An investigation of the ''Herd Effect'' at the NSE during the Global Financial Crisis.

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Declaration

I, Ombai Paul Oluoch acknowledge that to the best of my knowledge and belief this research project is my original work and that it contains no material previously published or written by another person, except when due reference is made in the text of the proposal.

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Reg. No. D61/71962/2008 Date ………………………………………

This research project has been submitted with my approval as the university supervisor:

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DEDICATION

To three ladies in my life: Emily, Tamara and Susan for their love and understanding during my academic pursuit. May God bless you abundantly.

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First and foremost, I thank God for his grace, mercy and providence that privileged me to undertake this project.

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ABBREVIATIONS

ARM-Adjustable Rate Mortgages

CAPM-Capital Asset Pricing Model

CDO-Collateralized Debt Obligations

CSAD-Cross-Sectional Absolute Deviation

IPOs-Initial Public Offerings

MBS-Mortgage Backed Securities

NSE- Nairobi Stock Exchange

ABSTRACT

The NSE 20 share Index constituents generally witnessed decreased mean returns on the aftermath of the global credit crunch. As a result the NSE 20 share Index also registered a decline in returns in the post credit crunch period. The existence of such a phenomenon can in part be attributed to less than rational aspects of investor behavior and human judgment. Behavioral finance provided a fundamental theoretical framework for this study. The general dip in returns of stocks comprising the NSE 20 share index coupled with the decline in returns in the NSE 20 share index itself was a pointer to the existence of herding behavior. Subsequently, regression analysis undertaken indicated that the coefficient $\gamma 2$ was significant and negative in the period after the global financial crisis only, thus giving strong indication that herding behavior was prevalent at the NSE as a psychological response by stock investors to the global financial crisis.

CHAPTER 1.

1.0. Introduction

1.1. **Background to the study**

Traditional neoclassical finance theory assumes a single representative investor who rationally sets asset prices. This rationality in the beliefs of the representative investor implies that markets are efficient in the sense that actual asset values coincide with their fundamental values. Furthermore, the lack of investor heterogeneity in the neoclassical framework implies no trading. The famous examples of the models built on the concept of rational representative investor are portfolio theory by Markowitz (1952) the capital asset pricing model by Sharpe (1964) and Lintner (1965), and capital structure theory by Modigliani and Miller (1958). In the late 1970s, however, asymmetric information models were introduced to the finance literature. These models typically contain two types of investors: informed and uninformed investors (or noise traders). The early examples of these models are Grossman (1976) and Holmstrom (1979). Although asymmetric information models provided some challenge for traditional finance theory, the neoclassical model with its representative investor remained, in the language of Kuhn (1970), as the dominant paradigm.

The mid-80s witnessed the gradual rise of the new paradigm – behavioral finance – in this young branch of science. The theoretical and experimental premises of behavioral finance were already laid down in the psychology literature in the 70s by Kahneman and Tversky (1972, 1973, 1979). The most prominent early behavioral finance applications included the work of Shefrin and Statman (1985), who applied the prospect theory of Kahneman and Tversky to explain the so-called disposition effect. Behavioral finance is characterized by investors' limited ability to analyze information and systematic biases in their decision making. The leading theoretical models of behavioral finance such as Daniel, Hirshleifer and Subrahmanyam (1998) and Barberis, Shleifer and Vishny (1998) were built on the traditional premise of a representative investor.

The noise trading theory stems from the fact that investors with a short time horizon are influencing the stock prices more than the long term investors. Investors with no access to inside information, irrationally act on noise as if it were information that would give them an edge Thaler, (1993). Christie and Huang (1995), regarding irrational perspective of herding behavior, believe that investors are more likely to herd during market stress when they face the most uncertainty; the anxiety of making incorrect decisions and losing will disturb their ability to analyze rationally and investors will tend to follow market consensus because it helps reduce their anxiety through their conformity with others.

Further, Chang et al. (2000) show the study of herding behavior is important as share prices are substantially affected by market participants' investment behavior. It has been linked to some market inefficiency which cannot be explained by the Rational Asset Pricing Model, such as high market volatility and market destabilization. According to Andrew Oswald (2008) herds form when relative position matters. In the lead up to the global credit crunch, people in the U.S. paid extraordinarily high prices for houses, even though not justified by fundamentals, because they felt they were trailing behind the Joneses. Brokers sold unsound mortgages because they had to keep up with rival brokers. Money managers remunerated on their relative performance against other managers traded shares with the same motive.

Since Stock Market Returns are not fixed to insure returns and are subject to market risks, Hamilton, (1922) it is often the case that herding effects result in market losses that are significantly more when the risks unravel than their previous cumulative market returns based on these risky positions. According to Christie and Huang (1995), periods of considerable divergence in market returns arising from significant changes in stock prices are particularly informative because a “herd” is more likely to form under conditions of market stress, when individual investors tend to suppress their own beliefs and follow the market consensus. Further, Lux (1995), Lux and Marchesi (1999) argue that although price volatility in markets does not influence the number of traders, it transforms traders from fundamentalists to noise traders. That is, high volatility tends to make it difficult for traders to invest in assets independently and instead react according to herd behavior.

According to Chang, Cheng and Khorana (2000), when investing in a financial market where herding is present, a larger number of securities are needed to achieve the same level of diversification than in an otherwise normal market. Moreover, herding effect on stock price movements can lead to mispricing of securities since rational decision making is disturbed through the use of biased views of expected return and risk (Tan et al., 2008).

Schmeling (2007), while assessing the relationship between market sentiment and stock returns, also finds that the sentiment-return relation is at odds with standard finance theory, which predicts that stock prices reflect the discounted value of expected cash-flows and that irrationalities among market participants will be erased by arbitrageurs. Sentiment does not play any role in this classic framework of the stock investment decision process. The behavioral approach instead suggests that waves of irrational sentiment, i.e. times of overly optimistic or pessimistic expectations, can persist and affect asset prices for significant time spans.

In the stock market, performance is commonly assessed on the basis of comparisons with the average industry performance. Therefore, each manager cannot afford to neglect any high yield investment opportunity that other competitors seem to embrace, even if she believes that, on the long run, it could turn out badly. Herding provides a sense of safety in the numbers: how could everybody be so wrong? Evolutionary psychology and neuro-economics inform us that herding is one of the unavoidable consequences of our strongest cognitive ability, that is, imitation. Hence Herd behavior describes how individuals in a group can act together without planned direction. Individual investors join the crowd of others in a rush to get in or out of the market. Burke *et al.,* (2010) also showed that herd behavior may result from private information not publicly shared.

The collapse of a global housing bubble caused the values of securities tied to housing prices to plummet thereafter, damaging financial institutions globally and subsequently paving way for the global credit crunch. Questions regarding bank solvency, declines in credit availability, and damaged investor confidence had an impact on global stock markets, which suffered large losses during 2008. According to Calvo and Mendozza (1997), portfolio allocations become more sensitive to changes in perceived asset returns as market grow and thus herd behaviour is more likely to prevail and to produce larger capital flows in globalized security markets. Hence the events on the aftermath of the global credit crunch were likely to result in increased herd behaviour both at the global level and the domestic level with specific regard to the Nairobi Stock Exchange (NSE) which is Africa's fourth largest stock exchange in terms of trading volumes, and fifth in terms of market capitalization as a percentage of GDP.

A credit crunch (also known as a credit squeeze or credit crisis) is a reduction in the general availability of loans (or credit) or a sudden tightening of the conditions required to obtain a loan from the banks. A credit crunch generally involves a reduction in the availability of credit independent of a rise in official interest rates. In such situations, the relationship between credit availability and interest rates has implicitly changed, such that either credit becomes less available at any given official interest rate, or there ceases to be a clear relationship between interest rates and credit availability (i.e. credit rationing occurs). Many times, a credit crunch is accompanied by a flight to quality by lenders and investors, as they seek less risky investments, Graham (2008).

During the past years, the Kenyan equity market has been characterized by increasing volatility and fluctuation. More integrated financial markets are increasingly exposed to macroeconomic shocks, which affects markets on a global scale. From the investor’s point of view, the vulnerability of markets has led to increased uncertainty and unpredictability, as market conditions cannot always be judged with the help of standard financial measures and tools. Market participants have for long relied on the notion of efficient markets hypothesis and rational behavior when making investment decisions. The idea of fully rational investors who always maximize their utility and demonstrate perfect self control is becoming inadequate. Market inefficiency in the form of anomalies and irrational behavior has become frequent, Shiller (2000).

1.2. Statement of the Problem

The recent economic meltdown of major economies of the world exemplifies a situation, which includes both unpredictability and irrational reactions.

A “credit crunch,” “credit crisis”or“credit contraction” is a fairly common feature of free market economies. The US economy, for example, has experienced at least a minor financial crisis roughly every five or ten years since World War II. The crunch occurs when people with money to lend stop lending it out. This happens because they fear they will not be repaid or more accurately, they fear that default rates will expand significantly and lending will become an unprofitable activity. This unwillingness to lend can arise from many different causes. If the economy seems to be weakening, lenders recognize that marginal borrowers will be much more likely to default on their loans. For example, if housing prices are dropping, rather than rising, mortgage lenders realize that mortgagors will be less likely to make their payments.

Behavioral finance is new field in the finance theory and it seeks to understand and predict systematic financial market implications of psychological decision making Olsen, (1998). Approaches based on perfect predictions, completely flexible prices, and complete knowledge of investment decisions of other players in the market, are increasingly unrealistic in the global financial markets. By understanding the human behavior and psychological mechanisms involved in financial decision making, standard finance models may be improved to better reflect and explain the reality in today’s evolving markets such the Nairobi Stock Market. In this context, there was a phenomenal increase in the Nairobi Stock Exchange 20 share index in the period preceding the Global credit crunch. A sudden decline in the NSE 20 share index to a low of about 2176 from a high of 4879 was experienced in the period of credit crunch.

In regard to herd behavior, there appears to be two dominant schools of thought. There are those such as Christie and Huang (1995) that believe that investors are more likely to herd during market stress. Consequently, they assume that individuals are more likely to suppress their own beliefs and are inclined to follow market consensus during periods of large market volatility. In contrast, Chang, et al., (2000) argue that herding behavior does not only occur during market stress. They believe that there is some degree of herding behavior apparent in the market during normal market conditions and that they simply become more obvious and significant when the market experiences extreme upward or downward volatility.

Consequently, the episodes of high market volatility during the two year period to October 2009 when the equity market was at its worst, call into question whether this was a separate incident of herding behavior occasioned by a herd response to the global credit crunch in line with Christie and Huang (1995) point of view or whether instances of herd behavior existed prior to the 2008 global financial meltdown in the period when the market was not victim to powerful external forces. Economou et al (2010) examined the possible asymmetric effects of herding with respect to trading volume and market volatility in four Mediterranean stock markets (Greek, Italian, Portuguese and Spanish). They found evidence of herding during the global financial crisis of 2008 only for the Portuguese stock market and evidence of anti-herding for the Spanish and the Italian stock markets. Waweru, et al. (2008), found that fundamental analysis was the most widely used decision making model at the NSE.

This is consistent with traditional finance theory, which stresses the need for market information so as to promote market efficiency. However, the findings show that behavioral factors do influence the investment decision making process.

Whereas the effects of behavioral factors have been studied prior to the global financial crisis both at the global and local levels much less is known about the effect of behavioral factors on the Nairobi Stock Exchange on the aftermath of the global credit crunch. Hence, the study seeks to fill this gap by investigating the extent to which herd effects influenced stock market returns at the Nairobi Stock Exchange during the global financial crisis.

1.3. Objectives of the study

The purpose of this proposed research is to investigate herd effects at the NSE during the global financial crisis.

1.4. Importance of the study

To *investors*, they will be able to make informed decisions at times of unpredictable economic situations besides dependence on fundamental stock price estimations as a basis of their decisions. The investor decision making would be made on abroad spectra of market information.

To *government*, in her efforts to stabilize security market through participation and policy making, the government will be able to make accurate assumptions about market reaction to her actions.

To *academicians* and *scholars*, it will fill the knowledge gap of behavioral understanding at times of unpredictable economic conditions at the local security market. It will also open a new field of research and understanding of behavioral influences on the local security market.

Market condition, the study is an improved step towards achieving market efficiency in the local security market. Market participants will acquire a better understanding of behavioral factors that influence investments activities at the Nairobi Stock Exchange.

CHAPTER 2

Literature Review

2.1. Introduction

The chapter outlines the overall literature review used in this study. This includes the comparisons between the various finance theories including behavioral finance. The chapter also includes an overview of the global credit crunch and contagion. It finally concludes with empirical studies and literature review summaries.

2.2. Standard finance

Standard finance is a body of knowledge built on the pillars of arbitrage principles of Miller and Modigliani, the portfolio principles of Markowitz, the capital asset pricing theory of Sharpe, Litner and Black and the option pricing theory of Black, Scholes and Merton Statman, (1999). These approaches consider markets to be efficient and are highly analytical and normative.

Modern financial economic theory are based on the assumption that the representative market actor in the economy is rational in two ways; the market actor makes decisions according to the axioms of the expected utility theory and makes unbiased forecasts about the future. Assets prices are set by rational investors and consequently rationality based market equilibrium is achieved Shiller (2000).

2.2.1. The efficient Market Hypothesis

The efficient market hypothesis is based on the notion that people behave rationally, maximize the expected utility accurately and process all available information Shiller, (1998). This implies that financial assets are priced rationally due to the fact that information is in public knowledge. Stock prices represents random walks through time, the price changes are unpredictable since they occur only in response to genuinely new information, which by the very fact that it is new, is unpredictable Shiller, (2000). Because all information is contained in stock prices, it is impossible to make above average profits and beat the market over time without taking excessive risk.

2.2.2. Stock Market Returns and Investment Decisions

Stock Market Returns are the returns that the investors generate out of the stock market. This return could be in the form of profit through or in the form of dividends given by the company to its shareholders from time-to-time. Stock Market Returns are not fixed ensured returns and are subject to market risks, Hamilton, (1922).

Investment decisions are made by investors and investment managers. Investors commonly perform investment analysis by making use of fundamental analysis, technical analysis and gut feel. Schmeling (2007), while assessing the relationship between market sentiment and stock returns, finds that the sentiment-return relation is at odds with standard finance theory, which predicts that stock prices reflect the discounted value of expected cash-flows and that irrationalities among market participants will be erased by arbitrageurs. Sentiment does not play any role in this classic framework of the stock investment decision process. On the other hand, Lux

(1995), Lux and Marchesi (1999) argue that although price volatility in markets does not influence the number of traders, it transforms traders from fundamentalists to noise traders. That is, high volatility tends to make it difficult for traders to invest in assets independently and instead react according to herd behavior.

2.2.3. Behavioral finance

This is a new paradigm which seeks to supplement the standard finance theories by introducing behavioral aspects to the decision making process. In sharp contrast to Markowitz and Sharp approach, behavioral finance deals with individuals and ways of gathering and using information. Behavioral finance seeks to understand and predict systematic financial market implications of psychological processes. In addition, it focuses on the application of psychological and economic principles for the improvement of financial decision making, Olsen, (1998).

Market efficiency, in the sense that market prices reflect fundamental market characteristics and that excess market returns on the average are leveled out in the long run, has been challenged by behavioral finance. A number of studies pointing at the market anomalies have been done to show abnormal price movements in connections with initial public offerings (IPOs), mergers, stock splits and spin offs. Investors have been shown not to react logically to new information but to be overconfident and to alter their choices when given superficial changes in the presentation of investment information Olsen, (1998).These anomalies suggest that the underlying principles of rational behavior underlying the efficient market hypothesis are not entirely correct and there is need to look, as well, at the other models of human behavior, as have been studied in other social sciences, Shiller, (1998).

2.3. Heuristics

This refers to the process by which people find things out for themselves through trial and error. The trial and error often leads people to develop rules of thumb but this process often leads to errors, Shefrin, (2000). Heuristics can also be defined as use of experience and practical efforts to answer questions or to improve performance.

Heuristics may help to explain why the market sometimes acts in an irrational manner, which is opposite to the model of perfectly informed markets. The interpretation of new information may require heuristic decision making rules, which might later have to be reconsidered.

Herd behavior is a form of heuristic where individuals are led to conform to the majority of individuals, present in the decision making environment, by following their decisions. However, herd behavior, as with other heuristics, may lead people astray when they follow for example a market trend. Overconfidence can also be traced to the representativeness heuristic, Kahneman and Tvesky, (1974) a tendency for people to try to categorize events typical or representative of a well known class.

2.3.1. Herd Behavior

Part of the reason people's judgments' are similar at similar times is that they are reacting to the same information. The social influence has immense power on individual judgments. When people are confronted with judgment of a large group of people, they tend to change their 'wrong' answers. They simply think that all the other people could not be wrong. In every day living, we have learned that when a large group of people are unanimous in its judgments they are certainly right, Shiller, (2000).

Herd behavior may be the most generally recognized observation on financial markets in a psychological context. The noise trading theory stems from the fact that investors with a short time horizon are influencing the stock prices more than the long term investors are. Investors with no access to inside information, irrationally act on noise as if it were information that would give them an edge, Thaler, (1993).

People choose not to waste their time and effort in exercising their judgment about the market and thus choosing not to waste their time and effort in exercising their judgment about the market and thus choosing not to exert any independent impact on the market, Shiller, (2000).

Christie and Huang (1995), regarding irrational perspective of herding behavior, believe that investors are more likely to herd during market stress. The logic behind this is that human beings always seek for certainty and conformity. When they face uncertainty, the anxiety of making incorrect decisions and losing will disturb their ability to analyze rationally and investors will tend to follow market consensus because it helps reduce their anxiety through their conformity with others. Consequently, they assume that individuals are more likely to suppress their own beliefs and are inclined to follow market consensus during periods of large market volatility. In contrast, Chang, et al., (2000) argue that herding behavior does not only occur during market stress. They believe that there is some degree of herding behavior apparent in the market during normal market conditions and that they simply become more obvious and significant when the market experiences extreme upward or downward volatility. Further, Chang et al. (2000) show the study of herding behavior is important as share prices are substantially affected by market participants' investment behavior. It has been linked to some market inefficiency which cannot be explained by the Rational Asset Pricing Model, such as high market volatility and market destabilization.

Fromlet (2001) argues that the herd behavior may be recognized on financial markets in a psychological context. Herd behavior can play a role in the generation of speculative bubbles as there is a tendency to observe ‘‘winners’’ very closely, particularly when good performance repeats itself a couple of times. He identified a plausibility to make distinction between voluntary and enforced behavior.

Shiller and Pound (1986), observes that another important variable to herding is word of the mouth. People generally trust friends, relatives and working colleagues more than they do the media. The conventional media have a profound capability of spreading ideas but their ability to generate active behavior is still limited to talking to other people. It is therefore likely that news about a buying opportunity will rapidly spread.

Nofsinger and Sias (1999) found that the institutional investors positive-feedback trade more than the individual investors and that institutional herding impacted prices more than herding by individual investors.

Herding may be either rational or irrational. Bikchandani and Sharma (2001) classify rational herding further into three subcategories: informational-based herding, reputation-based herding, and compensation-based herding. One of the first informational-based herding models was built by Banerjee (1992). He analyzed a sequential decision-making model in which each decision-maker takes into account the decisions made by the previous investors before taking her own. He finds a unique Nash equilibrium that is characterized by fairly extensive herding. In various circumstances, depending on the decisions of the first few agents, a decision-maker located later in the sequence rejects her private information and decides to mimic others' actions. In this case, the decision maker joins a so-called informational cascade, in which accumulation of information stops altogether.

Avery and Zemsky (1998) in contrast to earlier models, asserts that the advantage of this model is that, it allows flexible prices and potential asset pricing effects of herding. The authors consider multiple uncertainty dimensions and their effects on information cascades, herding and price dynamics. The first dimension of uncertainty is value uncertainty, which refers to uncertainty about the fixed fundamental value of the stock. This is the dimension of uncertainty that most of the traditional models of herding incorporate. With this single dimension of uncertainty, informational cascades and herding do not occur. Due to a steady flow of information, prices are always fully revealing and converge on the fundamental values. Stock prices, therefore, reflect all available information.

Traditional herding models, in contrast, assume fixed prices, which, of course, do not reveal any information, resulting in herding. The second dimension of uncertainty in the model by Avery and Zemsky (1998) is event uncertainty. In event uncertainty, the market is uncertain whether an information-revealing event has taken place by changing the initial expected value of an asset. It is reasonable to assume that some shocks to a fundamental value of an asset are not initially publicly known. The market may, for example, speculate whether there will be major corporate restructuring events, such as mergers and acquisitions coming up.

Avery and Zemsky (1998) argued that for the market as a whole, some information events have a high proportion of well-informed investors, while others have only few. If the market participants are uncertain *ex ante* about a mixture of investors, they face a third dimension of uncertainty called composition uncertainty.

Composition uncertainty complicates the learning process from trading history, particularly in the presence of herding. A sequence of identical trading decisions arises naturally in a market with well-informed traders, because the investors tend to have the same private signal. On the other hand, the same sequence of trading decisions could be attributable to herding of preceding traders. It could be relatively difficult for market participants to distinguish between these two alternatives. Avery and Zemsky (1998) show that composition uncertainty induced herding may create bubbles in asset prices.

2.3.2. Overconfidence and Over and Underreaction

People tend to exaggerate their talents and underestimate the likelihood of bad outcomes over which they have no control. The combination of overconfidence and optimism causes people to overestimate the reliability of their knowledge, underestimate risks and exaggerate their ability to control events, which leads to excessive trading volumes. The greater confidence a person has in himself, the more risk there is overconfidence. Ross (1987) argues that much overconfidence is related to a broader difficulty in making adequate allowance for the uncertainty in one's own view points. A consequence of overconfidence is that people tend to see patterns in data that is truly random, to feel confident, for example, that a series which is in fact a random walk is not a random walk.

The under reaction evidence shows that over horizons of one to twelve months, security prices under react to news. As a consequence, news is slowly incorporated into prices, which tend to exhibit positive autocorrelations over these horizons. The over reaction evidence shows that over longer horizons of three to five years, security prices over react to consistent patterns of news pointing in the same direction. That is, securities that have had a long record of good news tend to become overpriced and have low average returns afterwards.

Conservatism refers to a phenomenon where people mistrust new data and give too much weight to prior probabilities of events in a given situation Edwards, (1968).
Many investors feel that they do have speculative reasons to trade and apparently that this must have to do with a tendency for each individual to have beliefs that he or she perceives better than others' beliefs Shiller, (1998).

2.3.3. Anchoring

Anchoring refers to the decision making process where quantitative assessments are required and these assessments may be influenced by suggestions. Anchoring describes how individuals tend to focus on recent behavior and gives less weight to longer time trends. The tendency of investors to use anchor enforces the similarity of stock prices from one day to the next Shiller, (2000). Other possible anchors are remembered historical prices and the tendency of the past prices to serve as anchors may explain the observed tendency for trends in individual stock prices to be reversed. Gruen and Gizycki (1993) used anchoring to explain the widely observed anomaly that forward discounts do not properly explain subsequent exchange rate movements. As long as past prices are taken as a suggestion of new prices, the new prices will tend to be close to the past prices.

2.4. The prospect Theory

The utility theory offers a representation of truly rational behavior under certainty. According to the expected utility theory, investors are risk averse. Risk aversion is equivalent to the concavity of the utility function. According to prospect theory, individual have preference to certain outcomes. People behave as if they regard extremely improbable events as impossible and extremely probable events as certain Kahneman and Tvesky, (1979).

Kahneman and Tvesky (1979) value function differs from the expected utility function due to reference point, which is determined by the subjective impression of individuals. According to the conventional expected utility theory, the utility function is concave downwards for all levels of wealth. On the contrary, according to value function the slope of the utility function is upward sloping for wealth levels under reference point and downward sloping for wealth levels after reference point. Individuals determine the reference point as a point of comparison.

Because the reference point in the value function always moves with wealth to stay at the perceived current level of utility, investors will always behave in a risk adverse manner even when small amounts of wealth are in question. Subsequently, they will always prefer taking a risk when confronted with losses. This phenomenon is loss aversion.

2.4.1. Loss aversion

The value function shows the sharp asymmetry between the values that people put on gains and on losses. Empirical tests indicates that losses are weighted about twice as heavily as gains i.e. losing $1 is about twice as painful as the pleasure of gaining $1 Kahneman and Tvesky, (1991). Investors will tend to hold to losing positions in the hope that prices will eventually recover.

Samuelson (1963) asked a colleague whether he would accept a bet that paid him $200 with a probability of 0.5 and lost him $100 with a probability of 0.5. The colleague said he would not take the bet, but that we would take a hundred of them. With 100 such bets, his expected total winnings are $5000 and he has virtually no chance of losing money. The failure to accept several such bets when one considers them individually referred to as myopic loss aversion by Benartzi and Thaler (1995). Myopic loss aversion is the combination of a greater sensitivity to losses than to gains and a tendency to evaluate outcome frequently.

Loss aversion can help to explain the tendency of investors to hold on to loss making stocks while selling winning stocks too early. Shefrin and Statman (1985) called this occurrence of “selling winners too early and riding losers too long’’ as the disposition effect. When investors view stocks on an individual basis, then risk aversion in gains will cause them to sell too quickly into rising stock prices, thereby depressing prices relative to the fundamentals.

2.4.2. Mental Accounting

This describes the tendency of people to place particular events into different mental accounts based on superficial attributes Shiller, (1998). It involves decision makers separating different types of gambles they face into different accounts.

Mental accounting can serve to explain why investors are likely to refrain from readjusting his or her reference point for a stock Shefrin and Statman, (1985). When a stock is purchased, a new mental account for the particular stock is opened and the reference point is the purchase price. When another stock is purchased, a separate account is created. A normative frame recognizes that there is no substantive difference between the returns distributions of the two stocks, only a difference in names.

Shefrin and Statman (1994) argues that private investors think naturally in terms of having a ‘safe’ part of their portfolio that is protected from the downside risk and a risky part that is designed for getting rich.

2.4.3. Self control

Mental accounting and framing may also be used to mitigate self control problems, for example, setting up special accounts that are considered off limits to spending urges Thaler and Shefrin, (1981). Self control is also exhibited in the dividend puzzle. Old investors, who finance their living expenditures from their portfolios, worry about spending their wealth too quickly, thereby outliving their assets. They fear a loss of self control, where the urge for immediate gratification can lead them to overspend Shefrin, (2000).

2.4.4. Regret

There is the human tendency to feel pain at having made errors, even small errors. It is a feeling of ex-post remorse about a decision that led to a bad outcome. If one wishes to avoid the pain of regret, one may alter ones behavior in ways that would in some cases be irrational. The theory may be interpreted as implying that investors avoid selling stocks that have gone down in order not to finalize the error they make and in that way avoid feeling regret. They sell stocks that have gone up in order not to feel the regret of failing to do so before the stock later fell.

Cognitive dissonance is mental conflict that people experience when they are presented with the evidence that their beliefs or assumptions are wrong. Cognitive dissonance may be classified as the sort of pain of regret, regret over mistaken beliefs. Festinger’s theory (1957) asserts that there is a tendency for people to take actions that reduce cognitive dissonance that would normally be considered rational, such as avoiding new information or developing contorted arguments to maintain beliefs or assumptions.

2.5. Credit crunch

The collapse of a global housing bubble caused the values of securities tied to housing prices to plummet thereafter, damaging financial institutions globally. Questions regarding bank solvency, declines in credit availability, and damaged investor confidence had an impact on global stock markets, which suffered large losses during 2008. Governments and central banks responded with unprecedented fiscal stimulus, monetary policy expansion, and institutional bailouts, Ben Bernanke (1983). An increase in loan incentives such as easy initial terms and a long-term trend of rising housing prices had encouraged borrowers to assume difficult mortgages in the belief they would be able to quickly refinance at more favorable terms. However, once interest rates began to rise and housing prices started to drop moderately in 2006–2007 in many parts of the U.S., refinancing became more difficult. Defaults and foreclosure activity increased dramatically as easy initial terms expired, home prices failed to go up as anticipated, and adjustable rate mortgages (ARM) interest rates reset higher.

Falling prices also resulted in homes worth less than the mortgage loan, providing a financial incentive to enter foreclosure. While the housing and credit bubbles built, a series of factors caused the financial system to both expand and become increasingly fragile. Policymakers did not recognize the increasingly important role played by financial institutions such as investment banks and hedge funds, also known as the shadow banking system. Some experts believe these institutions had become as important as commercial (depository) banks in providing credit to the U.S. economy, but they were not subject to the same regulations. These institutions as well as certain regulated banks had also assumed significant debt burdens while providing the loans described above and did not have a financial cushion sufficient to absorb large loan defaults or MBS losses. These losses impacted the ability of financial institutions to lend, slowing economic activity. Concerns regarding the stability of key financial institutions drove central banks to provide funds to encourage lending and restore faith in the commercial paper markets, which are integral to funding business operations. Governments also bailed out key financial institutions and implemented economic stimulus programs, assuming significant additional financial commitments, Ben Bernanke (1983).

By approximately 2003, the supply of mortgages originated at traditional lending standards had been exhausted. However, continued strong demand for MBS and CDO began to drive down lending standards, as long as mortgages could still be sold along the supply chain. Eventually, this speculative bubble proved unsustainable.

2.5.1. Predatory lending

Flannery and Samolyk (2005), defines predatory lending as the practice of unscrupulous lenders, to enter into "unsafe" or "unsound" secured loans for inappropriate purposes. A classic bait-and-switch method was used by Countrywide, advertising low interest rates for home refinancing. Such loans were written into extensively detailed contracts, and swapped for more expensive loan products on the day of closing. This created negative amortization, which the credit consumer might not notice until long after the loan transaction had been consummated.

2.5.2. Deregulation

Kroszner and Strahan (1999), critics have argued that the regulatory framework did not keep pace with financial innovation, such as the increasing importance of the shadow banking system, derivatives and off-balance sheet financing.

Regulators and accounting standard-setters allowed depository banks such as Citigroup to move significant amounts of assets and liabilities off-balance sheet into complex legal entities called structured investment vehicles, masking the weakness of the capital base of the firm or degree of leverage or risk taken.

2.5.3. Financial innovation and complexity

Dynan and Sichel (2006), defines financial innovation as the ongoing development of financial products designed to achieve particular client objectives, such as offsetting a particular risk exposure (such as the default of a borrower) or to assist with obtaining financing. Certain financial innovation may also have the effect of circumventing regulations, such as off-balance sheet financing that affects the leverage or capital cushion reported by major banks.

2.5.4. Incorrect pricing of risk

The pricing of risk refers to the incremental compensation required by investors for taking on additional risk, which may be measured by interest rates or fees. For a variety of reasons, market participants did not accurately measure the risk inherent with financial innovation such as MBS and CDO's or understand its impact on the overall stability of the financial system, Vasicek, (1977).

2.5.5. Commodity bubble

Summers, (1986), argues that commodity price bubble was created following the collapse in the housing bubble. An increase in oil prices tends to divert a larger share of consumer spending into gasoline, which creates downward pressure on economic growth in oil importing countries, as wealth flows to oil-producing states.

2.5.6. Global contagion

The crisis rapidly developed and spread into a global economic shock, resulting in a number of European bank failures, declines in various stock indexes, and large reductions in the market value of equities and commodities, (Karolyi 2003).

Derivatives such as credit default swaps also increased the linkage between large financial institutions.

2.6. Empirical Studies

Recent empirical studies show that the disposition effect can generate momentum in stock returns Grinblatt and Han, 2005; Shumway and Wu, (2007), induce post-earnings announcement drift Frazzini, (2006), and affect trading volume e.g., Statman et al., (2006). Li and Yang (2008) investigated the US stock markets for the disposition effect; whereby investors have a greater tendency to sell assets that have risen in value since purchase than those that have fallen. This effect has been observed both in experimental markets and in many real markets. They showed that, in a full equilibrium setting, under Tversky and Kahneman (1992) preference parameters, prospect theory predicts a disposition effect, generating momentum in the cross-section of stock returns and leading to more trading in rising than in falling markets.

On the other hand, Yeyati, et al (2007) find that market downturns are positively correlated with volume traded and negatively correlated with trading cost. Second, they highlight a strong link between crisis episodes and liquidity measures. Specifically, we find no evidence of market "paralysis" at the beginning of crisis (secondary market activity does not appear to break down): if anything, trading activity increases as prices fall abruptly, to decline only later as crisis progress. However, the cost of making transactions increases sharply; prices react more strongly to each dollar transacted (pushing the Amihud illiquidity measure up) and bid-ask spreads widen. Thus, whereas trading activity moves inversely to trading costs during tranquil times (and across securities), both increase during crisis.

These results are consistent with many of the insights proposed by the analytical literature including, most notably, the view that crisis are associated with portfolio reallocation among heterogeneous agents that do not fully anticipate crisis (hence, volume increases *during* market downturns, rather than before) and with fire sales by liquidity-constraint investors paying a hefty premium to bring in outside capital.

In addition they also posit that the liquidity risk of a stock (e.g., as captured by the Amihud ratio) tends to increase at times of systemic illiquidity (e.g., as capture by EMP crisis), a pattern that should increase the stock volatility and be ultimately reflected in its risk-adjusted price.

Economou et al (2010) examined the possible asymmetric effects of herding with respect to trading volume and market volatility in four Mediterranean stock markets (Greek, Italian, Portuguese and Spanish). They found evidence of herding during the global financial crisis of 2008 only for the Portuguese stock market and evidence of anti-herding for the Spanish and the Italian stock markets.

Werah (2006), argued that the behavior of investors at the NSE were to some extent irrational when considered from the irrationality of the investors in their disregard of fundamental estimations as a result of herd behavior, regret aversion, overconfidence and anchoring.

Waweru, et al. (2008), found that fundamental analysis was the most widely used decision making model at the NSE. This is consistent with traditional finance theory, which stresses the need for market information so as to promote market efficiency. However, the findings show that behavioral factors do influence the investment decision making process. Heuristic processes and prospect theory were evident, with heuristics strongly dominating prospect theory in explaining the behavior of institutional investors operating at the NSE. Availability bias, anchoring and gamblers' fallacy were most prominent.

2.7. Summary of Literature Review

In respect of Waweru, et al (2008), findings were that fundamental analysis was the most widely used decision making model at the NSE. Evidence on the aftermath of the global financial crisis, such as that of Economou et al (2010), appears to suggest that behavioral factors were a major force in shaping global market outcomes.

An article by Finesol, (2009), a Kenyan stock research firm, *The ''beta pill'' fallacy*, indicates that prior to the global credit crunch the market had generally been overpriced and it is this excess liquidity phenomenon that tended to hold the general price level way above fundamentals and as a result it fomented a general price bubble, which was burst by three subsequent events. The first was the Safaricom IPO refund bungle in which there was a delay in refunding investors IPO moneys; second, the withdrawal of foreigners prompted by the global credit crunch led to share price decline as they dumped huge quantities of shares onto the NSE and finally the loss of market confidence, mainly by retail investors, arising from uncertainty in stock brokerage operations. The withdrawal by foreign investors is a pointer to the existence of institutional herding behavior as most of the foreign investor participation is largely institutional while the retail investor withdrawal appears to have been informed by herd behavior as the domino effect of collapsing brokerage houses kicked. Consequently, the study seeks to find out the extent to which herd behavior influenced stock market returns on the aftermath of the global credit crunch.

CHAPTER 3

Research Methodology

3.1 Introduction

The chapter outlines the overall methodology used in this study. This includes the research design, population of the study, sample size, data collection methods and data analysis and presentation.

3.2 Research Design

The study used empirical cross-sectional design in which data was gathered just once in a single point in time over a period of time in order to answer a research question. The cross-sectional design was appropriate since it exhibited some type of market consensus with regard to mean return and the data that was readily available from the NSE for disparity analysis.

3.3 Population

The population of the study consisted of all 49 companies quoted at the NSE. This was used because of the ease of availability of the relevant information on the quoted companies.

3.4 Sample Size

The sample consisted of the firms quoted the twenty companies comprising the NSE 20 share Index between October 2005 and October 2009; two years before the start of the global financial crisis and two years after. Firms comprising the NSE 20 share index accounted for at least 80% of the total market liquidity and as a result they provided a stable benchmark for the analysis of herd behavior given that four in five investors were likely to buy into those firms.

3.5 Data collection Method

In this study Secondary data was used. The data comprised the stocks that made up the NSE index from October 2005 to October 2009. The NSE 20 share Index constituted the market portfolio. This period took into account market volatility two years prior to the global financial turmoil when the market was not under the influence of global externalities and the subsequent two years to October 2009 in which the market operated in the shadow of the global credit crunch.

3.6. Data Analysis

Chang, Cheng, and Khorana (2000) proposed the first nonlinear model framework for testing herding. Their empirical model is built on the intuition that under CAPM assumptions, rational asset pricing models predict that the equity return dispersions are not only an increasing function of the market return but also that the relation is linear. In the presence of herding, the relation can become nonlinearly increasing or even decreasing. Chang, Cheng and Khorana (2000) proposed an alternative approach to the one suggested by Christie and Huang (1995), using the entire distribution of market returns, cross-sectional absolute deviation (CSAD), as in the following equation:

$$\text{CSADt} = a + \gamma_1 \left| \text{Rm,t} \right| + \gamma_2 \, \text{Rm,t}^2 + \varepsilon$$

$$CSAD\ t = \frac{\Sigma \left| \text{Ri,t - Rm,t}^2 \right|}{N}$$

Where,

$R_{i,t}$ = observed monthly stock return of a firm i that comprises the NSE-20 Index at time t,

$R_{m,t}$ = cross-sectional monthly average return of the NSE 20 share index at time t, N = number of stocks in the NSE 20 share index; N is 20.

A statistically significant negative coefficient $\gamma 2$ implies the presence of herd behavior. This is likely to increase the correlation among individual asset returns, and the dispersion among asset returns will either increase at a decreasing rate or decrease in the case of severe herding. If market participants are more likely to herd during periods of large price movements, then there should be a less than proportional increase (or decrease) in the CSAD measure. In the absence of herding, the relationship is linear and increasing, that is the dispersion increases proportionately with the increasing returns of the market, Economu *et al.*, (2010). In testing significance of the coefficients, the t-test was used.

Consequently, regression analysis was undertaken to derive the coefficient $\gamma 2$ in both the two year period before the global financial crisis and two years after. If coefficient $\gamma 2$ was found to be significant and negative in the period after the global financial crisis only, then this would give strong indication that there was prevalent herding behavior at the NSE occasioned by the global financial crisis.

CHAPTER 4

Data Analysis and Findings

4.1 Descriptive Statistics

-	MEAN		STDEV	
	Before	After	Before	After
REA	-0.01%	-1.48%	7.04%	10.74%
SASN	5.97%	-2.36%	46.68%	14.63%
CMC	2.44%	-1.00%	24.22%	12.27%
KQ	-0.55%	-2.70%	6.48%	13.67%
NMG	2.39%	-2.52%	11.00%	13.61%
SCOM*	0.61%	-1.78%	10.34%	13.63%
BBK	-2.26%	-1.42%	16.03%	10.48%
ICDC	4.59%	-2.14%	33.08%	17.35%
CFC	12.41%	-3.18%	66.38%	11.77%
DTB	5.76%	-0.23%	8.50%	11.48%
KCB	1.01%	-0.24%	21.79%	13.01%
NIC	6.47%	-4.93%	13.20%	16.86%
SCBK	1.61%	-0.93%	7.07%	5.42%
ARM	4.98%	0.69%	10.50%	8.79%
BAMB	1.77%	-0.42%	5.70%	7.01%
BAT	-1.46%	1.11%	5.02%	5.03%
CABL	1.67%	-2.11%	28.77%	12.62%
EABL	0.74%	0.70%	4.07%	11.98%
MSC	1.31%	-4.50%	11.97%	21.46%
XPRS	2.94%	-3.36%	12.22%	7.19%
NSE 20 SHARE INDEX	1.33%	-1.54%	4.51%	9.26%

*Safaricom (SCOM) replaced TPS Serena in the index in July 2008

The study concentrated on the constituents of the NSE 20 share Index that were there initially in the 2005 – 2006 period. Safaricom had to be incorporated since upon its listing, in June 2008, the firm accounted for 15% to 25% of total market capitalization. All the 20 share Index constituents, with the exception of BAT and Barclays (BBK) witnessed decreased mean returns on the aftermath of the global credit crunch. As a result the NSE 20 share index also registered a decline in returns in the post credit crunch period.

Further, the standard deviation in monthly returns for most of the NSE-20 stocks was generally higher before the global financial crisis trigger implying that the market had generally been rising at a considerable pace. On the other hand, the post financial crisis period saw increased volatility in the NSE 20 share Index as the market corrected downwards in response to the global events.

4.2 Regression Analysis

	Before	After
Intercept	0.022169	-0.00061
	(1.649378)*	(-0.14397)*
γ (R mt)	1.506608	0.896349
	(4.814176)*	(20.83039)*
γ2 (R mt^2)	-8.53887	-1.23555
	(-1.794161)	(-3.98391)*
R^2	0.551643	0.968829

*t-statistic (in parenthesis) is significant at the 5% level

The regression results indicate that the regression coefficient γ was significant both the regressions on monthly market returns before and after the inception of the global financial crisis. On the other hand, the regression coefficient $\gamma 2$ was significant and negative for the monthly market returns regression after but not before the inception of the global financial crisis.

In the monthly returns regression before the global financial crisis, the independent variables account for 55.16% of the explained variance in monthly returns while the post crisis regression on monthly returns accounts for 96.88% of the explained variance.

4.3 Summary of Findings

The 20 share Index constituents generally witnessed decreased mean returns on the aftermath of the global credit crunch. As a result the NSE 20 share Index also registered a decline in returns in the post credit crunch period. In addition, the regression coefficient $\gamma 2$ was significant and negative for the monthly market returns regression after but not before the inception of the global financial crisis.

4.4 Implications of Findings

The general dip in returns of stocks comprising the NSE 20 share index coupled with the decline in returns in the NSE 20 share index itself was a pointer to the existence of herding behavior. Subsequently, regression analysis undertaken indicated that the coefficient $\gamma 2$ was significant and negative in the period after the global financial crisis only, thus giving strong indication that herding behavior was prevalent at the NSE as a psychological response by stock investors to the global financial crisis. This findings are in line with Werah (2006), who argued that the behavior of investors at the NSE were to some extent irrational when considered from the irrationality of the investors in their disregard of fundamental estimations as a result of herd behavior, regret aversion, overconfidence and anchoring.

CHAPTER FIVE

5.0 CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The widening standard deviation and positive mean monthly returns for most of the NSE-20 stocks implied that the market had generally been rising at a considerable pace before just before the global credit crunch set in and subsequently the standard deviation narrowed as monthly mean returns turned negative indicating downward price reversal on the aftermath of the global financial crisis.

This trend was confirmed by the regression analysis undertaken thereafter which indicated that the coefficient $\gamma 2$ was significant and negative in the period after the global financial crisis only thus giving strong leading the study to conclude that there was strong evidence of herding behaviour at the NSE in the subsequent period after the inception of the global credit crunch. This findings appear to contradict those of Waweru, et al (2008), who found that fundamental analysis was the most widely used decision making model at the NSE.

Given that the findings of the study demonstrate that herding behaviour did not exist at the NSE prior to the global credit crunch but rather it arose in response to the financial crisis, this findings corroborate those of Christie and Huang (1995) that believe that investors are more likely to herd during market stress and contradict the argument of Chang, et al., (2000) who are of the view that herding behavior does not only occur during market stress.

5.2 Policy Recommendations

The strong evidence of herding behaviour implies that the NSE was impacted by the global contagion as foreign investors aggressively liquidated their stockholdings to cover their liquidity deficits in their home markets; as a result of which the general stock price levels declined substantially. In view of this, the management of the NSE should consider ways of insulating the market from effects of global contagion that might lead to irrational investor behaviour and generally dampen market valuations.

5.3 Limitations

The study focused on the period 2006 to 2009, which was laden with instances of changes in the NSE 20 share index constituents for various reasons. In this period Uchumi was suspended from the trading after it was declared insolvent while BOC was also suspended pending its proposed takeover of Carbacid. The listing of Safaricom saw it replace TPS Serena. Such events may have to certain extent unduly altered the monthly market returns posted by the NSE 20 share index given that it is price weighted.

5.4 Recommendations for further studies

Given the possibility that the fluctuations in the NSE 20 share index may result in undue alteration of monthly market returns, future studies should be carried out using returns based on an all share index such as the NASI index that prices the entire market rather than a portion of the stocks or even apply the AIG-27 Index which is value weighted thus minimizing negative price effects when stocks are replaced in the index.

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Appendix I: Regression Analysis on Market Returns before the Global Financial Crisis

Regression Statistics	
Multiple R	0.742727
R^2	0.551643
Adjusted R^2	0.508942
Standard Error	0.052349
Observations	24.000000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2.000000	0.070807	0.035404	12.918835	0.000220
Residual	21.000000	0.057550	0.002740		
Total	23.000000	0.128357			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	0.022169	0.013441	1.649378	0.113950	-0.005783	0.050120
R mt	1.506608	0.312952	4.814176	0.000093	0.855788	2.157428
R mt2	-8.538870	4.759255	-1.794161	0.087199	-18.436283	1.358542

Appendix II: Regression Analysis on Market Returns after the Global Financial Crisis

Regression Statistics	
Multiple R	0.984291
R^2	0.968829
Adjusted R^2	0.965860
Standard Error	0.017115
Observations	24.000000

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2.000000	0.191194	0.095597	326.349382	0.000000
Residual	21.000000	0.006152	0.000293		
Total	23.000000	0.197346			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.000610	0.004240	-0.143972	0.886896	-0.009427	0.008206
R mt	0.896349	0.043031	20.830392	0.000000	0.806862	0.985837
R mt2	-1.235549	0.310134	-3.983913	0.000675	-1.880508	-0.590589

Appendix III: NSE 20 share Index Constituents Market Returns before the Global Financial crisi

	REA	SASN	CMC	KQ	NMG	SCOM	BBK	ICDC	CFC	DTB
Oct	6.0%	0.0%	3.6%	-0.6%	3.9%	16.2%	4.2%	2.9%	10.1%	0.9%

Nov	-4.5%	0.8%	0.5%	-3.6%	1.6%	-9.5%	-1.6%	0.0%	-2.0%	2.7%
Dec	-1.2%	-17.1%	8.0%	1.2%	0.5%	0.0%	6.9%	1.4%	0.0%	12.2%
06 Jan	-1.2%	8.4%	-2.8%	11.6%	4.2%	0.0%	4.6%	2.8%	0.0%	22.5%
Feb	-4.9%	-4.3%	-4.8%	2.2%	1.0%	0.0%	-8.4%	1.3%	-9.3%	16.5%
Mar	-0.3%	-6.3%	3.0%	12.3%	-0.5%	29.6%	-0.8%	0.7%	-1.5%	-6.5%
Apr	-3.1%	-2.9%	5.8%	3.8%	-1.0%	-3.8%	0.0%	-0.7%	-4.5%	4.1%
May	-1.3%	11.9%	1.8%	13.8%	1.5%	18.8%	3.6%	6.0%	28.1%	3.9%
June	1.3%	0.9%	-1.8%	-2.4%	0.0%	-2.5%	0.4%	0.0%	-4.3%	-3.8%
July	5.6%	1.8%	40.4%	-7.4%	1.0%	-6.0%	5.4%	96.3%	-11.5%	21.8%
Aug	13.1%	6.0%	15.7%	1.8%	0.5%	-9.1%	11.3%	3.2%	15.1%	19.3%
Sept	5.6%	35.0%	22.0%	3.5%	2.5%	-1.5%	1.3%	24.1%	6.9%	8.5%
Oct	6.3%	203.6%	50.0%	0.8%	50.0%	-13.2%	-71.8%	81.6%	0.6%	-0.7%
Nov	-2.0%	-1.6%	-0.6%	0.0%	-0.3%	-0.6%	-3.4%	-3.6%	-0.6%	-0.7%
Dec	4.0%	13.7%	9.3%	0.0%	0.6%	1.8%	-8.3%	-7.7%	4.1%	4.3%
07 Jan	-16.5%	-0.7%	2.8%	-9.2%	-1.3%	2.9%	2.6%	-90.8%	313.5%	5.5%
Feb	0.0%	-84.1%	-91.1%	-5.6%	-10.0%	-10.1%	-17.1%	-17.5%	-69.3%	-9.2%
Mar	2.3%	-17.8%	-6.5%	-6.9%	-12.2%	6.9%	3.8%	-4.0%	-0.9%	5.8%
Apr	-10.2%	4.4%	-8.7%	-11.6%	-1.2%	1.8%	0.7%	3.2%	5.4%	0.0%
May	-3.5%	-6.0%	1.5%	-6.5%	2.9%	-2.9%	-2.2%	0.0%	-3.4%	0.7%
June	3.7%	4.2%	0.7%	-1.9%	0.0%	-11.2%	8.2%	9.2%	0.9%	8.8%
July	15.2%	-0.5%	10.0%	-2.6%	4.8%	15.3%	8.3%	6.5%	20.9%	15.5%
Aug	-8.8%	-1.1%	-0.3%	-6.0%	-0.4%	-4.6%	-0.6%	10.5%	-4.3%	5.9%
Sept	-5.8%	-4.9%	0.0%	0.0%	9.3%	-3.6%	-1.3%	-15.1%	3.8%	0.5%

Source: NSE Data

Appendix III: NSE 20 share Index Constituents Market Returns before the Global Financial crisis

	KCB	NIC	SCBK	ARM	BAMB	BAT	CABL	EABL	MSC	XPRS
Oct	16.1%	5.2%	1.5%	16.5%	2.2%	0.5%	8.0%	-4.8%	0.8%	-2.2%
Nov	11.8%	-2.0%	0.7%	6.8%	-1.4%	-0.9%	-2.0%	-0.7%	0.0%	-0.4%

Dec	3.7%	2.0%	0.0%	0.0%	2.9%	-2.9%	-6.2%	-2.2%	8.5%	1.8%
06 Jan	1.8%	3.9%	2.9%	14.6%	0.0%	0.0%	14.6%	0.0%	17.9%	15.9%
Feb	1.7%	-1.9%	-2.8%	1.1%	0.0%	-2.0%	1.3%	-3.7%	-1.8%	1.3%
Mar	0.9%	-3.8%	0.7%	-1.6%	0.0%	1.0%	11.3%	2.3%	6.2%	4.9%
Apr	-0.8%	0.0%	-0.7%	7.2%	0.0%	0.0%	14.7%	-1.5%	15.1%	32.4%
May	36.8%	40.0%	2.2%	30.6%	6.4%	-2.5%	21.2%	6.9%	20.2%	30.0%
June	-3.8%	0.0%	0.0%	1.6%	0.7%	0.0%	2.0%	-1.4%	-3.8%	-9.4%
										-
July	9.7%	7.1%	8.5%	9.4%	0.0%	-2.0%	32.3%	-2.9%	7.4%	20.8%
Aug	4.1%	19.3%	1.3%	23.6%	21.3%	-1.0%	78.3%	8.2%	-4.9%	8.3%
							-			
Sept	2.3%	8.4%	2.6%	-0.6%	4.4%	-2.6%	82.3%	-2.8%	-1.7%	1.1%
							-			
Oct	15.6%	5.2%	24.4%	-1.2%	5.3%	4.8%	59.0%	-1.4%	-6.1%	6.5%
Nov	1.0%	-2.5%	1.5%	-2.9%	-3.5%	0.0%	4.1%	-2.2%	2.8%	-6.1%
Dec	14.8%	2.5%	1.5%	0.6%	11.4%	1.0%	7.3%	2.2%	-2.7%	5.4%
07 Jan	-3.7%	12.7%	5.9%	-4.2%	-2.8%	14.2%	-0.5%	6.5%	-21.8%	10.3%
						-	-			
Feb	-10.8%	-16.1%	-17.1%	-5.7%	2.9%	11.1%	16.8%	-2.0%	-26.6%	-3.7%
										-
Mar	7.7%	-4.7%	8.3%	-3.3%	-7.0%	-0.5%	1.9%	-3.4%	-0.8%	16.5%
Apr	-88.8%	-0.5%	-7.7%	-3.4%	-0.5%	-4.5%	1.9%	3.6%	-12.2%	11.6%
May	-7.0%	3.8%	-0.6%	0.7%	-4.5%	-5.3%	6.7%	-0.7%	-1.9%	-5.2%
June	1.1%	9.5%	6.7%	5.0%	0.0%	2.2%	8.0%	6.9%	9.4%	-5.5%
July	20.2%	44.2%	-2.1%	29.1%	-0.5%	-5.4%	-2.1%	-0.6%	10.3%	8.1%
Aug	-4.4%	6.7%	2.1%	-2.1%	5.8%	-8.0%	4.3%	8.5%	23.4%	6.5%
						-				
Sept	-5.6%	16.3%	-1.0%	-2.1%	-0.5%	10.0%	-8.8%	3.0%	-6.3%	-4.0%

Source: NSE Data

Appendix IV: NSE 20 share Index Constituents Market Returns after the Global Financial crisis

	REA	SASN	CMC	KQ	NMG	SCOM	BBK	ICDC	CFC	DTB
Oct	4.6%	6.4%	4.2%	9.9%	7.0%	-1.3%	7.7%	3.9%	-7.7%	10.0%
Nov	8.5%	0.6%	15.0%	-4.5%	6.5%	4.0%	3.3%	12.3%	7.5%	1.1%
					-		-			-
Dec	-14.2%	-23.7%	-6.2%	-28.0%	10.4%	-28.7%	11.4%	-16.8%	-7.8%	15.9%

08 Jan	7.3%	11.6%	-12.2%	6.0%	9.2%	17.9%	2.9%	10.1%	0.8%	8.8%
Feb	-8.3%	-7.0%	-6.9%	7.2%	1.3%	4.5%	-6.3%	-8.3%	-8.3%	-4.6%
Mar	10.4%	18.4%	22.0%	1.0%	5.9%	5.8%	8.1%	16.0%	5.5%	16.4%
Apr	-11.3%	-14.6%	10.8%	-3.8%	-2.3%	2.7%	-2.7%	-6.9%	-0.9%	-1.6%
May	3.3%	1.4%	6.3%	-1.5%	4.8%	-3.3%	-0.7%	-2.8%	1.7%	1.1%
					-					
June	-1.6%	-8.8%	-2.2%	-8.0%	38.9%	-21.6%	-6.4%	-7.6%	-9.4%	-2.6%
					-					
July	-5.1%	-9.7%	0.8%	2.7%	25.2%	-5.2%	-4.5%	-5.2%	-3.8%	-2.7%
					-					
Aug	-4.2%	-33.8%	-5.5%	-8.0%	13.1%	-10.9%	-7.1%	-15.9%	-13.7%	-8.3%
					-		-			-
Sept	-11.8%	-1.3%	-21.8%	-38.2%	19.4%	-30.6%	22.6%	-28.7%	-36.9%	27.1%
Oct	-10.0%	-20.3%	5.1%	0.9%	23.2%	7.4%	6.1%	0.4%	18.9%	12.4%
Nov	3.3%	14.8%	3.2%	5.6%	4.3%	-1.4%	5.2%	35.4%	-9.1%	0.7%
Dec	-6.8%	-15.7%	-10.6%	-2.6%	-2.8%	-12.5%	-4.0%	-22.4%	-5.0%	2.9%
					-		-			-
09 Jan	-22.7%	-25.4%	-26.6%	-29.5%	17.9%	-19.0%	25.8%	-33.0%	-8.8%	29.1%
Feb	29.4%	22.7%	24.3%	1.0%	11.3%	17.6%	11.8%	5.1%	-9.1%	13.0%
Mar	3.8%	4.6%	-8.0%	12.7%	3.1%	-5.0%	8.1%	-2.4%	1.6%	8.8%
Apr	3.3%	7.1%	-3.8%	-2.2%	-3.8%	-3.5%	4.0%	30.5%	14.6%	10.6%
May	-6.8%	0.8%	11.7%	10.3%	13.4%	18.2%	21.5%	23.0%	20.9%	8.8%
June	-10.8%	4.9%	-7.4%	4.2%	-9.7%	15.4%	-4.5%	1.2%	-3.8%	-1.4%
							-			
July	3.4%	-3.9%	-8.4%	-10.0%	-3.8%	-2.7%	12.4%	-20.9%	-9.4%	-4.1%
Aug	-7.5%	-1.6%	-8.7%	-11.1%	-5.6%	1.4%	-4.9%	-10.5%	-4.3%	2.1%
Sept	8.1%	15.7%	1.0%	21.3%	2.5%	8.1%	0.6%	-7.8%	-9.9%	-4.9%

Source: NSE Data

Appendix IV: NSE 20 share Index Constituents Market Returns after the Global Financial crisis

	KCB	NIC	SCBK	ARM	BAMB	BAT	CABL	EABL	MSC	XPRS
Oct	6.9%	10.8%	13.0%	0.0%	1.1%	-1.4%	10.0%	14.0%	-66.1%	13.3%
Nov	4.6%	-66.0%	-1.0%	2.2%	2.1%	2.2%	-4.5%	3.1%	1.0%	-3.9%
										-
Dec	-11.4%	-20.4%	-1.9%	-2.7%	-3.1%	-2.9%	-3.6%	-12.5%	-13.2%	12.2%

08 Jan	10.9%	12.6%	5.9%	5.0%	-1.6%	12.6%	0.6%	5.4%	2.7%	7.0%
Feb	-7.1%	-7.1%	-7.0%	-4.7%	-0.5%	2.6%	-8.0%	-0.6%	-13.6%	-10.9%
Mar	27.9%	23.1%	4.5%	7.7%	2.2%	2.6%	16.7%	11.0%	15.4%	4.9%
Apr	-3.0%	-1.6%	3.4%	2.6%	0.0%	0.0%	-6.9%	8.2%	-6.8%	-1.2%
May	-3.9%	-5.6%	-2.3%	3.0%	2.6%	4.4%	-0.6%	7.6%	3.7%	-8.0%
June	-0.8%	-6.7%	-5.2%	6.8%	-2.6%	-4.2%	-9.9%	-4.5%	-16.9%	-10.0%
July	-12.2%	0.0%	-5.0%	3.6%	1.1%	-1.9%	0.0%	-4.7%	-5.2%	-3.4%
Aug	-6.5%	-11.3%	-3.7%	-6.1%	-3.6%	0.0%	-7.5%	-7.7%	-16.5%	-5.9%
Sept	-21.6%	-13.7%	-9.3%	-12.1%	0.0%	-3.8%	-28.1%	-26.9%	-13.2%	-13.8%
Oct	6.1%	-0.6%	-3.0%	-4.3%	-1.6%	-6.0%	3.1%	10.7%	-16.6%	-7.6%
Nov	11.9%	3.0%	0.0%	0.6%	-9.3%	-7.7%	5.0%	6.7%	11.6%	2.0%
Dec	-12.8%	-7.5%	0.6%	-6.1%	-9.1%	3.8%	-5.7%	-5.6%	-25.9%	-13.1%
09 Jan	-24.4%	-16.1%	-13.0%	-17.1%	-20.0%	2.9%	-35.6%	-26.5%	-29.0%	-2.7%
Feb	27.4%	-11.1%	-0.7%	-7.8%	-0.8%	-0.7%	20.7%	15.0%	29.6%	-9.1%
Mar	1.3%	3.3%	-2.9%	23.1%	-2.5%	0.7%	11.7%	3.5%	-9.8%	-10.5%
Apr	-4.3%	12.9%	1.5%	0.0%	3.4%	10.0%	-2.3%	0.0%	0.0%	0.6%
May	17.5%	12.9%	5.1%	20.0%	20.8%	11.7%	15.5%	26.1%	44.6%	0.6%
June	-3.3%	-7.0%	-4.9%	-5.7%	3.4%	3.5%	0.0%	-0.7%	-2.5%	8.8%
July	-5.7%	-12.9%	0.0%	0.6%	0.0%	-0.6%	-9.3%	0.0%	19.7%	-0.5%
Aug	0.0%	0.0%	2.2%	5.5%	6.7%	-1.1%	-5.7%	-6.0%	-2.1%	-3.1%
Sept	-3.2%	-9.4%	1.4%	2.6%	1.3%	0.0%	-6.3%	1.4%	1.5%	-2.1%

Source: NSE Data

Appendix V: NSE 20 share Index Market Returns before and after the Global Financial crisis

NSE 20 share index	Before		
2006 Oct	2.83%	Dec	-0.03%
Nov	0.88%	06 Jan	5.00%
		Feb	-2.76%
		Mar	1.11%

Apr	-1.86%
May	8.06%
June	-0.24%
July	-1.86%
Aug	10.13%
Sept	9.20%
Oct	8.43%
Nov	-1.13%
Dec	2.83%
07 Jan	2.28%
Feb	-6.70%
Mar	-4.71%
Apr	1.28%
May	-3.80%
June	2.90%
July	3.76%
Aug	0.59%
Sept	-4.19%

NSE 20 share index	After
2007 Oct	5.30%
Nov	4.02%
Dec	-13.45%
08 Jan	7.63%
Feb	-4.52%
Mar	10.18%
Apr	-3.00%
May	0.19%
June	-6.12%
July	-4.51%
Aug	-10.08%
Sept	-18.99%
Oct	-1.33%
Nov	5.38%
Dec	-9.15%
09 Jan	-22.64%
Feb	13.35%
Mar	-0.18%
Apr	1.87%
May	15.49%
June	-0.65%
July	-5.21%
Aug	-3.14%
Sept	2.60%

Source: NSE Data