the larger group. (Pervez &Kjell, 2005). There are at least three reasons for taking a sample instead of including all units or elements: the costs of including all units will often be prohibitive, the time needed to do so will often be so long and to improve on accuracy by reducing the error element.The NSE 20 share index was selected, which was considered appropriate due to its representativeness of the market. The index accounts for about 80% market liquidity providing a good platform of investigating how overconfidence affects trading volume. Moreover, for a company to be listed in the index it must have a turnover of 10% among other factors.

3.5 Method of Data Collection

This study utilized secondary data that was obtained from the Nairobi Securities Exchange official website. The data consisted of 52 weekly observations of the year 2012 both for past stock returns and the weekly observations of the current trading volume (turnover). Gervais&Odean, (2001) (see also, Griffin et al., 2007; Odean, 1998; Statman et al., 2006) argue that change in investor overconfidence can occur on a weekly, monthly or annual basis.This study analyzed weekly data. Daily data for the market from the selected listed companies was collected and then transformed into weekly (Monday to Friday) frequencies (if there were a holiday in a week, the next business day was treated as the next day).

3.6 Data Analysis Procedure

The study used simple linear regression technique to examine the effect of past returns on current turnover. The dependent variable was the current turnover while the independent variable was past returns. The methodology of the study was informed from the model of the study Overconfidence bias, trading volume and returns volatility, (2012) the researchers used the total market capitalization as a proxy to trading activity and the returns on KSE 100 index as proxy for market returnswhere the returns were calculated as the difference of natural log of ending values on monthly and weekly basis

Steps that were used conducting the linear regression analysis were as follows:

Firstly, the population model was determined. $\boldsymbol{Yt = bo + b1X1t - 1 + \varepsilon}$

Where**,Y** represented the turnover of the population, it was taken directly from the index and transformed by multiplying it to the natural log to avoid heteroskedasticityi.e***ln* *(volume)***$\boldsymbol{X_1}$ represented the average weekly returns for the population; the returns were computed using the index of the NSE 20 share index as shown below:

$$\boldsymbol{returns = ln(\frac{Pt}{Pt - 1})}$$

Where,

$\boldsymbol{Pt}$ **=** weekly index return at the end of week t

$\boldsymbol{Pt - 1}$**=** weekly index returns at the end of the previous week

For example, $\boldsymbol{return\ for\ 2011\ Dec.week\ 4 = \frac{index\ for\ December\ week\ 4\ 2011}{index\ for\ December\ week\ 3\ 2011}}$

,$\boldsymbol{bo}$ is the change in $\mathbf{Y}$ that does not occur in $\mathbf{X_1}$**,** $\boldsymbol{b_1}$is the coefficient of $X_1$and $\boldsymbol{\varepsilon}$ is the error term. The sample model for the 20 firms (NSE 20-Share index) was,$\boldsymbol{y = bo + b1x1}$**.** Where$\boldsymbol{y}$ is the turnover of the index,□□ is the change in the values of **y** that do not occur in the values of $\mathbf{x_1}$(this is the volume that will be trading in absence of the **x** variable i.e. when $\boldsymbol{x_1}$ is 0), $\square_{\mathbf{1}}$ is the coefficient of the change in the index returns,$\boldsymbol{x_1}$ *is* the average weekly returns of the index.

Secondly, a data matrix was determined, where in that matrix for every ***y*** observation there was a corresponding ***x*** observation i.e. the value of **y** for week 1 must correspond with the value for x in the same week. Thirdly, data was collected for the sample. The data was obtained from the NSE official website where values of ***x*** were the weekly observations for the year 2011 and the values for ***y*** were weekly observations for the year 2011. An appropriate lag period was determined by regressing the turnover/volume traded for week 1 against the returns for week 1 and so forth for other subsequent weeks. The lag period allowed for the effect of the past returns to be felt since due to the psychological biases new information including that of positive returns may take some time before it can it have an effect on the market. Finally, the regression analysis was run. The results were interpreted and then evaluated so as to determine the statistical significance of the obtained results (this was done by computing the model parameters)

Issues that were addressed through the linear regression analysis

Determining whether there is a linear relationship between past returns and current volume traded? How weak or strong is the relationship. This was determined by finding the coefficient of correlation between the **y** and the **x** variable, where □ ≤ □□□□□□□□ □ ≤ □**.**The relationship can either be weak, moderate or strong.

Secondly, if a relationship exists, the explanatory power (goodness of fit) of the deriving model will be determined? I.e. to what percentage or extent are the changes in the **y** variable accounted for by changes in the **x** variable? This will be validated using the coefficient of determination, where □ ≤R^2≤**1.** On a scale of 0-1, the “goodness of fit” can either be a bad fit, moderate fit or good fit.

Fourthly, the statistical significance of the deriving model or the resulting model was determined. This would help in establishing the reliability of the model in decision making. Testing for statistical significance of the overall model was evaluated via the *F* statistic. □ ≤ □ ≤ ∞Where the higher the ***F*** value, the more statistically significant the model will be.

The next step was to develop the deriving model which entailed finding the constant $\boldsymbol{b_o}$and coefficient $\boldsymbol{b_1}$. The nature of the relationship between the individual parameters and the dependent variable was determined which was expected to be either positive or negative

Lastly, the significance of individual parameters was determined. This helped to find out whether a particular parameter is more statistically significant than another parameter and by how much? This was done using the ***t*** statistic or ***P*-value**. The higher the *t* stat (the lower the ***P*-value**), the more statistically significant the parameter of interest will be.

The tool to be used for the analysis will be Microsoft ®Excel ™

CHAPTER FOUR

DATA ANALYSIS AND PRESENTATION

4.1 Introduction

This chapter presents the data analysis results and discussion of findings on the relationship between past returns and current trading turnover for the firms listed on the NSE. The chapter concludes with a summary and interpretation of the finding.

The research targeted 20 companies that have been listed in the NSE 20-Share Index. Secondary data was collected for the weekly index and trading volume was analyzed through Simple Linear Regression.

4.2 Data Analysis and Interpretation

A simple regression model was applied to determine the relationship between past returns and current trading volume for firms listed in the NSE.

The regression model used was $\mathbf{Y_t=\alpha+\beta x_{t-1}}$

where

Y_t= Current trading volume for the period, week t

α = A constant factor that affects changes observed in trading volume when x_{t-1} is zero

β = Coefficient of past returns

x_{t-1} = Past returns lagged for one week period i.e. previous week's returns

The researcher has assumed a 95% confidence interval or 5% significance level for the data used. These values help to give a general validity measurement for the data. Thus, the closer to 100% the confidence interval (and thus, the closer to 0% the significance level), the more valid the data is regarded to be.

Table 4.1: Regression Statistics

REGRESSION STATISTICS				
MODEL	Multiple R	No. of observations	R^2	Adjusted R Square
	0.0509	53	0.00259	-0.01697

Source: Author 2013

4.2.1 Multiple R

Multiple R is a value that normally lies between zero and one. It is the coefficient of correlation between past returns and current trading volume. It plays a double role. Firstly, it determines whether a linear relationship between the past returns and the current trading volume exists. Secondly, it measures the strength of that relationship. The Multiple R, being at 0.051, shows that there is a very weak relationship between the two variables i.e. at only 5.1%. It is not clear however whether the relationship between current trading volume and past returns is linear (though it is probably non-linear).

4.2.2 R-Squared/Adjusted R-Squared

This is the coefficient of determination. It is also referred to as the *goodness of fit.* It measures causality between the dependent and independent variables. If a relationship exists, it shows the explanatory power of the deriving model (whether it is bad, moderate or good). It determines to what extent or percentage the changes in current trading volume are accounted for by changes in past returns. It is a value between zero and one, and can be interpreted as a percentage. Thus, only 0.259% of the current trading volume is as a result of the changes in past returns. This sequentially means that 99.741% of the current trading volume observed in the data is as a result of other factors other than past returns or as a result of α.

Table 4.2: Anova

ANOVA TABLE					
Source	df	SS	MS	F-Statistic	Significance F
Regression	1	0.022326267	0.022326267	0.132445549	0.717414212
Residual	51	8.597039585	0.168569404		
Total	52	8.619365853			

Source: Author 2013

Table 4.3 Coefficients

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	*Lower 95.0%*	*Upper 95.0%*
Intercept	18.36330409	0.061621442	298.0019	2.50E-84	18.23959388	18.4870143	18.23959388	18.48701
Past returns	-1.71552642	4.713882208	-0.36393	0.717414212	-11.17903984	7.747986997	-11.17903984	7.747987

Source: Author 2013

4.2.3 F-Statistic and Significance F

They are used to determine whether the resulting/deriving overall model is statistically significant. It shows, therefore, whether the model is reliable/sufficient enough for decision making purposes i.e. whether it is reliable to predict the values of the current trading volume with the resulting model. At 95% confidence level, when F-Statistic is greater than 2.56, then the model is statistically significant. Alternately, at 5% significance level, when significance F is less than 0.05, then the model is statistically significant. Both the F-Statistic and the Significance F in the data output show that the resulting model is **NOT** statistically significant. Thus, it cannot be used for decision making purposes.

The deriving model is Y_t=18.3633-1.7155x_{t-1}

4.2.4 Coefficients

They show the nature of relationship between the individual model parameters and the dependent variable. The relationship between the current trading volume and the constant (α) is positive while the relationship between the current trading volume and the coefficient of change (β) is negative.

4.2.5 t Stat and P-value

These both show the significance of individual model parameters. The t Stat is an absolute value, thus the positive or negative nature of the parameters is disregarded. The P-value can be converted into a percentage but the t Stat cannot. These two statistics go hand in hand and are negatively related. The higher the t Stat the more significant the parameter of interest while the lower the P-value the more significant the parameter of interest. At 95% confidence interval (5% significance level), when the t Stat is greater than 1.96 the results are statistically significant. In the researcher's resulting model, therefore, the constant is statistically significant but the past returns are not statistically significant. Thus according to the data output, the past returns cannot be logically used to predict the values of future trading volume.

CHAPTER FIVE

FINDINGS, CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter presents a summary, conclusion and recommendations of the study. It presents a summary of the results of the relationship between past returns and current trading volume for the NSE 20-Share Index.

Based on the findings in Chapter 4, the study gives recommendations after which it draws policy recommendations. The recommendations are presented based on the objective of the study after which recommendation for further studies are drawn.

5.2 Summary of the findings

From the research findings presented in Chapter 4, the past returns have close to no effect on the current trading volume. For the returns to have an effect on the trading volume, the returns should be consistently rising for a given period of time. From the research findings the returns fluctuated highly (thus suggesting non-linearity). This may be because investors tend to attribute good performance of their shares to their thoughtful/tactful trading skills and what they regard as unique information that they capitalize on (normally an average investor cannot possess these), thereby building an overconfident attitude.

In a case where the returns are consistently rising, this overconfident investor tends to trade more in anticipation that the current trend will continue in the future. The fluctuation of returns suggests that the market may be somewhat efficient and investor psychology (as far as past returns are concerned) does not necessarily contribute to the observed patterns of trade i.e. trade volume.

From the findings, a very small and insignificant change in past returns accounts for change in trading volume. This indicates that much of the trading activity observed may be attributable to other factors such as effects of stock splits, the peace process after the 2007/2008 Post Election Violence (PEV), prospects that the reigning political regime had promised and stability of the exchange rates, among other underlying factors.

5.3 Conclusion

From the findings of the study and the summary of the findings discussed above, this study concludes that there is an insignificant relationship between past returns and trading volume.

Further the study concludes that past returns have little effect on trading volume and that other factor such as stock splits, foreign currency stability among other factors could be the drivers behind the massive trading that is being observed at the bourse.

In addition previous researchers have found the market to be in a weak-form or semi strong-state implying that a steady rise in returns is not possible which otherwise could have contributed to incidences of overconfidence being observed through increased trading thereof.

5.4 Limitations of the study

This study should be evaluated in light of these limitations;

In regression analysis it is impossible to make a definitive statement about causation and regression analysis i.e. unless the data are obtained in a carefully controlled environment we can never rule out some other variable is causing the variation. Secondly, outliers i.e. the variables away from the line of best fit are usually ignored and may greatly influence the regression results. In addition, lengthy process of obtaining data from the NSE official website especially if one does not have an account with them. Finally, using only one independent variable to try and explain causality is not sufficient. More than one explanatory variable may give room for better analysis on variables of interest.

5.5 Suggestion for future studies

The study concentrated on the relationship between past returns and trade volume for NSE 20 share index that comprise of different sectors. This study therefore recommends that another study be carried out but this time research on different sectors separately. A similar study could also be carried out using other indexes such as FTSE 15 Index, FTSE 25 Index and NSE All Share Index (NASI).

Also the study concentrated on year 2012 since it is the year that much of trading has been observed to take place. Future studies could use many years e.g. from 1990 to date and this can be helpful to confirm or disapprove the findings of this study

REFERENCES

Alpert, M., and Raiffa, H., (1982). A progress report on the training of profitability assessors' judgment under uncertainty: *Heuristics and biases*.

Annaert, J, Heyman, D., Vanmaele, M., and Vanosselaer, S., (2008). Disposition bias and overconfidence in institutional trades.

Barber B., and Odean T (2001), Boys will be boys: gender, overconfidence, and common stock investment, "*The quarterly journal of economics*", 116(1):261-292

Barber B., and Odean T. (2000), Trading is hazardous to your wealth: the common stock investment performance of individual investors, "*Journal of finance*", 55(2): 773-806.

Barnejee A., (2011). Application of behavioral finance in investment decisions: An overview of the management accountant 46(10): 869-872.

Benos, A.V., (1998). Aggressiveness and survival of overconfident traders.*Journal of Financial Markets,* 1:353-383.

Biais B., Hilton D., Mazurier K., and Pouget S., (2005). Judgmental overconfidence, self-monitoring and trading performance in an experimental financial market, "*Review of Economic Studies*", 72(251):287-312.

Chen G., Kim K., Nofsinger J.R., and Rui O. M., (2007).Trading performance, disposition effect, overconfidence, representative bias and experience of emerging market investors.

Chou, R.K., and Y.Y. Wang, (2011).A test of the different implications of the overconfidence and disposition hypothesis.*Journal of banking and finance*, 35:2037-2046.

Chuang, W.I., and B.S Lee, (2006).An empirical evaluation of the overconfidence hypothesis.*Journal of banking and finance*, 30:2489-2515.

Chuang, W.I., and R. Susmel, (2011). Who is the more confident trader? Individual vs. institutional investors.*Journal of banking and finance,* 35:1626-1644.

Crouch, R.L., (1970), "The volume of transactions and price changes on the new york stock exchange", *Financial analysis journal*, 26:104-109.

Daeves, R., Luders, E., and Luo, G.Y., (2009). An experimental test of the impact of overconfidence and gender on trading activity.*Review of finance*, 13(3):555-575.

Daniel, K., D. Hirshleifer, and A. Subrahmanyan, (1998).Investor psychology and security market under- and overreactions.*Journal of finance,* 53: 1839-1885.

Daniel, K., Hirshleifer, D., and Subrahmanyan, (2001).Overconfidence, arbitrage and equilibrium asset pricing.*Journal of finance*,56:921-965.

De Bondt, W., and Thaler, R., (1985). Does the stock market overreact? *Journal of finance*40:793-805.

De Long, J.B., Shleifer, A., Summers, L., and Waldman, R.J., (1991). The survival of noise traders in financial markets.*Journal of business*,64:1-20.

Deaves R., Luders E., and Schroder M. (2005). The dynamics of overconfidence: evidence from stock market forecasters, "*Discussion Paper*", No. 05-83, Centre *for European economic research (Zew), Mannheim*.

Dorota S., (2008). Overconfidence in psychology and finance an interdisciplinary literature review.

Epps, T.W., and Epps, M.L., (1976). “The stochastic dependence of security price changes and transaction volumes: Implications for the mixture-of-distributions hypothesis”. Econometrica44:305-321.

Fama, E., (1965). The behavior of stock-market prices. *The journal of business*, 38(1):34-105.

Fama E. F., (1998). Market efficiency, long term returns and behavioral finance. Journal of financial economics 49(1998):283-306.

FischhoffB., and Lichtenstein S. (1977). Knowing with certainty: The appropriateness of extreme confidence, “*Journal of experimental psychology*”,3(4):552-564.

Friesen G., and Weller P.A. (2006), Quantifying cognitive biases in analyst earnings forecasts, “*Journal of financial markets”*, 9(40):333-365.

Gervais, S., and T. Odean, (2001). Learning to be overconfident. *The review of financial studies*, 14(3): 411-435.

Glaser, M., and M.Weber, (2009). Which past returns affect trading volume? *Journal of financial markets*, 12:1-31.

Granger, C.W.J., and O. Morgenstern, (1963). “Spectral analysis of new york stock market prices”, *Kyklo*s, 16:1-27

Griffin, J.M., F. Nardari, and R.M Stultz, (2007). Do investors trade more when stocks have performed well? Evidence from 46 countries.*Review of financial studies*, 20 (3):905-951.

Grossman, S.J., and Stiglitz, J.E., (1980). On the impossibility of informationally efficient markets.*American economic review*, 70:393-408.

Harris, M., and Raviv, A., (1993). Differences of opinion make a horse race. *Review of financial studies*, 6:473-506.

Hilary G., and Menzly L. (2006), Does past success lead analysts to become overconfident?, “*Management science*”, 52(4):489-500.

Hirshleifer, D., and G.T Luo, (2001).On the survival of overconfident traders in a competitive securities market.*Journal of financial markets*, 4:73-84.

Kahneman D., and Tversky A. (1982), Heuristics and biases, In D. Kahneman, P. Slovic, A. Tversky (Eds.), Judgement under uncertainty: Heuristics and biases, Cambridge University Press, Cambridge.

Kimani V.W, (2011). A survey of behavioral factors influencing individual investors choices at the NSE, MBA Projects.

Kotieno, G.O (2012). The effect of investor psychology in investment decision making: the case of NSE, MBA project.

Kyle, A.S., and F.A Wang, (1997). Speculation duopoly with agreement to disagree: Can overconfidence survive the market test? *Journal of finance*, 52:2073-2090.

Lakonishock, J., Shleifer A., and Vishory R. W., (1994).contrarian investment, Extrapolation and risk. Journal of finance 49:1541-1578

Lakonoshock J., Shleifer A., and Vishay R.W., (1994).Contrarian investment, extrapolation and risk. Journal of finance 49:1541-1678

Langer E.J. (1975), Heads I win, tails it’s chance: The illusion of control as a function of the sequence of outcomes in a purely chance task,” *Journal of personality and social psychology*”, 32(6):951-955.

Langer E.J., and Roth J. (1975), Heads I win, tails its chance: The illusion of control as a function of the sequence of outcomes in a purely chance task, '*Journal of personality and social psychology*", 32(6):951-955.

Lee R., (1998). What is an exchange? The automation, management and regulation of financial markets. New York: Oxford University Press Inc.fr

Mbaluka P.K, (2008). Behavioral effects on individuals decision making using the prospect theory: A case of investors at the NSE, MBA Projects.

Monti M., and Legrenzi P., (2009).Investment decision making and hindsight bias.Annual meeting of cognitive science society. Amsterdam

Morgan, I.G., (1976). "Stock price and heteroscesdacity", Journal *of business*,49:496-508.

Murbark, F., and A.Y. Javed, (2009). Relationship between stock return, trading volume and volatility: Evidence from Pakistani stock market. *Asia pacific journal of finance and banking research*, 3(3)

Mutswenje V.S., (2009).A survey of factors influencing investment decisions.*The case of individual investors at the NSE*, MBA Projects.

Odean, T., (1998a).Volume, volatility, price and profit when all traders are above average. *Journal of finance*,53(6):1887-1934

Odean, T.,(1998b). Are investors reluctant to realize their losses? *Journal of finance*, 53(5):175-1798.

Odean, T.,(1999). Do investors trade too much? *American economic review*, 89:1279-1298

Pervez G., and Kjell G., (2005).Research methods in business studies.3rd edition.

Pompian M., (2006).Behavioral finance and wealth management. USA: John Wiley and sons.

Rahul S., (2011). Role of behavioral finance in portfolio investment decisions: Evidence from India

Ritter, J., (1991). The long run performance of initial public offerings. Journal of finance 46(1):3-27

Saatcioglu, K., and L. T. Starks, (1998). "The stock price-volume relationship in emerging stock markets: "The case of Latin America", *International journal of forecasting*, 14:215-225

Sewell, M., (2007).Behavioral finance.http://www.behavioral finance.net

Seyhun H. N., (1998). Investment intelligence from insider trading, Cambridge: MIT press.

Shefrin H., (2000). Beyond greed and fear: understanding behavioral finance and the psychology of investing. New York: Oxford University press

Shiller R. J., (1984).Stock prices and social dynamics. Brookings papers on economic activity 2:457-510

Silvapulle, P., and Choi, J.S., (1999). "Testing for linear and nonlinear granger causality in the stock price-volume relation: Korean Evidence", *Quarterly review of economics and finance,* 39:59-76

Smidt, S., (1990). Long run trends in equity turnover. *The journal of portfolio management*, 17: 66-73.

Statman M., Thorley S., and Vorkink K., (2003), Investor overconfidence and trading volume, "AFA 2004 San Diego Meetings Paper".

Statman, M., S. Thorley, and K. Vorkink, (2006). Investor overconfidence and trading volume.*Review of financial studies*, 19(4):1531-1565.

Taylor S., and Brown J.D., (1988). Illusion and well-being: A social psychological perspective on mental health," *Psychological bulletin*", 103(2):193-210.

Tversky A., and Kahneman D., (1981).The framing of decisions and psychology of choice. Science 211(4481): 483-458

Varian, H.R., (1989).Differences of opinion in financial markets.Judgement under uncertainty: Heuristics and biases, Kahneman, Slovic, And Tversky, Canbridge University Press, Cambridge And New York.

Wang, F.A., (1998). Strategic trading, Asymmetric information and heterogenous prior beliefs.*Journal of financial markets,*1:321-352.

Wang, F.A., (2001). Overconfidence, investor sentiment, and evolution.*Journal of financial markets,* 1:225-230

Weinstein N.D. (1980), Unrealistic optimism about future life events, "*Journal of personality and social psychology,*" 39(5):806-820

Werah, A.O (2006). A survey of the influence of behavioral factors on investor activities at the Nairobi stock exchange, *MBA Projects*.

www.nse.co.ke

APPENDIX 1:

WEEKLY INDEX

	INDEX	INDEX-1	RETURN	LN PAST RETURNS (x-variable)
WEEK48(2011)	**3103.04**			
WEEK49(2011)	**3115.64**	**3103.04**	1.004060534	0.004052312
WEEK50(2011)	**3118.92**	**3115.64**	1.001052753	0.001052199
WEEK51(2011)	**3145.72**	**3118.92**	1.008592718	0.008556011
WEEK1	3224.87	**3145.72**	1.025161171	0.024849841
WEEK2	3184.92	3224.87	0.987611904	-0.012465468
WEEK3	3185.14	3184.92	1.000069076	6.90731E-05
WEEK4	3202.34	3185.14	1.005400077	0.005385548
WEEK5	3196.7	3202.34	0.998238788	-0.001762765
WEEK6	3160.51	3196.7	0.98867895	-0.011385621
WEEK7	3182.14	3160.51	1.006843832	0.006820519
WEEK8	3248.4	3182.14	1.020822465	0.020608641
WEEK9	3329.16	3248.4	1.02486147	0.024557452
WEEK10	3401.6	3329.16	1.021759243	0.021525889
WEEK11	3318.95	3401.6	0.975702611	-0.024597441
WEEK12	3312.85	3318.95	0.998162069	-0.001839622
WEEK13	3366.89	3312.85	1.016312239	0.016180624
WEEK14	3400.48	3366.89	1.009976566	0.009927129
WEEK15	3456.35	3400.48	1.016430033	0.016296521
WEEK16	3554.46	3456.35	1.028385436	0.027990034
WEEK17	3534.53	3554.46	0.99439296	-0.005622819
WEEK18	3611.1	3534.53	1.021663418	0.021432101
WEEK19	3599.33	3611.1	0.996740605	-0.003264718
WEEK20	3699.69	3599.33	1.027882967	0.027501315
WEEK21	3699.69	3699.69	1	0
WEEK22	3650.85	3699.69	0.986798894	-0.013289015
WEEK23	3639.46	3650.85	0.996880179	-0.003124698
WEEK24	3694.23	3639.46	1.015048936	0.014936824
WEEK25	3704.7	3694.23	1.002834149	0.002830141
WEEK26	3703.94	3704.7	0.999794855	-0.000205166

WEEK27	3793.32	3703.94	1.02413106	0.023844507
WEEK28	3788.64	3793.32	0.998766252	-0.001234509
WEEK29	3840.36	3788.64	1.013651337	0.013558997
WEEK30	3870.51	3840.36	1.007850826	0.007820169
WEEK31	3843.58	3870.51	0.993042261	-0.006982057
WEEK32	3831.01	3843.58	0.996729611	-0.003275748
WEEK33	3814.1	3831.01	0.99558602	-0.00442375
WEEK34	3826.89	3814.1	1.003353347	0.003347737
WEEK35	3865.76	3826.89	1.010157073	0.010105836
WEEK36	3899.62	3865.76	1.00875895	0.008720813
WEEK37	3927.44	3899.62	1.007134028	0.007108702
WEEK38	3972.03	3927.44	1.011353452	0.011289485
WEEK39	3975.79	3972.03	1.000946619	0.000946171
WEEK40	3995.03	3975.79	1.00483929	0.004827618
WEEK41	3995.03	3995.03	1	0
WEEK42	4034.07	3995.03	1.009772142	0.009724703
WEEK43	4132.91	4034.07	1.02450131	0.024205967
WEEK44	4125.74	4132.91	0.998265145	-0.001736362
WEEK45	4155.99	4125.74	1.007332018	0.007305269
WEEK46	4155.99	4155.99	1	0
WEEK47	4166.55	4155.99	1.002540911	0.002537688
WEEK48	4083.52	4166.55	0.980072242	-0.020128994
WEEK49	4037.99	4083.52	0.988850306	-0.011212318
WEEK50	4056.18	4037.99	1.004504716	0.004494601
WEEK51	4119.1	4056.18	1.015512132	0.015393049
WEEK52	4122.22	4119.1	1.000757447	0.00075716
		4122.22		

APPENDIX 2: WEEKLY TRADING VOLUME

WEEKS	CURRENT TURNOVER	LN OF TOTAL VOLUME(y-variable)
WEEK48(2011)	84035800	18.24675346
WEEK49(2011)	99005600	18.41068697
WEEK50(2011)	74369000	18.12454975
WEEK51(2011)	43821400	17.59563284
WEEK1	76901900	18.15804114
WEEK2	71330400	18.08283316
WEEK3	140124500	18.75804187
WEEK4	38293800	17.46079856
WEEK5	128310700	18.66996522
WEEK6	103877000	18.45871806
WEEK7	51983600	17.76643884
WEEK8	73258600	18.10950621
WEEK9	62967800	17.95813404
WEEK10	85121000	18.25958433
WEEK11	86348000	18.2738962
WEEK12	96465000	18.38469081
WEEK13	101918600	18.43968501
WEEK14	150864100	18.83188999
WEEK15	133354500	18.70852155
WEEK16	129826000	18.68170565
WEEK17	97302000	18.3933301
WEEK18	106259100	18.48139101
WEEK19	95182900	18.37131086
WEEK20	138012800	18.74285699
WEEK21	117227200	18.57962449
WEEK22	74697800	18.1289612
WEEK23	112048300	18.53444059
WEEK24	89243800	18.30688251
WEEK25	109451900	18.51099574
WEEK26	76608700	18.15422121
WEEK27	64133900	17.97648364
WEEK28	79259300	18.18823531
WEEK29	132323400	18.70075948
WEEK30	84477400	18.2519946
WEEK31	112019100	18.53417995
WEEK32	46816100	17.66173772
WEEK33	44758100	17.61678299
WEEK34	81209500	18.21254279
WEEK35	89493709	18.30967889

WEEK36	101658800	18.43713267
WEEK37	109032700	18.5071584
WEEK38	94473100	18.3638257
WEEK39	74030100	18.11998233
WEEK40	74030100	18.11998233
WEEK41	88529200	18.298843
WEEK42	98917300	18.40979471
WEEK43	125317200	18.64635868
WEEK44	122001700	18.61954554
WEEK45	166399700	18.92990328
WEEK46	272761400	19.42410798
WEEK47	214577900	19.1841834
WEEK48	154769000	18.85744424
WEEK49	118469050	18.5901623
WEEK50	121469400	18.61517294
WEEK51	31753100	17.27350092
WEEK52		

APPENDIX 3: LIST OF COMPANIES LISTED IN THE NSE 20 SHARE INDEX

ATHI RIVER MINING LIMITED

BAMBURI CEMENT LIMITED

BARCLAYS BANK (KENYA)

BRITISH AMERICAN TOBACCO LIMITED

CENTUM INVESTMENT COMPANY

CMC HOLDINGS

EAST AFRICAN BREWERIES

EAST AFRICAN CABLES LIMITED

EQUITY BANK GROUP

EXPRESS KENYA LIMITED

KENGEN

KENYA AIRWAYS

KENYA COMMERCIAL BANK GROUP

KENYA POWER & LIGHTING COMPANY

MUMIAS SUGAR COMPANY LIMITED

NATION MEDIA GROUP

REA VIPINGO SISAL ESTATE

SAFARICOM

SASINI TEA AND COFFEE

STANDARD CHARTERED (KENYA)