RETAIL INVESTOR SENTIMENT AND RETURN COMOVEMENT: AN EMPERICAL ANALYSIS OF INDIVIDUAL INVESTORS AT THE NAIROBI STOCK EXCHANGE

BY

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DECLARATION

THE RESEARCH PROJECT IS MY ORIGINAL WORK, AND HAS NOT BEEN SUBMITTED TO ANY OTHER UNIVERSITY FOR ANY ACADEMIC AWARD.

SIGNED DATE

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THE RESEARCH PROJECT HAS BEEN SUBMITTED FOR EXAMINATION WITH MY APPROVAL AS THE UNIVERSITY SUPERVISOR

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MR>JOSEPH BARASA
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DEDICATION

My father,

Ker Riaga Ogalo.

My mum,

Mama Syprine Riaga.

K

And

my fiancee,

Vera Ochieng.

For your love and care by giving me, among other things, the opportunity and the support in my academic pursuit. To my brothers and sisters, and those who love and care for me with whose sacrifice and understanding I managed to get this far.

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ABSTRACT

Using databases of more than 680,000 retail investor transactions over 2005 - 2007, the research sought to show that these trades are systematically correlated. Individuals buy (or sell) in concert with noise trader models, I find that systematic retail trading explains return comovements for stocks with high retail concentration, small-cap, value and lower institutional ownership and lower priced stocks especially if these stocks are also costly to arbitrage. Macroeconomic news and analyst earnings forecast revisions do not explain these results. Collectively the findings of this study support a role for investor sentiment in the formation of stock returns.

ABBREVIATIONS

NSE	Nairobi Stock Exchange
RMRF	Rate of return in excess of risk free rate
SMB	Firm size factor
B/M	Book value to Market value ratio
CAPM	Capital Asset Pricing Model
DJIA	Dow Jones Industrial Average Index
CMA	Capital Market Authority
IPO	Initial Public Offer
BSI	Buy-Sell Index
MMIS	Main Market Investment Segment
AIMS	Alternative Investment market Segment
APT	Arbitrage Pricing Theory

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CHAPTER ONE

1.0 INTRODUCTION

1.1 Background

Capital market researchers frequently distinguish between two classes of investors namely the informed and the informed traders (Rosa et. al. 2005). Informed traders are those who possess some fundamental information about the value of the asset that is not readily available to other traders. Presuming that this information advantage is obtained from costly information search, there is a general assumption that these traders realize superior returns. Uninformed traders (the noise traders) do not possess this information and they trade for their liquidity needs or on the basis of the information that they incorrectly believe to be fundamental to the assets value, in most cases, they are guided by their intuition, feelings and attitudes.

Financial economists tend to view individuals and institutions differently. In particular, while institutions are viewed as informed investors, individuals are said to have psychological biases and are often thought of as the proverbial noise traders in the sense of Kyle (1985) and Black (1986). One of the questions of interest to researchers in finance is how the behavior of different investor clienteles or their interaction in the market affects returns. In this paper the researcher proposes to focus on the interaction between individual investors and stock returns.

Classical finance theory leaves no role for investor sentiment. Rather, this theory argues that competition among rational investors, who diversify to optimize the statistical properties of their portfolios, will lead to an equilibrium in which prices equal the rationally discounted value of expected cash flows, and in which the cross-section of expected returns depends only on the cross-section of systematic risks (Baker & Wurgler 2006). However investor sentiment as explained in the noise trader models of Kyle (1985) or Black (1986) may have significant effects on the cross-section of stock prices, which forms the basis of this study.

Prices of individual stocks reflect investors' hopes and fears about the future, and taken in aggregate, stock price movements can generate a tidal wave of activity (Chen and Siems 2002).The researcher's investigation is motivated by two alternative views of return comovements. The traditional view posits that the current price of a stock closely reflects the present value of its future cash flows (Kumar and

Charles 2006). According to this view, the correlations in the returns of two assets arise from correlations in the changes in the assets' fundamental values, with demand shocks or shifts in investor sentiment playing no role because the actions of arbitrageurs readily offset such shocks.

The traditional financial paradigm seeks to understand financial markets using models developed within bounds of rationality, which assume market efficiency, and, investor rationality. Shleifer (2000) discuss that market efficiency is assumed from its believed self-adjustment nature where security prices are deemed to reflect their fundamental values since any mispricing is eliminated by rational arbitrageurs. Barberis and Thaler (2001) describe rationality to mean two things; first, investors' beliefs are correct such that the subjective distribution they use to forecast future realizations of unknown variables is indeed the distribution that those realizations are drawn from. Second, given their beliefs, they make choices that are normatively acceptable and consistent with the market trends. They contend that traditional framework is appealing simple, and it would suffice if its predictions were reflected in empirical research findings. It includes standard finance theories and efficient market hypothesis. Standard finance theories consider markets to be highly analytical and normative represented by the arbitrage principles, portfolio theory, CAPM and the option-pricing model. Efficient market hypothesis espouses the incorporation of market information in security prices to reflect optimal estimates of true investment value at all times.

An alternative theory argues that the dynamic interplay between noise traders and rational arbitrageurs establishes prices (e.g., Shiller (1984), Shleifer and Summers (1990)). According to this second view, in addition to innovations in fundamentals, factors such as the correlated trading activities of noise traders also induce comovements and arbitrage forces may not fully absorb these correlated demand shocks.

Kumar and Charles (2006) in their paper, and consistent with noise trader models of Kyle (1985) or Black (1986), find that systematic retail trading explains return comovements for stocks with high retail concentration (i.e., small-cap, value, lower institutional ownership, and lower-priced stocks), especially if these stocks are also costly to arbitrage. Macroeconomic news and analyst earnings forecast revisions do not explain these results. Collectively, their findings support a role for investor sentiment in the formation of returns, despite the fact that irrational investor sentiments play little role in the standard risk based asset pricing literature. The issue of investors' irrationality is ignored due to the central role of rational arbitrageurs who trade against noise traders and bring stock price close to its fundamental value. However, numerous recent studies have countered this argument and suggested that arbitrage is limited and that stock prices can deviate from the fundamental value due to unpredictability in irrational sentiments. The theoretical framework describing the role of sentiments in asset pricing is provided by researchers such as Black (1986), Trueman (1988), DeLong et. al„ (1990,1991), Shleifer and Summers (1990).

Ever since the theoretical work of Delong et.al. (1990) researchers have sought empirical evidence of a sentiment factor that reflects fluctuations in the opinions of traders regarding the future prospects for the stock market. It is potentially valuable to find an empirical measure of sentiment because of the suggestion that it may be priced. In particular, it could be source of non-diversifiable risk generated by the very existence of an asset market that simultaneously serves as a mechanism for impounding expectations and beliefs about the future, and provides liquidity to savers. Finding an empirical instrument for the sentiment factor would allow a test of the Delong et.al. (1990) model and its implications, including the possibility that market prices temporarily deviate from true economic values as a function of investor sentiment.

Kumar and Charles (2006) analysis tested a particular form of the noise trader model in which individual (i.e., retail) investor sentiment can affect stock returns. They use a clientele-based model that closely parallels the models of Bodurtha, et. al. (1995) and Barberis, et. al., (2005). In these models, different investor groups restrict themselves to trading within different natural "habitats," or groups of stocks. Thus, the returns of individual stocks reflect not only fundamental risk, but also changes in the systematic time-varying preferences (i.e., "sentiment") of important investor groups.

1.2 Investor Sentiments

Which stocks do retail investors choose to buy, and what motivates the purchase of one stock over another? Kaniel (2006) documents that since individuals tend to buy after prices decrease and sell after prices increase, their profits may also relate to the short-horizon return reversals first observed by Jegadeesh (1990) and Lehmann (1990). In principle, these reversals can be due to either illiquidity or investor overreaction. One best explanation for these findings is that the contrarian tendency of individuals leads them to act as liquidity providers to institutions that require immediacy.

Specifically, investor sentiments are defined as situations where individual investors act on beliefs unwarranted by fundamental values and thereby their buy and sell transactions have a common directional component, De Long et al. (1990). Investor sentiments thus are the expectations about future absolute returns rather than the relative returns. It is the propensity to speculate, sentiments in this regard is thus seen to drive the relative demand for speculative investments and therefore, causes cross-sectional effects even if arbitrage forces are the same across stocks. What makes stocks to be more vulnerable to broad shifts in the propensity to speculate can be suggested as the subjectivity of their valuations, (Baker and Wurgler 2006).

1.3 Return Comovement

This is defined as the variability of stock returns in one direction. Changes in investor sentiment is measured by the direction of these retail trades, in addition to evaluating the impact of retail investor trading on comovement in stock returns as conjectured in models of noise trading and investor sentiment (De Long et al., 1990 and Barberis and Shleifer, 2002).

The research project's main conjecture is that systematic trading by retail investors could lead to stock return comovements beyond the usual risk factors. Equity markets are characterized by widespread direct stock ownership by retail investors (Kumar and Charles 2006). Extant evidence shows that these investors spend far less time on investment analysis, they engage in more attention-based trading, and they typically rely on a different set of information sources from their professional counterparts. If the buy-sell patterns of retail investors do not move in lock-step with overall market movements, assets in market segments dominated by these investors could be characterized by pricing anomalies that are associated with their trading activities and the study proposes to explore this possibility.

Baker and Wurgler (2006) show that retail investors' trades are systematically correlated, that is, individuals tend to buy or sell stocks in concert with each other. Specifically, they document two related findings: a strong positive correlation in the buy-sell imbalance (BSI) of retail investors across non-overlapping portfolios of different stocks, that is, when retail investors buy (sell) one group of stocks, they tend to buy (sell) other groups of stocks; and correlated trading behavior holds across different individuals, that is, when one set of retail investors buys (sells) stocks, a different set of retail investors also tends to buy (sell) stocks. This second finding is also reported in Barber et. al., (2003). However, their study explores factors that affect the degree of correlation across traders, and does not examine pricing implications. These findings indicate the existence of a systematic (or common directional) component in the trading activities of retail investors.

Kumar and Charles (2006) examined whether the systematic component of retail trades, which they dub "retail investor sentiment," has incremental power in explaining return comovement. To measure changes in retail sentiment for a certain basket of stocks, they construct a BSI measure for various stock portfolios. They then estimate multifactor time-series models in which they use the portfolio BSI as one of the explanatory variables.

For stocks with high retail concentrations, Kumar and Charles (2006) find that a portfolio-level BSI measure has a significant incremental ability to explain return comovements. This result holds even after controlling for the effects of both innovations in macroeconomic variables (unexpected inflation, monthly growth in industrial production, change in term spread, and change in value spread) and empirically inspired risk factors, namely, the market excess return (RMRF), the size factor (SMB), the book-to-market (B/M) factor (HiML), and the momentum factor (UMD).

Collectively, Kumar and Charles (2006) findings are relevant to the debate on whether investor sentiment plays a role in financial markets. The traditional case against such a role for investor sentiment in markets is based on two key assertions: the cognitive foibles that individuals commit do not aggregate across the investing populous (individual irrationalities do not result in systematic directional behavior across large groups of investors); and even if systematic noise trading exists, an army of rational arbitrageurs stands ready to offset this behavior, and thereby render prices unaffected (Shiller (1984), Shleifer (2000) and Lee (2001).

Kumar and Charles (2006) analysis speaks directly to these issues, suggesting that, at least in the case of retail investors, both of the above assertions are questionable hence the need to determine if this holds at NSE. Specifically, they find that retail trades do aggregate across individuals, and that the collective action of these individuals can influence stock returns. Their results therefore support a friction- or sentiment-based theory of returns comovement, such as Barberis Shleifer & Wurgler (2005). BSW argue that the observed return patterns that rotate round the inclusion or deletion of a stock from the S&P500 stock index are clientele-related. Their evidence suggests that their habitat-based model applies not only to institutional indexers, but also to retail investors.

Finally, the research project is motivated and related to a growing literature in behavioral finance that examines the correlated trading behavior of retail investors and its impact on stock returns. For instance using a Chinese data set, Feng and Seasholes (2004) find that the trading activities of investors that live within a certain geographic region are strongly correlated. Similar in spirit, Jackson (2003) provides additional evidence of systematic trading patterns among Australian investors. Also, as mentioned earlier, Barber, et.al., (2003) provide evidence of correlated trading among retail investors in the United States, and explore psychology-based explanations for these patterns. Kumar and Charles (2006) findings are consistent with these studies and the study will extend this line of inquiry by linking the correlated trading behavior of individual investors to stock returns. The researcher believes that, at a minimum, these past results highlight the need to study further the role of investor behavior in financial markets and especially the NSE that is still underdeveloped.

1.4 Contextual Framework

Classical Finance Theory leaves no room for investor sentiment. Rather it argues that competition among rational investors, who diversify to optimize the statistical properties of their portfolios, will lead to an equilibrium in which prices equal the rationally discounted value of expected cash flows, and in which the cross section of expected returns depend only on the cross-section of risks. Even if some investors are irrational, classical theory argues that their demands are offset by arbitrageurs and thus have no significant impact of prices. (Baker and Wurgler **2006).**

In this paper, the researcher seeks to present evidence that investor sentiment may have significant effects on the cross-section of stock prices. Because mis-pricing is as a result of an informed demand shocks in the presence of a binding arbitrage constraint, The study seeks to predict that a broad based wave of sentiment has cross-sectional effects when sentiments based demands or arbitrage vary across stocks. In tandem with the above, the researcher will focus on firms listed on the Nairobi Stock Exchange and will consider the trading habits of individual/retail investors' daily buy and sell trading volumes. The research will be based on the data sourced from the databases of the following stock brokerage firms: Discount Securities, CFC Financial Services Limited and Suntra Investment Bank specifically on individual trading volumes for the period 2005 and 2007.

1.5 Statement of the Problem

Efficient markets hypothesis has been the central proposition in finance for several years. Harry Roberts (1967) coined the term 'efficient market hypothesis' in the wake of his research on financial market behaviour. He defined it as the incorporation of market information by the financial security prices such that the prices are regarded as optimal estimates of true investment value at any specific time. It assumes efficient markets and rational market agents. It states that securities prices in financial markets should equal their fundamental values, either because all investors are rational or because arbitrage eliminates pricing anomalies

According to Shiller (1998), efficient market hypothesis is based on the notion that people behave rationally expecting to maximize returns from their investments by accurately processing all available information. Kendal (1953) had anticipated efficient market hypothesis by arguing that stock prices approximately describe random walks through time as they change unpredictably due to genuine new information, which, by the very fact that its new, is unpredictable. Due to the fact that all information is contained in stock prices according to the hypothesis, Shiller (1998) concludes that it is impossible to make an above average profit and beat the market over time except by chance or by taking excess risks.

Standard finance is a body of knowledge built on the pillars of the portfolio principles of Markowitz, the capital asset theory of Sharpe, arbitrage principles of Miller and Modigliani and the options pricing model of Black and Scholes. It is compelling because, according to Statman (1984), it uses minimum tools to built a unified theory intended to answer certain facets of financial security trade outcomes.

Markowitz (1952) explains how an efficient portfolio is constructed by use of mean variance analysis. He describes how to combine assets into efficiently diversified portfolio. In this way, a portfolio's risk can be reduced and the expected rate of return can be improved if investments having dissimilar price movements were combined. In furtherance of the portfolio theory, Sharpe (1964) discusses the existence of great opportunity for risk reduction by the incorporation of all the assets in the market including the risk free assets. According to Sharpe, the only relevant risk is the diversifiable risk. Black and Scholes (1997) developed a model for pricing derivative instruments. Their model is used in the valuation of stock options before maturity. Modigliani and Miller (1958) extensively wrote on the irrelevance of capital structure on a firm's valuation. Their finding discussed the market value of any firm to be independent of its capital structure and is given by capitalization of its expected return at the rate appropriate to its asset class. In modern terms, they concluded that capital structure is irrelevant and the firm value is equal to the present value of the free cash flow discounted at the relevant cost of capital.

The failure of traditional finance theories in explaining certain security price movements and market anomalies based on rationality, suggested that this framework of financial market understanding could be incomplete, wrong or inapplicable in all the markets (Olsen, 1998). This poses the major challenge to this class of theories. Prices of individual stocks reflect investors' hopes and fears about the future, and taken in aggregate a tidal wave of activity (Chen and Siems, 2002). Despite strong evidence that the stock market is highly efficient, there have been scores of studies that have documented long-term historical anomalies in the stock market that seem to contradict the efficient market hypothesis. This includes the January effect, the weather effect and small size effect among others. This coupled with behavioral finance are seen as the major factors affecting the stock market in the contemporary world.

In the recent past, NSE has seen many unlikely investors tryout their luck in the Exchange. Like in many developed stock markets, this is set to see improved performance of the NSE that had less than 150,000 investors out of a potential investing population of 5,000,000 people. This implies that the NSE could be experiencing first time investors who do not have the capability of carrying out financial analysis. (NSE Newsletter 2006)

It is against this backdrop that the study proposed to use the trading records of individual investors to investigate the effect of retail trading on stock returns with the ultimate aim of improving the efficiency of the NSE. Evidence produced by financial analysts find that important inferences, for instance portfolio formation, pertaining to the issue of capital market reaction to investor sentiments can be drawn from the direction of return comovements. The basis of this research is thus to determine whether retail investor sentiments at the NSE have played any role in the formation of returns.

This study aimed at answering the following questions; (i) Do buy-sell transactions of retail investors contain a common directional component? (ii) If the buy - sell transactions contain a common directional component, does the direction of these retail trades indicate changes in investor sentiments? (iii) What impact does the retail investor trading have on comovement in stock returns? (iv) Can financial analysts make important inferences pertaining to portfolio formation based on the direction of these retail trades?

1.6 Objectives of the Study

The study sought to:

(i) To determine whether the buy-sell transactions of retail investors contain a common directional component.

(ii) To measure changes in investor sentiment and evaluate its impact on comovement in stock returns.

(iii) To determine which sectors are most affected by the systematic retail trading.

1.7 Importance of the Study

The study is significant to the NSE and the CMA because retail investors form the bulk of the investing public at NSE and if their trading sentiments can influence return formation, then there need to be good financial regulatory framework and policies geared towards them. It will highlight the importance of the retail investor at NSE.

Investors are concerned about the returns they get from their investments. The study will be informative on the points to take into account when deciding which investments to go for and to what extend their sentiments play a role on this.

To the academicians, the study shows that the strength of the sentiment-return relation is affected by factors associated with retail investor habitat and cross-sectional differences in arbitrage costs. Specifically, it proves that retail investors concentrate their holdings and their trading activities in smaller, lower-priced, higher B/M ratio, and lower institutionally owned firms. At the same time, it proves that these are the firms most sensitive to changes in retail investor sentiment and additionally, controlling for retail investor concentration, firms with higher arbitrage costs (i.e., higher idiosyncratic risk, liquidity betas, etc.) exhibit much stronger sensitivity to changes in retail sentiment.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Introduction

National capital markets can be positioned along a continuum from embryonic to mature and emerged markets according to a decreasing 'national cost of capital' criterion (Jacque, 2002). Newly emerging countries are handicapped by a high cost of capital because of 'incomplete' and inefficient financial markets. As capital markets graduate to a higher level of 'emergedness', their national firms avail themselves of a lower cost of capital that makes them more competitive in the global economy and spurs economic growth.

Rational asset pricing theories, such as the Capital Asset Pricing Model (CAPM), Merton's intertemporal CAPM, and Ross's APT, posit that non-diversifiable risks and their risk premiums determine asset prices (Anchada, 2005). In these models, investors' beliefs affect price through perception of risk and expected returns, and a measure of aggregate risk aversion, which determines the risk-return trade off. In the rational expectation framework, investors' perceptions are correct on average, allowing researchers to test asset pricing models with realized risk and return in place of investors' ex ante perceptions or expectations. However, much of the empirical evidence has not been supportive of these rational models. To reconcile theory and empirical evidence, two lines of inquiries have emerged: development of more dynamic asset pricing models and development of behavioral pricing models.

In the first line of inquiry, the rational investor assumption is maintained. The theoretical advances have been in; first, identifying other risks to better capture investors' perception of risk (e.g., Lettau and Ludvigson, 2001) second, improving methods to account for time-varying risks and risk premiums (e.g., Ferson and Harvey, 1991) and finally using alternative risk-return trade off models, the modifying assumptions about what kinds of risks are insurable, and having heterogeneous consumers/investors (e.g.. Constantinides 1990, and Constantinides and Duffie, 1996).

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In the second line of inquiry, the behavioral finance literature allows investors' beliefs to deviate from those of rational investors. These deviations are attributed to psychological biases, such as overconfidence or self attribution, documented in the psychology literature (Hirshleifer, 2001). Misvaluations by irrational investors can affect stock prices when coupled with limits on arbitrage activities of rational investors, which would otherwise eliminate the pricing effect of irrational investors (Shleifer and Vishny, 1997). These two lines of inquiries generate a heated debate concerning a fundamental issue in asset pricing: are stock returns determined solely by risk factors and risk premia or instead are stock returns determined by risk factors and risk premia plus the valuation of irrational investors who misperceive the distribution of asset values? This beliefs of irrational investors is referred to as investor sentiment.

A robust stock market assists in the rational and efficient allocation of capital, which is a scarce resource (NSE, 2005). The fact that capital is scarce means systems have to be developed where capital goes to the most deserving user. An efficient stock market sector will have the expertise, the institutions and the means to prioritise access to capital by competing users so that an economy manages to realize maximum output at least cost. This is what economists refer to as the optimum production level. If an economy does not have efficient financial markets, there is always the risk that scarce capital could be channeled to non-productive investments as opposed to productive ones, leading to wastage of resources and economic decline. Stock markets are thus supposed to create wealth for both the investors and listed firms. It, therefore, remains to be seen whether investor sentiments yielded any results towards this direction through formation of returns.

2.1.1 Investor Sentiments and Stock Returns

Baker & Wurgler's (2006) study on Investor Sentiment and the Cross-section of Stock Returns, predict that a wave of investor sentiment has larger effects on securities whose valuations are highly subjective and difficult to arbitrage. They captured investor sentiment using a conditional characteristics multiple regression model. Consistent with this prediction, they also found that when beginning-of-period proxies for sentiment are low, subsequent returns are relatively high for small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. Their approach was to determine systematic patterns of trading prices however the study's limitation is that it did not control for two more basic effects, namely, the generic impact of investor sentiment on all stocks and the generic impact of characteristics across all time periods. Their model thus did not determine whether retail investors are net buyers or net sellers for a particular group of stocks at any time which this research proposal seeks to measure.

Dorn's (2003) paper, "Does Sentiment Drive the Retail Demand for Initial Public Offers?" used a novel data set of pre- and post-Initial Public Offers trades made by a sample of clients at a large German retail broker. The buy and sell transactions of retail investors were used to determine the direction of this stock trades and thus act as a measure of investor sentiment. He documented that retail investors are willing to overpay and they, end up overpaying for Initial Public Offers, especially following periods of high returns in recent new issues. His main objective was to test whether retail investors act on beliefs about the value of a company that cannot be justified by the company's fundamentals and, if so, whether such beliefs can affect prices.

Dorn (2003) found that Initial Public Offers (IPO) that are more aggressively bought by retail investors post higher first-day returns. They however experience lower aftermarket returns, controlling for market returns and firm characteristics such as size and book-to-market ratio. They concluded that sentiment drives retail purchases of Initial Public Offers and appears to have a transitory effect on prices. Because retail investors end up systematically overpaying for stocks bought in the Pre- Initial Public Offers market, one can infer that they act on overoptimistic beliefs. The study therefore establishes a link between investor sentiment and stock returns, however it is only limited to Initial Public Offers.

Kumar and Charles, (2006) analysis tests a particular form of the noise trader model in which individual (i.e., retail) investor sentiment can affect stock returns. Consistent with noise trader models, Kumar and Charles, (2006) find that systematic retail trading explains return comovements for stocks with high retail concentration (i.e., small-capitalization, value, lower institutional ownership, and lower-priced stocks), especially if these stocks are also costly to arbitrage. Macroeconomic news and analyst earnings forecast revisions do not explain these results. Collectively, their findings support a role for investor sentiment in the formation of returns.

2.2 Drivers of Trade

The extraordinary degree of trading activity in financial markets represents one of the great challenges to the field of finance. Many theoretical models in finance, such as those found in Aumann (1976), Milgrom and Stokey (1982), argue that there should be no trade at all. Empirical research by Odean (1999) also shows that the trades of many investors not only fail to cover transaction costs, but also tend to lose money before transaction costs. To address the puzzle of why so much trading occurs, one needs to understand what motivates trades and whether such motivations are rooted in behavioral hypothesis, such as aversion to realizing losses, a mis-guided belief in contrarianism or momentum that might be evidence of over confidence (Daniel, et. Al., 1998), or a love of gambling. Alternatively, it would be equally useful to learn if more rational motivations, such as portfolio rebalancing consistent with the mean-variance theory, tax-loss trading, and life-cycle considerations are the fundamental drivers of trade.

Kumar and Charles, (2006) show that retail investors' trades are systematically correlated, that is, individuals tend to buy or sell stocks in concert with each other and not due to the rational motivations above. This motivates the study to attempt to determine if the trades at NSE contain a common directional component as this may help explain why investors trade. Specifically, Kumar and Charles, (2006) document two related findings: a strong positive correlation in the buy-sell imbalance (BSI) of retail investors across non-overlapping portfolios of different stocks, that is, when retail investors buy (sell) one group of stocks, they tend to buy (sell) other groups of stocks; and correlated trading behavior holds across different individuals, that is, when one set of retail investors buys (sells) stocks, a different set of retail investors also tends to buy (sell) stocks. These findings indicate the existence of a systematic (or common directional) component in the trading activities of retail investors.

Matti and Mark (2001) used logit regressions to analyze separately the sell versus buy decision and find that the disposition effect and tax-loss selling are two major determinants of the propensity to sell a stock that an investor owns. They also find that the disposition effect interacts with past returns to modify the propensity to sell.

2.2.1 Market Anomalies

Despite strong evidence that the stock market is highly efficient, there have been scores of studies that have documented long-term historical anomalies in the stock market that seem to contradict the efficient market hypothesis. While the existence of these anomalies is well accepted, the question of whether investors can exploit them to earn superior returns in the future is subject to debate. Investors evaluating anomalies should keep in mind that although they have existed historically, there is no guarantee they will persist in the future. If they do persist, transactions and hidden costs may prevent out-performance in the future.

2.2.1.1 The January Effect

Stocks in general and small stocks in particular have historically generated abnormally high returns during the month of January. According to Haugen and Jorion (1996), "The January effect is, perhaps the best-known example of anomalous behavior in security markets throughout the world". The January Effect is particularly intriguing because it does not appear to be diminishing despite being well known and publicized for nearly two decades. Theoretically, an anomaly should disappear as traders attempt to take advantage of it in advance.

The effect is usually attributed to small stocks rebounding following year-end tax selling. Individual stocks depressed near year-end are more likely to be sold for tax-loss recognition while stocks that have run up are often held until after the New Year. Many believe the January effect has moved into November and December because of mutual funds being required to report holdings at the end of October and from investors buying in anticipation of gains in January. Some studies of foreign countries have found that returns in January were greater than the average return for the whole year. Interestingly, the January effect has also been observed in many foreign countries including some (Great Britain and Australia) that don't use December 31 as the tax year-end. This implies that there is more to the January effect than just tax effects, Haugen and Jorion (1996).

2.2.1.2 Turn of the Month Effect

Stocks consistently show higher returns on the last day and first four days of the month. Russell (1998) examined returns of the S&P 500 over a 65-year period and found that U.S. large-cap stocks consistently show higher returns at the turn of the month. Hensel and Ziemba (1986) presented a theory that the effect results from huge cash flows expected at the end of each month when liquidity levels among investors occasioned by end month settlement of account positions. Russell (1998) found out that returns for trades at the turn of the month were significantly above average from 1928 through 1993 and further, documents that the total return from the S&P 500 over this sixty-five-year period was received mostly during the turn of the month. The studies implied that investors making regular purchases may benefit by scheduling to make those purchases prior to the turn of the month.

2.2.1.3 The Monday Effect

Monday tends to be the worst day to be invested in stocks. Fields (1931) documented the first study on weekend effect. At that time, stocks traded on Saturdays. Fields (1934) also found that the DJ1A commonly registered percentage gains the day *before* holidays. Several studies have shown that returns on Monday are worse than other days of the week. Interestingly, Harris (1986) examined intraday trading and found that the weekend effect tends to occur in the first 45 minutes of trading on Fridays where prices generally took a downward trend with minor gains for subsequent trades. He further found out that on all other days of the week, prices rose during the first 45 minutes of trading.

This anomaly presents the interesting question: Could the effect be caused by the moods of market participants? People are generally in better moods on Fridays and before holidays, but are generally grumpy on Mondays. Hersh & Shefrin(1996) cited the example of the expectations revisions by securities analysts following with the expectation that the markets will not have picked up at the start of the trading week. He noted that trade generally picked up as the week progressed. He thus concluded that grumpy Mondays are characterized by low expectations and thus negative earnings and as the week progresses, expectations grew and this reflected in the very positive earnings across stocks.

2.3 Trading Approaches

Trading approaches gives a brief understanding of the methods that investors use in the stock market. These methods contradict investor sentiment, as they mostly require some analysis on the stocks to be done. Alexander (1961) explained that there are two main schools of professional analysts, the fundamentalists and the technicians who operate in the belief that there exists certain trend generating facts that will guide a speculator to profit if only he can read them correctly. They only differ in the method used to gain knowledge before others in the market. The other group in the market includes the investors who are aggressive in trading in the stock market, taking advantage of the speculative price changes (active approach) and those investors who prefer the buy-and-hold method of trading (passive approach).

2.3.1 Fundamental Vs Technical Approaches

For an individual to gain from investing, it is important that the investor performs security analysis, which involves examining several individual securities in Nairobi Stock Exchange and classify them using technical or fundamental approach. In its simplest form, technical analysis involves the study of stock market prices in an attempt to predict future price movements for the common stock of a particular firm. Initially, past prices are examined in order to identify recurring trends or patterns in price movements. Then more recent stock prices are analyzed in order to identify emerging trends or particular patterns that are similar to past ones. This is done with the belief that these trends repeat themselves. Thus by identifying an emerging trend or pattern, the analyst hopes to predict accurately, future price movements for that particular stock. (Sharpe et al., 1999).

Fundamental analysis involves the assertion that the true or intrinsic value of any stock equals the present value of all cash flows that the owner of that stock expects to receive. Once the true value of the common stock of a particular firm has been determined, it is compared with the current market price of the common stock in order to see whether the stock is overpriced, under priced or fairly priced. In the simplest form, fundamental analysis begins with the assertion that the "true" or intrinsic value of any financial asset equals the present value of all the cash flows that the owner of the asset expects to receive. Accordingly, the fundamental stock analyst attempts to forecast the timing and the size of these cash flows and then converts them to their equivalent present value using the appropriate discount rate. Once the true value of the share is determined, it is compared with the current market value to establish whether it is fairly priced. Fundamental analysts believe that any noteable cases of mispricing will be corrected by the market in the near future; the prices of the undervalued stocks will show unusual appreciation and prices of overvalued stocks will show unusual depreciation. (Sharpe et al., 1999).

2.3.2 Active and Passive Approaches.

Within the investment industry, a distinction is often drawn between *passive management-holding* securities for relatively long periods with small and infrequent changes- and *active management.* Thus passive approach involves a long term, buy-and-hold approach to investing where the investor selects appropriate target and buys a portfolio designed to closely track the performance of that target.

Active management on the other hand, involves a systematic effort to exceed the performance of a selected target (Sharpe, 2004). All active management entails the search for mispriced securities or mispriced group of securities. Accurately identifying and adroitly purchasing or selling these mispriced securities provides the active investor with the potential to outperform the passive investor.

There has been a big bone of contention between passive and active management and their profitability. However no good conclusion has been reached ever. Because, passive managed portfolios usually experience very small transaction costs, whereas active management costs can be very high, depending on the amount of trading involved. Seemingly then, passive management will out perform active managers because of cost differences.

2.4 Return Comovements

The research investigation was motivated by two alternative views of return comovements. The traditional view posits that the current price of a stock closely reflects the present value of its future cash flows. According to this view, the correlations in the returns of two assets arise from correlations in the changes in the assets' fundamental values, with demand shocks or shifts in investor sentiment playing no role because the actions of arbitrageurs readily offset such shocks (Kumar and Charles, 2006).

An alternative theory argues that the dynamic interplay between noise traders and rational arbitrageurs establishes prices. Shiller (1984), Shleifer and Summers, (1990). According to this second view, in addition to innovations in fundamentals, factors such as the correlated trading activities of noise traders also induce comovements and arbitrage forces may not fully absorb these correlated demand shocks.

The central question in the debate over market efficiency is whether small noise traders significantly distort asset prices. According to Barber et al., (2006), three things are necessary for this to happen. First, noise traders must misinterpret available information or trade for non-informational reasons. Second, noise trades must be systematically correlated, that is, noise traders must be net buyers or net sellers of the same stocks; if, instead, noise traders buy and sell randomly, their trades tend to cancel, rather than reinforce, each other. Third, there must be limits to the ability of rational, well-informed investors to correct mis-pricing through arbitrage. If these conditions hold, noise trades will distort asset prices. Furthermore, if asset prices gravitate back towards underlying value, then noise trader buying and selling will predict future asset returns.

2.5 Sentiment versus Information and Liquidity

There are alternative interpretations to sentiment. Edelen and Warner (2001) and Warther (1995, 1998) considered several reasons why trading order flows and stock returns might be positively correlated. The most traditional account is perhaps information about future payoffs. In fact, the models of Brennan and Cao (1996, 1997) imply that, when investors have differential information precision, less-informed investors behave like trend-followers. That is, trade flows of the less informed are positively correlated with returns. Their trade motives are rational—the less informed investors increase their demands upon good public price signals, because they update their beliefs more than the better informed do.

DeLong, et al. (1990) and Shleifer and Vishny (1997) proposed that noise traders may influence prices even in markets where some investors are well informed, because informed traders face risks that are likely to limit their actions. This theory relied on the assumption that psychological biases and sentiment cause noise traders to trade systematically as a group and that, when there are no perfect substitutes for mispriced assets, transactions costs and risks limit the ability of informed would be arbitrageurs to eliminate mispricing affecting the liquidity of the market.

Suppose, for example, an informed trader considers a stock to be overvalued so that he believes that its price exceeds its intrinsic/fundamental value and if there exists a perfect substitute for the stock and transactions costs, including short-selling costs, are low, the informed trader can potentially profit from buying the substitute and selling the overpriced stock. If enough informed traders do this, the relative prices of the overpriced security and its substitute will converge. If, however, information is imperfect, no perfect substitutes exist, or transactions costs are high, the informed trader faces a variety of risks. One, the informed trader's information may be incorrect, secondly though the stock is currently overpriced, unanticipated events may increase its value but not that of the substitute, thirdly mispricing due to investor sentiment may increase as sentiment intensifies rather than subside and finally markets may be illiquid when the informed trades wishes to unwind his position.

By way of market clearing, better-informed investors follow a contrarian strategy. If mutual fund investors are relatively less informed than the market average, then it is possible that we are capturing their information-based trades. Liquidity needs can also drive trading. Some investors might simply need to liquidate their portfolios in a timely manner independently of price movement (Brennan and Cao, 1997). Liquidity trading has important pricing implications; because it must be absorbed by those whose marginal valuation affects prices. In contrast to such "mechanical" traders, liquidity traders in practice may have "wills," in that they might minimize trading costs by allocating trades over time or over securities.

Individual investors play the role of noise traders in equity markets. Since individual investors tend to place small trade volumes, their purchases and sales must be correlated if they are to appreciably move markets. Barber et al.(2005) show that the trading of individual investors at a large discount brokerage (1991-1996) and at a large retail brokerage (1997-1999) is systematically correlated. In any month, the investors at these brokerage houses tend to buy and sell the same stocks. Furthermore, the monthly imbalance of purchases and sales by these investors (i.e., (purchases - sales)/ (purchases + sales)) is correlated over time. Thus, investors are likely to be net buyers (or net sellers) of the same stocks in subsequent months as they are this month.

Finally, there are other factors that are studied relatively less well and that nonetheless may affect investor order flows and hence prices; for example, common changes in risk aversion, demographic changes, and employment changes. In fact, Jagannathan and Wang (1996) find that return on human capital adds significant explanatory power over the static Capital Asset Pricing Model. Some of these may even be subject to daily fluctuations. These are maintained as reasonable alternative hypotheses to the sentiment story.

2.5.1 Evidence of Market -W ide Systematic Component

Kumar and Charles (2006) study was designed to evaluate the extent to which the trading activities of retail investors are correlated. An important assumption common to all noise trader models is that uninformed noise trader demand aggregates across a population of individuals, that is, individuals buy or sell baskets of stocks in concert with each other. In the absence of this type of systematic behavior, it is unlikely that noise trader sentiment can affect returns.

To examine whether retail investors trade in concert, Kumar and Charles (2006) measured the correlations in the Buy-Sell Imbalance (BSI) time series of pairs of non-overlapping stock portfolios. In addition, they examined the correlation in buy-sell behavior across individual investors and conducted a series of variance-based tests with the same objective. The primary data for Kumar and Charles (2006) study consisted of trades and monthly portfolio positions of the retail investors at a major U.S. discount brokerage house over the period 1991-1996. While there were 77,995 households in the database, they focused on the 62,387 that trade stocks. The aggregate value of investor portfolios in their sample was, on average, $2.18 billion in a given month. They determined that on average investor holds a four-stock portfolio (median is three) with an average size of $35,629 (median is $13,869). Fewer than 10% of the investors held portfolios over $100,000 and fewer than 5% held more than 10 stocks. The average monthly portfolio turnover rate, which measures the frequency of trading, was 6.59% (median is 2.53%) and a typical investor executes nine trades per year. The average trade size was $8,779 (median is $5,239)

2.5.2 Measuring Changes in Retail Investor Sentiment

The measure of investor sentiments shall be based on volume of trading activities of retail investors thereby be able to measure changes in sentiments. Shiller (1984) suggests that common sentiments arise when investors trade on pseudo-signals such as price and volume patterns, popular forecasting models, or the forecasts of Wall Street gurus. Pseudo-signals refer to signals that are non-informative in estimating a firm's fundamental value, but that may nevertheless be persuasive in their own right. Prior evidence (Lee (1992), Odean (1999), Dhar and Kumar (2001), Barber and Odean (2003)) suggested that, indeed, at least a portion of the trading by retail investors is likely to be induced by pseudo-signals. Kumar and Charles (2006) did not claim that systematic patterns in retail trades are necessarily non-fundamental in nature, to the extent that a systematic directional pattern is not explained by known risk factors, they refer to it as "retail sentiment." The aggregate trading activities of investors for a certain group of a portfolio of stock can be measured in a variety of ways. One such measure is a portfolio's Buy Sell Index (BSI) over a particular time period *t*.

2.5.3 Retail Sentiment Shifts and Stock Returns

The existence of a common directional component in the trading activities of retail investors suggests that changes in retail sentiment might induce comovements in stock
t
returns. To examine the incremental ability of retail sentiment shifts to generate comovement in stock returns, Kumar and Charles (2006), performed an investigation that followed procedures that have become standard in recent asset pricing studies. They

employed a five-factor time series model in which the first three factors are those of Fama and French (1992, 1993), the fourth factor is the momentum factor (e.g., Jegadeesh and Titman (1993), Carhart (1997)), and the fifth factor is the appropriate portfolio BSI measure.

The link between the behavioral aspects of investors and the fluctuations in the market price of risk stems from the presence of heterogeneity in sentiments of market participants and its effect on market imperfections. Investor's heterogeneity in beliefs leads to an additional factor implying that standard asset pricing models overestimates/underestimates the equity risk premium depending on investor's relative optimism/pessimism. Recent studies strongly support the notion that difference of opinion among market participants plays an important role in asset pricing (Verma and Soydemir 2004).

Basak (2005) presents a tractable continuous-time pure-exchange model and highlight model on the equilibrium behavior of investors and price of risk, and show that when sentiments are homogenous, investors would price risk equally, with the market price of risk given by the aggregate endowment risk, weighted by investors relative risk aversion. Under such scenario, investors would share risk in proportion to their risk tolerances. However, when the sentiments are heterogeneous across the market, the risk is transferred from the more pessimistic investor to more optimistic investor. This transfer of risk is proportional to the degree of difference of opinion, which brings another factor in the investors' perceived market price of risk. As there is an increase (decrease) in the price of risk of the overly pessimistic (optimistic) investor.

Jouini and Napp (2005) presented a model to analyze the impact of heterogeneity in sentiments on the market price of risk and the risk free rate. In light of the risk premium and risk free rate puzzles (Mehra and Prescott, 1985; Weil, 1989), they showed that when investors are pessimistic, there is a bias towards a higher market price of risk and a lower risk free rate than in the standard setting. Also, there is a higher market price of risk if risk tolerance and investors' pessimism are positively correlated. They argued that the reason why investors' pessimism increases objective expectation of the market price of risk is not that; a pessimistic investor requires a higher price of risk. He/she requires the same market price of risk but his/her pessimism leads him/her to underestimate the average return such that the perceived market price of risk is greater than the standard market price of risk.

Yu and Yuan (2005) constructed a general model with heterogeneous beliefs and demonstrate that market's reaction to volatility is not homogenous through time but depends on irrational sentiments. They argued that in the absence of irrationality, the Sharpe ratio is positive and constant. However, in the presence of irrationality, Sharpe ratio is a decreasing function of irrational sentiments i.e. mean-variance relation in the low sentiments period is higher than that of the high sentiment periods.

Kumar and Charles (2006) went ahead, in their study, to examine the incremental explanatory power of portfolio-level BSI measures (i.e. portfolio-level sentiment changes) rather than the market-wide BSI measure (i.e. aggregate sentiment changes). As expected, portfolio-level BSI measures are highly correlated with the market-wide BSI measure. For example, the correlations between market-wide BSI and the BSI measures for individual size quintile portfolios range from 0.714 to 0.890. However, they used portfolio-level BSI measures because they found that the market-wide measure is not a sufficient statistic for individual portfolio BSI measures.

In ancillary tests, they found that the mean BSI correlations for non-overlapping portfolios are higher when stocks are selected from the same stock category than when stocks are selected from different categories. In other words, within category correlations are reliably higher than cross-category correlations. This pattern obtains across stock categories defined using size, book-market value, price, and institutional ownership. Moreover, Kumar and Charles 2006 find that the BSI correlations *across* stock categories are reliably lower than unity, suggesting that a market-wide measure is likely to omit some information that is contained in portfolio-level BSI measures. For all these reasons, they use portfolio-level BSI measures computed for each stock category, rather than a market aggregate BSI measure, in all their tests.

2.6 Institutional vs Other Investors

Financial assets can be thought of as composite commodities. Their main attribute is the ownership rights over an uncertain stream of future cash flows. Most asset-pricing applications focus on this attribute and compute asset prices using some weighting of these cash flows. There are, however, other attributes of financial assets that influence investor demand. For example, most investors would prefer liquid assets to illiquid ones and would be willing to give up some amount of expected future cash flows to buy into more liquidity (Gompers and Metrick 1998). Are institutions different from other investors in their demand for asset characteristics? If the demand of individuals and institutions for stock characteristics were identical, then the fraction of institutional shareholdings would be identical across all stocks.

There are reasons, however, to expect institutions' demand for financial assets to be different from that of individuals. To some degree, all institutions except those in the "other" category will often be acting as agents for other investors. This agency relationship is standard for investment advisors and mutual funds, but also occurs for banks through their trust departments and for insurance companies through consumer products such as variable annuities. Once individuals have ceded investment discretion to an institution, however, they can only imperfectly monitor the choices of that institution, and institutional incentives may often differ from those of their clients. In addition, individuals do not always exercise complete and costless discretion over the choice of an investment agent: retirement plans often have limited investment options, trustees are difficult to replace, and other advisory changes often require portfolio turnover, transactions costs, and taxes.

Thus, even though individuals have some control over the ultimate investment choices of their agent institutions, this control is imperfect, and we would expect different incentives to result in different demand patterns between the two groups. These differences are costly to individuals, but they may be willing to pay such agency costs because of economies of scale or other investment advantages enjoyed by institutions (Gompers and Metrick, 1998).

One possible cause of differences between individuals and institutions is the legal environment that institutions face as fiduciaries. Del Guercio (1996) examined the issue of prudence as it relates to stock ownership by banks and mutual funds. She provided intuition and evidence to show that different types of institutions are affected by prudence restrictions to varying degrees. Banks are the only institution governed by the common-law "prudent-man rule"; a standard which is often interpreted more strictly than the written regulations governing the investment behavior of other institutions. Empirical studies and survey evidence, however, suggest that many non-bank institutions also consider prudence characteristics.

Although standards for prudence vary, Del Guercio (1996) identified several variables that have appeared in the prudence case law as firm age, dividend yield, S&P membership and stock-price volatility. The large positions held by institutions may lead them to demand stocks with large market capitalization and thick markets. In addition, if institutions turn over their portfolios and trade more often than individuals do (Shapiro and Schwartz (1992), then they would be more sensitive to the transactions costs caused by large-percentage bid-ask spreads for illiquid or low-priced stocks.

Grinblatt and Kelohatju , in their paper, "What Make Investors Trade" 2001, noted that Contrarian's Trading is more profound with individual/retail investors than with the institutional investors with respect to recent price run-ups. Retail investor trading is thus more characterized by the "Disposition Effect" where stocks that are perceived by the traders as winners are disposed of while those that are deemed losers are held. This they argue could be easily be interpreted as a contrarian's behaviour with respect to past results.

Academic research (Oluoch, 2004 and Oliech, 2004 inter alia) have shown that small stocks, stocks with high book-to-market ratios, and stocks with high returns over the previous year ("momentum") have all enjoyed higher historical returns than stocks without those characteristics. Thus, there is need to test whether a firm's size, book-to-market ratio, and momentum are related to the level of institutional ownership. There are two reasons why institutions may differentially invest in stocks that have these characteristics. First, institutions may have better knowledge about historical return patterns and believe them to be exploitable anomalies. Second, institutions may have different preferences for risk and return and may believe that differences in historical returns across stocks are due to differences in risk.

Existing empirical work has analyzed various proxies for sentiment. In the closed-end fund literature, some researchers argued that investor sentiment can be measured by the discount on closed-end funds, and investigate its relation to the return generating process of individual stocks or portfolio of stocks grouped by size (market capitalization). However, these studies find conflicting evidence. Lee et al., (1991), Chopra et al., (1993) reported that closed-end fund discounts are a determinant of returns of small capitalization stocks, while Chen et al., (1993) and Elton et al., (1998) concluded that the discount on closed-end funds is not a determinant of stock returns.

Neal and Wheatley (1998) examined the relation of three proxies of sentiment with long-term returns and find inconclusive results. They found that net fund redemption can forecast portfolio returns of small capitalization stocks and the size premium, while closed end fund discounts do not. They also reported that the ratio of odd lot sales to purchases has forecasting power but the sign is counterintuitive. Brown and Cliff (2005) developed a sentiment measure constructed from the number of bull, bear, and neutral market newsletters. They investigated the relation of this measure and returns of size and book-to-market sorted portfolios, and find that high sentiment levels are followed by lower returns at horizons of two and three years for portfolios with large size and low book-to-market firms.

Brown and Cliff (2004) used principal component analysis to extract a composite measure of sentiment from various sentiment measures that have been previously proposed, such as fund flows to mutual funds, the ratio of advance over declining issues, and the number of bull, bear, and neutral market newsletters. They investigated the relation of this composite sentiment measure and monthly and weekly stock returns, but found it does not predict near-term returns. The prior literature review highlights the lack of consensus on the best measure of sentiment or on whether sentiment in fact affects stock prices. While existing studies test the impact of sentiment on individual stocks and small portfolios of stocks, this research proposal takes a different approach. The researcher proposed a different measure of sentiment, and examines whether sentiment affects stock prices focusing on whether sentiment affects the aggregate market returns.

2.7 Historical Development of Nairobi Stock Exchange (N.S.E)

The Nairobi stock exchange was established in 1954. It operated as an association of stockbrokers with no trading floor until October 1991. The introduction of the trading floor has led to a substantial increase in trading volumes and upward movement in the various indexes. The Nairobi Stock Exchange (NSE) has been instrumental in enabling the public and private sectors in Kenya to raise large amounts of capital for expansion of new businesses (NSE Manual, 2005).

The NSE thus represents the financial markets in Kenya. It has 18 registered brokers and currently has about 58 firms listed on the exchange. It deals in ordinary shares and fixed income securities such as preference shares and most recently treasury bounds. The NSE also has some of its shares cross-listed with other stock exchanges in South Africa, Uganda and Tanzania. Both operational and informational efficiencies are key to ensuring that the NSE fulfils its mandate as the capital markets intermediary for Kenya and the world over (NSE Handbook, 2005).

2.7.1 Market Structure Reforms at Nairobi Stock Exchange (N.S.E)

The structure of the Nairobi stock exchange has witnessed tremendous transformation during the last 10 years that has seen its operating environment and trading systems improve as part of measures aimed at improving market transparency and efficiency. Fundamental reforms of the market structure were undertaken in year 2000. The reforms saw the market reorganized into two independent market segments.

2.7.2 Market Segmentation

Market segmentation groups firms generally based on the required level of regulations as provided for in the CMA Act. There are two categories of listed firms at the NSE; first, is the Main Investment Market Segment (MIMS).This is the main quotation market with more stringent listing requirements. Main investment market segment is further divided into four market sectors namely; Agricultural Market Sector, Commercial and Services Sector, Finance and Investment Sector and Industrial & Allied Market Sector.

Currently the above segments have the following number of firms listed: Agricultural sub-segment; 4 firms, Commercial and Services; 11 firms actively trading with 1 firm, Uchumi Supermarket, under suspension. Under the Finance and Investment sub-segment, 13 firms are actively trading whereas the Industrial and Allied sub-segment has a listing of 16 actively trading firms and two suspensions (BOC Gases and Carbacid Investments) occasioned by merger talks.The second category, is the

Alternative Investment Market Segment. The second segment is the Alternative Investment Market Segment. This segment is made up of the firms whose public listing at the NSE is governed by less stringent rules in terms of the capitalization levels. 8 firms are listed under this segment.

2.7.3 The Role of Capital Markets Authority (CMA)

In the 1980s the Government of Kenya realized the need to design and implement policy reforms to foster sustainable economic development with an efficient and stable financial system. In particular, it set out to enhance the role of the private sector in the economy, reduce the demands of public enterprises on the exchequer, rationalize the operations of the public enterprise sector to broaden the base of ownership and enhance capital market development. It had become evident that the commercial banks could not support and sustain a desirable economic development because they could not offer the necessary long-term credit.

In 1984, a study on the Development of Money and Capital Markets in Kenya was jointly undertaken by the Central Bank of Kenya and the International Finance Corporation with the objectives of making recommendations on measures that would ensure active development and strengthening of the financial sector. This became a blueprint for structural reforms in the financial markets. The Government further re-affirmed its commitment to the creation of a regulatory body for the capital markets in the 1986 Sessional Paper on "Economic Management of Renewed Growth".In November 1988, the Government set up Capital Markets Development Advisory Council and charged it with the role of working out the necessary modalities including the drafting of a bill to establish the Capital Markets Authority. In November 1989, the bill was passed in parliament and subsequently received Presidential assent, The Capital Markets Authority was thus set up in 1989 through an Act Parliament (Cap 485A, Laws of Kenya). The Authority was eventually constituted in January 1990 as a body corporate with perpetual succession and a common seal.

The principle objectives of the Authority are; the development of all aspects of the capital markets with particular emphasis on the removal of impediments to, and the creation of incentives for longer term investments in, productive activities; facilitate the existence of a nationwide system of stock market and brokerage services so as to enable wider participation of the general public in stock market; create, maintain and regulate a market in which securities can be issued and traded in an orderly, fair, and efficient manner, through the implementation of a system in which the market participants regulate themselves to the maximum practicable extent; protect investor interests by operating a compensation fund to protect investors from financial loss arising from the failure of a licensed broker or dealer to meet his contractual obligations and finally, facilitate the use of electronic commerce for development of capital markets in Kenya

CHAPTER THREE

3.0 RESEARCH METHODOLOGY

3.1 Research Design

An empirical study of the NSE was conducted. The aim of the study was to explore the effect of retail investor sentiments on return comovements and as such, the study used convenience sampling method to sample out the stock brokerage firms after which survey method of research was applied in analysing the trading activities of all the retail investors trading through the sampled firms.

3.2 Population of Study

The population of interest in this study consisted of the buy-sell transactions by all retail investors enlisted in the stock brokerage firms licensed by NSE (Appendix II). Their trading patterns were considered over the period 2005 to 2007. To improve the validity of result the items in this population were grouped according to the sector categorizations currently in use at the NSE; the Main Investment Market Segment (MIMS) which is further subdivided into four sectors consisting of Commercial and Services Sector, Agricultural Market Sector, Finance and Investment Sector and finally Industrial and Allied Sector together with the Alternative Investment Market Segment (AIMS), *(see Appendix I)*

3.3 Samples and Sampling Procedure

The sample for this study consisted of trades and monthly portfolio positions of the retail investors at three major brokerage firms in the local equity market on account of market share of clientele base. The buy-sell transactions of retail investors at Discount Securities Limited, Suntra Investment Bank Limited and CFC Financial Services Limited were considered. For each stock traded by retail investors, prices were obtained from the Nairobi Stock Exchange. Convenience sampling was used because the three brokerage firms commanded a large percentage of the retail trades and further that research data could be obtained with ease from the their databases.

3.4 Data Collection

This study was facilitated by the use of secondary data. The Buy-Sell transactions in terms of volume and Kenya shilling amount traded specifically for the retail investors were obtained from the databases of Discount Securities Limited, CFC Financial Services and Suntra Investment Bank Limited for the years 2005 and 2007. Data from the three brokerage firms were collected from the various dealers within the firms in statement form and were uploaded to Microsoft Excel. Upon uploading in MS Excel, the trading data were categorized as either a sale or a purchase order, thus segregated between the buy and sell volumes. The unnecessary pieces of information with regard to CDS account number, investor contacts and stock brokerage internal documentation trails were deleted as they were of no significance for the purpose of the study. Share prices were obtained from the Nairobi Stock Exchange library for the computation of the Kenya shilling equivalent of the trading volumes. The appropriate computations of the average share price was based on the recorded daily prices and was undertaken to establish the applicable price for use in the study. Data on share prices were obtained from the records of the Nairobi Stock Exchange.

3.5 Data analysis

The data collected from the stock brokerage firms were uploaded to Microsoft Excel and thereafter the unnecessary pieces were deleted and later the processed data were categorized as either a sale order or a purchase order and matched with the respective prices prevailing during the period of trading. The cleaned data was then analysed using Ms Excel and SPSS. A regression analysis of the calculated BSI values against the risk free rate of return was conducted. Regression analysis served the purpose of excluding the common dependence of the portfolio BSI on the market factor with a key objective of removing the common components in investor net demand that were due to overall market movements.

To examine correlation among stock portfolios, the researcher formed portfolio pairs of non-overlapping stock portfolios of stocks that were chosen randomly from the set of stocks traded by the sample investors. The researcher constructed monthly BSI time series for the 36-month sample period and thereby orthogonalise these monthly BSI measures with respect to the market index return. Finally, the correlations between the pairs of BSI indices that were derived from the non-overlapping portfolios to obtain an empirical distribution of BSI correlations. The variables of the study were computed as follows:

Changes in Retail Investor Sentiment

The study's measure was related to Kumar and Charles', 2006 who used the trading activities of retail investors to measure changes in their sentiments. One such measure is a portfolio's Buy-Sell Imbalance (BSI) over a particular time period *t.* To compute the monthly portfolio BSI, the study first defined the month-/ BSI for stock *i* as:

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$$BSI_{pt} = \frac{\quad_{j=1}}{\sum_{j=1}^{N_t}\left(VB_{jt}+VS_{jt}\right)}$$

Where, *N, was taken as* the number of investors in group *i*; $VB_{;}$, ($VS_{y/}$), the shilling-denominated buy (sell) volume for stock / on day *j* of month *t.* A given month's stock-level BSI indicated whether, at an aggregate level, retail investors were net buyers (stock BSI > 0, that is, a positive change in their aggregate stock sentiment) or net sellers (stock BSI < 0, that is, a negative change in their aggregate stock sentiment) of a given stock over a given period of time measured in months. The BSI measures were analysed relative to the movements of the market index.

Secondly, the researcher computed the portfolio BSI by calculating an equal-weighted average of individual stock BSIs as follows:

$$BSI_{pt} = \frac{100}{N_p}\sum_{i=1}^{N_p} BSI_{it}$$

Where, N_p *was* the number of stocks in portfolio *p.* The monthly portfolio-level BSI provided a measure of the number of investor buys minus sales for each stock, where each stock was weighted equally in the portfolio. The intent here was to capture the mean retail sentiment shift for stocks in the portfolio, with equal weight given to each stock. For example, consider a portfolio of the four stocks A, B, C, and D, which have prices of Kshs 80, Kshs 10, KshslO, and KshslO, respectively, in a particular month. Assume further that investors would sell 100 shares of stock A, and buy 100 shares each of stocks B, C, and D in the specified month. Given this trading pattern, the BSI for stock A would be 1 while that of stocks B, C, and D would be -1. The portfolio BSI would be (-1 + 1 + 1 + l)/4 = 0.50, indicating a bullish sentiment shift. In short, the portfolio BSI is a reflection of net investor demand across the stocks within the portfolio.

An alternative approach was to compute the aggregate shilling volume in-flow (AVB) and aggregate shilling volume out-flow (AVS) for all the stocks in a portfolio, defining the portfolio BSI as (AVB - AVS)/(AVB + AVS). However, under this alternative approach, a particular month's portfolio BSI could be strongly influenced by a single stock (Kumar and Charles, 2006). This however could prove problematic, especially in the case that a stock experienced unusually high trading volume due to an information event such as an earnings announcement or a stock recommendation change. Additionally, such a measure would be sensitive to within-portfolio changes in the stock price distribution.

Return Comovement

Return comovement is defined as the variability of stock returns in one direction. Changes in investor sentiment is measured by the direction of these retail trades, in addition to evaluating the impact of retail investor trading on comovement in stock returns as conjectured in models of noise trading and investor sentiment. It thus a measure of the reactions of the investors towards price changes and has sought to explain the fact that retail investor trades are systematically correlated, thus individuals have tended to buy or sell in concert with each other.

Baker and Wurgler (2006) document two related findings: a strong positive correlation in the buy-sell imbalance (BSI) of retail investors across non-overlapping portfolios of different stocks, that is, when retail investors buy (sell) one group of stocks, they tend to buy (sell) other groups of stocks; and correlated trading behavior holds across different individuals, that is, when one set of retail investors buys (sells) stocks, a different set of retail investors also tends to buy (sell) stocks. The returns from the share prices and the capital gains will be computed as follows.

$$R_{it} = \frac{P_{i-1} - P_t}{P} \square d_o$$

Where:

R, - is the stocks return in time 7'

P, - is the last traded price in time'/'

P,.y - is the last traded price of stock (share) in time7-7'

do- Dividend distributions during the period

The analysis here was conjectured that systematic trading by retail investors could lead to stock return comovements beyond the usual risk factors.

Multifactor Time-Series Model

Thirdly to examine the incremental ability of retail sentiment shifts to generate comovement in stock returns, the researcher will employ a five-factor time-series analysis model in which the first three factors are those of Fama and French (1992,1993), the forth factor is a momentum factor and the fifth factor is the appropriate portfolio BSI measure. The factor model is as follows:

$$^{R}{}_{P}r_{pi} \quad n \quad i_{P}\, RMRF_t \;\; jp \quad SMBpp\; {}_{3p}HML, \quad \hat{}UMD,Ufi\; {}_{5p}\; BSI\, \hat{}e$$

Where:

R_{pt}	_ the portfolio rate of return
Rr,	. the risk-free rate of return
$RMRF_t$	. the market rate of return in excess of the risk-free rate
SMB,	. the difference between the value-weighted return of a portfolio of small stocks and the value-weighted return of portfolio of large stocks
HML,	- the difference between the value-weighted return of a portfolio of high B/M stocks and the value-weighted return of a portfolio of low B/M stocks.
UMD_t	. the difference between the value-weighted return of a portfolio of stocks with high returns during months t-12 to t-1 and the value-weighted return of a portfolio of stocks with low returns during the months t-12 to t-1.
BSIpt	. the equal-weighted BSI of stocks in portfolio p
£pt	. is the residual return on the portfolio.

The researcher examined the incremental explanatory power of portfolio-level BSI measures (the portfolio-level sentiment changes) rather than the market-wide BSI measure (the aggregate sentiment changes). In the asset pricing tests, the researcher examined the incremental explanatory over of portfolio level BSI measures, the portfolio-level sentiment changes, rather than the market -wide BSI measures, the aggregate sentiment changes. The portfolio-level BSI measures were found to be highly correlated with the market-wide BSI measure.

Finally, to remove the common dependence of the portfolio BSI on the market factor, the researcher perfomed the following regression:

$$BSIp = b_0 + b_x RMRF_l + e_{pt}$$

Here, BSI„, was the month-/ BSI index for portfolio *p,* RMRF, was the month-/ market return in excess of the risk-free rate, and e_{pt} is the month-/ residual BSI for portfolio *p.* The purpose of this regression is to remove the common component in investor net demand that is due to overall market movements.

The data were analyzed using Microsoft Excel and SPSS, regression and correlation analyses together with multi factor time series analysis were then used to determine whether retail investor sentiments affect the return comovements hence applied to establish the existence of a correlation. The problem of non-normality was dealt with by conducting regression analysis to remove of outliers from the data occasioned by market wide movements and components and hence improved the validity of the results.

The stocks traded by the population were grouped according to the industry classifications that enabled inter-sector comparisons to be made. Such an approach was also a means of minimizing deviations from normality (Vintanen and Yiliolli 1989). The firms were grouped in portfolios by size in an attempt to identify the impact on stock market returns since size has been shown to be strongly correlated with expected returns (Kwon, Chung S 1997). In addition, firms were grouped by industrial sectors in order to observe the effect of change in sentiments on the various industrial groups.

CHAPTER FOUR

4.0 DATA ANALYIS AiND FINDINGS

4.1 Introduction

The objective of the study was to assess the impact of retail investor sentiments on return comovements of ordinary shares at the Nairobi Stock Exchange. The data used for analysis were the daily prices and the Buy-Sell transactions in terms of volume and Kenya Shilling amount traded for the retail investors obtained from Discount Securities Limited, CFC Financial Services and Suntra Investment Bank Limited for the years 2005, 2006 and 2007. The study was based on the perceived existence of a relationship between retail investor sentiments and return comovement on ordinary shares. This was done by first establishing whether the buy-sell activities of retail investors contained a common directional component after which, the researcher sought to establish a measure of the changes in the impact of retail investor sentiment based on these retail trades and consequently, evaluated the impact of retail investor trading on comovement in stock returns.

4.1.1 Summary Statistics: Retail Investor Trading Behaviour

Table 1 showed the aggregate trading, stock-level, and investor-level trading statistics. The sample consists of 52,687 retail investors who execute 680,839 trades in 60 listed stocks during the years 2005, 2006 and 2007 sample period. The statistics are reported only for trades for which returns data are available from the three stock brockerage firms sampled in this study. In Panel A and B, it is evident that there was a general trend to sell than to buy except for 2007 where the converse was upheld. In Panel C, the researcher documented investor-level statistics that is indicative that most of trades carried out in the market were done within the confines of smaller portfolios as compared to the bigger portfolio positions.The study used the number of stocks and the number of investors with a valid stock position at the end of the most recent month prior to a trade to obtain the proportions in Panels B and C, respectively.

Table 1: Summary of the Trading Statistics

Panel A: Aggregate Trading Statistics

Statistic	2005	2006	2007
Number of Buy Trades	101,589	106,344	123,119
Number of Sell Trades	102,789	134,231	112,767
Average Trade Size (Buys) "Kshs Millions"	12,698	13,004	12,815
Average Trade Size (Buys) "Kshs Millions"	12,977	13,043	12,853
Total Number of Stocks Traded	58	58	60
Total Number of Investors	11,678	13,869	27,140

In Panel A, it is evident that there was a general trend to sell than to buy except for 2007 where the converse was upheld. There was reflected, a significant drop in the Kenya shilling value of the trades in the year 2007 even with increased buy orders. This was alluded to the prevailing political risk propagated by the presidential elections that were due at the end of that year.

Panel B: Monthly Stock Level Trading Statistic (Proportion of Stocks)

Number of Monthly Trades	2005	2006	2007
At least 1 trade	55.98	58.63	60.29
5 or more trades	15.81	17.66	18.12
10 or more trades	7.26	8.53	8.98
25 or more trades	2.37	2.87	3.25
50 or more trades	0.89	1.07	1.38
75 or more trades	0.49	0.59	0.82
100 or more trades	0.32	0.40	0.56

In panel B above, the study demonstrated that a significant proportion of the trades were explained by retai; investors whose holding were limited to portfolios of up to a limit of one stock. By simple statistical description, the lower portfolio size holdings contributed to the highest volumes of trade over the study period.

Panel C: Monthly Investor Level Trading Statistcis:

Number of Monthly Trades	2005	2006	2007
At least 1 trade	27.06	36.61	44.72
5 or more trades	2.92	5.03	6.99
10 or more trades	0.68	1.37	2.17
25 or more trades	0.26	0.56	10.0
50 or more trades	0.12	0.29	0.55
75 or more trades	0.07	0.17	0.34
100 or more trades	0.02	0.03	0.07

The above tables report the aggregate, the stock level and investor-level trading statistics. The research sample consisted of 52,687 retail investors who execute 680,839 trades in the 58 plus listed stocks during the study period 2005 through to 2007. Panel A, the researcher reported the various aggregate trading statistics. In Panel B, I consider the stock level trading statistics whereas Panel C reported on the investor-level statistics. The researcher used the number of stocks and the number of investors with a valid stock position at the end of the most recent month prior to a trade to obtain the proportions in Panels B and C. the results above indicate that a huge proportion of the trades is accounted for by the small scale investor trades. There is a consistent increase in the trading buy volumes across the period of study. However, a significant reduction in the trading buy volumes for the final year was recorded even after some growth having been registered for the first two years of the study period.

Evidence of Market-Wide Systematic Component

To examine correlations among stock portfolios, 1,000 pairs of nonoverlapping stock portfolios were formed that consisted of *k* stocks (where *k* = 2, 5, 7, 10, 15, and 20). Stocks were chosen randomly from the set of stocks traded by the sampled investors. For each of the randomly chosen portfolios, a construction of monthly BSI time series for the 36-month sample period was determined. The monthly BSI measures were regressed with respect to the market index return. Finally, the correlations between pairs of BSI indices that were derived from non-overlapping portfolios were computed, and then generated an empirical distribution of BSI correlations.

Table 2: Correlation Statistics

Panel A: Random Stock Portfolios

Statistic	2 Stocks	5 Stocks	7 Stocks	10 Stocks	15 Stocks	20 Stocks
Mean	0.234	0.367	0.461	0.534	0.600	0.612
Median	0.237	0.372	0,464	0.543	0.605	0.618
Std Dev.	0.127	0.104	0.093	0.080	0.069	0.065
25 Percentile	0.142	0.299	0.399	0.484	0.566	0.566
75 Percentile	0.317	0.441	0.524	0.588	0.648	0.659

Panel A, above, showed the correlation statistics for different portfolio sizes for instance, the empirical distribution of the pair-wise correlations for k = 15. The average BSI correlation was positive and significantly different from zero (p-value < 0.05) for all chosen portfolio sizes. The results indicated that the average BSI correlation increased with portfolio size. For instance, for 15-stock portfolios, the average BSI correlation is 0.600; for 2-stock portfolios, this measure is 0.234. These results indicate the presence of a systematic component in the trading activities of our sample investors, a component that is uncorrelated with movements in the market index.

Panel B Random Stock Portfolios

Number of Randomly Chosen Investors

Statistic	500	1,000	1,500	2,000	2,500	5,000
Mean	0.147	0.210	0.272	0.326	0.365	0.496
Median	0.141	0.209	0.278	0.339	0.367	0.506
Standard Dev.	0.127	0.112	0.124	0.117	0.220	0.108
25 Percentile	0.068	0.133	0.188	0.252	0.295	0.436
75 Percentile	0.240	0.295	0.352	0398	0.434	0.582

Panel , above, B reported on the correlation statistics for different sizes in investor groups. Analogous to the reported portfolio-based results, the average BSI correlation is positive and statistically significanr (p-value < 0.05) for all the selected investor group sizes. Furthermore, the average BSI correlation increases monotonically as group size increases. For instance, for investor groups that consist of 1,000 investors each, the average BSI is 0.210, whereas for groups that consist of 5,000 investors, the average BSI correlation is 0.496 Thus, Table 2 above reports the simulation results (correlation statistics) from two sets of randomization tests that examine the existence of a systematic component in the trading activities of retail investors in the sample of study. These tests thus have shown that correlations between BSI indices are significantly positive over non-overlapping stock portfolios as well as non over-lapping investor groups.

4.1.2 Multifactor Model Estimation Results for Size-Sorted Portfolios

Table 3 reported the relation between the measures of retail sentiment shifts and four empirically inspired risk factors that are common in the literature. Th asset pricing tests examined the incremental explanatory power of portfolio-level BSI measures as opposed to market-wide BSI measure. Panel A presents descriptive statistics for the BSI time series in each size quintile portfolio. The results indicate that the BSI time-series for the small-cap portfolio realizes higher volatility. Furthermore, Panel B shows that the portfolio BSI measures are moderately correlated with the four risk factors (market or RMRT, small-minus-big or SMB, high-minus-low or HML, and momentum or UMD).

Table 3: Quintile Statistics

Panel A: Time-Series Statistics

	Mean	Median	Standard Dev.	Min.	Max
Quintile 1	3.48	3.25	9.32	-24.39	22.10
Quintile 2	0.42	-0.17	7.06	-14.08	15.74
Quintile 3	-3.29	-33.40	7.02	-18.74	12.01
Quintile 4	-6.68	-6.61	6.98	-22.64	8.87
Quintile 5	-10.60	-11.58	8.14	-25.82	9.18

Panel B: Correlations

	RMRF	SMB	HML	UMD
Quintile I	0.141*	0.215**	0.196**	-0.449***
Quintile 2	-0.239**	-0.148*	0.135*	-0.373***
Quintile 3	-0.201**	-0.192**	0.036	-0.222**
Quintile 4	-0.322***	-0.192**	0.144*	-0.174*
Quintile 5	-0467***	-0.127*	0.130*	-0.163*

Table 3 above reported the basic statistics and correlations (with standard risk factors) of the portfolio BSI time series for quintile portfolios obtained by sorting on size. The quintile portfolios are formed at the end of each year using the size break-points from the end of December. The portfolios are held constant throughout the following year. Panel A, documented the basic statistics and Panel B presented the correlations. *, **, and *** denote degree of significance at the 10%, 5%, and 1% levels, respectively. At 10% degree of significance, we realise averagely low negative sentiment for the lower quintile trades whereas the low degree of significance of 5%, the higher quintile ranges register higher negative sentiments among the investors.

In ancillary tests, the researcher found that the mean BSI correlations for non-overlapping portfolios were higher when stocks were selected from the same stock category than when stocks were selected from different categories. In other words, within categories correlations were reliably higher than the cross-category correlations. This pattern obtained across stock categories defined using size, B/M and price. Morover, the researcher found out that the BSI correlations across stock categories were reliably lower than unity, hence suggested thata market-wide measure is likely to omit some information that will otherwise be contained in portfolio-level BSI measure.

4.5 Time-Series Factor Model Estimate for Size Portfolios

Table IV presented the time-series factor model estimates for each of the five size-quintile portfolios. The quintile portfolios are formed at the end of each year in December using the size breakpoints of the data obtained at the three stock brokerage firms sampled for purposes of this study and are then held constant throughout the following year. The researcher then estimated the time-series factor model whose findings were as scheduled in the table below.

Table 4: Multi Factor Time Series Statistics

	Alpha	RMRF	SMB	HML	UMD	Port BSI	Adj. R^J
Ql	0.463	0.867	1.448	0.694	-0.244		
	-1.825	-10.188	-9.895	-5.634	-2.835		0.814
	0.165	0.870	1.409	0.634	-0.134	0.069	
	-0.649	-10.841	-9.103	-4.827	-1.540	-3.030	0.857
Q2	-0.050	0.994	0.924	0.188	-0.166		
	(-0.490)	(27.356)	(21.787)	(4.573)	(-4208)		0.958
	-0.058	0.995	0.926	0.188	-0.161	0.004	
	(-0573)	(27.002)	(21.703)	(4.604)	(-4.021)	(0.335)	0.957
Q3	-0.148	1.018	0.732	0.131	-0.018		
	(-2.063)	(46.190)	(24.334)	(4.097)	(-0.591)		0.974
	-0.140	1.020	0.734	0.132	-0.015	0.004	
	(1.935)	(45.150)	(23.985)	(4.056)	(-0.536)	(0.508	0.976
Q4	-0.026	1.035	0.421	0.103	-0.039		
	(-0.367)	(46.599)	(14.454)	(4.515)	(-1.478)		0.959
	-0.0818	1.036	0.422	0.103	-0.038	0.001	
	(-0.209)	(43.858)	(14.073)	(4.467)	(-1.58)	(0.148)	0.959
Q5	0.011	1.053	0.009	0.067	-0.061		
	(0.246)	(50.614)	(0.510)	(3.371)	(-2.343)		0.982
	0.031	1.056	0.010	0.067	-0.060	0.002	
	(0.512)	(47.394)	(0.546)	(3.426)	(-2.303)	(0.426 _L	0.980

For the small-cap (size quintile 1) stock portfolio, the BSI loading is positive (0.069) and statistically significant (f-statistic = 3.030), whereas for the remaining four size quintile portfolios, the portfolio BSI factor loadings are small in magnitude and statistically insignificant. For small-cap (Ql) stocks, *a* and the loading on UMD both become insignificant with the inclusion of BSI, suggesting that retail sentiment helps explain small-firm excess returns through an interaction with the momentum factor.

The results computed have shown that the BSI loadings estimates remain statistically significant for a fairly wide range of *k* values. For instance, a retail investor holding just 1 asset, the BSI loading is 0.054 with a t-statistic of 2.423. as the portfolio size increases, the BSI loading estimate decreases and it becomes statistically insignificant. The trend can thus be applied in deducing that BSI loading estimate are sensitive to volume turnover.

Collectively, the findings indicated that retail sentiment shifts have incremental ability to explain return comovements among small-cap stocks. Consistent with behavioral theory, stocks in the lowest size quintile earn positive (negative) excess returns when retail investor sentiment grows more bullish (bearish). However, the results indicated no significant relation between retail sentiment shifts and the returns of other size quintile portfolios.

CHAPTER FIVE

5.0 SUMMARY, CONCLUSION & RECOMMENDATIONS

The major contribution of this study has been; (i) the determination of whether the buy-sell transactions of retail investors contain a common directional component, (ii) measure changes in investor sentiment, (iii) evaluate its impact on comovement in stock returns. The results have important implications because retail investors have played an important role in the stock market and their sentiments are of value too.

The study used a large data set of retail trades from three major discount brokerage houses in Kenya, to examine the effect of retail trading patterns on comovement in stock returns. First, the results indicate that the trading activities of retail investors contain a common directional component—when retail investors sell one group of stocks, they tend to buy other groups. Similarly, when some investors are buying stocks, other individuals also tend to be selling the same stocks offered. This evidence suggests that changes in portfolio-level retail sentiment may induce comovement in stock returns. Next, using retail investors' trading activities, the researcher obtain direct measures of retail investor sentiment changes and found that these measures have incremental explanatory power, over the standard risk factors and innovations in macroeconomic variables, for small stocks, value stocks, stocks with low institutional ownership, and stocks with lower prices. The direction of the relation indicates that when retail investors grow relatively bullish, the stocks in these portfolios enjoy higher excess returns and when such stocks grow relatively bearish, there is generally a loss of value as the stocks in these portfolios relatively register low or at worst negative returns.

Finally, the results show that the strength of the sentiment-return relation is affected by factors associated with retail investor habitat and cross-sectional differences in arbitrage costs. Specifically, they show that retail investors concentrate their holdings and their trading activities in smaller, lower-priced, higher B/M, and lower institutionally owned firms. At the same time, the study found that these are the firms most sensitive to changes in retail investor sentiment. Collectively, these findings are broadly consistent with the predictions of noise trader models in which the systematic activities of retail investors affect the returns of those stocks in which they are concentrated. In particular, the results provide support for a sentiment-based theory of returns comovement advanced by Barberis et al. (2005). Consistent with the "habitat" version of the BSW model, the study found that stocks preferred by retail investors are the ones most sensitive to shifts in retail investor sentiment. Also consistent with the predictions of their model, the study found out that the strength of the sentiment-return relation is a function of arbitrage costs.

More broadly, the results support a role for investor sentiment in the study of financial markets. The traditional case against such a role for investor sentiment is based on two key assertions. First, the cognitive foibles committed by individuals do not aggregate across the investing populous so that individual irrationalities do not result in systematic directional behavior across large groups of investors. Finally, even if systematic noise trading exists, an army of rational arbitrageurs stands ready to offset this behavior, leaving prices unaffected. The results suggest that, at least in the case of retail investors, both assertions may not hold.

5.1 Policy Implications

Financial economists tend to view individuals and institutions differently. In particular, while institutions are viewed as informed investors, individuals are said to have psychological biases and are often thought of as the proverbial noise traders in the sense of Kyle (1985) or Black (1986). One of the questions of interest to researchers in finance is how the behavior of different investor clienteles or their interaction in the market affects returns. This study focused on the interaction between individual investors and stock returns, the results support a role for investor sentiment in the study of financial markets. NSE and CMA thus in their regulations should take keen interest of the activities of retail investors in the stock market as far as the regulations of sentiments-based trade is concerned. This would be necessary and sentiments affects significantly the operations of the market.

5.2 Limitation of the Study

There were factors that affected the macro economic environment in the years under study in addition to the general election in the year 2007, did affect the accuracy of this research. The macro economic factors include the increased inflation between 2007. The second factor was the sky rocketing bank interest rates between 2006 and 2007 due to high domestic borrowing. These factors affected the decision making of retail investors to sell when in normal circumstances they would not have done so.

5.3 Recommendations for Further Research

It is important that a similar study with a bigger sample, time horizon and taking into account more buy-sell transactions be conducted by using advanced time series models to enhance our understanding of the association between the retail investor sentiments and share returns and liquidity of the NSE. The findings also raised a number of interesting issues for future research. For instance, it would be interesting to examine whether the time-varying Retail Investor Sentiment and Return Comovements preferences of retail investors are due to liquidity concerns, risk aversion, or irrational sentiment. The results suggested that retail sentiment is not a simple artifact of the news events that are generally associated with changes in stock fundamentals such as the macroeconomic news or analyst earnings forecast revisions. Nevertheless, questions remain as to the drivers of retail demand for stocks. Indeed, the findings highlight the need to better understand the processes by which individual investors formulate their trading decisions, including an identification of the information sources they use in decision-making, and the nature of their belief updating process.

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APPENDICES

APPENDIX 1

LIST OF COMPANIES QUOTED AT N.S.E. AS AT 1st JANUARY 2006

MAIN MARKET INVESTMENT SEGMENT

AGRICULTURAL SECTOR

Uniliver Tea Kenya
Kakuzi.
Rea Vipingo Plantations
Sasini Tea & Coffee Ltd.

COMMERCIAL AND SERVICES SECTOR
AccessKenya Group
Car & General (K) Ltd
CMC Holdings ltd
Hutchings Blemer
Kenya airways ltd
Marshalls E A Limited
Nation Media Group
Standard Group ltd
Safaricom Limited - Listed in 2008
ScanGroup ltd
TPS Eastern Africa
Uchumi Supermarket - Suspended in 2006

FINANCE AND INVESTMENT SECTOR
Barclays bank ltd
C.F.C bank Ltd
Diamond Trust Bank Kenya
Equity Bank Ltd
Housing Finance Co.
Centum Investment Co. Ltd
Jubilee Holdings Ltd
Kenya Re Corporation - Listed in 2007
Kenya Commercial Bank
National Bank of Kenya Ltd
NIC Bank Ltd
Kenya commercial Bank Ltd
National Bank of Kenya Ltd
NIC Bank Ltd
Pan Africa Insurance Holding
Standard Chartered Bank

INDUSTRIAL AND ALLIED SECTOR

Athi River Mining
B.O.C Kenya Ltd - Suspended
Bamburi Current Ltd
Bat Kenya Ltd
Carbacid Berger Ltd - Suspended
Crown Berger
E.A. Cables Ltd
E.A. Portland cement
East African Breweries
Eveready E A
Kenya Oil Co. Ltd
Kenya Power & Lightning Ltd
KenGen Ltd.
Mumias Sugar Company
Olympia Capital Holdings Ltd
Sameer Africa Ltd
Total Kenya Ltd
Unga Group Ltd

ALTERNATIVE INVESTMENT MARKET SEGMENT

A. Bauman & Co.

City Trust Ltd

Eaagds Ltd

Express ltd

Williamson Tea Kenya

Kapchorua Tea Co.

Kenya Orchards Ltd

Limuru Tea Co. Ltd

APPENDIX II

LIST OF NSE LICENSED BROKERS

CFC Financial Services Ltd

Dyer and Blair Investment bank

Standard Investment Bank

Francis Drummond & Co Ltd

Suntra Investment Bank Ltd

Kestrel Capital (EA) Ltd

NIC Capital Limited (formerly Solid Investment Securities)

Discount Securities Ltd

Reliable Securities Limited

Bob Mathews Stockbrokers Limited

Crossfield Securities Ltd

Ngenye Kariuki Company Limited

African Alliance Securities Kenya Limited

Apex Africa Investment bank Limited

Faida Investment bank Limited

Ashbhu Securities Limited

Renaissance Capital