THE PROFITABILITY OF MOMENTUM TRADING STRATEGIES IN EMERGING MARKETS: EVIDENCE FROM NAIROBI STOCK EXCHANGE

By
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Doctoral thesis submitted in fulfillment of the requirements for the award of the degree of Doctor of Philosophy in Finance, School of Business, University of Nairobi.
2011
DECLARATION

I declare that this is my original work, and, to the best of my knowledge—except where due reference is made in the text, has not been submitted to any other university for a degree.

Signed .................................. Date ...........................................

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This thesis has been submitted for examination with my approval as the University of Nairobi supervisor.

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   Signed .................................. Date 16th Nov 2011

2. Prof. Peter K’Obonyo
   Signed .................................. Date 21/11/2011
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DEDICATION

I dedicate this doctoral thesis to my dear departed parents, Bernadette Isaisi and Alphonse Lishenga; to my brothers and sisters, Sr. Carolyne Iswa, Dymphina Indasi, the late Alfred "Scaramanga" Mugaisi, Hilda Wilimila, Maurice Mitekho, and Benedine Sarah Khalachi; to my nephews and nieces, Boniface, Bernard, Godfrey, Roseline, Jackline, Patrick, Origine, Evans, Brian, Assumpta, Praxicedes, Anthony, Edwin, Yvonne and Faith; to the 1974 Musaa Primary class mates, Alfred, Titus Richard, Gerald Khayiya, Everline Shimonyo, Beatrice Litswa and Francis Mudakha; to Sigalagala 1978 class of Jonnah Lijodi, Johnny Ngaya, Charles Mambili, Phillip Nyasio, Mike Odero, George Undusu, Reuben Mudigululi and Joseph Walunywa; to my teachers and lecturers, Shichere, Paulus Nguwa, Kasiki, Prof. Nzomo, and Vincent Kamasara; and, to all the University of Nairobi fraternity.
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This thesis has taken the time and effort and financial resources of many. The dearth of space and dimming memory constrains me to mention but a few, but the contribution of all was invaluable and is appreciated.

The pride of place goes to my supervisor, Dr. Rose Ngugi, who patiently bore with my sometimes dithering efforts while firmly steering the enterprise to its ultimate conclusion. I owe her an abiding debt.

In the same breath, I acknowledge the sterling input and insight of Prof. Peter K’Obonyo, the co-supervisor, who inspired by example and confidence. I thank you for always being available and forthcoming.

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I acknowledge the support and motivation that I received from my family; my wife, Hilda, who created the conducive atmosphere at home for study; my daughter, Sylvia who gave me a reason to endure the course, and her siblings Stacy, Aaron and Brigitte who inspired hope.

The University of Nairobi, especially its School of Business facilitated in every aspect the commencement and completion of this academic pursuit that culminated into this thesis. My gratitude is boundless.

God, the almighty and the provider, allowed the enterprise to proceed to conclusion: May praise and fealty be only to him.
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<tr>
<td>AMEX</td>
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<td>CAPM</td>
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<tr>
<td>EAFE</td>
<td>Europe, America, Australia and Far East</td>
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<td>EAAFE</td>
<td>Europe, America and Far East</td>
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<td>EU</td>
<td>Expected utility</td>
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<td>FF</td>
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<td>FFJR</td>
<td>Fama, Fisher, Jensen and Roll</td>
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<td>HML</td>
<td>High minus low</td>
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<td>ICAPM</td>
<td>Inter-temporal capital asset pricing model</td>
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<td>IFC</td>
<td>International Finance Corporation</td>
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<td>IMF</td>
<td>International monetary fund</td>
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<td>LDC</td>
<td>Low developed countries</td>
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<td>NSE</td>
<td>Nairobi Stock Exchange</td>
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<td>NYSE</td>
<td>New York Stock Exchange</td>
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<td>RSS</td>
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<td>SEU</td>
<td>Subjective expected utility</td>
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<td>SMB</td>
<td>Small minus big</td>
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<tr>
<td>UMD</td>
<td>Up minus down</td>
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<td>WML</td>
<td>Winner minus losers</td>
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Abstract

A generation ago, the intellectual dominance of the efficient markets hypothesis as the accepted asset pricing paradigm was unchallenged. It was generally believed that securities markets were extremely so efficient that prices in capital markets reflected the "true" intrinsic values of the underlying assets, commensurate with their risk. By the start of the twenty-first century, however, the acceptance of the efficient market hypothesis had become far less universal. Mounting anomalous evidence evoked a multi-disciplinary approach to asset pricing incorporating, among others, psychological and behavioural theories. The main thrust of the new proposition was that asset prices had elements of mis-valuation that could be profitably exploited by a properly designed trading strategy. Many financial economists, researchers and statisticians have joined in the enterprise seeking to vindicate the hypothesis that stock prices in capital markets are, at least partially, predictable.

This thesis uses data from the NSE to test whether past-price momentum based trading strategies could generate significant profits. Further, consistent with prior literature that has sought to link momentum profits to various firm and market characteristics, this study inquired into the role of size, market wide risk, transaction costs, and trading volume in momentum profitability, and in addition, whether the phenomenon was permanent or transient, had a calendar regularity or otherwise, and whether it was behavioural or risk based.

The study used monthly stock returns for all shares traded at the NSE from 1995 to 2007, inclusive. The strategies considered chose stocks and formed overlapping winner and loser portfolios on the basis of the returns over the past 3, 6, 9, and 12 months. For each of these formation periods, we also consider holding periods of 3, 6, 9, and 12 months. These combined to give a total of 16 strategies. To investigate the existence of price momentum, we tested whether past winners continued to outperform past losers.
In addition, factor-mimicking portfolios were formed and tested for evidence the profitability was a result of size, trading volume and risk. We then formed and followed portfolios for up to 60 months to check for any reversal and calendar regularity. Finally the momentum profits were decomposed and tested to ascertain whether it was a time-series or cross-sectional phenomenon.

The results of the initial unrestricted tests revealed the existence of significant momentum, which could be the basis of profitable investment strategies. An analysis of factor-mimicking portfolios revealed the absence of a discernible size effect, that momentum profitability is a feature restricted to only those stocks that experience low to medium activity, and is absent in high volume stocks, and that market risk could not adequately explain the profits. It was also found that the incorporation of transaction costs in our strategies could significantly dissipate the profits, that there was April calendar regularity to the profits, and that there was mild reversal of profitability in the medium term. Finally, we concluded that momentum is a time-series rather than a cross-sectional phenomenon.

Through this research, we found that unlike the neo-classical finance theory suggests, individual investors do not always make rational investment decisions. Their investment decision-making is influenced, to a great extent, by behavioural factors. These behavioural factors must be taken into account while making investment decisions. Investment advisors and finance professionals must incorporate behavioural issues as risk factors in order to formulate effective investment strategies for individual investors.

The findings of this study are to be accepted and evaluated in the context of the following limitations and qualifications. First, is the fact that the methods and approaches used are just a selection among the diverse set (skip v non-skip, overlapping v non-overlapping, value weight v equal eight, decile v quintile). Secondly, because of the small listing at the NSE, we included in our sample low priced or low market capitalization stocks, which could have contributed to decreased significance. Thirdly, the incidence of momentum could be sample period specific, with some periods
exhibiting the phenomenon to a higher degree than others. Fourthly, there were gaps in data that necessitated a degree of subjectivity or a restriction of the extent of testing. Lastly, structural inefficiencies, lack of automation, thin trading and weak legal and administrative institutions could make comparisons of results tenuous.

We suggest that researchers could test the robustness of the results by using alternatives methods, revisit the controversial results by using out of sample data, use strategies with different formation/holding period combinations, and test inter market regional strategies that include NSE.
CHAPTER ONE
INTRODUCTION

1.1 Background
The decades of the 1950s and 1960s were the most productive periods in finance thought. These were the periods in which finance changed from a descriptive discipline to a modern science full of new ideas that needed to be refined. The focus of the academic community on exploiting the full potential of mathematical, probabilistic and optimization models and techniques led to the following central paradigms: (i) portfolio allocation based on expected return and risk (ii) risk-based asset pricing models such as the CAPM and other similar frameworks, (iii) the pricing of contingent claims, and (iv) the Miller-Modigliani theorem and its augmentation by the theory of agency (Markowitz, 1954; Sharpe, 1964; Black & Scholes, 1973; Miller & Modigliani, 1963). These ideas and principles would constitute a key influence in the years to come.

Neo-classical finance is founded on the concept of a "rational" economic agent, or *homo economicus*. Under this positivistic doctrine of financial economics, *homo economicus* refers to a greatly simplified model of human behaviour where an individual is characterised by perfect self-interest, perfect rationality, free access to perfect information regarding a specific condition, and unlimited capacity to speedily and correctly analyze vast amounts of information. The key rationale for the development of this concept lies in the complex nature and unpredictability of human behaviour and its inability to be used effectively as a means for accurately predicting and explaining human behaviour itself. By this conceptualization, human behaviour was oversimplified and quantified following methodologies developed and used in the field of the 'hard' sciences. Since its first appearance in financial economics literature, the oversimplification of human behaviour represented only one part of a more generic empirical deductive procedure aiming to define price behaviour and create a theory for it. A notable contributor to development of financial economics was Louis Jean-Baptiste Alphonse Bachelier, whose PhD thesis in 1900 still represents a creation of exceptional merit in the area of financial mathematics. The introduction of new ideas in the theory of stochastic
processes such as that of Brownian motion and martingales soon became a starting point for the amalgamation of economics, mathematics, accounting and finance disciplines that created the basis of the modern finance doctrines.

Eventually, the end product of this early work was the creation of the Efficient Market Hypothesis (Fama, 1970), a theory that still even today constitutes the cornerstone of modern academic finance thinking. According to this theory, markets are considered to be efficient relative to given information set, if there are no abnormal profit opportunities for investors trading on the basis of this information (Fama, 1970). Hence, it is practically impossible for investors to consistently earn abnormal returns on the basis of universally available information. This proposition has dominated investment theory for the last forty years and mathematically is illustrated using Fama’s notation as $E(X_{t,t+1}/\Phi_t) = 0$, where $X_{t,t+1}$ represents the difference between the actual price of security $i$ at time $t+1$ and its expected price based on the given set of information $\Phi_t$. If the expectation given by the above equation is equal to zero there are no available opportunities for investors to beat the market, as no overpriced or underpriced stocks exist at time $t$. The stochastic process $X_i$ is then considered to be a fair game (Le Roy, 1989). This theory implies the existence of a stochastic process with independent, identically distributed binomial random variables, or what is commonly known as a random walk (Roberts, 1959; Osborne, 1959; Granger & Morgenstern, 1970).

For quite some time, the efficient market hypothesis, a centrepiece of neoclassical financial theory, has dominated the working mechanism of financial markets. This hypothesis, posits that current information flows are the sole determinant of current asset price movements and that market prices are the best reflectors of the fundamental values of their underlying assets. Fama argues that an efficient market is one in which firms can make production-investment decisions and investors can choose among the securities that represent ownership of firms’ activities under the assumption that security prices at any time fully reflect all available information. This implies that the price of a company’
Stock always accurately reflects the company's value given the information available on the firm's earnings and its business prospects.

EMH itself follows from certain more basic assumptions, including that of *homo economicus*. Sufficient conditions for the EMH can be summarized into four categories relating to: (i) The public availability of information, (ii) The speed with which this information can be absorbed and lead to a new price equilibrium, (iii) Investor self-interest and (iv) Investor rationality and the extent to which investors exhibit effective and efficient cognitive behaviour.

From the early years of the 1970s, burgeoning anomalous evidence began to emerge, calling into question the faith in the belief that markets were efficient. The copious literature documenting market efficiency anomalies include the equity premium puzzle of Mehra & Prescott (1985), the post event drift evidence (Sharpe, 1998), evidence of excess market volatility (Shiller, 1981), calendar regularities (Haugen & Jorion, 1996; Hensel & Ziemba, 1996; and, French, 1980), the size effect (Banz, 1981), and the fundamental/price ratios of Fama & French (1992, 1996).

Financial economists also offer a different insight into some of the most puzzling phenomena in empirical finance and argue that there is some concrete evidence for inefficient markets, primarily in the form of systematic errors in the forecasts of stock analysts. Lakonishok, Shleifer, and Vishny (1995) argue that analysts extrapolate past performance too far into the future and, consequently, overprice firms with recent good performance and underprice firms with recent poor performance. This accounts for the reversal effect when market participants recognize their errors. Since firms with sharp drops in price may be small or have high book-to-market ratios, their explanation is consistent with the small-firm and book-to-market effects. A study by La Porta (1996) offers a similar explanation. La Porta finds that the equity of firms for which analysts expect low growth rates in earnings actually beat those with high expected earnings growth. Therefore, several anomalies regarding fundamental analysis have brought into question the validity of market efficiency.
These contradictory findings and new approaches to explaining phenomena have generated sustained pressure on traditional neo-classical finance, ultimately forcing it to cede space to an alternative finance paradigm commonly referred to behavioural finance. Sewell (2001) defines behavioural finance as the study of the influence of psychology on the behaviour of financial practitioners and the subsequent effect on markets. Sewell adds that behavioural finance is of interest because it helps explain why and how markets might be efficient.

Psychology shows that people’s beliefs are often predictably in error mainly because of inherent cognitive biases that force people to use heuristics (rules of thumb) when faced with decision situations. In addition, emotions have the effect of provoking loss of control in those they afflict. As a consequence of these biases in investors, a substantial amount of stock pricing is performed by investors who do not accurately perceive underlying business values, and hence produce prices that do not equal those values. Investor sentiment, rather than rational economic calculation, contributes significantly to price formation.

Investor preferences constitute the second key element of behavioural finance models. The traditional finance applies the expected utility framework, that views an investor as a rational utility maximize. On the other hand, the best known behaviourally based preference framework is prospect theory, developed by Kahneman and Tversky (1979). Prospect theory, differs from expected utility theory in a number of important respects. First, it replaces the notion of “utility” with “value.” Whereas utility is usually defined only in terms of net wealth, value is defined in terms of gains and losses (deviations from a reference point). Moreover, the value function for losses is different than the value function for gains: the value function for losses (the curve lying below the horizontal axis) is convex and relatively steep; in contrast, the value function for gains (above the horizontal axis) is concave and not quite so steep. The asymmetry in investor reaction to gains and losses makes her risk seeking when confronted with losses and risk averse when in the domain of gains.
The investor preferences, from the prospect theory perspective, lead to several noteworthy behavioural and psychological biases in investors: among them, loss aversion, mental accounting, frame dependence, overconfidence, conservatism, ambiguity aversion, and house money effect. Hastie and Dawes (2001, p. 310), while discussing the merits of prospect theory, deliver the following verdict:

“Prospect theory is the best comprehensive description we can give of the decision process. It summarizes several centuries’ worth of findings and insights concerning human decision behaviour. Moreover, it has produced an unmatched yield of new insights and predictions of human behaviour in decision-making.”

Finally, it is now apparent that arbitrage is not the vaunted efficient leveller of market inefficiencies that EMH proponents claim it to be. There is now widespread evidence that even those smart investors who do accurately perceive underlying business values will not always step in to offset the sentimental actions of noise traders, for they face risks and costs too great for such an undertaking (See Barberis & Thaler, 2002 for examples). This limitation arbitrage process, when coupled with investor sentiment and preferences, yields pricing that does not equate to fundamental values, making prices a distillation of many variables, economic but also behavioural.

Scholarly research efforts to incorporate behavioural finance into standard models are multiplying. For instance, Delong et al. (1990, p. 703) “present a simple overlapping generations model of an asset market in which irrational noise traders with erroneous stochastic beliefs both affect prices and earn higher expected returns.” The authors also argue that the random nature of noise traders’ beliefs creates variability in the price of assets that prevents unemotional arbitrageurs from aggressively betting against them. Therefore, some of the results have raised questions about the non-existence of noise traders in the market. This has necessitated the understanding of behavioral theories to better grasp investor behavior and asset pricing. A growing body of psychological evidence suggests that people’s beliefs are often predictably in error.
Several studies regarding some of the biases in human beliefs, such as mental accounting and overconfidence, have attempted to shed insight on how human investors make systematic errors. For instance, Daniel, Hirshleifer and Subrahmanyam (2001) suggest that investors exhibit overconfidence and self-attribute bias. As a result, proponents of behavioral asset pricing have attempted to show that asset prices reflect sentiment.

Recent research studies strive to model investor sentiment. Baker and Wurgler (2007) study the theoretical effects of investor sentiment on different types of stocks. They create the Sentiment Seesaw with stocks on the x-axis according to how difficult they are to value and arbitrage, and the prices that denote fundamental values on the y-axis. The Seesaw shows that “high sentiment should be associated with high stock valuations, especially for the stocks that are hardest to value and arbitrage, and low sentiment works in the opposite direction” (Baker & Wurgler 2007, p. 133). With no sentiment, stocks are said to be correctly priced at the equilibrium price.

Similarly, Barberis, Shleifer and Vishny (1998) present a model of investor sentiment to show how the beliefs of an investor affect both prices and returns. The model is based on psychological evidence that “people pay too much attention to the strength of the evidence they are presented with and too little attention to its statistical weight” (p. 332). These works represent only a small segment of the substantial research done on modeling investor sentiment and its effect on asset pricing.

Substantial research shows that modern asset pricing is built around the notion of investor sentiment. Further, significant evidence of puzzling phenomena in finance opposes the underlying assumptions of the EMH. This has motivated researchers to add sentiment functions in the stochastic discount factor (SDF) model and observe whether the behavioural asset pricing theory better explains the historical asset pricing patterns. As a result, the current study investigates whether significant linkage exists between investor sentiment and stock prices, employing the price momentum phenomenon.
**Price Momentum**

Momentum can be described as the rate of acceleration in the price or volume of a stock, enabling trends in price to develop that could be the basis of profitable trading strategies. The idea of price momentum in securities is that their price is likely to keep moving in the same direction than to reverse direction. In technical analysis, momentum is considered an oscillator and is used to help identify trend lines (www.investorwords.com). While the existence of momentum in many markets is an acknowledge fact (See Jegadeesh & Titman’s 1993; Chan, Jegadeesh, & Lakonishok, 1996; Rouwenhorst, 1998; and Bernard & Thomas, 1989, 1990), the sources and explanation for momentum has remained controversial to date.

There is a plethora of theories competing to explain momentum. Daniel et. al. (1998) attribute momentum to overreacting markets because investors are prone to psychological biases of overconfidence and self-attribution. Barberis et. al. (1998) present a model that combines the conservatism bias with what Tversky and Kahneman (1974) refer to as a “representative heuristic”. To them momentum profits arise because investors underreact to ranking period information, which is gradually incorporated into stock prices during the holding period. In Hong and Stein (1999) the emphasis is on heterogeneities across investors, who observe different pieces of private information at different points in time. Hong and Stein make two key assumptions, namely i) firm-specific information diffuses gradually across the investing public, ii) investors cannot perform the rational-expectations trick of extracting information from prices. Taken together, these two assumptions generate underreaction and positive return autocorrelations.

Momentum trading strategies will form portfolios that buy past winners and short past losers and hold for a period of time. If there is momentum in prices, such a strategy should result in abnormal returns. Many momentum strategies in literature (Jegadeesh & Titman, 1993) choose stocks and form portfolios on the basis of the stocks’ returns over the past 3, 6, 9, and 12 months. For each of these formation periods, they also consider holding periods of 3, 6, 9, and 12 months. These combine to give a total of 16 strategies.
Limitless number of strategies could be formed, depending on the formation/holding period combinations selected.

1.2 Statement of the Problem

The profitability of the momentum strategy- the strategy of buying recent winning stocks and shorting recent losing stocks- as first documented in Jegadeesh and Titman (1993) remains one of the anomalies that cannot be explained by the otherwise very successful Fama-French three factors model, and is thus very puzzling (Fama and French (1996). Jegadeesh and Titman (2001) show that momentum profits remain large even subsequent to the period of their 1993 study. Rouwenhorst (1998), and Griffin. Ji. and Martin (2003), report economically significant and statistically reliable momentum profits in areas outside the US. These studies suggest that the momentum phenomenon is not a product of data mining or snooping bias, and neither is it market specific.

Although the momentum phenomenon has been well accepted, the source of the profits and the interpretation of the evidence are widely debated. A variety of papers ranging from behaviour models to rational-expectation models attempt to offer an explanation. For the behavioural arguments, the momentum phenomenon is often interpreted as evidence that investors under-react, or overreact to new information. Along this line, Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), and Hong and Stein (1999) have developed behavioural models to explain the momentum. The behavioural argument commands support of empirical evidences that momentum profits are related to several characteristics not typically associated with the priced risk in standard asset pricing models (See, for earning momentum (Chan. Jegadeesh. and Lakonishok (1996)); volume and turnover (Lee and Swaminathan. 2000); analyst coverage (Hong , Lim and Stein (2000)); and 52-week high price (George and Hwang. (2003)). Grundy and Martin (2001) show that the momentum strategy’s profitability cannot be explained by the Fama-French three factors model. They argue that the gain instead reflects the momentum in the stock–specific components of returns.

Against the backdrop of the behavioural arguments, others have suggested that the profitability of momentum strategies may simply be compensation for risk. Conrad and
Kaul (1998) argue that the momentum profit is attributed to the cross-sectional dispersion in (unconditional) expected returns. Lewellen (2002) finds that the negative cross-serial correlation among stocks, not underreaction, is the main source of momentum profits. Using the frequency domain component method to decompose stock returns, Yao (2003) provides strong evidence that momentum is a systematic phenomenon. Models have been developed that are based on momentum on economic risk factors affecting investment life cycles and growth rates. Berk, Green and Naik (1999) illustrate that momentum profits arose because of persistent systematic risk in a firm's project portfolios. Johnson (2002) posits that momentum comes from a positive relation between expected returns and firm growth rates. Chordia and Shivakumar (2002) report that the profits to momentum strategies are completely explained by predicative returns using the lagged common macroeconomic variables (e.g. dividend yield, term spread, default spread, and short term rate). The momentum profits are related to the business cycles and mainly reflect the persistence in the time varying expected returns.

To date, the great preponderance of evidence on financial market efficiency/inefficiency debate has been documented in the major world markets of Europe, America and Far East (E.A.F.E.). However, evidence on emerging markets is now building up as financial scholars and practitioners recognise the significant emerging markets' diversification benefits for the international portfolio investor. The interest in emerging markets has been driven by the global wave of economic liberalization which has caused unprecedented capital mobility into these markets (Errunza and Losq (1987), Medewitz et al. (1991), and Harvey (1995)). Studies dealing with emerging markets have focussed on the degree of market efficiency, the extent of integration with developed markets and the distributional properties of stock returns (Sewell et al. (1993), Hawawini (1994), El-Erian and Kumar (1995). Cashin and McDermott (1995), Bailey (1990), Chung and Liu (1994), Bekaert and Harvey (1995), Aggarawal and Mougoue (1996).

The study of Bailey et al. (1990) presents evidence that stock prices of several Asian equity markets do not follow a random walk. This they attribute to frictions in trading mechanisms, turnover taxes, price limits and restrictions on trade size and ownership.
Evidence of the day-of-the-week effect and other calendar anomalies are reported by Wong and Ho (1986), Nassir and Mohammad (1987), Kim (1988), Ho (1990) and Hong and Cheung (1994). Bessembinder and Chan (1995) investigate whether market participants in emerging markets take advantage of profit opportunities that may be present due to deviations from the random walk model and find that some technical rules have some predictive power. Lyn and Zychowicz (2004) find similarities between the usefulness of book-to-market and dividend yield ratios in the transitional Eastern European markets as predictors of returns over 6-to 12-month horizons that is consistent with what has been observed in more established emerging and developed markets.

Dickinson and Muragu (1994) investigated the efficiency of stock markets by focussing on evidence from the NSE during the ten-year period from 1979 to 1988. They concluded that the behaviours of the price series in the market were consistent with the weak form of the Efficient Markets Hypothesis i.e. that past stock performance could not be a predictor of future performance at the Nairobi Stock Exchange.

Many other related studies using NSE data (a large proportion unpublished MBA projects) have tended to agree with Dickinson and Muragu. Olukuru (2007) studied the time dependence between the returns of shares traded at the NSE. Using simulated time series, he reported that market dependence is not always related to market volatility. Ndungu (2005) tested the applicability of the CAPM and found that the beta of the CAPM explained market returns better than the market model. Omosa (1989) and Munyao (1998) tested the effectiveness of models in predicting stock price movements and concluded their inability to forecast movements of stock prices at the NSE. Makara (2004) documented that low Price/earnings ratio (PER) stocks outperformed their high PER counterparts. The small firm effect was confirmed to exist in Kenya in a study by Oluoch (2004), while an inverse relationship between trading volume and stock returns was reported in the study of Gakuru (2006).

Emerging market evidence on price momentum is now trickling in. Rouwenhorst (1999) documents evidence to the effect that stocks returns in emerging markets exhibit
momentum. Bekaert et al. (1997) find momentum strategies implemented in emerging markets are not consistently profitable, though they perform better when only the investable indexes are examined. More recently, contradictory evidence has been documented by Hameed and Kusnadi (2002) who investigated the profitability of momentum investment strategy in six Asian markets. Hameed and Kusnadi find that unrestricted momentum strategies do not yield significant profits and conclude that factors that contribute to the momentum phenomenon in the United States are not prevalent in the Asian markets.

Direct testing of the momentum phenomenon employing NSE data is an enterprise that has scarcely began. My search of literature yielded only two studies. Atiti (2004) tested for the existence of momentum in stock prices at the NSE and reported strong evidence price momentum at the bourse. The study was, however, for limited period of 5 years and did not go as far a mounting trading strategies and evaluating their profitability. Neither did the researcher attempt to relate the momentum phenomenon to firm characteristics. In a second study at the NSE, Karwega (2004) investigated the role of behavioural factors in trading decisions of investors at the NSE. Karwega concludes that apart from economic fundamentals, psychological factors are influential in investor decisions.

The researcher's own preview of the trends of the NSE-20 index exhibits a pattern that attest to momentum in one direction, then reversal, to be followed by continuation in the opposite direction. This clear in my rendering of index data in Figures 1 and 2. Over the past decade, the Nairobi Stock Exchange-20 Index has swung like a pendulum from a peak of 3784 in 1996, then to a low of 1384 in 2003 followed by a tremendous rally that reached an all time high of 5679 in 2007. What is remarkable is that, between the peaks and lows, there is a sustained momentum in a given direction of change of the index. Whenever a downward spiral sets in (as happened in 1996) it continues until it bottoms up 4 to 5 years later. This is followed by an upward recovery that is also unbroken until the high of 5679 of 2007 is reached.
The current study deals with momentum in individual assets rather than at market level, but since the market index represents an aggregation of the performance of the quoted stocks, the continuation in index movement followed by a turning and a subsequent recovery is consistent with the meaning of momentum. This study sought to find out whether the market wide momentum could translate into momentum at the individual stock level.

![Figure 1: Shows NSE-20 Index monthly returns for the period 1997-2007. The earlier months 1997-2002 are dominated by negative returns as contrasted with the preponderance of positive returns in the latter months of 2003-2007](image1)

![Figure 2: Shows the free fall generated by negative momentum in the years 1997-2002 which then reverses and turns into sustained price rally creating a positive momentum 2003-2007](image2)

The current study had multi-pronged motivations. First was the incontrovertible evidence of the shifting of asset pricing paradigm in the developed markets of the west. Here we have been witnessing the hitherto dominant efficient markets paradigm reel under, and ceding ground to the relentless assault of behavioural finance. In these
markets. A lot of intellectual effort has been devoted to testing the applicability of behavioural paradigms. The time to test the robustness of the new paradigm at NSE cannot come sooner.

My second motivation is the lack of consensus in the results of the still nascent studies investigating existence of momentum in emerging markets. The evidence emanating from developing markets has been mixed, with some reporting existence of momentum (Bekaert et al. (1997), while others find the opposite results (Hameed and Kusnadi. 2002). This begs the question: what is the case of NSE?

My final inspiration for the research was the desire to contribute to the debate by bringing to light the position a market that was relatively undocumented. As was the situation in 1990s in the developed markets, in the first decade of the new millennium, the NSE appeared pregnant for such resolution. In the 1990s Dickinson and Muragu and the majority of other researchers had led many to believe the NSE was weak-form efficient. Come the new millennium, Atiti (2004) and Karwega (2004) release the opening salvo of evidence that forces the intellectual finance community to question its faith in the NSE being weak form efficient. The current study is conceived as a serious mission in the pursuit of a resolution of the efficiency (or inefficiency) debate at the NSE, a low developed country (LDC) market. And in this goal I deploy the weapon of price momentum.

By investigating stock price behaviour at the NSE the study will have addressed the data snooping problem by bringing to bear out-of-sample evidence. The study addressed the following research questions:

1. How pervasive is the price momentum phenomenon?
2. Is momentum profitability robust to incorporation of risk and transaction costs?
3. Are size and volume factors discriminating features in a stock’s susceptibility to price momentum?
4. Is their a calendar pattern to momentum profitability, and is the profitability permanent or does it reverse?
6. Is momentum profitability behavioural, or does it have rational explanations?

1.3 Context of study.

Perspective of the Nairobi Stock Exchange (N.S.E.)

The Nairobi Stock Exchange is currently the only capital market in Kenya. It ranks with Johannesburg Stock Exchange, Cairo Stock Exchange and the Nigerian Stock Exchange as one of the most vibrant stock markets in Africa. The Nairobi Stock Exchange was constituted as a voluntary association of stockbrokers registered under the Societies Act in 1954. The business of dealing with shares was then confined to the resident European community until 1963 when Kenya attained political independence. After the initial fears of the jittery settler community were allayed, the post independence years were marked by steady growth, confidence in the market was rekindled and the exchange witnessed a number of over-subscribed issues. But the 1970s were a period of gloom, engendered by, first, the effect of the O.P.E.C. oil crisis of 1972, followed by the introduction of a 35% capital gains tax, and, finally the break-up of the East African Community which, besides the disruptive nationalizations actions of individual states, deprived the N.S.E. the character of a regional financial hub.

The 1980s were years of stasis and stagnation. It was evident that fresh initiatives were needed to transform the bourse from its comatose stature to a vehicle for the mobilization of funds necessary for economic growth in the coming millennium. The IFC/CKB study, Development of Money and Capital Markets in Kenya became a blueprint for structural reforms in financial markets and culminated in the formation of a regulatory body, The Capital Markets Authority (C.M.A.), in 1989 to assist in the creation of a conducive environment for the growth and development of the country’s financial markets.

In the 1990s major far-reaching reforms were implemented at the N.S.E. First the NSE was registered under the Companies’ Act, phased out the ‘Call Over’ trading system in favour of the ‘Open Outcry System’ and moved over to a more spacious and automated premises at Nation Centre. Secondly the Kenya Government relaxed
restrictions on foreign ownership of locally controlled firms, repealed the entire Exchange Control Act, introduced incentives for capital growth including the setting up of tax-free Venture Capital Funds, removal of Capital Gains Tax on insurance companies' investments, permitting beneficial ownership by foreigners in local brokers and fund managers and the licensing of Dealing Firms. Thirdly, commission rates were decreased considerably from 2.5% to 1%; the number of stockbrokers increased from 6 in 1954 to 20 in 1995 and the accounting profession adopted the International Accounting Standards (IAS) with effect from 1 January 1999. Finally, the success in the 1990s was exemplified by two hallmarks: the largest share issue in its history (the World Bank Award of Excellence winning privatisation of Kenya Airways) and the NSE 20-share index historical all time peak at 5030 on 18 February 1994.

The advent of the new millennium was greeted with euphoric optimism and great expectations on the general Kenyan populace. On the political front long awaited changes occurred and these were expected to translate into economic gains. Though the score so far is not flattering there is still in the air a wisp of guarded optimism that the economic boon will be delivered.

**Current State of NSE**

Presently the NSE has 20 member stockbrokers. Trade is conducted on ordinary shares, preference shares, debentures, corporate bonds and government bonds. Trading is carried out between 10 a.m. to 12 noon, daily except on public holidays.

The current and future developments at the NSE can be captured in its mission statement, which is:

"*To develop and operate an efficient and transparent securities market to the best of international standards for the benefit of all stakeholders*" (NSE Handbook (2002 p.7).

This mission is to be achieved through proper design and implementation of systems, vigilant innovation, and value-adding customer service. The intention is to remove
legal administrative, structural and technological bottlenecks and make the NSE an investment destination of choice.

(a) Systems The operating systems at the stock exchange are undergoing profound change as exemplified by:

Automation. The power of the internet and the world wide web has enabled stock exchanges to integrate into a global market place. Automation of trading systems, clearing and settlement systems, clearing and settlement systems and corporate communications have, and continue to enhance efficiency at the NSE.

Central depository system (CDS) The system was launched at the end of 2004 and is intended to shorten the registration period, boost liquidity in the market, increase trading volumes, reduce risk and place the NSE on the same footing as major international bourses.

Compliance To earn the trust and confidence of investors, appropriate and regulations must be set and compliance enforced. These comprise listing rules, disclosure standards, trading rules, and management and membership rules.

(b) Innovation Innovations are geared towards enhancing market accessibility to stakeholders. It focuses on liquidity, and diversification of the range of instruments and market segments. The traditional equity base has been expanded and deepened to include money market instruments; collective investment schemes such as mutual funds and unit trusts now have an enabling legal and regulatory framework; and, in an attempt towards meeting the needs of diverse stakeholders, the market has been reorganized into four segments, the main investment market segment (MIMS), the alternative investment market segment (AIMS), the fixed income securities market segment (FISMS), and the futures and options market segment (FOMS).

(c) Customer focus The bourse is striving to make customer satisfaction the critical litmus test of success. To this end services are to be value adding, a product menu of sufficient diversification and depth, trading practices that are equitable and...
transparent, and an entrenched acute sense for innovation and sensibility to customer needs.

1.4 Objectives

The goal of this research project was to address the challenge to finance theorists and practitioners posed by the emergence of the momentum profitability, an anomaly that has defied arbitrage forces despite it being well known. This goal was broken into the following objectives:

(i) **Investigate the existence of the momentum phenomenon at the NSE.** The aim of this first objective is to collate evidence on the existence or otherwise of the momentum phenomenon at the NSE. We shall seek to determine whether the momentum has significant effect on profitability of investment strategies and, especially, whether zero-cost investment momentum strategies designed and implemented at the NSE can earn statistically significant non-zero economic profits.

(ii) **Investigate the existence of size, and trading volume effects in momentum returns at the NSE.** Stock returns will be cross-tabulated on the basis of size and momentum, and trading volume and momentum, and the effect of one on the other tested.

(iii) **Examine the extent to which momentum profitability is robust to incorporation of market wide risk factors, and transaction costs.** We investigated the ability of the capital asset pricing model, and the Fama-French three factor model to explain and predict momentum profits, and whether momentum profits are still significant in the face of transaction costs.

(iv) **Investigate the existence of seasonalities in momentum returns at NSE, and inquire into the long term behaviour of cumulative momentum profits.** Specifically, we shall be testing whether, as documented in other stock markets, the January effect has the effect of attenuating momentum profits, and whether momentum profits reverse in the long term.
Decompose momentum profits into cross-sectional, and time series components. This decomposition should contribute to resolving whether momentum profitability has an "irrational" or "rational" genesis.

1.5 Justification for the Study

This study targets a Low Developing Country (LDC) market. By investigating stock price behaviour at the NSE, the study aims to garner evidence as to whether the momentum phenomenon exhibited in developed, and advanced emerging markets also exists in LDC markets and whether such momentum is evidence of market inefficiency.

There are several reasons why emerging markets’, especially the LDC markets’, behaviours could be expected to differ from the behaviours in the developed markets of Europe, America, Australia and the Far East (EAAFE) economies. First, the LDCs stock markets are completely segmented from the developed and emerging markets. This is underscored by the non-existence of cross listing of securities, a practice prevalent in major world markets. A consequence of cross listing is that an occurrence in one major market can impact on other markets. The global effects of NYSE crash on ‘black’ Monday and the Asian stock market bubble burst in 1994 demonstrate this. Because of the absence of cross-listed securities at the NSE and the weak correlation with major world markets, data on the NSE offers an independent test of momentum.

Second, LDCs markets are severely prone to market inefficiencies compared to other markets. The LDCs markets are characterised by structural and systemic weaknesses, less advanced technological applications, ineffective legal regulatory and administrative mechanisms and a weak financial analysis press and half-hearted adherence to financial reporting norms and standards. Samuels (1981, p.129) underscores the difficult of achieving efficiency in such markets by asserting that

"Prices cannot be assumed to fully reflect all available information. It cannot be assumed that investors will correctly interpret the information that is released. The corporation has greater potential to influence its own stock market price and there is a greater possibility that its price will move in a manner not justified by the information available".
The current study examined whether, in economies infested by the above weaknesses, the impact of price momentum is vitiated or accentuated.

Finally, one has to contend with the widely recognised fact that the operations of LDCs' markets do not lend themselves to the effective functioning of the arbitrage process. Two problems emanating from this weakness, also noted even in developed markets, are especially crippling in the LDCs' markets. These are the unavailability of the necessary capital to enable arbitrageurs to eliminate any mispricing, and the risk aversion of arbitrageurs that prevents them from taking on positions large enough to correct any mispricing. This study seeks to investigate the effect on price momentum in those markets where the omnipotent forces of arbitrage are critically hamstrung.

This research effort will contribute to the theory and practice of finance in the following ways:

(a) Dickinson and Muragu (1994) carried out extensive testing of the weak-form EMH on the NSE data between 1979 and 1988. He concluded that the NSE was weak-form efficient: that past returns could not predict future returns. In his words, "overall this study provides evidence that small markets such as the NSE, may provide empirical results consistent with weak-form efficiency" (p. 148).

The question the current study will seek to answer is whether, in light of the paradigm shift from efficient markets to behavioural finance Dickinson and Muragu's conclusion is still tenable for the NSE. The current study will differ in several important aspects. It will use more reliable recent, partially computer generated data; will cover a longer period; and it will employ different analytical tests other than the serial correlation tests, runs tests and spectral tests of the earlier study. Noteworthy also is that the causal comparative research design used affords a more powerful test of efficiency. Finally the study focuses on momentum, a behavioural explanation of market inefficiency that has captured academic interest only rather recently.
(b) Emerging markets (more so LDC markets) are especially segmented from other world markets and, until recently restricted foreign participation. Harvey (1995) points out that the correlation between the most emerging markets and other stock markets has historically been low. Bekaert and Harvey (1995) make the interesting observation that, despite the recent trend towards the abolition of foreign participation restrictions and the substantial increase in inflows in foreign capital, some emerging markets have actually become more segmented from developed capital markets. Consequently, local investors who are likely to evaluate their portfolios in line with local economic and market conditions hold a large portion of the equity of emerging economies. In addition, emerging markets are plagued with thin trading, are technologically challenged, and are served by primitive legal, institutional and administrative structures. This study will test the global robustness of behavioural theories in predicting and explaining asset pricing processes.

Studies that examine the U.S. data for explanations in trends and predictable patterns have an important drawback: Lo and MacKinlay (1990) and Forster, Smith, and Whaley (1997) note that these studies can suffer from data snooping biases because other researchers have tested momentum strategies using the same data. This makes it difficult to obtain independent evidence. In this research project, out-of-sample evidence will be collected and used to test the universal profitability of momentum trading strategies.

(c) Another reason driving the need for research on the price generating process at the NSE is the changing investment landscape in Kenya. After the promulgation of the Retirement Benefits Act (RBA), pension managers can now invest in securities. The need for analysts and market consultants, to advice on market dynamics, has never been more acute. The call for the analysis of stock price behaviour and the interrelationships of the factors influencing it at the NSE is one that has to be answered now, not later.
Subrahmanyam (2007, p. 12-13) expresses the view that “Finance education in general can be more useful if it sheds specific light on active investing by addressing aspects such as (i) what mistakes to avoid while investing, and (ii) what strategies in financial markets are likely to work in terms of earning supernormal returns.” The current study can be justified on the ground that it will help address the second objective identified by Subrahmanyam. From the results of the study investment analysts and investors in general will be able to assess the effectiveness of technical trading rules such as momentum oscillators.

The topic of the research is located at the core of the finance discipline. Finance deals with all that affects economic value, and value finds reflection through prices. The findings of this study will contribute to the building of a body of theory on asset pricing, a topic that is currently in flux.

Many investors, existing or potential, lack awareness and information on the role, functions and operations of the stock exchange. Even as they are quick to join bandwagons to supposed largesse, they are unwilling to stay the course, prematurely jumping out at the first sign of trouble. Investors are in need of financial literacy to appreciate that stock market investing requires patience to bear fruits. The insights from this study would form part of a program to educate the public on the price setting mechanism of a stock exchange.

With an objective to create investors confidence in the stock market, behavioural issues are the newest of the things which must be considered while formulating investment strategies. This research will help investment advisors and finance professionals judge investors attitude towards risk in a better way, thus leading to better investment decision-making.

An added motivation for the study comes from Jegadeesh and Titman (2001, p.699-700) who state

“The criticism that observed empirical regularities arise because of data mining is typically the hardest to address because empirical research in
non-experimental settings is limited by data availability. Fortunately, with the passage of time, we now have nine additional years of data that enable us to perform out-of-sample tests as well as to assess the extent to which investors may have learned from earlier return patterns.”

In this paper we provide out-of-sample evidence by investigating the momentum strategies for equities in the NSE
CHAPTER TWO
LITERATURE REVIEW

2.1 Introduction
This chapter reviews the literature on the asset pricing debate for the past 5 decades. We begin with the advent of the efficient markets hypothesis (EMH) in the 1960s that resulted in the dominance of factor models (i.e. CAPM) in the 1970s. Literature on the limitations of the EMH starts accumulating in the 1970s and 1980s mainly in the form of empirical anomalies is reviewed next. This culminates, in the 1990s, into the burgeoning corpus of literature on investor “irrationality”, the product of human psychological biases, errors and limitations. The interface of psychology and Finance has spawned the new field of Behavioural Finance whose literature opens new perspective in the theory of asset pricing. I review recent models of asset pricing that draw inspiration from behavioural finance. The chapter then reviews extensive evidence on the momentum phenomenon. I then underscored the growing importance of emerging markets for the global portfolio investor. The chapter concludes with exposition of the conceptual framework of the study and an enumeration of the research questions.

2.2 The Idea that Markets are Efficient
In the early 1960s the prevailing view among academics in finance and economics was that the stock market was not a proper subject of serious study: modelling the, apparently chaotic, stock market in rational economic terms was academic heresy. What little research existed on the market was done by statisticians who observed that daily price changes seemed for the most part “independent”, displaying no discernible trends or patterns. The researchers described this, in statistical lingua, as the “the random walk hypothesis”. Economists did not take long to perceive the logical rationale underlying the hypothesis. Dependence across time was viewed as inconsistent with rational behaviour in competitive markets and thus evidence of what came later to be known as “market inefficiency”.

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The use of the term “efficient market” first appeared in the 1965 paper by Eugene Fama, which carried the following definition:

“A market where there are large numbers of rational, profit maximizers actively competing, with each other, trying to predict future market values of individual securities, and where important current information is almost freely available to all participants…”

“In an efficient market” Fama argued “on the average, competition will cause the full effects of new information on intrinsic values to be reflected instantaneously in actual prices” (1965, p.4).

The economics underlying the efficient markets idea are very simple. Publicly available information being by definition accessible to all at zero cost, then its expected economic value should also be zero. Ball (1994, p.5) concludes “security prices should therefore adjust to information as soon as (if not before) it becomes publicly available. Ideas don’t come much simpler in economics”.

Almost forty years have gone by since Fama introduced the idea of “efficient” stock markets to financial economics literature, and it continues to stimulate both insight and controversy: and the waters of asset pricing theory have never been murkier than at present. Put simply, the debate now is whether the credo that security prices act as though they fully reflect all available information can be maintained and sustained in spite of empirical evidence to the contrary.

Historically, the impact of the efficient markets hypothesis (EMH) has been extensive and enduring. The boom in the EMH research was facilitated by three developments. First, with the emergence of a new research instrument (after Fama, Fisher, Jensen, and Roll (FFJR)’s 1969 study) known as ‘event study’, a large body of empirical research during the 1970’s provided consistent evidence of the stock markets ability to process information in a rational fashion. Ray Ball (together with Phil Brown (1968) one of the pioneer researchers of stock markets), in his paper in 1994 reminisces,

“This research (of FFJR) so transformed our view of stock markets that contemporary observers cannot begin to appreciate the general suspicion of, and ignorance about stock markets that prevailed 30 years ago” (p.3). Ray Ball continues: “Where we had previously seen only chaos of daily stock price
movements. FFJR's research design enabled us to see order. And the large empirical literature that followed both refined their event study technique and accumulated impressive evidence-unimaginable until the late 1960's—that stock prices respond in an apparently ingenious ways to information" (p.3).

For a survey with detailed analysis of individual studies and their findings see Fama (1970, 1991), and LeRoy (1989).

The second notable factor contributing to the remarkable success of the EMH in the 1960s and 1970s was the establishment (with notable foresight) of the University of Chicago's Centre for Research in Security Prices (CRSP) by James H. Lorie in 1960. The CRSP provided a comprehensive data base on the universe of all NYSE stocks going back to 1926. Such a rich source of data might have been a luxury to be grasped by both hands by many a researcher.

Lastly, the advent of the computer data processing technology gave impetuous to the testing of EMH hypotheses worldwide. The effect of computing power on EMH has been double-edged. In earlier years the technology was employed to confirm EMH claims; currently, however, it has been employed mercilessly in dredging up the many anomalies that are now sounding the death knell to the EMH.

The EMH and the evidence of efficiency influenced the climate for other financial economic theories. Indeed without the impressive body of empirical research on efficiency as a background, the dividend and capital structure theories of Miller and Modigliani (1958), the capital asset pricing model of Sharpe (1964) and Lintner (1965) and the Black and Scholes (1973) option pricing model would not have been so well and so quickly received. In a surprisingly short time, academic attitudes toward research results on stock markets shifted from one extreme to the other. Diffidence was replaced by confidence; scepticism by ardent support; and suspicion by reverence. And empiricism on the EMH proceeded apace.

Following Fama (1970), the testing of the informational efficiency of stock markets has been categorised into three major forms, namely; Weak-form efficiency tests. The weak
form of the EMH states that the sequence of past price changes contains no information about future price changes. The tests here are designed to show that successive price changes are random and no trading strategies based on a study of past prices can yield abnormal returns. The information set used in empirical tests in this case is the vector of past security prices.

**Semi-strong form efficiency tests.** The semi-strong form of the EMH states that the security prices fully reflect all the available public information. The empirical tests here are designed to show that no trading strategies based upon the release of any information to the public can enable an investor to generate abnormal returns consistently. That is, if the market is efficient in the semi-strong sense, it will instantaneously impound all information as it becomes publicly available into security prices.

**Strong-form efficiency tests**. The strong form of EMH states that security prices reflect all the information available both to the public and private at each point in time. The consequence of it is that no investor can devise trading strategies based on such information (even inside information) to earn abnormal returns.

Strong efficiency implies semi-strong form efficiency, and semi-strong form efficiency implies weak-form market efficiency. Conversely, the non-existence of weak form in a market precludes the existence of higher forms of efficiency; and the evidence of semi-strong form inefficiency precludes the existence of the strong-form efficiency in a market.

**2.3 Empirical Evidence: Securities Returns And Risk-Factor Patterns**

EMH and all factor return generating models posit that risk (or risk proxies) is the sole predictor variable in asset returns. Empirical results are, however, mixed. A positive univariate relation of beta with expected returns is found in some studies and not others, depending on the country and the time period examined. After controlling for market value and fundamental/price ratios, an incremental effect of beta is found in some studies, but not others.
Black, Jensen and Scholes (1972), and Fama and McBeth (1973) provide evidence of a significant univariate relation between security betas and expected returns. Both studies find significant positive relation between beta and asset returns. In a more recent sample, Fama and French (1992) also find a positive but insignificant unconditional relation between returns and market beta. Internationally, Rouwenhorst (1999) finds no significant unconditional relation between average return and beta, relative to local market index, on common stocks on 20 emerging markets. Heston, Rouwenhorst, and Wessels (1999) find some evidence of an unconditional univariate relation between market beta and future returns across stocks in 12 European countries.

On the incremental importance of conventional risk measures versus fundamental scaled price variables, Fama and French (1992) find that size and book/market predict future returns, and that when firms are sorted simultaneously by beta and size, or by beta and book/market, beta has no power to explain cross-sectional return differences. However in contrast to Fama and French (1992) results, Jagannathan and Wang (1996) find that the incremental effect of beta on future returns is significant when human capital is included in the definition of the market, and conditional rather than unconditional betas are calculated. Heston et al. (1999) find that size and international beta are both positively associated with future returns in 12 European countries.

There is strong evidence from numerous studies that firm size as measured by market value predicts future returns. This predictive power vanishes when firm size is measured by book value or other non-market measures (see Berk (2000)).

Fama and French (1993) provide evidence that a three-factor model explains the average returns of stocks sorted on market equity and book/market ratio, which they interpret as a model of equilibrium risk premia. However, Daniel and Titman (1997) argue that the Fama and French (1993) results are also consistent with a "characteristics" model, and present evidence that, after controlling for size and book/market ratios, returns are not related to loadings on the Fama and French (1993) factors. Davis et al. (2000) find that they can reject neither the three-factor model nor
the characteristics model over the longer period with U.S. data. Jagannathan, Kubota, and Takehara (1998) find some evidence that, in Japan, both the factor model and the characteristics model determine future returns. However, Daniel, Titman and Wei (2000) find that for Japanese common stock data over the period from 1975 to 1997, they can reject the three-factor model but not the characteristics model. Ferson and Harvey (1998) find that internationally both factor and characteristics model determine future returns.

Furthermore, MacKinlay (1995) finds evidence that high Sharpe ratios (relative to the market) can be achieved with strategies based on fundamental-scaled price variables. As Hansen and Jagannathan (1991) point out, high Sharpe ratios are only possible in a rational pricing model when there is highly variable marginal utility across states. Brennan et al. (1998) show that these strategies produce Sharpe ratios about three times as high as what is achievable with the market. They argue, like MacKinlay, that these are too high relative to the market Sharpe ratio to be plausible within a rational, frictionless asset-pricing model. Moreover, as pointed out by Hawawini and Keim (1995), the returns from these strategies have very low correlations across international stock markets, meaning that the achievable Sharpe ratio with a globally diversified portfolio, and the implied variation in marginal utility, would have been still higher.

The ability of fundamental-scaled priced variables to predict cross-sectional differences in future returns is confirmed by numerous studies. Jaffe, Keim, and Westerfield (1989) find that the ratio of earnings to price has predictive power for the future cross section of returns. Rouwenhorst (1999) finds evidence that firm size and fundamental-scaled price measures predict returns for common stocks for 20 emerging markets. He finds little correlation between book/market- and size-sorted portfolios across the 20 countries.

other fundamental-scaled price variables also have power to predict the cross section of future returns, but that these other variables cannot forecast more powerfully than size and book/market.

For the size or book/market ratio of a firm to be a good proxy for risk, the returns of small and high book/market firms' stocks would have to negatively correlated with marginal utility, meaning that the returns should be particularly high in good times (relative to other stocks) and low in bad times. No such correlation is obvious in the data (see e.g. Lakonishok, Shleifer and Vishny (1994)). Also, fundamental-scaled price variables may be related to the liquidity of a firm's stock. However, Daniel and Titman (1997) find that, if anything, the common stocks of firms with higher book/market ratios are more liquid.

2.4 Empirical Anomalies

The 1960s were the golden years of the EMH where it reached the peak of dominance of finance thinking. It was not long, however, before researchers began to report evidence that contradicted the EMH. There is now a large body of anomalous evidence that appears to contradict market efficiency. Literature classifies them into three broad classes, namely: technical, calendar, and non-CAPM-factor anomalies (See Daniel et al. (1998) for a summary of findings of empirical studies focussing market anomalies).

Technical anomalies

A question that has been subject to extreme research and debate is whether past prices and charts can be used to predict future prices. "Technical analysis" is a general term for a number of investing techniques that attempt to forecast securities prices by studying past prices and related statistics. Evidence of technical anomalies vitiates the claim of a market to weak-form market efficiency. Early strategies by chartists to exploit technical anomalies included moving averages and trading range breaks. In recent years relative strength strategies are in vogue: they include momentum strategies, positive feedback trading strategies, and 'contrarian' strategies. Referring to a study by Brock, Lakonishok, and LeBaron (1992), The Economist of October 9, 1993 stated in an article on the relative strength strategies that:
“Contrary to previous tests, the rules work quite well. Buy signals were followed by an average of 12% return at annual rate and sell signals were followed by a 7% loss at annual rate... The previous conclusion that technical analysis is useless was ‘premature’.”

The list of technical anomalies is long and includes the following. **Price overreactions.** There is evidence that the prices of individual stocks overreact to information and then undergo ‘corrections’. The resulting negative correlation in prices appears to create profit opportunities for ‘contrarian’ trading strategies.

**Post-event drift** Price changes seem to persist after the occurrence of an event or an announcement. Stocks with positive news ‘surprises’ tend to drift upward, while those with negative ‘surprises’ tend to drift downwards. Some refer to this as the ‘cockroach’ hypothesis because when you find one there are likely to be more hiding. Sharpe (1998) puts as follows "There is evidence, and try as they might, the accountants and finance people can't make it go away, that when you get an earnings surprise, somehow or other the market does not seem to absorb it right away".

**The Equity Risk Premium Puzzle** This refers to the existence of a very large historical equity risk premium that seems inconsistent with the actual riskiness of common stocks as can be measured statistically. For example, using the Ibbotson data from 1926 through 2001, common stocks have produced rates of return of approximately 10½ percent while high grade bonds have returned only about 5½ percent. It is difficult to reconcile the magnitude of this premium with modern asset pricing theory (Mehra and Prescott, 1985) since it implies that the representative investor is exceedingly risk-averse

**Excess volatility** Shiller (1981) has argued that markets in general overreact to events because of investors’ pursuit of fads, and other herd-like behaviour. In support of his argument he presents evidence suggesting that the volatility of stock prices is much too large to be explained by the volatility of dividends.

**Price under-reactio** Research indicates that prices react sluggishly in impounding the effects of information events or announcements.
Calendar Anomalies (Seasonality)

Researchers have provided evidence of seasonal patterns of varying duration. The regularity of the patterns means one can predict future stock returns. This flies against weak-form market efficiency. Notable examples are explained below.

The January effect: Stocks, in general, and small 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 behaviour in security markets throughout the world. The effect is usually attributed to stocks rebounding following year-end tax selling. Ritter (1988) postulates the “parking of proceeds “ hypothesis as a reason why individuals are realising losses at the end of December but wait until January to reinvest the proceeds. His argument is as follows:

“Instead, individuals typically ‘park’ the proceeds in their brokerage accounts for a period of time, and only later reinvest them. Discussions with stockbrokers indicate that, throughout the year, it is common for individuals who have sold stocks to wait for several days or weeks before reinvesting the proceeds”.

The bottom line is that January is the best month in which to invest in stocks.

Turn of the month effect: Stocks consistently show higher returns on the last day and first four days of the month. Hensel and Ziemb (1996) presented the theory that the effect results from cash flows at the end of the months in form of salaries, rents, interest payments etc. The two authors found returns for the turn of the month were significantly above average from 1928 through 1993 and ‘that the return from S&P 500 over these 65 year period was received mostly during the turn of the month’. This implies that investors making regular purchases may benefit by scheduling to make the purchases prior to the turn of the month.

The Monday (weekend) effect: Monday tends to be the worst day to be invested in stocks. Several studies have found a tendency towards negative returns on US stocks in the period between Friday close and Monday close—that returns on Monday are worse than other days of the week. French (1980) claims that the effect was a ‘weekend effect’ rather a more general ‘closed market’ effect. Theobald and Price (1984) found a
similar effect in UK equity market indices. Jaffe and Westerfield (1985) and Condoyani, O’hanlon, and Ward (1986) by using international data demonstrate that the weekend effect is a pervasive feature of capital markets around the world. Lakonishok and Maberly (1990) suggest that a possible reason why sell pressure is higher on Monday is that investors have had the weekend to make independent decisions (away from analysts who are prone to give buy recommendations) and demonstrate the freedom by tilting towards decisions to sell. Other explanations include Ritter’s (1988) ‘parking of proceeds hypothesis: that firms wait until the end of the week to disclose bad news; and the ‘market closed effect’. An interesting perspective presented by the weekend effect is that since moods of market participants are better on Fridays than on Mondays, the effect is a function of moods.

**Other anomalies**

Research evidence indicates that stock fundamentals/price ratios, and size have predictive power over future stock returns.

*Size effect:* A paper by Banz (1981) yielded the surprising result that small firms tend to have higher abnormal returns than do larger firms. Later studies by Reinganum (1983), and Brown, Kleidon, and Marsh (1983) found evidence consistent with the small firm effect. Attempts to explain the effect are many. Roll (1981) attributes it to incorrect measurement of systematic risk due to the infrequent trading of small cap stocks. Arbel and Strebel (1983) suggest that small stocks are actually riskier because they are less well known.

*Fundamentals/price ratios effect:* Investment managers classify firms that have high book-to-market equity (B/M), earnings to price (E/P) or cash flow to price (C/P) as value stocks. Fama and French (1992, 1996) and Lakonishok, Shleifer, and Vishny (1994) show that for US stocks there is a strong value premium in returns. High B/M, E/P, or C/P stocks have higher average returns than low B/M, E/P, or C/P stocks. Fama and French (1995) and Lakonishok, Shleifer, and Vishny (1994) also show that the value premium is associated with relative distress. High B/M, E/P, or C/P firms tend to
have persistently low earnings: low B/M, E/P, or C/P tend to be Strong (growth) firms with persistently high earnings.

Lakonishok et al. (1994) and Haugen (1995) argue that the value premium in average returns arises because the market undervalues distressed stocks and overvalues growth stocks. When these pricing errors are corrected, distressed (value) stocks have high returns and growth stocks have low returns. In contrast Fama and French (1993, 1995, and 1996) argue that the value premium is compensation for risk missed by the capital asset Pricing Model (CAPM) of Sharpe (1964) and Lintner (1965).

2.5 Behavioural Finance

In response to the difficulties faced by modern finance in fully explaining activity in stock markets a new field has developed that applies investor psychology to the markets. Behavioral finance is the study of how psychology impacts financial decisions in households, markets and organizations. The main question is: What do people do and how do they do it? The research methods are mostly (but not exclusively) inductive. Behavioral researchers collect “facts” about individual behavior (based on experiments, surveys, field studies, etc.) and organize them into a number of “superfacts.” (DeBondt et al., 2008). Behavioural finance stands on two pillars (Barberis & Thaler, 2003). These are: first, psychology, under which falls investor sentiment or beliefs, preferences and emotions. Second pillar consists of the limits to arbitrage. By incorporating investor psychology, and recognizing the limited sweep of arbitrage, behavioural finance lays assault on EMH’s basic axioms of investor rationality, and omnipotence of arbitrage forces. We follow with a review of literature on these building blocks of behavioural finance.

2.5.1 Investor’s Psychology

Economics has conventionally assumed that economic agents have stable and coherent preferences, and which they rationally maximize. Given a set of options and probabilistic beliefs, a person then maximizes the expected value of a utility function, \( U(x) \). Psychological research suggests various modifications to the classical economic
decision making model that will result in a $U(x)$ that is more realistic than under standard economic assumptions.

Mainstream economics employs a powerful combination of methods. These include methodological individualism, mathematical formalization of assumptions, logical analysis of the consequences of those assumptions, and sophisticated empirical field-testing. As Rabin (1998) comments, these methods, though possessing the strength of modelling "tractability" and "parsimony", nevertheless raise problems for doing full justice to behavioural reality. Rabin (1998, p.13) expresses the view that ".... we should begin the process of integrating them (psychological findings) into economics." In this subsection we briefly review literature on judgment biases, and errors in preferences.

I  Judgment and decision biases

Even though financial decisions are made in situations of high complexity and uncertainty, economists have nonetheless assumed that people correctly form their subjective probabilistic assessments according to Bayesian laws of probability. Empirical evidence, to the contrary, documents many systematic departures from rationality in judgments under uncertainty. Tversky and Kahneman (1974, p. 1124) attribute this departure to people's reliance to "heuristic principles which reduce the tasks of assessing probabilities and predicting values to simpler judgmental operations". David Hirshleifer’s (2001, p. 1541) broader view argues, "Heuristic simplification, self-deception and emotional loss of control provide a unified explanation for most known judgment and decision biases". Following Hirshleifer we discuss the biases under three heads.

(a) Heuristic simplification

Because of limitation of time and cognitive resources humans resort to rules of thumb (algorithms, heuristics, or mental modules) selectively to solve problems. Heuristic simplification finds expression in human behaviour in various forms.

(1) Limited attention, memory, and processing capacities force a focus of subsets of available information. This results in the salience heuristic where information signals
that hook attention or create associations have more weight: *The availability heuristic* (Tversky and Kahneman (1973)) when items that are easier to recall are judged to be more common; *The halo heuristic* (Nisbett and Wilson (1977a)) where the possession of one outstanding characteristic affects how the other characteristics are judged. In the stock market this misattribution bias could cause mispricing (see Lakonishok, Shleifer, and Vishny (1994) and Shefrin and Statman (1995)).

(2) *The representativeness heuristic:* (Kahneman and Tversky (1973)) involves assessing the probability of a state based on the degree to which the evidence is similar to or typical of the state of the world. According to this, so called, “law of small numbers”, people exaggerate how closely a small sample will resemble the parent population from which the sample is drawn. Because we expect close to the same probability distribution of types in small groups as in large groups the *Gamblers’ fallacy* manifests itself: if a fair coin has come up tails for a while, then on the next flip it is “due” for tails (Clotfelter and Cook (1993)). In securities markets use of the representativeness heuristic can cause trend chasing because people are too ready to believe trends have systematic causes. There is a *clustering illusion* with people perceiving random clusters as representing a pattern. According to Hirshleifer (2001), the law of small numbers could explain why the stock market overreacts. Furthermore, in order to explain a few lengthy streaks in sequences of random numbers people coin spurious explanations such as the “hot hands” in basketball (Gilovich, Vallone, and Tversky (1985)).

(3) *Belief perseverance and confirmatory bias:* A range of research suggests that once people have formed strong beliefs they are inattentive to new information contradicting their beliefs. Once an investor is convinced that the trading strategy (or stock) of her choice is superior to another, information suggesting the contrary does not get a receptive ear. Edwards (1968) referred to the phenomenon as *conservatism*. While Braner and Potter (1964) demonstrate it as an ‘anchoring’ effect. Related to belief perseverance is the observed tendency of individuals to seek information that confirms their already held positions. Rabin (1998, p.18), contemplating economists’
reaction to behavioural evidence that might be damaging to dearly loved paradigm (i.e. the EMH) states.

"With confirming evidence—people rapidly reduce the complexity of the information and only remember a few well-chosen, supportive impressions. With disconfirming evidence, they continue to reflect upon any information that suggests less damaging 'alternative interpretation'. Indeed they may even come to regard the ambiguities and conceptual flaws...as somehow suggestive of the fundamental correctness of those hypotheses."

Confirmation bias is prominent in assessment of correlations extended over time. Nisbett and Ross (1980) argue that inability to accurately perceive correlations is one of the most robust shortcomings in human reasoning, and people imagine correlations in events when none exists. Jenning, Amabile and Ross (1982) argue that illusory correlations play an important role in the confirmation of false hypotheses, finding that people underestimate correlation when they have no theory of the correlation, but exaggerate correlation and see it where it is not when they have a preconceived theory.

(b) Self-deception

This is a family of biases that are interrelated and include the following. They include overconfidence, optimism, hindsight and sunk-cost. We review each below.

Overconfidence: Studies of calibration of subjective probabilities find that people tend to overestimate the precision of their knowledge (See Alpert & Raiffa, 1982; Fischhoff, Slovich, & Lichtenstein, 1977; Lichtenstein, Fischhoff, & Phillips, 1982). Evidence of overconfidence is robust: it has been reported in clinical psychologists (Oskamp (1965), Physicians and nurses Chistensen-Szalanzki and Bushy-Head (1981), engineers (Kidd, 1970), investment bankers (Stael von Holstein, 1972). lawyers (Wagenaar & Keren, 1986), negotiators (Neale & Bazerman,1990), and managers (Russo & Shoemaker, 1992). The widely reported findings on overconfidence is that it is more pronounced when a person is answering questions of moderate to extreme difficulty, it afflicts both experts and laymen (in some cases experts have been more overconfident), but people tend to be well-calibrated when predictability is high. the tasks are repetitive and with fast unambiguous feedback (i.e. expert bridge players, race bettors and meteorologists).
There are several reasons why financial market participants could be expected to be overconfident. The first reason why you would expect traders to overconfident is that overconfidence is pervasive. Secondly, most of those trading in the market try to choose winners. This is a difficult task and it is precisely in such tasks (when feedback is noisy and untimely) that people display the greatest overconfidence. Griffin and Tversky (1992) add, moreover, that when predictability is very low, as in stock markets, experts exhibit more overconfidence than novice because experts have theories and models, which they tend to overweight.

Thirdly, the related bias of self-deception and loss aversion boosts overconfidence in investors. If investor’s charge their original purchase decisions on the basis of returns realised, rather than those accrued, then, they will be prone to the disposition effect. By holding losers, they will judge themselves to have made fewer poor decisions. Shefrin and Statman (1985) propose and Ode (1986 b) confirms that investors prefer to sell winners and hold losers. Thirdly selection bias may cause participants in financial market to be especially more overconfident. This is because the nature of their assignments demands certain abilities, real or imagined. If people are uncertain judges of their own ability, then we might expect financial markets to be populated with those with the most ability or those who most overestimate their ability.

Finally, survivorship bias can also lead to overconfidence. Unsuccessful traders may be driven out or, if they survive, control less wealth. The successful traders may grow more overconfident bolstered by the enhancing bias of positive self-attribution, and control more of the wealth. Odean (1998) writes that it is not that overconfidence makes them wealthy, but the process of becoming wealthy contributes to their overconfidence.

Optimism: Optimism is another manifestation of overconfidence. Most people’s beliefs are biased asymmetrically in the direction of optimism. Optimists exaggerate their talents, they overestimate their ability to do well on tasks and this overestimates increase with the personal importance of the tasks (Frank, 1935). Other empirical observations of optimism are that people expect good things to happen to them more
often than to their peers (Kunda, 1987); People have unrealistically positive self-evaluation (Greenwald, 1980), and see themselves better than others see them (Taylor & Brown, 1988). Taylor and Brown argue that exaggerated beliefs in one's abilities and unrealistic optimism may be positive in that it may lead to 'higher motivation, greater persistence, more effective performance, and ultimately greater success'. But as Odean (1998) comments it may also lead to biased judgments. Evidence also indicates that people overestimate their own contribution to past positive outcomes, recalling information related to their success more easily than failures. In this regard, Fischhoff (1982) writes" they even misremember their own predictions so as to exaggerate in hindsight what they knew in foresight".

_Hindsight:_ One of the most widely studied biases in the judgment literature is the hindsight bias. Fischhoff first proposed this bias by observing that.

"(a) Reporting an outcome's occurrence increases its perceived probability of occurrence; and (b) people who have received outcome knowledge are largely unaware of its having changed their perceptions (along the lines of (a) above)---people exaggerate the degree to which their beliefs before an informative event would be similar to their current beliefs".

Rabin adds "people do not sufficiently 'subtract' information they currently have about an outcome in imagining what they would have thought without that information. Hindsight is an important element of _regret_—it helps our esteem to think that we knew it all along.

_Sunk-cost effect, cognitive dissonance, rationalization and biased self-attribution_ are all self-delusory biases that reinforce overconfidence and optimism, acting as shock absorbers that prevent people from being surprised (and learning from past mistakes) as they should when things turn-out otherwise than they had predicted.

(c) _Emotional Loss of Control_

Elster (1998) lists the following among the states that unambiguously qualify as emotions: First, social emotions; anger, hatred, guilt shame, pride and admiration. Second, counterfactual emotions; regret, rejoicing, disappointment and elation. Third,
emotions generated by the thought of what may happen: fear and hope. Fourth, emotions of what has happened, joy and grief. Finally, emotions triggered by possessions of others; envy, malice, indignation. Borderline controversial cases include contempt, disgust, romance, boredom, interest, sexual desire worry and frustration.

According to Frijda (1986) emotions have the characteristic of action tendency i.e. “states of readiness to execute a given kind of action...” The action tendency of shame is to hide or disappear; that of guilt, to confess or make atonement. In many situations where emotions are involved rational choice theory is indeterminate in that it does not allow one to select the uniquely optimal action. Johnson-Laird and Oatley (1992) argue that because the ideal of “impeccable rationality” assumes that “there are no surprises, no misunderstandings, no irresolvable conflicts”, it cannot guide action in situations that are characterised by features of emotion. According to LeDoux (1996, p.195), if you are a small “rational” animal faced with a bobcat and

“had to make a deliberate (rational) decision about what to do, you would have to consider the likelihood of each possible choice succeeding or failing and could get so hogged down in decision making that you would be eaten before you made the choice.”

Literature shows that sunshine affects moods as evidenced by song, verse, daily experience, and formal psychological studies. Hirshleifer and Shumway (2003) comment that individuals who are in good moods make more optimistic choices, have more positive evaluations of many sorts, such as life satisfaction, past events, people and consumer products. On the reverse, people who are in bad moods tend to find negative material more salient and available (see Isen et al. (1978)). Studies have also shown that people who are in good moods engage in more use of simplifying heuristics (see the reviews of Bless, Schwarz & Kemmelmeier, 1996 and Isen, 2000)).

Several studies have reported that bad moods tend to stimulate people to engage in detailed analytical activity, whereas good moods are associated with less critical modes of information processing (Schwarz, 1990; and Mark, 1995) so that people in good moods are receptive to both weak as well as strong arguments. But do moods and emotions affect asset prices? There is some evidence that sunshine influences markets.
Saunders (1993) shows that when it is cloudy in New York City, New Stock Exchange index returns tend to be negative. More recently, Hirshleifer and Shumway (2003) examined the relationship between whether a day is sunny and stock returns that day on 26 stock exchanges internationally from 1982 to 1997. They found that sunshine is highly significantly correlated with daily stock returns.

II Errors of Preferences

Having discussed, in the preceding section, the psychological evidence of biased judgment by investors of probabilities associated with different options, we now present relevant psychological findings on people's erroneous use of probability information in evaluating risky prospects, assigning values to outcomes and combining values and probabilities into a preference profile.

(a) Reference levels, mental accounting and loss aversion

Overwhelming evidence shows that humans are often more sensitive to how their current situation differs from some reference level than to absolute characteristics of their situation (Helson, 1964). For instance the same temperature that feels cold when we are adapted to hot temperatures may appear hot when we are adapted to cold temperatures. Recognition of this tendency requires that economist incorporate into utility analysis such factors as habitual levels of consumption. Instead of utility at time $t$ depending solely on present consumption, $C_t$, it may also depend on a “reference level”, $R_t$, determined by factors like past consumption, or expectations of future consumption. Consequently the traditional utility function of $U_t (C_t)$ should take the more general form, $U_t (R_t, C_t)$.

Researchers have identified another feature of reference dependence: In a wide variety of domains, people are significantly more averse to losses than they are attracted to same sized gains (see Kahneman, Knetsch & Thaler, 1990). This loss aversion is a feature of Kahneman and Tversky’s (1979) descriptive model of decision making under risk, prospect theory, which uses experimental evidence to show that people get utility from gains and losses in wealth rather from absolute levels. Tversky and Kahneman
(1991) suggest that in the domain of money people value modest losses roughly twice as much as equal-sized gains.

When the gains and losses are taken to be changes in total wealth, we say they are “broadly” defined. When they refer to changes in the value of isolated component of wealth - the investor’s stock portfolio or individual stock - we say that they defined “narrowly”. Which gain or loss the investor pays attention to is a question about mental accounting, a term coined by Thaler (1980) to refer to the process by which people think about and evaluate their financial transactions.

Numerous experimental evidence suggest that when doing their mental accounting people engage in narrow framing, that is, they pay attention to narrowly defined gains and losses. Kahneman and Riepe (1998, p. 7) state, “...rationality is best served by adopting broad frames, and by focussing on states (such as wealth) rather than on changes (such as gains and losses). We admit however that narrow framing is easier, more natural, and much more common.”

The standard concave-utility-function explanation for risk aversion is simply not a plausible explanation. To take account of loss aversion the value function must needs abruptly change slope at the reference point: i.e. there is a reference-based kink in the utility function required to explain these risk attitudes within the expected utility framework. An important article by Bernartzi and Thaler (1995) explores the role of loss aversion in the pricing of stocks and bonds, explaining the equity-premium puzzle by the tendency by investors to loss aversion when faced with risk.

Loss aversion is related to the striking endowment effect identified by Thaler (1980): Once a person comes to possess a good, she immediately values it more than before she possessed it. Kahneman, Knetsch and Thaler’s “mugs” study nicely illustrated the phenomenon: once a person had received a “mug” she felt the loss of being deprived of the mug more than the one who never received at all.

As established by Knetsch and Sinden (1984), and Samuelson and Zeckhauser (1988), a comparable phenomenon---the status quo bias---holds in multiple-good choice
problems. Here loss aversion implies that individuals tend to prefer the status quo to changes that involve losses of some good, even when the losses are offset by the gains of other goods. Knetsch (1989) shows that such preferences can be usefully captured by utility functions defined over reference levels as well as consumption levels.

We generally expect investors to be aware of the price at which they made a substantial investment in a stock and to continue to use this price as a reference point: the price determines whether selling the stock now will yield a gain or loss. An important consequence of this psychological predilection is known as the disposition effect. Statman and Shefrin (1985) documented evidence showing that investors had a tendency to hold on securities that have declined in value and to sell winners.

(b) Social preferences and fair allocations

Adam Smith's 18th century poetic characterization of the "self-interest" motivating economic behaviour is accurate even today. In The Wealth of Nations (1776, p.26-27), he states:

"It is not from the benevolence of the butcher, the brewer or the baker that we expect our dinner, but from their regard of their own interest. We address ourselves not to their humanity, but to their self-love, and never talk to them of our necessities, but of their advantage."

Yet pure self-interest is far from a complete description of human motivation. Realism suggests that economists should move away from the presumption that people are solely self-interested. Experimental research in psychology, industrial relations and economics makes clear that preferences depart from pure self-interest in non-trivial ways. Driven by equity, for example, public contribute to public goods more than can be explained by self-interest; they often share money when they could readily grab it for themselves, and they often sacrifice money to retaliate against unfair treatment. Inspired by altruism, it has been documented that that people put positive value to the well being of other people.

In moving from abstract, context-free allocation problems to every day economics fairness judgments, things become significantly more complicated. First, as elsewhere,
reference levels are crucial. Thaler (1985) demonstrates that loss aversion plays a very strong role of people’s notion of fairness. Relatedly, people’s perception of fair behaviour may adjust over time. Kahneman, Knetsch and Thaler (1986, p. 730) argue “Terms of exchange that are initially seen as unfair may in time acquire the status of a reference transaction. Thus, the gap between the behaviour that people consider fair and the behaviour that they expect in the market tend to be rather small.” Francois et al. (1995) experimentally support this hypothesis by testing reactions to unfair price increases in a laboratory-posted offers market; they show that the role of fairness considerations in price determination diminishes with repetition, suggesting that in competitive spot markets people may eventually come to believe that the prevailing market price is fair.

Finally, it is important to note that people seem to implicitly consider equitable sharing over changes in total endowments, and not the total endowments themselves. Preferences defined over final wealth states cannot plausibly explain rules such as 50/50 division or the maximin criterion. Apparently people have the insurmountable tendency to consider each division problem one at a time. Formal economic models must confront the “piecemeal” nature of the behavioural norms of fairness and distributional justice.

(c) Reciprocity and attribution

Psychological evidence indicates that social preferences over other people’s consumption depend on the behaviour, motivations, and intentions of those other people. The same person who may be altruistic towards a deserving person may be indifferent to the plight of an undeserving person, and even motivated to hurt those who may have misbehaved. Tit-for-tat becomes an acceptable mode of social intercourse. In a word it means that preferences are reciprocal in nature.

Reciprocity motives manifest themselves not only in people’s refusal to cooperate with others who are being uncooperative, but also in their willingness to sacrifice to hurt others who are being unfair. A consumer may refuse to buy a product being sold by a monopolist at an “unfair” price, even if she hurts herself by foregoing the product. An
employee who feels he has been mistreated by a firm may engage in costly acts of sabotage. And members of a labour union may strike longer than is in their interests because they want to punish an employer for being unfair.

*Volition and intentions* are also central to the propensity to retaliate. If for example you knock a jar and spill water on a child seated with his parents at a dinner table the reaction of the parents to you depend on whether they think your action was intentional, or that your flailing hands were an uncoordinated attempt to prevent the spill. Charness (1996) conducted an experiment to identify the source of high effort levels by workers in response to high wages by firms. The result showed that workers were substantially more likely to reward high wages with high effort and punish low wages with low effort when the wages reflected the volition of the firm.

### 2.5.2 Failure of Arbitrage Mechanism

One of the fundamental concepts in finance is arbitrage, defined as “the simultaneous purchase and sale of the same, or essentially similar, security in different markets for advantageously different prices” (Sharpe & Alexander, 1990, p.45). In Fama’s (1965) classic analysis of efficient markets and in the models such as the CAPM and the APT the market is assumed to be populated with a very large number of atomistic arbitrageurs each taking an infinitesimal position against the mispricing in a variety of markets. Such market participants have no capital constraints and are effectively risk neutral. When such an arbitrageur short sells a more expensive security and buys a cheaper one, his net cash flows are zero for sure, and he gets his profit up front. Arbitrage is therefore the great financial market leveller, whose effect is to eat away any mispricing in the market ensuring that prices are in line with fundamental values and that markets are efficient.

If it is indeed the case that financial market prices are driven at least in part by irrational agents, then two issues arise: (i) why does arbitrage not remove any mispricing? (ii) why do irrational traders, who would lose money on average, not get driven out of the market in the long-run? Recently, progress has been made in answering both of the preceding questions.
First, Shleifer and Vishny (1997) argue that arbitrage may be restricted because it is costly precisely when it would be useful in removing pricing inefficiencies. For example, because of marking-to-market, arbitrageurs may require more and more capital as prices diverge more and more from their efficient values. Furthermore, Daniel et al. (2001) argue that owing to risk aversion, arbitrageurs may not be able to remove all systematic mispricing.

There are at least three counter-arguments to the notion that irrational traders would cease to be influential in the long-run. First, DeLong et al. (1991) argue that irrational agents, being overconfident, can end up bearing more of the risk and can hence earn greater expected returns in the long-run. Second, Kyle (1997) argue that even if agents are risk-neutral, overconfidence acts as a pre-commitment to act aggressively, which causes the rational agent to scale back his trading activity. In equilibrium, this may cause overconfident agents to earn greater expected profits than rational ones. Finally, Hirshleifer et al. (2006) argue that when stock prices influence fundamentals by affecting corporate investment, irrational agents can earn greater expected profits than rational ones. This happens because irrational agents act on sentiment sequentially. Agents who act on sentiment early benefit from late arriving irrationals who push prices in the same direction as the early ones. If private information is noisy, this can result in situations where the irrationals as a group, outperform the rationals in terms of average profits.

Recent evidence collected from research suggests that arbitrage need not eliminate mispricing. First, as Shleifer and Vishny (1997) argue, the reality in the market place is that arbitrage is conducted through the agency of relatively few highly specialised professionals who combine their knowledge with the resources of outside investors to take large positions. In this agency relationship arbitrageurs suffer from capital constraints that can significantly limit arbitrage effectiveness in achieving market efficiency. Compounding the problem is risk aversion that might make the arbitrageur to choose to liquidate in extreme circumstances because of a premature fear that a possible further adverse price move will cause a really dramatic outflow of funds later on. In effect, he quits when he is most needed. Indeed, one would expect wealth to flow from
smart to dumb traders (instead of the other way round), exactly when mispricing becomes more severe (Xiong (2000)) which could contribute to self-feeding bubbles.

A second reason why arbitrage is a limited instrument of efficiency is that when traders are risk-averse, prices reflect a weighted average of beliefs. Just as rational investors trade to arbitrage away mispricing, irrational investors trade to arbitrage away rational pricing.

Thirdly, Burgeoning “limits to arbitrage” literature suggests that when a mispricing occurs, (arbitrage) strategies to correct it could be both risky and costly, thereby allowing mispricing to persist. Barberis and Thaler (2002) identify these risks and costs to include an asset’s fundamental risk, noise trader risk in the market, and the costs of implementation of the strategy. Empirical evidence on limits to arbitrage suggests that if irrational traders cause deviations from fundamental value, rational traders (faced with these risks and costs) will almost be powerless to do anything about it.

It is also important to note that for certain types of noise trading, arbitrageurs may prefer to trade in the same direction as the noise traders, thereby exacerbating rather than diminishing the mispricing (De Long et al., 1990). In a related model, rational, expected utility maximizing smart money never choose to offset all of the effects of irrational investors because they are rationally concerned about the risk of the irrational investors and do not want to assume the risk necessary to wipe out all the mispricing. Theoretically therefore, there is reason to believe that arbitrage is a risky process and therefore that it is only of limited effectiveness.

Fourthly, recent research has focussed on an important obstacle to arbitrage – i.e. constraints on short sales. The informed arbitrageur can always buy the stock, but if the arbitrageur does not already own the stock and finds it difficult to short the stock then arbitrage cannot eliminate an overvaluation. The arbitrageur may know that a stock is trading at a ridiculously high price but if he cannot short the stock (short selling is nonexistent in most emerging markets including the NSE); he will be standing on the
sidelines, unable to profit from his information. Miller (1977), in a widely discussed paper, pointed out this flaw in the argument for market efficiency.

Finally, as noted by LeRoy (1989), if rational agents are risk averse, they will find that the portfolio they would have to acquire in order completely to reverse the effects of irrational trades imply excessive risk. Consequently, foolishly aggressive traders may earn higher returns for bearing more risk (DeLong et al. (1990, 1991)), or for exploiting information signals more aggressively (Hirshleifer and Luo (2001)), and may gain from intimidating informed traders (Kyle and Wang (1997)).

2.6 Empirical Evidence of Momentum

Momentum in prices has been recognized as the most robust market efficiency anomaly. It has been documented in stock exchanges the world over and has persisted even after wide publication. Fama (1998), indeed, recognizes the momentum phenomenon as constituting the chief embarrassment to EMH.

The first and most impressive examples of return momentum (continuation in price movement) came from cross-sectional returns of individual stocks. In this category is the seminal study of Jegadeesh and Titman’s (1993) whose findings are the first in the copious body of momentum literature. Using a U.S. sample of NYSE/AMEX stocks over the period from 1965 to 1989, they find that a strategy that buys six-months winners and shorts past six-month losers earns approximately one per cent per month over the subsequent six months. Chan, Jegadeesh, and Lakonishok (1996) theorize that prices respond gradually to earnings news i.e. there is continuation after earnings announcements. The authors show that sorting stocks into ten deciles by prior six months returns yields spreads in returns of extreme deciles of 8.8% over the subsequent six months suggesting a price momentum effect, which is due to underreaction. Hong, Lim and Stein (1999) attribute the underreaction of stock prices to analysts’ coverage, which is more pronounced in the case of bad news.

The evidence of momentum is not restricted to the U.S.A. Rouwenhorst (1998) obtains similar numbers as those of Jegadeesh and Titman in a sample of 12 European countries.
over the period 1980 to 1995. Strong and Xu (1999) follow the methodology of Jegadeesh and Titman (1993) to document profitable price momentum strategies in the U.K. market that are consistent with market underreaction to industry-or-firm specific news. Ryan and Overmeyer (2004) adduce evidence from Germany showing that relative strength (momentum) strategies based on the constituents of the DAX 100 index are "extremely profitable." In addition Ryan and Overmeyer find that the profits are neither driven by differences in betas, nor attributable to size and market-to-book characteristics, nor are they caused by the presence of a delayed price reaction to common factors. On the other hand, Haugen and Baker (1996) and Daniel (1996) show that, although there is evidence of strong book-to-market effect in Japan, there is little or no evidence of a momentum effect.

It has been widely shown that investors tend to 'flock' together. This herding behaviour is documented (among others) in Grinblatt, Titman and Wermers (1995) who find that the majority of mutual funds purchase stocks based on their past returns i.e. buying past winners. Lakonishok, Shleifer and Vishny (1992) find evidence of pension fund managers either buying or selling in herds with evidence that they herd around small stocks.

In the event study area, it has been observed that, conditional on the occurrence of a public event, stocks tend to experience post-event drift in the same direction as the initial event impact. The most studied events in this genre include earnings announcements (Bernard & Thomas, 1989, 1990); stock issues (Loughran & Ritter, 1995; and Spiess & Affleck-Graves, 1995); repurchases, (Ikenberry, Lakonishok, & Vermaelen, 1995); dividend initiation and omissions (Michaely, Thaler, & Womack, 1995); and analyst recommendations. (Womack, 1996).

Bernard (1992), and Chan et al. (1996) use the surprise contained in earnings announcements to show that the market underreacts. Ranking stocks by standardized unexpected earnings (SUE) they find that stocks with higher earnings surprises also earn higher returns in the period after portfolio formation. Chan et al. (1996) found
spreads of 4.2% in returns of extreme deciles formed on the basis of SUE. The findings support the hypothesis of drift to earnings announcements.

Apart from earnings, there is also evidence of price ‘drift’ following other corporate announcements. Ikenberry et al. (1995) find that stock prices rise on the announcement of share repurchases but then continue to drift in the same direction over the next few years. Michaely et al. (1995) documents drift evidence following dividend initiation and omission. Ikenbery (1990) finds evidence of drift following stock splits while Loughran and Ritter, and Spiess and Affleck-Graves (1995) find evidence of drift following seasoned equity offerings.

Analysis of aggregate stock market indices has also produced corroborating but weak underreaction evidence. Cuttler et al. (1991) examine auto-correlation in excess returns on various indexes over different horizons for stocks, bonds and foreign exchanges, and generally find, though not uniform, positive auto-correlation in excess returns of around 0.1 for stocks, and in bonds of 0.2. This auto-correlation is statistically significant and consistent with the underreaction hypothesis. Chan, Hameed, and Tong (2000) implement momentum strategies on stock markets of 23 countries, taking exchange rate movements into consideration. They find that a great proportion of momentum profits come from price continuation in stock indices, and very little from movements in exchange rates. The momentum profits are statistically significant, are not confined to emerging markets, and cannot be explained by non-synchronous trading, though they diminish when adjusted for market risk.

Extensive literature exists on how trading volume impacts the profitability of momentum strategies. Early technical analysts believed that volume data provided important information about future price movements. A common believe noted by Chan et al. (2000) is that, ‘it takes volume to move prices,’ meaning that when stocks are thinly traded (as happens occasionally at the NSE) information may not be impounded quickly into prices. Studies using data on thinly traded markets would be provide valuable insights on the role of volume and liquidity on the profitability of momentum strategies.
Other studies that also conclude that trading volume contain information about future stock prices include Conrad et al. (1994) who find that high volume securities experience price continuation. Gervais et al. (1998) who show that individual stocks whose volumes are unusually large (small) tend to experience large (small) subsequent returns and Lee and Swaminathan (1998) who illustrate that past trading volume predicts both the magnitude and persistence of future price momentum, and that over the intermediate horizons, price momentum strategies work better among high volume stocks.

Volume has also been found to be informative on the profitability of strategies based on market indexes. Chan et al. (2000) found that when momentum strategies were implemented on markets that experienced increases in volume in the previous period, the profits were higher than average. Hong et al. (1999) find that the underreaction of stock prices depends on the analyst coverage of the stock: less coverage means underreaction is severe and the opportunities for profitable trading are enhanced.

While momentum is associated to a large extent with underreacting markets, overreaction could also generate momentum. Daniel (1996), and Asness (1995) observe that, in post World War II U. S data, the cross-sectional and aggregate overreaction effects observed are partly masked by a momentum effect (positive serial correlation) at one-year horizon. One of the first and influential papers in the overreaction category is DeBondt and Thaler (1985) who find that stock returns are negatively correlated at the long horizon of 3 to 5 years. Chopra, Lakonishok, and Ritter (1992) support DeBondt and Thaler. Other contributions have been made by Fama and French (1996), Poterba and Summers (1998), Richards (1997) and Carmel and Young (1997) among many others.

2.7 Review of Literature on Behavioural Finance Models

As an alternative to the risk based models, many researchers are turning to 'behavioural' theories "where behavioural can be broadly construed as involving some departure from the classical assumptions of strict rationality and unlimited computational capacity on the part of investor’s" (Hong and Stein (1999, p. 2143)).
Because of the potentially huge number of such departures that one may entertain. Hong and Stein (1999) attempt to impose some discipline on the prolific process of building new theories (based on psychological evidence) by specifying the criteria that a new behaviour-based theory should be expected to satisfy, at a minimum: i.e. rest on assumptions about investor behaviour that are consistent with evidence; explain the existing evidence of return anomalies in a unified and parsimonious way; and. make a number of further predictions that can be subject to ‘out-of-sample’ testing and that are ultimately validated.

Efforts to develop behavioural-based models to explain the asset pricing process are numerous and multi-pronged. We now review four recent papers that have taken up the challenge to develop models that meet the criteria outlined above in Hong and Stein (1999).

Barberis, Shleifer and Vishny (BSV) (1998) develop a representative agent model based on psychological evidence where agents (investors) are vulnerable to two types of judgment errors: conservatism and representativeness. Conservatism states that individuals are slow to change their beliefs in the face of new evidence. Representativeness is the tendency to overweight the most recent or the salient and the extreme, in spite of the low probability of occurrence such events in the population. BSV then attempt to explain under-reactions by conservatism and overreactions by representativeness: in their model, earning follow a random walk, but investors do not realize this, rather they switch between two regime switching process that investors think to exist is modelled as a Markov process. Under-reaction occurs when investors conserve the mean reverting regime in the face of changes in earnings and overreaction occurs when they switch to trending regime after a string of shocks in the same direction eventually make them believe that earning surprises are trending. Barberis et al. formalize this intuition by solving a mathematical model of investor behaviour described above. The model produces both under reaction and overreaction for a wide range of parameter values.
Daniel, Hirshleifer and Subrahmanyam (DHS) (1998) propose a theory of under and overreaction based on two psychological biases: investor overconfidence about the precision of her/his private information, and biased self attribution, which causes asymmetric shifts in investor confidence as a function of her investment outcomes. Note that, interestingly DHS and BSV employ different psychological biases but end up with similar conclusions. In DHS model, overconfident informed traders (trading with the rational uninformed) overweight their private signals relative to the priors, causing the stock price to overreact. In other words, investors overreact to their private information signals and under react to public information signals. In contrast with the common correspondence of positive returns autocorrelations with under-reaction, they show that short-term positive return autocorrelations can also be a result of continuing overreaction.

Figure 3 displays the typical price adjustment to new information. It shows prices as a function of time for the dynamic model both with self-attribution (dashed line) and without (solid line). Date 1 (on the horizontal axis) signifies the arrival of private signal. On date 2 a confirming noisy public signal arrive, and on date 3 further public signals arrive. In constant confidence model (self attribution bias not introduced) prices peak with the private signal, and only partly corrected with the public signal, since investors underweight the public signal. In self-attribution model, prices peak when the public signal arrives. As an implication of the model, any conditional short-term autocorrelation of returns measured on either side of the peak will be positive, and long-term autocorrelation across the extremities will be negative.
As investors update their confidence in a biased manner with self-attribution, overreaction is initially sustained (when on firming publish signal arrives, their confidence rises). This is followed by long-run correction, consistent with long-run negative autocorrelation. The correction is slow (when disconfirming public signal arrives, their confidence fall only modestly); it takes several steps of public signal arrival until prices reaches its rational expected value. Thus, another episode of short-run positive autocorrelation follows during the correction phase. With comparison to noise trading models (Black (1986) and DeLong et al. (1991)), the DHS model endogenously generates noise trading correlated with fundamentals. In their model, overconfident informed traders lose money on average. If informed traders are underconfident, the model also predicts under-reaction, long-run return continuation and insufficient volatility relative to the rational level.

To explain a number of event study anomalies, DHS define a selective information event as an informed (for example, management’s) action to exploit mis-pricing. Their model suggests that returns around selective events such as IPOs, seasoned Equity Offering, dividend omissions and initiations, etc. are correlated with post event returns. Thus, the model is able to offer an explanation for empirically documented anomalies such as long-term negative abnormal performance of IPOs, following SEOs and
dividend omissions, and long-term positive abnormal performance following stock repurchases and dividend initiations.

A rejectable hypothesis that their model produces is that mis-pricings should be greater when there is information asymmetry. In addition, evidence from psychology literature suggests that individuals tend to be more overconfident in settings when feedback on their decisions is slow or inconclusive as opposed to rapid and clear. Thus, mis-pricing should be greater in stocks that require more judgment to evaluate, where the feedback on this judgment is ambiguous in the short-run, such as growth stocks or stocks with high R&D expenditures or intangible assets.

Odean (1998) takes the DHS theory further by adding that how overconfidence affects financial markets depends on who is overconfident and how information is distributed. In his model, investors are rational in all respects except how they value information. In his model he analyses the consequences of the overconfidence of three classes of market participants: price-taking traders, a strategic trading insider and risk averse market makers. The main results are as follows: overconfidence always increases trading volume and market depth, and reduces traders expected utility (because overconfident traders hold undiversified portfolios); overconfident price takers worsen the price quality while overconfident insiders (informed traders) improve it; over confidence increases volatility, though overconfident markets-makers may dampen this effect; and, that overconfident traders can cause markets to under-react to the information of rational traders, leading to positive serially correlated returns. Odean suggests that if information is usually publicly disclosed and then interpreted differently by a large number of traders each of whom has little market impact, the overconfident price taker model applies. He concludes, given the broad disclosure of information in U.S. equity markets, one would expect overconfidence, in net, to decrease efficiency.

Another major point of the paper is that returns are positively serially correlated when traders underweight new information and negatively serially correlated when they overweight it; and the degree of this under-or overreaction depends on the fraction of all traders who under or over weight the information. A review of the psychology literature
of inference finds that people systematically underweight abstract, statistical, and highly relevant information and overweight salient, anecdotal, attention grabbing and extreme information. As an extension of these findings, a signal to which we might expect overreactions is a price change, possibly the most salient signal because unlike other signals it directly contributes to changes in wealth and is the most publicized signal.

Hong and Stein (1999), while sharing the same goal with the other researchers of building a unified behavioural model, focus on the interaction between heterogeneous agents, rather than the psychology of the representative agent. Their model features two types of agents: “News watchers” and “Momentum traders”, both are boundedly rational in the sense that each is only able to process some subset of the publicly available information. The news watchers make forecast based on signals that they privately observe about future fundamentals, they do not condition on current or past prices. Momentum traders, in contrast, do condition on past price change (univariately on \(P_t - P_{t-1}\)), ignoring fundamental information. Their other crucial assumption is that private information diffuses gradually across the news watcher population.

**Figure 4:** Cumulative Impulse Response and Momentum Trader’s Risk Tolerance Parameter

Source: Hong and Stein (1999). *The Journal of Finance* 56, p. 2158. Note: The momentum trader’s risk tolerance gamma takes on values of 1/11, 1/7 and 1/3. Base is the cumulative impulse response without momentum trading. The other parameter values are set as follows: The information diffusion parameter \(z\) is 12, the momentum trader’s horizon \(j\) is 12, and the volatility of news shocks is 0.5. (Hong and Stein, 1999)
combining gradual information diffusion with the assumption that newswatchers do not extract information from prices. When momentum traders are introduced to the model, they arbitrage away any under-reaction left by the newswatchers, so with sufficient risk tolerance, they improve market efficiency by accelerating price adjustment to new information. But, this comes at the expense of creating an eventual overreaction to any news.

**Figure 5:** Cumulative Impulse Response and the information diffusion process

A crucial insight is that early momentum buyers impose a negative externality on late momentum buyers (momentum traders do not know whether they are early or late in the cycle). Thus, the very existence of under-reaction leads to overreaction. As momentum traders start profit taking, correction phase starts; early momentum buyers profit at the expense of the late momentum buyers. Under risk neutrality assumption, an unconditional strategy of buying at t upon observing a price increase at (t-1) and holding until (t+j) must have zero expected value, so that the composition of market players is in equilibrium. Then, the authors present some examples by varying parameters such as information diffusion rate, momentum traders’ horizon and risk tolerance. The results are reprinted in Figures 4 and 5. As a testable prediction...
concerning the pattern for autocorrelations, for example, the model suggests that the longer the momentum traders' horizon, the longer it takes for the autocorrelation to switch from positive to negative.

Then, extensions of the basic model are analysed: Adding "contrarian traders" who, as a third group, try to exploit the overreaction caused by momentum traders does not alter the major qualitative results for a wide range of parameter values. Combining contrarian and momentum strategies (i.e.: bivariate – regression – running arbitrageurs), though is more stabilizing, does not change the overall pattern. Adding fully rational traders (who can rationally condition on everything in the model) with finite risk tolerance again does not change the pattern. But, if the risk tolerance of fully rational traders is infinite, then prices follow a random walk (in which case the motivation for momentum trading disappears). If momentum traders can condition on fundamental information, the response to public news is not necessarily hump-shaped (i.e.; first underreaction, then overreaction, and then correction). But, in actual markets, it is the private information that reinforces this hump shape by keeping momentum traders from conditioning on fundamental information.

"Why perfectly rational arbitrageurs cannot assure prices to reflect fully rational fundamental values?" is a natural critique from proponents of efficient markets. In answering this question, behavioural theories commonly refer to DeLong et al. (1991) who showed that noise traders as a group can dominate a market.

On the other side, Fama (1998), defending the efficient markets theory, argues that market efficiency survives the challenge from literature on return anomalies. His argument is based on two reasons: first, if anomalies are randomly split between underreaction and overreaction (which, he argues, is the case), then the explanation is simply chance, consistent with market efficiency. Second, the anomalies documented in the literature are not robust to alternative models for expected returns or statistical approaches used to measure them. Fama also criticizes the behavioural theories for working, "not surprisingly", well only on the anomalies they are designed to explain; thus failing the test of generazability states.
Consequently, while these recent behavioural theories are receiving increasing attention and recognition, caution is advisable. Fama continues "Given the demonstrated ingenuity of the theory branch of finance and given the long litany of apparent judgment biases unearthed by cognitive psychologists, it is safe to predict that we will soon see a menu of behavioural models that can be mixed and matched to explain specific anomalies. My view is that any new model should be judged on how it explains the big picture." Nevertheless, while efficiency can be maintained as an ideal case, documented deviations from efficiency are so pervasive and their economic consequences so far reaching that they cannot be ignored.

2.8 Summary and Critique of Literature

The literature on the momentum of prices of stocks has been flowing fast and thick. Since the seminal study of Jegadeesh and Titman (1993), studies investigating the anomaly have multiplied with branches sprouting up in several directions. The table below summarises a small selection of the studies that helped identify the research gaps that this study sought to fill. We begin with the literature of momentum profitability, size, trading volume, risk, transaction costs, seasonality, reversal and finally decomposition of the profits.

<table>
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<th>Author (s)/ Topic</th>
<th>Major Findings</th>
<th>Relationship to Current Study</th>
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<tr>
<td><strong>Momentum Profitability</strong></td>
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<tr>
<td>Jegadeesh and Titman (1993)</td>
<td>Using NYSE/AMEX data base found that a strategy of buying past 6-month winners, and shorting past 6-month decile losers results in a significant 1% return per month</td>
<td>Although momentum is an anomaly that has been documented in many world markets, its existence is by no means universal. Quite a significant number of markets have reported non-existence of, or existence of only</td>
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<td>Author(s) and Year</td>
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<td>Bekaert, Erb, Harvey, and Viskanta (1997)</td>
<td>They find that momentum strategies are not considerably profitable for emerging markets, although they perform better when ingestible indexes are examined.</td>
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<td>Hameed and Kusnadi (2002)</td>
<td>They investigated the profitability of momentum investment strategy in six Asian markets. Hameed and Kusnadi find that unrestricted momentum strategies do not yield significant profits and conclude that factors that contribute to the momentum phenomenon in the United States are not prevalent in the Asian markets.</td>
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<td>Hong, Lim, and Stein (2000)</td>
<td>They found that the momentum effect in the U.S. securities is strongest in small firms and declines sharply as market capitalisation increases. Hong, Lim, and Stein argue that, since price momentum results from gradual information flow, there should be relatively stronger profits in those stocks for which information gets out slowly, that is, the small stocks.</td>
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<tr>
<td>Hameed and Kusnadi (2002)</td>
<td>The authors found no size influence in momentum profits in five of the six Asian markets they studied.</td>
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<td>Ndung'u (2004)</td>
<td>Ndung'u reports that the size effect is present at the NSE.</td>
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<tr>
<td>Conrad, Hameed, and Nider (1994)</td>
<td>They find that high volume securities experience price reversals, while low volume stocks experience price continuation.</td>
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<td>Geviades, Kaniel, and Mingelgrin (1998)</td>
<td>Show that individual stocks whose volumes are unusually large (small) tend to experience large (small) subsequent returns.</td>
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<td>Lee and</td>
<td>Illustrate that past trading volume</td>
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<td>Swaminathan (1998)</td>
<td>predicts both the magnitude of and persistence of future price momentum and, over the intermediate horizons, price momentum strategies work better among high volume stocks.</td>
<td>O’Hara, 1994). Studies on the impact of trading volume on momentum profits have returned mixed results. Although the weight of the evidence cuts for a positive relationship, contradictory conclusions have also been reached. The current study collects and analyses data to ascertain on which side NSE incline.</td>
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**Risk**

| Fama and French (1998) | Could not explain momentum profitability using their 3-factor risk model. | Momentum profits can be considered anomalous only if they cannot be attributed to the riskiness of the strategies. Two commonly used models for risk are the CAPM and the Fama-French 3-factor model. We applied the models on NSE data to test the markets efficiency. |
| Jegadeesh and Titman (2000) | Find evidence indicating that the cross-sectional differences in expected returns under the CAPM and the Fama-French three-factor model cannot account for the momentum profits. |  |
| Conrad and Kaul (1998) | Found that cross-sectional variance (risk) of sample mean returns is close to the momentum profits for the WRSS, leading them to conclude that the observed momentum profits can be entirely explained by cross-sectional differences in expected returns rather than any “time-series patterns in stock returns” |  |

**Transaction Costs**

| Korajczyk and Sadka (2004) | They conclude that transaction costs could eliminate momentum profits, depending on the type of strategy and the frequency of trading. Some strategies are robust to transaction cost incorporation while for others the profit is completely dissipated. | By modelling only the explicit costs of trading at the NSE, we made a |
| Lesmond, Schill and Zhou (2003) | They find that relative strength strategies require frequent trading in disproportionately high cost securities |  |
such that trading costs prevent profitable strategy execution. They conclude that the magnitude of the abnormal returns associated with these trading strategies creates an illusion of profit opportunity when, in fact, none exists.

Conservative assessment of the probable impact of transaction costs on momentum profits

Calculated Seasonality

Jegadeesh and Titman, (1993)

Maintain that relative strength portfolio returns exceed the costs of trading.

Jegadeesh and Titman, (1993, 2001) find an interesting seasonality in momentum profits in the United States. They document that the Winners outperform the Losers in all months except January, when the Losers outperform the Winners. Grundy and Martin (2001) also report similar results in the U.S., where the momentum portfolio earns significantly negative returns in Januaries and significantly positive returns in months other than January.

Studies have not been unanimous on the existence of a year end effect in momentum profits

Grinblatt and Moskowitch (2004)

Claim that momentum profits are higher in December than the average other months because of investors tax loss selling

Sias (2007)

They attribute the observed high rate of December profitability on two explanations. First tax-loss selling and, secondly, window dressing by institutional investors, who 'massage' their quarter-end, and especially, year-end financial reports by buying lagged winners and selling lagged losers prior to quarterly reporting dates in order to avoid "embarrassing" reports.

Wang (2008)

The momentum profits in January showed significant positive returns in the United Kingdom, Germany, and China; not different from those in non-January months in each market. The only exception was found in Japan, in which the January returns
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<td>Two competing schools exist as to the source of momentum profits. The first school views any such profit as compensation for risk. The second school seeks an explanation from behavioural and psychological biased that afflict investors, making them underreact to news or follow a “herd” instinct in their investing decisions. The current study contributes to the resolution of the stalemate by decomposing momentum profits at the NSE into its elements.</td>
</tr>
</tbody>
</table>
2.9 Conceptual Framework

The question that is being addressed in this research project is at the centre of finance, namely, how are asset prices established and how are they related to the fundamental values of underlying assets? Standard finance (EMH) posits that the price at which a commodity is exchanged is a function of the forces of demand and supply for the commodity. But unlike other commodities, which are demanded because they possess intrinsic utility, shares have value only to the extent that the underlying companies are capable of generating cash flows to the shareholders in the future. The demand for shares is therefore derived demand, and the conclusion that a company’s economic fundamentals drive share prices follows logically. The more profitable the prospects of the company the higher should be its share price, and vice versa.

Behavioural finance on the other hand recognises that it is not only economic fundamentals that drive share prices. “Irrational” factors are increasingly claiming economists’ attention as providing complementary, if not alternative and more potent explanations of the price formation process in financial assets. Mass psychology, fads, overreaction, under reaction and herding are irrational factors now contending to supplant risk as predictors of assets returns. With the evidence from empirical testing and analysis overwhelmingly indicating that the irrational factors influence share prices, the research agenda in the field of asset pricing theory no longer is whether these factors are relevant but rather how to model and mesh them into a cogent, coherent and parsimonious theory of prices.

One pervasive manifestation of investor irrationality is price momentum. One explanation claims that momentum occurs because investors underreact to information events with the consequence that the full impact of the event is not reflected in instantaneous price change but rather incorporated only gradually over a period of time (Barberis, Shleifer, & Vishny, 1998)). During this period there is momentum in the price to the level necessitated by the event. Another explanation ascribes momentum in the short term to the overreaction by investors that pushes prices relentlessly over (below) the fundamental value of the stock, but later the price gains (losses) are reversed when prices correct back to fundamental value levels (Daniel, Hirshleifer, & Subrahmanyam, 1998)).
This figure portrays graphically the researcher's conceptualization of the study. The framework has benefited from the intuition from Lee and Swaminathan (2000) Momentum Life Cycle (MLC). The causal factors are the momentum strategies which for portfolios on the basis of past winners and losers. The portfolios are held in the capital markets for selected months after which the holding period returns, which are the predicted variables, are determined. The returns could be boosted or vitiated by various intermediating factors, including size, risk, sentiment, volume, reversal and seasonalities.

The current study posits that price momentum is a potent driving force determining asset returns in capital markets. If the thesis were to hold, we expect to find that active momentum trading strategies mounted in the stock market should result in returns that are significantly different from the returns from a passive market strategy. The paper conceptualizes that price momentum can cause abnormal returns in the capital market (See Figure 6). Our model also recognizes that various intervening factors could operate to amplify or ameliorate the basic momentum profitability. On one hand we have attenuating factors. The effect of these factors will be to dampen the incidence of momentum on stock returns. Included in this category are risk, transaction costs and
seasonality and reversibility. If the momentum strategies employed are too risky, or if they involve too frequent trading and consequently high transaction costs, then the profits could be illusory. In addition, any seasonality or reversibility discernible in returns means that any momentum profitability is at best transient, not permanent.

On the other hand, intermediating factors could operate to enhance the momentum profits. Size of the stocks traded, the volumes traded, and investor sentiment prevailing in the market fall in this second category. Because theoretically, news gets out less fast for small capitalization stocks than big ones, for less traded stocks than most frequently stocks, it is conceptualized that small, and low trading volume stocks should exhibit more momentum. In addition, when the market sentiment is more optimistic, the momentum wave is likely to ride higher and longer.

2.10 Hypotheses

The hypotheses to be tested flowed from the objectives, which in turn are anchored to the conceptual framework that seeks to understand the role of price momentum in generating abnormal returns and how momentum profitability is affected by selected firm characteristics. The hypotheses, stated in the alternate were as follows.

H1: Momentum based trading strategies at NSE are profitable.
H2: Small capitalization stocks exhibit more momentum than big cap stocks.
H3: Low trading volume stocks have more momentum premium than high volume stocks.
H4: Market wide risk factors are responsible for momentum profits.
H5: Momentum profits are robust against transaction costs.
H6: There is a calendar pattern to momentum profitability
H7: Momentum profits eventually reverse in the long term.
H8: Behavioural factors are the source of momentum profits.
CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Introduction
This chapter expounds in detail the structure of the research. It is a blueprint that weaves together and shows how all of its major parts – the samples, formation of portfolios, measurement of variables, methods of analyses - work together to address the research questions. We begin with the research design, and then we explain the philosophy guiding the research, followed by a description of the population and sample, then how momentum strategies are formed, and finally an exposition of data analysis methods.

3.2 Research Design
This research was quantitative in design. The nature of the quantitative research paradigm is to demonstrate that a relationship exists between variables. The three broad types of research designs that could be employed to achieve this end are the experimental, the correlational, and the causal comparative designs (Fraenkel and Wallen (2000)).

Experimental designs exemplify the spirit of purposeful and active investigation in an effort to draw causal inferences concerning independent and dependent variables. By systematically manipulating the independent variable and randomisation of assignment of subjects to treatment and control groups, experimental techniques are the best suited in testing and establishing a cause-and-effect relationship.

Fraenkel and Wallen (2000), however, hold that in many studies, it may not be possible (or even desirable) to manipulate or randomly assign subjects: correlational and causal comparative designs come in handy. Correlational studies have twin purposes of measuring the nature and magnitude of the relationship between two or more quantitatively coded variables, and, predicting the values of the criterion variable given the value of the predictor variable. This design requires that the variables of interest be measured within one group, rendering it unsuited for the current research project, which involves the formation and comparison of two groups i.e. the ‘winners’ and ‘losers’.
The basic causal comparative design (a.k.a. *ex-post-facto* design) involves selecting two or more classes or groups that differ on a particular variable of interest and comparing them on another variable(s). Two basic variations of the same basic design can be used. Either, one group possess a characteristic (a criterion) that the other group does not possess, or, the groups differ on known characteristics. Figure 7 below illustrates these two variations.

**Figure 7: The Basic Causal-Comparative Design**

Two variations of the same basic design (also called a criterion group design) are shown below. The letter C is used in this design to represent the presence of the characteristic. The dashed line is used to show that intact groups are being compared.

<table>
<thead>
<tr>
<th>GROUP</th>
<th>INDEPENDENT VARIABLE</th>
<th>DEPENDENT VARIABLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>C</td>
<td>O</td>
</tr>
<tr>
<td>(a)</td>
<td>(Group possess characteristic)</td>
<td>(Measurement)</td>
</tr>
<tr>
<td>II</td>
<td>-C</td>
<td>O</td>
</tr>
<tr>
<td>(Group does not possess characteristic)</td>
<td>(Measurement)</td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>C1</td>
<td>O</td>
</tr>
<tr>
<td>(b)</td>
<td>(Group possesses characteristic 1)</td>
<td>(Measurement)</td>
</tr>
<tr>
<td>II</td>
<td>C2</td>
<td>O</td>
</tr>
<tr>
<td>(Group possesses characteristic 2)</td>
<td>(Measurement)</td>
<td></td>
</tr>
</tbody>
</table>

Adapted from Fraenkel and Wallen (2000, p. 397)

Phenomena are observed as they occur or after they have occurred. Researchers typically use between-group comparative methods (e.g. t-test, analyses of variances, and multivariate analyses of variances) to gauge whether the observed differences between groups, on selected outcome measures, are statistically significant.

### 3.2.1 Application of the Causal Comparison Design

For the study at hand, the causal comparison design was the most appropriate. This is because since it is not possible to manipulate stock returns at the stock exchange, we must needs use the data as we got it. The great majority of studies on Stock Exchange
databases all over the world employ this design. Examples include Jegadeesh and Titman (1993, 1999), Rouwenhorst (1998), Bernard and Thomas (1989), among others. Although in this design no attempt was made to draw causal inferences at the level of individual investigation, when the results were considered in totality, causality could be inferred. Indeed, Fraenkel and Wallen (2000, p.396) write.

“In a causal comparative research investigators attempt to determine the cause or consequences of differences that already exists between or among groups of sampled data”.

We formed momentum-factor mimicking portfolios, based on whether stock returns at the NSE during a formation period were in the top or bottom decile and classified them as ‘winners’ and ‘losers’. The returns of the two portfolios over a subsequent holding period were documented and analysed. In the context of the current study the basic model in Figure 7 was adapted as below in Figure 8.

**Figure 8: The Basic Momentum-effect Causal Comparative Design**

<table>
<thead>
<tr>
<th>GROUP</th>
<th>INDEPENDENT VARIABLE</th>
<th>DEPENDENT VARIABLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winners</td>
<td>C1</td>
<td>O</td>
</tr>
<tr>
<td>Top decile past returns</td>
<td>Level of future returns</td>
<td></td>
</tr>
<tr>
<td>Losers</td>
<td>C2</td>
<td>O</td>
</tr>
<tr>
<td>Bottom decile past returns</td>
<td>Level of future returns</td>
<td></td>
</tr>
</tbody>
</table>

There are several approaches to constructing factor mimicking portfolios i.e. cross-sectional regression approach (CSR), the portfolio approach, and the time series approach (TSR). This study used the portfolio approach, where stocks were first sorted according to the loadings on past returns (the independent variable). Secondly the stocks in the highest and lowest decile past returns were grouped into two different portfolios and designated “Winner” and “Loser” portfolios respectfully. Finally a factor-mimicking zero-cost portfolio was constructed by taking a long position in the winner portfolio and a short position in the loser portfolio. The ex post returns of the factor-mimicking portfolio (the dependent variable) were determined and analysed.

The key research questions that were addressed were three-fold. First, did the Winner portfolio consistently outperform the Loser portfolio? Secondly, were the future returns
of the two portfolios significantly different? Finally, how well did rival hypotheses explain the momentum effect (if any) at the NSE?

3.2.2 Threats to Validity

For results of a study to be relevant and reliable they must pass the test of validity. The two types of validity are internal validity and external validity.

**Internal Validity:** Two major weaknesses in causal comparative research are the lack of randomisation and the inability to manipulate the independent variable. Random assignment of securities to either portfolio was not possible since this was already a fait accompli through self-selection. The independent variable could not also be manipulated because the securities had already experienced the treatment. The consequence of these was that the internal validity of the results of the tests could be in question. An experiment is internally valid to the extent that it shows a cause-effect relationship between the independent and dependent variables (Fraenkel and Warren (2000)). Campbell (1969) lists nine sources of threats to internal validity as selection, history, maturation, repeated testing, instrumentation, regression to the mean, experimental mortality, selection-maturation interaction, and experimental bias. In this study, the analysis of the impact of rival explanations on the momentum effect would control internal validity threats. In effect the purpose of the majority of the hypotheses after the first hypothesis were to test the internal validity of the first (core) objective.

**External Validity:** External validity is related to using sample results to generalise to the population. It is the degree to which conclusions in a study would hold for other persons (subjects), in other places (settings) and at other times. Trochim (2002) therefore identifies three threats to external validity because there are three ways generalisations could go wrong i.e. people, place and times. In the current study, threats to external validity could emanate, first from use of data that is not representative. The consequence of this would be that the results of the study would not reflect the behaviour in the NSE as a whole, leave alone other markets. Secondly, the results would lack external validity if the NSE were subject to idiosyncratic peculiarities not shared by other stock markets. This would mean that the results of the study cannot be
extrapolated for other markets. Finally, external validity could be vitiated if the time period covered by the study experienced extraordinary events. The results would therefore have no predictive value for other periods.

Threats to external validity in the current study were addressed first by using the population rather than a sample. Secondly, the theory of proximal similarity (Trochim (2002)), was used more effectively. Using this approach we described, in our discussion of results, the ways in which the contexts of this study differed from related studies, and provided insight about the degree of similarity between various groups of data, markets and even times. The third way of strengthening external validity would be by replicating studies using different sets of data, markets and time periods. This is an approach that was best left to later studies.

There is, generally, a trade-off between external validity and internal validity. A study which makes the tight control over a narrow and homogeneous set of subjects a priority is unlikely to find results that are widely applicable to a large number of other settings or relevant to a diverse audience. Conversely, a study that tries to capture the unpredictability, uncertainty, diversity and ambiguity of all settings is unlikely to find results that are immune from criticism about poor internal validity. The astute researcher’s brief is to strike that delicate balance so neither internal nor external validity was unduly sacrificed (or appeased) to the benefit (detriment) of the other.

3.3 Research Philosophy
Research is defined by Proctor (1998) as a process to find out the unknown. To guide the whole research effort, the research strategy should be imbued with the appropriate research philosophy. Research in social sciences boasts two main philosophical orientations, namely, positivism and interpretivism. Positivism presumes the social world exists objectively and externally, that knowledge is valid only if it is based on observations of this external reality and that universal and general laws exist or that theoretical models can be developed that are generalizable, can explain cause and effect relationships, and which lend themselves to predicting outcomes (Blaikie, 1993; Hatch
and Cunliffe, 2006; and Saunders, Lewis, and Thornhill, 2007). There is focus on quantitative data, objectively and independently gathered and statistically analysed.

On the other hand interpretivists hold that the social world, individuals and groups make sense of situations based upon their individual experience, memories and expectations. Meaning is therefore constructed and reconstructed through experience, resulting in many differing interpretations. Since “all knowledge is relative to the knower”, interpretivist work alongside others as they make sense of, draw meaning from, and create their realities in order to understand their points of view; and to interpret these experiences in the context of the researchers academic experiences (Hatch and Cunliffe, 2006). Given the subjective nature of this paradigm, it is associated with qualitative approaches to data gathering.

Figure 9 illustrates the philosophy underpinning the current study’s research strategy. The study was guided by positivist philosophy and principles. The study is scientific because it seeks to establish the existence of a cause and effect relationship between stock returns and price momentum. It is positivist because it starts with theory, defines quantifiable variables, and tests theory using empirical data. The study’s positivism is also evident from its highly structured nature: independence of data collected from the researcher’s influence and the statistical analyses of data that result in quantifiable and generalizable conclusions. The figure is the researcher’s adaptation of Partington (2008) model of positivist philosophy.
3.4 Population, Sample and Data

The target population addressed by this study comprised all companies quoted on the NSE from 1995 to 2007. The population was subdivided into three sub-samples by sub-periods covered, namely 1996-2002, 2003-2007, and 2000-2007. The period covered was dictated mainly by data availability and recency. The NSE computerized data base dates to back to 1995, which forms the start of the current study. The basic data for the study were daily prices of stocks listed at the NSE obtained covering the period 1995 to 2007.
The prices were used to derive average monthly returns which were adjusted for stock splits and bonus issues. With these data, we calculated profits of various momentum strategies from January 1996 to December 2007. The data for 1995 were mainly used in constructing the beginning relative strength portfolios. Because some of our tests employed Fama and French three-factor model, it was necessary to collect data on relevant variables. To this end we used the NSE_20 index as proxy for the market, and the risk free rate of return was estimated from The Government Treasury Bill rates which were obtained from the Central Bank of Kenya.

Table 1 gives broad statistics and trends of some of the data used in the study. The return on the NSE 20 index (proxy for the market portfolio) averages approximately 0.5% per month for the whole sample period. The sub-period 1997-2002 was characterized by a decline in the index, with markets monthly returns registering -1.04%. In contrast, the sub-period that followed between the years 2003 to 2007, coincided with and exuberant mood among investors with the consequence that monthly market returns averaged 2.42%.

The risk-free rate of return experiences an opposite trend to the market return. For the sub-period 1997-2002, the Treasury bill rate was up, registering a monthly average return of 1.3%. In this period the government of the day raised the interest on treasury bills so as to attract domestic finance to bridge a gap left by international donors who reneged on the aid pledges. The sub-period 2003-2007 sees a drastic fall in the average monthly risk-free rate to 0.6%, reflecting a phase of prudent financial management and the unlocking of donor funds, mainly because of the change in political power dispensation at the end of 2002. The average monthly risk free rate of return is 1.0% for the whole sample period.

Table 2 also reports the small minus big (SMB) and high minus low (HML) factors of Fama-French model for the sample periods. To calculate these factor values, we followed the method described in Fama and French (1993) in forming the 6 Size-BE/ME stock portfolios based on all the equities at the Nairobi Stock Exchange. It is evident that the value effect is quite significant at an average of 5% while the size effect is negative at an average of -3% for the full sample period 1996-2007. The effects are magnified in the
sample period 1996-2002, then declines in the final sub-period of 2003-2007 to 0.65% for size factor, and 1.3% for the value factor.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Average number of stocks</td>
<td>48</td>
<td>49</td>
<td>45</td>
</tr>
<tr>
<td>Return on NSE-20 index $R_m$ Mean</td>
<td>0.00492</td>
<td>-0.01037</td>
<td>0.02424</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.05408</td>
<td>0.04835</td>
<td>0.05514</td>
</tr>
<tr>
<td>Risk-free interest rate $R_f$ Mean</td>
<td>0.00968</td>
<td>0.01289</td>
<td>0.0075</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.00751</td>
<td>0.00521</td>
<td>0.00251</td>
</tr>
<tr>
<td>Market Wide Risk $R_m - R_f$ Mean</td>
<td>-0.00544</td>
<td>-0.02497</td>
<td>0.01767</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.05422</td>
<td>0.04688</td>
<td>0.05354</td>
</tr>
<tr>
<td>Size-factor $R_{SMB}$ Mean</td>
<td>-0.03133</td>
<td>-0.06131</td>
<td>0.00654</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.40659</td>
<td>0.54192</td>
<td>0.05394</td>
</tr>
<tr>
<td>Value-factor $R_{HML}$ Mean</td>
<td>0.05526</td>
<td>0.09122</td>
<td>0.01301</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.59618</td>
<td>0.80665</td>
<td>0.05307</td>
</tr>
</tbody>
</table>

This table gives the monthly descriptive statistics of the NSE-20 index (a proxy for the market), and the Fama-French factors for the Nairobi stock Exchange for the whole sample period and sub-samples. To calculate these values the method of Fama and French (1993) was followed by forming 6 Size, BME stock portfolios based on all equities listed. Size is measured by market capitalization. $R_{SMB}$ is the average excess return of small stocks over the return of big stocks. $R_{HML}$ is the excess return of book-to-market stocks over low book-to-markets stocks.

As in the study of Dickinson and Muragu (1994) the current study will have to content with significant data problems. But luckily, unlike Dickinson and Muragu, the problem is assuaged somewhat by the fact that computerised databases are available since 1996.

Thin trading at the NSE is a major design issue. Ways of combating the problem include testing large amounts of data and by prolonging the period covered. Taylor (1986) argues that the use of more data improves variance estimates, increases the power of tests and is essential for the investigation of trading strategies. This study considered and covered 12 years, a period long enough to ameliorate the thin trading problem (Dickinson and Muragu, 1994) employed a 10-year period while Barnes, (1986) used 6 years. Other studies that had to confront the paucity of data in emerging markets include Yacout, (1981), and Parkinson, 1984).
Furthermore, we used only monthly return data rather than daily returns. Lo and MacKinlay (1986) argue that monthly data reduces the potential bias associated with non-trading, the bid-ask spread, and non-synchronous trading. Finally, the overlapping strategies employed were precisely geared towards strengthening the power of the tests by significantly increasing the data points of the study.

Return data, and data on other key stock characteristics (size, trading volume) were computed for the sample period, for all stocks listed at the NSE. The data was screened by requiring that sampled stocks have:

1. Complete dividend and other corporate events history for all the 12 years of the study.
2. At least 6 observations, to ensure viability of the goodness of fit tests (Praetz and Wilson (1980)).

3.5 Formation of Momentum Trading Strategies

To take advantage of evidence of the widely documented momentum in stock prices, profitable trading strategies that buy past winners and sell past losers have been designed and implemented in many markets. Perhaps the earliest modern finance evidence of momentum-like trading is the relative strength strategies constructed by Levy in 1967. The intention of this study was to investigate the existence and characteristics of momentum opportunities at the NSE by examining a number of similarly constructed factor-mimicking strategies.

A factor mimicking portfolio is a portfolio of assets constructed to stand for a background factor. This design is usually preferred to directly using the factor when the realisations are not returns. By this approach we only use the information captured in the economic factors, which are relevant to asset returns and reduce the noise in the asset pricing model. The purpose is to construct a portfolio with return equal to the risk premium of the background factor and with a beta equal to one against the factor (Cochrane (2000)). The background factor may be either a latent or an observable
variable and its values are, in general, not returns (factors include size, value, trading volume, price continuation etc).

In line with Fama and French (1993), we constructed portfolios in such a way as to "mimic" price momentum (the background factor in this study). Asgharian and Hansson (2001) identify three approaches to constructing factor mimicking portfolios. These are the cross-sectional regression approach, the portfolio approach, and the time series regression approach. The current study is suited for the portfolio approach.

In the portfolio approach, stocks were first sorted according to loadings on a specific factor. Secondly, the stocks with high and low loadings were grouped into two different portfolios, and finally a factor mimicking portfolio was constructed by taking a long position in the portfolio with high loadings and a short position in the portfolio with low loadings.

In constructing the high-loading and low-loading portfolios, three alternative methods may be used to weight the constituent stocks i.e. the equally-weighted portfolios (Chan, Karceski, & Lakonishok 1998); value-weighted portfolios (Fama & French, 1993), and the relative loadings-weighted portfolios (Asgharian & Hansson, 2001). The third weighting approach is theoretically more defensible as the stocks are weighted by the relative distance of their loadings in order to maintain the link between the relative loading and the weights.

This study, however, used the equally-weighted approach because, while it performs just as well as the others, it is simpler and more tractable to implement. Following Jegadeesh and Titman (1993), and Rouwenhorst (1997), the strategies considered chose stocks and formed portfolios on the basis of the stocks' returns over the past 3, 6, 9, and 12 months. For each of these formation periods, we also consider holding periods of 3, 6, 9, and 12 months. These combined to give a total of 16 strategies. Jegadeesh (1990) and Lehman (1990) document evidence showing that the power of tests on overreaction in the short term is adversely affected by the bid-ask bounce, price pressure and lagged
effects. To test the impact of these effects, they in addition, implement strategies that skip a month between the portfolio formation date and the beginning of the holding period. Since the results of their 'skip' strategies do not differ materially from those of "non-skip" strategies, this study concentrated only on the non-skip strategies.

In order to increase the power of statistical tests, as observed by Jegadeesh and Titman (2001), the strategies examined comprised portfolios with overlapping holding periods. Thus, in any month \( t \), the strategies held a series of portfolios selected in the current month as well as in the previous \( K-1 \) months, where \( K \) is the holding period. A strategy that selected stocks on the basis of returns over the past \( J \) months and held them for \( K \) months is referred to as the \( J=\)month, \( K=\)month strategy. Such a strategy was constructed as follows: At the end of each month \( t \), all securities with 12 months return data were ranked in ascending order on the basis of their returns in the past \( J \)-months (\( J = 3, 6, 9, \) and 12). The stocks were then assigned to one of the five relative strength decile portfolios (\( P1 \) represented the "loser" portfolio or the portfolio with the lowest past performance, and \( P5 \) represented the "winner" portfolio or the one with the highest past performance). These portfolios were equally weighted at formation and held for the next \( K \)-months (\( K = 3, 6, 9, \) and 12). This gave sixteen combinations of \( J \)- and \( K \)-months and, hence, sixteen momentum strategies.

Because only monthly returns were used, when the holding period exceeded one month (as it always did), we created an overlap in the holding period returns. The result was \( K \)-composite portfolios, each of which was initiated one month apart. In each month we revised \( 1/K \) of the holdings, with the rest being carried over from the previous month. For example, towards the end of month \( t \), the \( J=6, K=6 \) portfolio of Winners consisted of six cohorts made up of the previous six rankings i.e. a position carried over from portfolios formed at the end of \( t-6 \) of the quintile of the firms with the highest prior six month performance as of \( t-6 \), and five similar positions consisting of investments in the top-performing quintiles of the firms at the end of months \( t-5, t-4, t-3, t-2, \) and \( t-1 \), respectively. At the end of month \( t \), we liquidate the first position, (initiated at time \( t-6 \)) and replace it with an investment in the quintile of stocks that show the highest past six-month performance at time \( t \). In other words, a December Winner portfolio of the J-
6. K-6 strategy comprises the quintiles of the stocks with the highest returns over the previous June to November period, the previous May to October period, the previous April to September period, the previous March to August period, the previous February to July period, and the previous January to June period. Each monthly cohort is assigned an equal weight in this composite portfolio. We form the corresponding *Loser* portfolios in a manner similar to the one used for the formation of *Winner* portfolios as above.

Finally, we constructed the momentum strategies. In each month \( t \), the relative strength strategy (RSS) goes long (buys) on the *Winner* portfolio and shorts (sells) the *Loser* portfolio, holding the position for \( K \) months. By so doing we form the zero-cost portfolio, ("winner" minus "loser" or "WML"), which is our basic measure of momentum profitability (See also Moskowitz, 1997; Rouwenhorst, 1997; and Hong, I.im. & Stein, 2000).

The profits of the above strategies can be calculated for both a series of buy and hold portfolios and a series of portfolios that were rebalanced monthly to maintain equal weights. Jegadeesh and Titman (1993) find that the two approaches yield similar results. In this study, the portfolios will be implicitly rebalanced every month. This means that should the return of a stock disappear in any given month after the formation of the portfolio, the average portfolio profit calculation will involve an implicit readjustment by liquidating, at the end of the previous month, what was held in this stock and investing the money obtained in the remaining stocks of the portfolio so that it remains equally weighted.

### 3.6 Data Analysis Methods

In this section, we explain the approaches that were employed in the analysis data in order to address the eight hypotheses of the study as set out in section 2.8. In the first hypothesis, detailed analyses were conducted to ascertain the extent of profitability of all the sixteen strategies, and for all the sub-periods. Having analyzed the momentum effect for all the sixteen strategies and arrived at general conclusions, the remaining hypotheses were pursued by employing the *standard J=-6month, K=6month* strategy. This is consistent with Jegadeesh and Titman (1993), Rouwenhorst (1997), and Hameed
and Kusnadi (2002) who focus only one representative strategy: This strategy is formed on the basis of the preceding 6 month ranked returns, immediately at the end of the ranking period, and held for next 6 months.

3.6.1 Measuring the Returns to Momentum Strategies (Hypothesis 1)

We analyzed the returns of the portfolio strategies formed as explained in the preceding section for the period 1997 to 2007 on data from the NSE. The monthly data to be used was adjusted for dividends, seasoned equity offerings, stock dividends and stock splits. The number of stocks in the sample ranged from 60 to 48 during the sample period. All stocks with return data in the J-months preceding portfolio formation date were included in the sample from which the buy and sell portfolios were constructed. We tabulated and analysed the average returns of the different Winner and Loser portfolios as well as the zero-cost, Winners minus Losers (WML) portfolios for the 16 strategies. T-statistics were computed and used to test the hypothesis that Winners do not outperform Losers, and that momentum profits, Winners minus Losers (WML), are not significantly different from zero. Further, the effect of variations in the lengths of holding periods and formation periods on momentum profits were investigated and reported upon.

3.6.2 Size and Momentum Profits (Hypothesis 2)

Ever since the publication of Banz (1981) findings, size of stock has been recognised as one of the anomalous determinants of stock returns. In recent years, size together with book-to-market price and dividend-to-price has been used to distinguished value from glamour stocks. Fama and French (1992) find that size and book-to-market predict future returns. Fama and French (1993) provide evidence that sorting stocks according to market capitalisation and book-to-market explains a big proportion of stock returns. Daniel and Titman (1997). Davis et al (2000) corroborate Fama and French studies. Hong, Lim, and Stein (2000) find that the momentum effect in the U.S. securities is strongest in small firms and declines sharply as market capitalisation increases. Hong, Lim, and Stein argue that, since price momentum results from gradual information flow, there should be relatively stronger profits in those stocks for which information gets out slowly, that is, the small stocks. Hameed and Kusnadi (2002) find no size influence in
momentum profits in five of the six Asian markets they studied. Ndung'u (2004) reports that the size effect is present at the NSE.

To examine whether the small firm price momentum holds at the NSE, we considered a size-neutral strategy, comprising of 15 portfolios of 3 size sorted, and 5 momentum based. Firm size is measured by the market capitalization of equity at the beginning of each year under consideration while momentum is measured by a stock’s past six-month’s performance. Consequently size portfolios were categorized into “Big” stocks which made up of 30% of the largest capitalization stocks; The “medium” which made up the 40% medium capitalization stocks, while the remaining 30% made up the “Small” stocks. The momentum sorted stocks were made up of Loser (P5) portfolio which consisted of twenty percent of stocks with the lowest past six-month performance from each size group, while the Winner (P1) portfolio consisted of twenty percent of stocks with the highest past six-month performance from each size group. The P2, P3, and P4 will be similarly constituted. Both the Winner and Loser, and the three intermediate portfolios therefore contained the same number of stocks for the three size classifications, and were in that sense size-neutral. The summary statistics of returns for each classification were established: any evidence observed of significant differences in the winner and loser portfolios would confirm that continuation effect was not a mere reflection of the effect of firm size.

3.6.3 Trading Volume and Momentum Profits (Hypotheses 3)

Lee and Swaminathan (2000), report that trading volume can predict the magnitude and persistence of momentum profits. They suggest that turnover may serve as indicator of the level of investor interest in a stock. For example, the low volume loser is likely to be at the bottom of its “life cycle” and that a price reversal is likely, while a high volume loser may have plenty of negative price momentum. Chan, Hameed and Tong (2000), show that the momentum profits are higher for the portfolio of countries with higher lagged trading volume than portfolio of countries with lower lagged trading volume. Odean (1998) proposes a behavioural reason: that overconfident traders trades result in market underreaction to the information by rational traders and the subsequent
momentum in stock prices in high volume stocks. These papers seem to suggest that higher trading volume would accentuate the return continuation effect.

To examine the role of trading volume, we implemented volume-based momentum strategies by means of a two-way sort of price- and trading-volume. We formed 3 portfolios based on price performance over the 6 month formation periods. The winner portfolios P1 had stocks with highest tercile returns, while the loser portfolio P3 comprised the tercile with lowest formation returns.

Thereafter, 3 portfolios based on monthly turnover (trading volume) were independently formed, also over the formation periods. Turnover is defined as the ratio of monthly trading volume divided by number of shares outstanding. The top (bottom) 30 percent of securities in terms of turnover were ranked into high (low) turnover groups. The middle 40 percent of securities represent the medium turnover group. Consequently, the V3 portfolio had 30% stocks with the lowest average turnover and the V1 portfolio had 30% of the stocks with the highest average turnover, while V2 comprised stocks with the 40% medium turnover.

The summary statistics of returns for each classification were established; any evidence observed of significant differences in the winner and loser portfolios would confirm that continuation effect was not an artefact of trading activity.

3.6.4 Risk-Adjusted Momentum Returns (Hypothesis 4)

To date, there is no risk-based explanation that completely accounts for momentum returns. Although a number of authors have found that long term reversals are not robust to risk adjustment (Fama & French, 1996; Lee & Swaminathan, 2000; and Grinblatt & Moskowitz, 2003), the intermediate return continuation has been a more resilient anomaly. Fama and French (1998) cannot explain the phenomenon using a three factor pricing model. Grundy and Martin (2001), studying the risk of momentum strategies, conclude that factor models cannot explain mean returns. Indeed the unexplained persistence of intermediate term momentum returns is viewed as one of the most serious challenges to asset pricing literature (Korajczyk & Sadka, 2004). Nevertheless, despite
the burgeoning evidence to the contrary, proponents of risk-based explanation have not
given up (Conrad & Kaul, 1998; and Moskowitz & Grinblatt, 1998).

This subsection sought to incorporate risk in momentum returns to ascertain the degree to
which momentum returns depended on risk. Consistent with many studies this study employed the two traditional risk/return models factor models, namely, the capital asset pricing model and the Fama-French three factor model.

The capital asset pricing model was tested in the following form.

\[ R_{RSS,t} - rf_j = \alpha + \beta_m (R_{M,t} - rf_j) \]  

(3.1)

Where,

- \( R_{RSS,t} \) = Average return of momentum strategy for the month t.
- \( rf_j \) = The risk free rate of return observed at the beginning of the month, t.
- \( R_{M,t} \) = Average monthly return on the overall market factor
- \( \alpha \) = The intercept in the regression equation

We posited that excess momentum profits can be fully explained by their co-variation with the returns from the market as whole (The market is proxied by the NSE-20 Index returns).

Next we explored the relationship between the returns of momentum portfolios and Fama-French risk factors, namely, the overall market factor (the value-weighted NSE20 index minus the risk-free rate), the size factor (SMB, small stocks minus big stocks), and the book-to-market factor (HML, high minus low book-to-market stocks). We regressed the monthly returns of the momentum strategy in excess of the risk-free interest rate, on the excess return of the NSE-20 index over the risk-free interest rate, and the Fama-French SMB and HML factors over the sample periods. The regression took the form below:

\[ R_{RSS,t} - rf_j = \alpha + \beta_m (R_{M,t} - rf_j) + \beta_{smb} SMB_i + \beta_{hml} HML_i + \epsilon_i \]  

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Where

\[ R_{RSS,t} \] = Average return of the relative strength strategy for the month \( t \).

\[ rf_j \] = The risk free rate of return observed at the beginning of the month, \( t \).

\[ R_{M,t} \] = Average monthly return on the overall market factor

\[ SMB_t \] = The monthly difference between the returns of a portfolio of small stocks and the portfolio of big stocks

\[ HML_t \] = The monthly difference between the returns of a portfolio of high BE/ME stocks and the portfolio of low BE/ME stocks

\( \alpha \) = The intercept in the regression equation

\( \beta_{SMB} \) = The sensitivity of the size factor to relative strength strategy (RSS) profits

\( \beta_M \) = The sensitivity of RSS profits to the overall market factor

\( \beta_{HML} \) = The sensitivity of RSS profits to the B-M factor

\( \epsilon \) = The error term of the regression

From the regression of the three factor model, the coefficients (the betas) were analyzed and tested to ascertain the explanatory powers of the factors for momentum profits. The alphas and the \( R\)-squared were determined and interpreted in light of the evidence from the coefficients.

The validity of conclusions in the above OLS regressions depend on assumptions of normality of distributions of data and error terms. We tested for assurance that there was of absence of non-normality, serial correlation, heteroskedasticity and multi-collinearity. Jarque-Bera statistic was calculated and tested against the critical chi-square at 5% to assure normality. The Durbin-Watson statistic was calculated and tested to assure that there was no evidence of autocorrelation in the residuals of the estimated equation. The White test was conducted to test the problem of heteroskedasticity which involves an irregular variance in the constant error, which is a violation of homoskedasticity (Pindyck & Rubinfeld 1998). A correlation matrix of all the independent variables was run to
detect correlation among different independent variables (multi-collinearity). If any of the off-diagonal values were bigger than 0.5, transformation of some of the independent variables was conducted to solve this problem.

### 3.6.5 Transaction Costs and Momentum Profits (Hypothesis 5)

A number of studies investigate the effects of trading costs on momentum (and contrarian) strategies. Ball et al. (1995), for example, show that market microstructure effects, such as bid-ask spreads, significantly reduce the profitability of contrarian strategies. Grundy and Martin (2001) find that the profits to their momentum strategy become statistically insignificant at round-trip transaction costs of roughly 1.50%. At round-trip transaction costs of 1.77%, the profits to their momentum strategies are driven to zero. Lesmond, Schill and Zhou (2004), also find that standard price momentum strategies require frequent trading in disproportionately high cost securities such that trading costs prevent profitable strategy execution. They conclude that the magnitude of the abnormal returns associated with their momentum strategies creates an illusion of profit opportunity when, in fact, none exists. Carhart (1997), notes that chasing momentum can generate high turnover and much of the potential profits from momentum strategies may be dissipated by transaction costs. Indeed, after estimating the magnitude of transaction costs, Carhart concludes that momentum is not profitably exploitable after those costs are taken into account.

Korajczyk and Sadka (2004), in contrast, investigate the effects of trading costs, including the price impact of the trades, on the profitability of momentum strategies. Specifically, they employ several trading cost models and momentum strategies and find that the estimated excess returns to some momentum strategies disappear only after US$ 4.5 to over US$ 5.0 billion (relative to the market capitalization in December 1999) is engaged by a single fund in such strategies. They conclude that momentum strategies are robust to transaction costs in the form of spreads as well as price impacts of trades. Grinblatt and Moskowitz (2004) note that a large part of the gains associated with momentum strategies are due to short positions in small and illiquid stocks, leading to high transaction costs. They also find that a large part of momentum profits come from
short positions taken in November, anticipating tax-loss selling in December. However, they still conclude that momentum profits are large enough to be economically exploitable.

The evaluation of the usefulness of such momentum strategies requires that their profitability is measured bearing in mind that trading is by no means a free activity. In earlier studies there are several attempts to make momentum strategies less expensive with respect to transaction costs, for example by restricting the sample to large caps (e.g., see Chan et al., 1999), by excluding stocks with a share price below $5 (e.g., see Jegadeesh & Titman, 2001), or by concentrating on long and neglecting short positions (e.g., see Grinblatt & Moskowitz, 2004).

Evaluating the profitability of momentum trading strategies requires a measure of the trading costs facing the arbitrageur. For the developed markets, the menu of transaction costs include the bid-ask spread, applicable commissions, price impact costs, taxes, short-sale costs, and other immediacy costs. Investors also face holding costs such as tracking error and short-sale constraints. For the NSE, where the dealers market is undeveloped, and short selling is non-existent, the most plausible estimate of the transaction costs were the commissions and brokerage fees charged by regulatory bodies and brokers. The NSE 2006 Handbook gave a total of 2 percent of the value of each transaction as the total transaction cost (Transaction Levy Breakdown: NSE Transaction Levy- 0.12%; NSE Investor Compensation Fund-0.01%; CMA Transaction Levy-0.12%; CMA Investor Compensation Fund-0.01%; CDSC Transaction Levy- 0.06%).

In order to analyze the sensitivity of our strategy returns to trading costs, we needed an estimate of the magnitude of the costs and the frequency of trading in our portfolios. Transaction costs for a single round-trip in NSE, made up of commissions and brokerage fees, could amount to 4 percent. The study compared the transaction costs with momentum strategy returns for a round trip of trading to assess whether momentum profits remained significant in the face of transaction costs.
3.6.6 Seasonality Effect (Hypothesis 6)

Papers that document 'anomalies' include 'seasonalities' in stock returns as one of the affronts to weak form market efficiency. It has been documented, for example, that Monday returns are, on average, lower than returns on other days of the week (Cross, 1973; French, 1980; Gibbons & Hess, 1981); and that returns are, on average, higher the day before a holiday (Ariel, 1990), and the last day of the month (Ariel, 1987).

But the premier seasonal is the January effect. Fama (1991) presents evidence that shows that stock returns, especially for small cap stocks, are, on average, higher in January than in other months. Based on earlier evidence (Roll (1983)), we have reason to expect that momentum strategies will not be successful in the month of January. Jegadeesh and Titman (1993) and Rouwenhorst (1997) find striking seasonality in momentum profits. Jegadeesh and Titman document that Winners outperform Losers in all months except January (indeed Losers outperform Winners in January).

In a follow up study, Jegadeesh and Titman (2001) using more recent data, confirmed that this January effect, far from being a statistical fluke, was persistent. These findings are also consistent with DeBondt and Thaler (1985), who report that contrarian traders, exploiting overreaction in stock markets, realised most excess profits in January. Grundy and Martin (2001) adduce more evidence, reporting that momentum portfolios earn significantly negative returns in Januaries and significantly positive returns in months other than January. Might this seasonality be a statistical fluke? We first examined the performance of the strategy in January and non-January months to see whether the January effect applies at the NSE.

Secondly, we broadened the seasonality tests to cover all the calendar months of the year. The data was studied for any sign of other seasonalities. Jegadeesh and Titman, for example report that returns are fairly low in November and December and are particularly high in April. They ascribe the large (3.33%) and consistently positive April returns to corporations' practice of transferring money to their pension funds and schemes prior to April 15 in order to qualify for a tax deduction in the previous year. The relatively low returns in November and December, they attributed to price pressure as
fund managers engage in tax-loss selling of losing stocks in these months in order to benefit from the resultant reduction in tax liability. Expanding the tests was informed by the fact that Kenyan tax regime and institutional reporting requirements (not always in tandem with the USA structures) could exhibit its own unique seasonal regularities. We sought to unearth any such seasonal regularities in NSE returns.

3.6.7 Post-holding Period Cumulative Profits to the Momentum Strategy (Hypothesis 7)

In this subsection we examined the results of momentum portfolios over various holding time horizons ($K$) to check the behaviour of the momentum returns over time. This provides information on the duration of the continuation effect and the extent to which it is permanent, and if at all there is reversal.

Literature treating the sources of momentum profits has multiplied exponentially. A number of hypotheses have been put forward to explain the profitability of momentum strategies. By examining the returns of portfolios following the formation period we will attempt to differentiate between the efficacies of these competing hypotheses. The first hypothesis is based on underreaction generated by "conservatism" bias, as identified by Edwards (1968) and suggests that investors underweight new information and are slow to update their priors. Consequently, prices will tend to adjust slowly to information, but once all information is incorporated in prices, there should be no more change. This prognosis suggests that the post holding period returns will be zero.

The second hypothesis, the overreaction hypothesis, has been attributed to behavioural biases as "representative heuristic" (Tversky & Kahnemann, 1974), and "self-attribution" syndrome will make traders overconfident pushing prices of winners above their fundamental values. The delayed overreaction lead to a build up of momentum in prices that is eventually reversed as prices self correct to fundamentals. This model envisages a situation where post holding returns are in fact negative.

The last hypothesis exposed by Conrad and Kaul (1998) argues that stock prices follow a random walk with drifts, and the unconditional drifts vary across stocks. They conjecture
that stocks with high (low) past returns will tend to be stocks with high (low) future average returns. In other words, one should expect winners to continue outperforming losers in any post ranking period. Thus momentum profits should persist into the post holding period. Figure 10 summarises the predictions of (1) the underreaction, (2) the overreaction and price correction, and (3) the Conrad and Kaul (1998) hypotheses. All three predict momentum profits in the holding period but differ in the post holding period predictions as discussed in the preceding paragraphs.

To test the behaviour of our strategies over the long term horizon, we followed their performance and cumulated returns over a period of 60 months after formation. A study of the cumulative returns should shed light on the validity of the three predictions above.

**Figure 10: Long Horizon Momentum Profits under Different Alternative Hypotheses**

This figure presents expected pattern of momentum portfolio returns under three hypotheses: (1) underreaction, (2) overreaction, and (3) Conrad and Kaul (1998) (Adapted from Jegadeesh and Titman (2001)).

### 3.6.8 Decomposition of Sources of Momentum Profits using WRSS (Hypothesis 8)

Although the momentum phenomenon has been well accepted, the source of the profits and the interpretation of the evidence are widely debated. A variety of papers ranging from behaviour models to rational-expectation models attempt to offer an explanation.
For the behavioural arguments, the momentum phenomenon is often interpreted as evidence that investors underreact/or overreact to new information. Along this line, Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), and Hong and Stein (1999) have developed behavioural models to explain the momentum.

On the other hand, others have suggested that the profitability of momentum strategies may simply be compensation for risk. Conrad and Kaul (1998) argue that the momentum profit is to be attributed to the cross-sectional dispersion in (unconditional) expected returns. Lewellen (2002) finds that the negative cross – serial correlation among stocks, not underreaction, is the main source of momentum profits.

To enable us decompose momentum profits we generated them using the weighted relative strength strategy (WRSS) method of Conrad and Kaul (1998). As in the section under relative strength strategies, the test period is divided into J-month formation period (from time $t-2$ to $t-1$) and $k$-month holding period (from time $t-1$ to $t$). When applying this method, the weight of each security in the trading portfolio in the holding period is determined by the relative performance of the security to the equal-weighted market portfolio in the formation period.

Specifically,

$$W_{i,j-1}(k) = \frac{1}{N} \left[ R_{i,j-1}(J) - R_{m,j-1}(J) \right]$$  \hspace{1cm} (3.3)

Where $W_{i,j-1}$ is the fraction of the trading strategy portfolio devoted to security $i$, in holding period, $R_{i,j-1}$ is the return of security $i$ in the formation period, and $R_{m,j-1}$ is the equal-weighted market portfolio return in the formation period. $N$ is the number of securities in the portfolio at time $t-1$, and $i=1... N$. The plus sign in the equation emphasizes that we will implement a moment strategy, i.e., going long in a security if it outperforms the equal-weighted market portfolio and going short in a security if it underperforms the market portfolio.

By construction, the portfolio is an arbitrage portfolio since the weights of securities sum to zero. And the total investment position (long or short) is given by:
The profit in the holding period for the strategy is:

$$ I_t = \frac{1}{2} \sum_{i=1}^{N} w_{i,t-1}(k) $$

(3.4)

After generating the WRSS returns, we next decompose them and investigate the source of the momentum profits. To decompose the WRSS profit, we assume that the realized return of stock $i$ is expressed as:

$$ R_{i,t}(k) = \mu_{i,t}(k) + u_{i,t}(k) $$

(3.6)

Where $\mu_{i,t}(k)$ is the unconditional expected return of stock $i$ and $u_{i,t}(k)$ is the unexpected return at time $t$. Then the momentum profits in Eq. 3.5 can be decomposed into components based on expected and unexpected components of returns as follows:

$$ E[\pi_t(k)] = -\text{Cov}(R_{m,t}(k), R_{m,t-1}(J)) + \frac{1}{N} \sum_{i=1}^{N} \text{Cov}(R_{i,t}(k), R_{i,t-1}(J)) + \frac{1}{N} \sum_{i=1}^{N} [\mu_{i,t-1}(k) - \mu_{n}]$$

$$ = -C_1(k) + O_1(k) + \sigma^2[\mu(k)]$$

$$ = P(k) + \sigma^2[\mu(k)]$$

(3.7)

Where $C_1(k)$ is the first-order auto-covariance of the returns on the market portfolio. $O_1(k)$ is the average of the first-order auto-covariances of the $N$ individual stocks in the zero-cost portfolio, $\mu_{m,t}(k) = \frac{1}{N} \sum_{i=1}^{N} \mu_{i,t}(k)$, and $\sigma^2[\mu(k)]$ is the cross-sectional variance of expected returns. In calculating the components of the trading portfolio profits, we assume that individual stock returns are mean stationary. Eq. (3.6) decomposes the total expected profits into two components: $P(k)$, the time-series predictable components in asset returns, and $\sigma^2[\mu(k)]$, the profits generated by cross-sectional variance of the mean returns. The equation indicates that any cross-sectional variation in expected returns contributes positively to momentum profits. Since
realized past returns are positively correlated with expected returns, if a large part of realized returns is due to expected returns, past Winners (Losers) will on average continue to earn higher (lower) than average returns in the future.

Following Conrad and Kaul (1998), we assume that the serial covariances and the cross-sectional variances of mean returns of individual stocks are time dependent.

Then, \( C_1(k) \), \( O_1(k) \), and \( \sigma_i^2(\mu(k)) \) are estimated as:

\[
-C_1(k) = -\frac{1}{T(k)-1} \sum_{i(k)=2}^{T(k)} C_{1,i}(k) \tag{3.8}
\]

Where

\[
C_{1,i}(k) = R_{m,i}(k) R_{m,j-1}(J) + \mu_{m,j-1}(k)^2 + \frac{1}{N} \sum_{i=1}^{N} [R_{i,i}(k) R_{i,j-1}(J) - \mu_{i,j-1}(J)]^2
\]

\[
O_1(k) = \frac{1}{T(k)-1} \sum_{i(k)=2}^{T(k)} O_{1,i}(k) \tag{3.9}
\]

Where

\[
O_{1,i}(k) = \frac{N-1}{N^2-1} \sum_{i=1}^{N} [R_{i,i}(k) R_{i,j-1}(J) - \mu_{i,j-1}(J)]^2
\]

And

\[
\sigma_i^2(k) = \frac{1}{N} \sum_{i=1}^{N} [\mu_{i,j-1}(J) - \mu_{m,j}(J)]^2 \tag{3.10}
\]

Where, \( T(k) \) is the total number of overlapping returns in the sample period for a trading strategy of holding period \( k \). \( \mu_{m,j-1}(J) \), \( \mu_{i,j-1}(J) \) are the estimated expected returns of stock \( i \), and market portfolio at time \( t-1 \). \( \mu_{i,j-1} \) is estimated through average realized returns of each stock:

\[
\mu_{i,j-1} = \frac{1}{T_i} \sum_{i=1}^{T_i} R_{i,i}
\]

where \( T_i \) is the number of observations available for stock \( i \). Then,

\[
\mu_{m,i-1}(k) = \frac{1}{N} \sum_{i=1}^{N} \mu_{i,j-1} \tag{3.12}
\]
Going back to Eq. 3.6 i.e. $E[\pi_i(k)] = P(k) + \sigma^2[\mu(k)]$, we will be looking for evidence of the dominant factor in the momentum profits. If it is the first factor we would conclude that momentum profitability is a time-series phenomenon and evidence of market inefficiency.
CHAPTER FOUR
FINDINGS AND DISCUSSION

4.1 Introduction
This chapter presents and discusses the findings from the data analyses. An effort is made to interpret the findings and link them with findings from other related studies elsewhere. The chapter is structured according to the eight hypotheses of the study. We start with evidence of momentum profits, followed by size effect, effect of trading volume, effect of market risk factors, impact of transaction costs, seasonality, reversal and finally decomposition of momentum profits.

4.2 Findings and Discussions
The data were analysed and the results are discussed in line with the study hypotheses in Section 2.7. First we report the findings of our data analysis for each hypothesis. Then we follow by a discussion of the findings, contrasting where possible with findings elsewhere.

4.2.1 Profitability of Momentum Strategies
Findings
To test this hypothesis, we first formed the relative strength portfolios as described in Section 3.5. Table 3 reports the average monthly buy-and-hold returns on the composite portfolio strategies implemented during different periods at the NSE. For each strategy, the table lists the returns of the “Winner” and the “Loser”, as well as the excess returns (and \( t \)-stat) from buying “Winner” and selling “Loser”. For instance, during the full sample period 1996-2007, buying “Winner” from a 3-month/3-month strategy earns an average return of 1.31 percent per month. 0.85 percent higher than buying “Loser” in the same strategy, which returns 0.46 percent. The excess return is significant at the 1 percent level, with a \( t \)-statistic of 1.714.
The table shows average monthly profits to relative strength (or momentum) strategies (RSS) mounted at the NSE from 1995 to 2007, and two sub-periods to distinguish a markedly bullish post-2002 period from the earlier period. At the end of each month t, all stocks at the stock market are ranked in descending order on the basis of their J-months' past returns. Based on these rankings, the stocks are assigned to each of the equally weighted 5 (quintile) portfolios. The top quintile portfolio is called the “Winner”, while the bottom quintile portfolio is called the “Loser”. These equally weighted portfolios are held for K subsequent months. T-statistic is the average return divided by its standard error. * represents significance at the 5% level and ** significance at 1% level.

For the entire period 1996-2007, significantly positive excess returns are observed at the 5 percent level for nine strategies among the sixteen strategies implemented. Specifically, the excess monthly returns of buying “Winner” over buying “Loser” range from -0.28 percent for the 3-by-12 strategy to 1.72 percent for the 9-by-9 strategy. The 6-by-6 strategy
that is standard for most studies registers a mean return of 1.18% per month which is statistically and economically significant. The average Winner-Loser return for the entire sample is 0.54 percent. Figure 11 is a chart showing average monthly momentum returns for the entire sample period, 1996 to 2007.

![Average monthly momentum profits 1996-2007](chart)

Holding period (months)

The portfolio returns of the two sub-periods are in stark contrast to each other. Figure 10 summarises the experience for the 1996-2002 sub-period (See Figure 12). Evidently, consistent momentum is virtually non-existent; to the contrary, the sub-period is much more prone to price reversal. Of the 16 strategies implemented over the period, 8 strategies register negative returns that are significant at the 1% level, while only 4 strategies show significant momentum profitability. The 6-by-6 strategy mean return is 0.43 percent per month. The average Winner-Loser return for the period is virtually zero percent (at +0.019 percent).
In contrast to the 1996-2002 sub-period, the sub-period 2003 to 2007 exhibited intense level of price continuation that is responsible, in large measure, for the average positive momentum effect witnessed in the entire sample. Figure 13 shows that fourteen of the sixteen strategies during this period exhibit positive momentum profits that are significant at the 1% level. Average monthly momentum profits are at 1.23 percent, and range from −0.16 percent for the 3-by-12 strategy to 3.92 percent for the 6-by-3 strategy. The 6-by-6 strategy mean return is 2.23 percent per month.
We introduce the sub-period 2000-2007 so as to prepare the background for the subsequent tests that will be confined to data from this period. As explained earlier, data inavailability for prior periods has forced the researcher to restrict further tests to the period beginning 2000 to 2007.

Table 3 (a): Average Monthly Returns to Momentum Strategies for the Period 2000 to 2007

<table>
<thead>
<tr>
<th>Formation Period (J)-months</th>
<th>Portfolio</th>
<th>2000-2007 Holding period (K)-months</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>3</td>
</tr>
<tr>
<td>3</td>
<td>Winner(W)</td>
<td>0.0268</td>
</tr>
<tr>
<td></td>
<td>Lose(L)</td>
<td>0.0109</td>
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<tr>
<td></td>
<td>W-L</td>
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</tr>
<tr>
<td></td>
<td>(t-stat)</td>
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</tr>
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<td>Winner(W)</td>
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</tr>
<tr>
<td></td>
<td>Lose(L)</td>
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<tr>
<td></td>
<td>W-L</td>
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<tr>
<td></td>
<td>(t-stat)</td>
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<td>9</td>
<td>Winner(W)</td>
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<td></td>
<td>Lose(L)</td>
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<tr>
<td></td>
<td>Lose(L)</td>
<td>0.0209</td>
</tr>
<tr>
<td></td>
<td>W-L</td>
<td>0.0018</td>
</tr>
<tr>
<td></td>
<td>(t-stat)</td>
<td>0.24</td>
</tr>
</tbody>
</table>

The table 2 (a) shows average monthly profits to relative strength (or momentum) strategies (RSS) mounted at the NSE from 2000 to 2007. This sub-table 2(a) of Table 2 was necessitated by data limitations that have forced the study to confine the remaining tests to the period 2000 to 2007. This sub-table is thus the springboard for the remaining tests. The construction and interpretation of this table follows the Table 2 closely.
Figure 14: Average monthly momentum returns 2000-2007

Figure 14 is a chart constructed from Table 3 (a). During the sub-period analyzed, momentum was evidently widespread. Twelve of the sixteen strategies exhibit significant momentum (6 at the 1% level and the remaining 6 at 5% level of significance). Average monthly returns were as high as 2.32% for the 9 by 9 strategy, with the only negative return at −0.25% (significant at 5% level) being registered in the 3 by 12 strategy.

The Table 4 list a summary of some of the US studies that report significant momentum returns

| Table 4: Momentum Returns Reported in the Literature |
|---------------------------------|-----|---|-----|-----|
| Momentum                        | T-Value | Sample       | Weight | Percentage |
| Jegadeesh and Titman (1993)     | 0.95  | 3.07 | 1965-1989 | EW | 10 |
| Conrad and Kaul (1998)          | 0.36  | 4.55 | 1962-1989 | WRSS | N/A |
| Moskowitz and Grinblatt (1999)  | 0.43  | 4.65 | 1973-1995 | VW | 30 |
| Lee and Swaminathan (2001)      | 1.05  | 4.28 | 1965-1995 | EW | 10 |

In the first column of the, the references are listed and the second and third columns the reported excess returns on winner minus loser strategies with corresponding t values. The last three columns indicate the sample period, the weighting scheme (EW= equally weighted, VW=value weighted, and WRS=weighted relative strength) and the percentage of the sample stocks in the portfolio.
Considering the results for all the 64 strategies (16 each for each of the 3 sub-periods, and the full sample) implemented, there is concrete evidence of momentum in individual stocks at the NSE. The evidence is pervasive in all sub-periods, the only difference being in the degree of its incidence. Comparing the findings of the current study with those of studies from the US (See Table 4) most of which report the existence of momentum, it is clear the NSE is in the same league. Thus, to the first hypothesis, the verdict is incontrovertible that stocks at the NSE exhibit strong price momentum.

**Discussion**

An increasing literature finds evidence that momentum strategies which buy stocks with the best past performance and sell stocks with the worst past performance generate significant abnormal returns (see Jegadeesh & Titman, 1993, 2001; Rouwenhorst, 1998; Chan, Jegadeesh & Lakonishok, 1996). Contrary evidence has been documented by Hameed and Kusnadi (2002) who implement the momentum trading strategies on securities traded on six Asian markets, namely, Hong Kong, Malaysia, Singapore, South Korea, Taiwan and Thailand over the sample period 1981-1994 and find no evidence of price momentum. They reported that none of their 16 unrestricted momentum strategies yielded significant profits.

Evidence from the NSE shows that for the entire sample period 1996-2007, significant positive excess returns are observed at the 5 percent level for nine strategies. The 6-by-6 strategy that is standard for most studies registers a mean return of 1.17% per month which is statistically and economically significant. The average Winner-Loser return for the entire sample was 0.54 percent. The portfolio returns of both sub-periods are in stark contrast, with the sub-period 1996 to 2002 being characterized by a complete lack of momentum in the returns, while the sub-period 2003 to 2007 exhibits a high degree of price continuation with fourteen of the sixteen strategies recording significant positive momentum profits and the 6-by-6 strategy mean return is 2.23 percent per month.

The implication of the findings are two-fold; one, that one can earn abnormal returns by implementing momentum-based trading strategies at the NSE. The market is therefore
not efficient at the basic weak-form level. Secondly, it is clear that investor sentiment is a strong driver in price momentum. The contrasting sub-sample results for 1996-2002 and 2003-2007 periods is a product of the opposing despondency and exuberance respectively in investors’ future outlooks in each period.

4.2.2 Size and Momentum Profits

Findings
To examine whether the small firm price effect holds at the NSE, we constituted a size-neutral strategy, comprising of 15 portfolios of 3 size sorted, and 5 momentum based.

<table>
<thead>
<tr>
<th>MOMENTUM PORTFOLIOS</th>
<th>SIZE CLASS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All stocks</td>
</tr>
<tr>
<td>$P_1$ (winners)</td>
<td>0.0293 (3.31)</td>
</tr>
<tr>
<td>$P_2$</td>
<td>0.0380 (3.33)</td>
</tr>
<tr>
<td>$P_3$</td>
<td>0.0246 (2.39)</td>
</tr>
<tr>
<td>$P_4$</td>
<td>0.0192 (2.84)</td>
</tr>
<tr>
<td>$P_5$ (losers)</td>
<td>0.0149 (2.25)</td>
</tr>
<tr>
<td>$P_1 - P_5$</td>
<td>0.0144 (0.38)</td>
</tr>
</tbody>
</table>

In this table, equally weighted quintile momentum portfolios were formed on the basis of 6 months lagged returns and held for 6 months. The winner–portfolios comprised the top performing quintile $P_1$, while the loser portfolio comprised worst performing quintile, $P_5$. The stocks were next ranked independently on the basis of size (market capitalization at the beginning of the year). “Big” comprised 30% of the large cap stocks, “Medium”, 40% of medium stocks, and “Small”, 30% of the small cap stocks. Average monthly returns of the resultant sub-samples are reported here. The sample period is January 2000 to December 2007.

The first column in Table 5 confirms that there is significant momentum in the full sample. A strategy that goes long in the best performing quintile and short in the worst
performing quintile generates 1.44 percent per month. The next columns break the momentum effect down by size: the “Big” stocks, the “medium” stocks, and the “Small” stocks. The average return for the big and medium stocks is 1.14% and 1.55% per month respectively. For the small cap stock the momentum return is in fact, marginally negative, at -0.08%. The evidence as shown in the table fails to confirm the hypothesis that small capitalization stocks should have more momentum than large capitalization stocks.

Discussion

A possible explanation for the absence of a size effect at the NSE could be that the “small” caps in our sample all, virtually, belong in the alternative segment of the market. With a mean capitalization of Sh.486 million, the small caps are on average, 20% and 2.5% the size of the medium and large cap stocks, respectively. From the perspective of size alone the small cap stock in the sample can be considered outliers. To compound the ‘outlier’ problem is the high degree of thin trading in the alternative segment. Ndungu (2004) reports that trades in the alternative segment are on average as low as 5% of the average daily trading frequency for the NSE as a whole, with some counters not registering even a single transaction for months. The thin trading means that information, on which momentum thrives, cannot be incorporated in prices enough to generate momentum. This may have distorted our results.

We could test the size effect by excluding the small cap stocks i.e. stocks in the alternative segment. The results of our test are shown below in table 6. An overall momentum effect is very much evident as a strategy of buying the best performing quintile and selling the worst performing quintile generates 1.27 percent per month. The next columns break the momentum effect down by size: the “Big” stocks, the “medium” stocks, and the “Small” stocks. The average returns for the big and medium stocks are 1.21% and 1.04% per month respectively. For the small cap stock, the momentum return has is now significantly positive at 1.56 percent. This finding deviates from the initial findings with the stocks from the alternative segment. The size effect is now manifest at the NSE with the overall “Small minus Big” momentum effect of 0.35 percent per month.
Table 6: Returns to size-based momentum portfolios excluding the outlier stocks of the alternative investment segment

<table>
<thead>
<tr>
<th>MOMENTUM PORTFOLIOS</th>
<th>SIZE CLASS</th>
<th>All stocks</th>
<th>Big</th>
<th>Medium</th>
<th>Small</th>
<th>Small minus Big</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$ (winners)</td>
<td></td>
<td>0.0375</td>
<td>0.0397</td>
<td>0.0463</td>
<td>0.0265</td>
<td>-0.0132</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.23)</td>
<td>(2.59)</td>
<td>(1.90)</td>
<td>(1.33)</td>
<td></td>
</tr>
<tr>
<td>$P_2$</td>
<td></td>
<td>0.0272</td>
<td>0.0235</td>
<td>0.0123</td>
<td>0.0459</td>
<td>0.0224</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.33)</td>
<td>(2.51)</td>
<td>(2.24)</td>
<td>(2.05)</td>
<td></td>
</tr>
<tr>
<td>$P_3$</td>
<td></td>
<td>0.0238</td>
<td>0.0232</td>
<td>0.0214</td>
<td>0.0268</td>
<td>0.0036</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.39)</td>
<td>(0.65)</td>
<td>(1.16)</td>
<td>(1.39)</td>
<td></td>
</tr>
<tr>
<td>$P_4$</td>
<td></td>
<td>0.0109</td>
<td>0.012</td>
<td>0.0153</td>
<td>0.0054</td>
<td>-0.0066</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.34)</td>
<td>(1.220)</td>
<td>(0.83)</td>
<td>(2.55)</td>
<td></td>
</tr>
<tr>
<td>$P_5$ (losers)</td>
<td></td>
<td>0.0248</td>
<td>0.0276</td>
<td>0.036</td>
<td>0.0109</td>
<td>-0.00167</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.15)</td>
<td>(1.67)</td>
<td>(1.21)</td>
<td>(1.02)</td>
<td></td>
</tr>
<tr>
<td>$P_1 - P_5$</td>
<td></td>
<td>0.0127</td>
<td>0.0121</td>
<td>0.0104</td>
<td>0.0156</td>
<td>0.0035</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.28)</td>
<td>(0.66)</td>
<td>(1.27)</td>
<td>(-0.04)</td>
<td></td>
</tr>
<tr>
<td>$P_3 - P_5$</td>
<td>$P_1 - P_5$</td>
<td>0.384</td>
<td>1.406</td>
<td>1.019</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In this table, equally weighted quintile momentum portfolios were formed on the basis of 6 months lagged returns and held for 6 months. The winner portfolios comprised the top performing quintile $P_1$, while the loser portfolio comprised worst performing quintile, $P_5$. The stocks were next ranked independently on the basis of size (market capitalization at the beginning of the year). “Big” comprised 30% of the large cap stocks, “Medium”, 40% of medium stocks, and “Small”, 30% of the small cap stocks. Average monthly returns of the resultant sub-samples are reported here. The sample period is January 2000 to December 2007. The sampled stocks excluded those in the alternative segment.

Some past research has found that most of the return to a long/short momentum trading strategy is due to the short position in losers rather than the long position in the winners. Hong, Lim, and Stein (2000) find that between 73% to 100% of the returns of the winner/loser strategy is attributable to losers. Grinblatt and Moskowitz (2003) find a stronger relationship between momentum return and past returns for losers than winners. Jegadeesh and Titman (2001) find larger abnormal returns for loser portfolios than for winner portfolios. Lesmond et al. (2003) find 53% to 70% of profits of long/short trading strategy come from the short side.

In Table 6, the row 7, \( \frac{P_3 - P_5}{P_1 - P_5} \), measures the proportion of momentum profits that is attributable to the short position in the zero-cost winner/losers strategies. The results of
all size categories are consistent with prior research findings. Our findings (in Table 6) indicate a positive impact on momentum profitability by the big, medium and small cap losers (+38.4% for big, +140.6% for medium and 101.9% for small). On the whole, the results fail to reject the hypothesis that momentum is more pronounced in small stocks than in other size categories.

4.2.3 Trading Volume and Momentum Profits

<table>
<thead>
<tr>
<th>Table 7: Trading volume and momentum profitability</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Volume Portfolios</strong></td>
</tr>
<tr>
<td><strong>Momentum Portfolios</strong></td>
</tr>
<tr>
<td>P1 (winners)</td>
</tr>
<tr>
<td>(3.28)</td>
</tr>
<tr>
<td>P2</td>
</tr>
<tr>
<td>(3.03)</td>
</tr>
<tr>
<td>P3</td>
</tr>
<tr>
<td>(2.67)</td>
</tr>
<tr>
<td>P4</td>
</tr>
<tr>
<td>(2.54)</td>
</tr>
<tr>
<td>P5 (losers)</td>
</tr>
<tr>
<td>(2.87)</td>
</tr>
<tr>
<td>P1 - P5</td>
</tr>
</tbody>
</table>

The table presents momentum returns based on two-way independent sorts of price performance and trading volume for the period between 2000 and 2007. We focus only the J-6, K-6 strategies whose results we consider representative of all strategies. First stocks were sorted into five quintiles based on their 6 months formation period returns. P1 represented the portfolio with the highest past returns, P2 the next highest and so on up to P5 which comprised the losers. Next tercile portfolios were formed on the same stocks based on average turnover of the stocks over the same formation periods used for the first sort. V1 was the portfolio with the highest average trading volume, V2 the stocks with medium trading activity, and V3 was the portfolio with the lowest average trading volume over the formation period. We therefore had 15 momentum/trading volume portfolios, in which P1-V1 contained stocks with highest past six month return and highest average past six month trading volume. In contrast P3-V3 represented stock with poorest past six month performance and lowest past six month average trading volume. Equally-weighted monthly returns for each portfolio are calculated and shown in the table. The t-statistics are in parenthesis, ** indicates significance at 1% level, and * indicates significance at 5% level.
Findings

Table 7 reports the results of volume-based momentum strategies for the 6-month/6-month strategies. The table reveals that high volume winners outperform low-volume winners by about 1 percent, while the corresponding difference in the losers’ performance is 2.4 percent, significant at the 1 percent level.

When we neutralize the effect of momentum, the results show that, for the high volume stocks, the return is negative (-0.73%), while for the low-volume portfolios the return is positive and significant at 5 percent level (0.72%). Thus, the momentum effect is more pronounced for low volume stocks than higher volume stocks. The momentum return for $V_3$ is 1.4 percent higher that that of $V_1$. The table also contains evidence that suggest that momentum portfolios consistently produce positive returns only at medium and low volume levels ($V_2$ and $V_3$).

The table also shows that the spread between high volume winners and high volume losers is lower than the one between high volume losers and low volume losers. For the former it is 1% while for the latter it is 2.4%. This implies losers generate most of the momentum.

Discussion

The findings of our study are consistent with Lee and Swaminathan (2000). High volume stocks are frequently traded on the market meaning that information about them gets around fast. The reaction of price to information is likely to be slower for low volume stocks. This implies that momentum strategies are most likely to work better in low volume stocks. On the other hand, it could be argued that low volume stocks could be impervious to the flow of information. Consequently momentum which depends on the impounding of information into prices would be impeded.

In sum, the negative return of the momentum portfolio for high volume stocks ($P1V1-P5V1$) is as hypothesized. The empirical results are in agreement with the fact that incomplete (under-) reaction, rather than trading activity is the major cause of continuation of price performance. The findings are consistent with the expectation that
low-volume stocks should earn higher expected returns as a compensation for their relative illiquidity (Datar et al., 1998; Pastor & Stambaugh, 2003).

4.2.4 Risk-Adjusted Momentum Returns

Findings

The momentum effect can only be correctly labelled an anomaly if the effect defies risk based explanations. In this subsection we subjected our momentum returns to two risk inspired asset pricing models. First we employed a market version of the CAPM, and secondly the broader Fama-French three factor model.

<table>
<thead>
<tr>
<th>Table 8: CAPM Adjusted Excess Returns of Momentum Portfolios</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>1996-2007</td>
</tr>
<tr>
<td>1996-2002</td>
</tr>
<tr>
<td>2003-2007</td>
</tr>
</tbody>
</table>

The table provides the results from regression of the monthly returns of the 6-month/6-month momentum strategy in excess of the risk-free interest rate on excess return on the market portfolio. The testable version of the CAPM is

\[ R_{RSS,i} - rf_i = \alpha + \beta_m (R_{M,i} - rf_i) \]

\( t(\cdot) \) is the related coefficient divided by its standard error. T-statistics are in parenthesis. **significant at 1%: * significant at 5%. (See section 3.6.4 for definitions of terms)

The Table 8 tested the ability of CAPM’s beta to explain momentum returns. The findings are not reassuring on CAPM’s efficacy. First the alphas are significant for the whole sample and for the sub-period 2002-2007. The 2002-2007 was the period that exhibited a sustained degree of momentum (See Table 2). The significant alphas can be interpreted as evidence that momentum is an anomaly that defies risk explanations (Or it could that the CAPM is mis-specified). The second confounding fact from Table 6 is that all the beta values, though significant are negative, implying illogically that returns and risk have a negative relationship. The inevitable inference is that momentum profitability is robust to a CAPM explanation.
Table 9: Fama-French 3 Factor Risk Adjusted Excess Returns of Momentum Portfolios

<table>
<thead>
<tr>
<th>Year</th>
<th>( \alpha )</th>
<th>( t(\alpha) )</th>
<th>( \beta_{SMB} )</th>
<th>( t(\beta_{SMB}) )</th>
<th>( \beta_{HML} )</th>
<th>( t(\beta_{HML}) )</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996-2007</td>
<td>0.00</td>
<td>4.5**</td>
<td>-0.308</td>
<td>-5.51**</td>
<td>0.026</td>
<td>0.756</td>
<td>0.016</td>
</tr>
<tr>
<td>1996-2002</td>
<td>0.00</td>
<td>0.653</td>
<td>-0.576</td>
<td>-10.01**</td>
<td>0.018</td>
<td>0.646</td>
<td>0.11</td>
</tr>
<tr>
<td>2003-2007</td>
<td>0.00</td>
<td>3.83**</td>
<td>-0.244</td>
<td>-1.846</td>
<td>-0.072</td>
<td>-1.015</td>
<td>-0.035</td>
</tr>
</tbody>
</table>

Table 7 provides the results from regression the monthly returns of the 6-month/6-month momentum strategy in excess of the risk-free interest rate on Fama-French three-factors: \( R_{m} - r_{f} \), \( R_{SMB} \), and \( R_{HML} \) over the sample period. The testable version of the F-F 3-factor model is as follows:

\[
R_{m-1} - r_{f} = \alpha + \beta_{m} (R_{m-1} - r_{f}) + \beta_{SMB} R_{SMB,1} + \beta_{HML} R_{HML,1} + \epsilon,
\]

\( R^2 \) is the coefficient of determination adjusted for degrees of freedom: \( t(\alpha) \) is the related coefficient divided by its standard error. \( R^2 \) statistics are in parenthesis. **significant at 1%; * significant at 5%. 

We alternatively employed the broader model of Fama and French (1993). Fama-French model uses three risk factors, namely, the overall market factor (the value-weighted NSE20 index minus the risk-free rate), the size factor (SMB, small stocks minus big stocks), and the book-to-market factor (HML, high minus low book-to-market stocks). We regressed the monthly returns of the momentum strategy in excess of the risk-free interest rate, on the excess return of the NSE-20 index over the risk-free interest rate, and the Fama-French SMB and HML factors over the sample periods.

Table 9 reports the results of the regression for the whole period and the two sub-periods. As is shown in column 4, all the market factor coefficients \( \beta_{m} \) are negative, indicating that market wide risk factors far from explaining excess returns instead confound them. It is also reflects that losers are somewhat more sensitive to the market risk factor than the winners. A closer look at column 5 shows that coefficients for the
whole sample and 1996-2002 sub-period are significantly different from zero, meaning that market betas for winners and losers differ significantly.

Columns 6-9 reveal the effect of the size factor coefficients ($\beta_{SMB}$) and book-to-market factor coefficients ($\beta_{HML}$). The signs are positive for the entire sampled period, and the period 1996-2002; but negative for the sample sub-period 2003-2007. Tests of significance reveal that the coefficients are not significantly different from zero. This leads to the inference that size and the value factor have only minimal explanatory power for momentum profits.

Columns 2 and 3 of Table 9 report the alpha ($\alpha$) of the various momentum portfolios as estimated by regressing the monthly momentum returns on the Fama-French factors. The alphas for these risk-adjusted portfolios are positive and significantly different from zero. This means that the three factor model is not adequate to explain the sources of momentum profits; there may be other variables with more correlation with momentum profits not specified.

Finally, the last column of the table presents the $R$-square of each regression, ranging from 0.082 to 0.0627. This means the Fama-French factors can only explain 6% to 8% of the momentum profits. We are let to conclude that momentum profits cannot be explained by the risk factors contained in the Fama-French three-factor model. We therefore, fail to confirm the hypothesis that momentum profitability is a compensation for additional risk inherent in the momentum strategies.

**Discussion**

From the time Jegadeesh and Titman (1993) documented the momentum phenomenon, concerted efforts were directed towards finding a risk-based explanation for the source of the profits. Though some finance scholars still harbour a hope for successful explanation of the momentum anomaly within the efficient markets paradigm, there are many who have become despondent of such an eventuality. Jegadeesh and Titman (1993, 2001) fail to establish a link between the CAPM beta and the momentum
profitability, while Fama and French (1996) fail to price the momentum profitability by exposure to the risk factors in Fama and French (1993).

Following Fama and French (1996), this study aimed at testing the efficacy of the CAPM and the Fama-French three factor model in explaining the momentum profits at the NSE. We considered the possibility that the excess returns are rewards for exposures to market wide risk factors by regressing momentum returns.

Overall, the analysis revealed that the market wide co-variation, the book-to-market and the size risk factors cannot explain the out-performance of momentum stock selection strategies at the Nairobi Stock Exchange. This corroborates the results obtained by almost all studies, including Lee and Swaminathan (2000), Grinblatt and Moskowitz (2003), and (Korajczyk and Sadka (2004). As the evidence we have documented at the NSE confirms, momentum profitability still remains the major embarrassment to the efficient markets paradigm (Fama, 1998).

4.2.5 Transaction Costs Impact on Momentum Profits

Findings

Evaluating the profitability of momentum trading strategies requires a measure of the trading costs facing the arbitrageur. For the developed markets, the menu of transaction costs include the bid-ask spread, applicable commissions, price impact costs, taxes, short-sale costs, and other immediacy costs. Investors also face holding costs such as tracking error and short-sale constraints. For the NSE, where the dealers market is undeveloped, and short selling is non-existent, the most plausible estimate of the transaction costs are the commissions and brokerage fees charged by regulatory bodies and brokers. The NSE 2006 Handbook gives a total of 2 percent of the value of each transaction as the total transaction cost.

In order to analyze the sensitivity of our strategy returns to trading costs, we need an estimate of the magnitude of the costs and the frequency of trading in our portfolios.
Transaction costs for a single round-trip in NSE made up of commissions and brokerage fees could amount to 4 percent.

The transaction costs of trading momentum portfolios would thus be bounded on the upper side by the 4 percent round trip brokerage and commission fees. In reality however transaction costs are bound to be lower for two reasons: First, because the strategies we have employed at NSE are constituted by relatively few stocks (20 to be exact), transaction costs are likely to be small compared to the values estimated in prior research allowing the strategies to invest in a much larger number of stocks (listed at NYSE, AMEX, and NASDAQ or the CRSP universe). For example an extreme case is provided by Rey and Schmid (2005), whose strategies do not invest in decile portfolios but in single stocks and report the interesting finding that, arbitrage portfolios investing in only one winner and one loser stock experienced annualized average returns of up to 44%, depending on the length of the formation and holding periods.

Secondly, the turnover of positions in the strategies is far from 100 percent per month since any two neighbouring formation periods share $K/I$ months in common. Thus, Winner/Loser stocks over a $K$ month formation period are likely to still qualify as Winner/Loser for the next formation period. Grundy and Martin (2001) report an average 40 percent of turnover for both the winner and the loser portfolios. Adopting this 40 percent frequency of trading for the 6 month/6 month strategy, and with 4% round-trip cost of transacting, results in a cost of 1.6 percent of value per transaction.

For momentum trading to earn abnormal profits at NSE, it must return a rate significantly higher than 1.6 percent. Does our 6 month/6 month strategy meet this minimum condition? The 6 month/6 month strategy requires four trades per six month period (opening and closing positions for both the Winner and loser portfolios). Our strategy reported earlier in Table 2, results in six-month average return of 7.02% (1.17*6). With a requirement of four transactions to close the position, this delivers a return of 1.8 percent per transaction. This return is marginal in light of the transaction costs of 1.6 percent. Even when one revises the adapted trading frequency, which should be lower for illiquid markets like the NSE, the level of comfort for these strategies is still slim. The situation is
compounded by the realization that the approximation of transaction costs neither considers market frictions induced by trading (i.e., a price impact) nor attempts to account for potential differences in trading costs associated different stocks or stock characteristics. For tractability, we assumed that transaction costs for buying and selling winner stocks as well as selling and buying back loser stocks are of equal size. Lesmond et al. (2004) have indeed shown that many of the stocks included in relative strength strategies are illiquid and extreme, and require disproportionately high levels of transaction costs to trade.

Discussion
A number of studies investigate the effects of trading costs on momentum (and contrarian) strategies. Ball et al. (1995), for example, show that market microstructure effects, such as bid-ask spreads, significantly reduce the profitability of contrarian strategies. Grundy and Martin (2001) find that the profits to their momentum strategy become statistically insignificant at round-trip transaction costs of roughly 1.50%. At round-trip transaction costs of 1.77%, the profits to their momentum strategies are driven to zero. Lesmond et al. (2004), also find that standard price momentum strategies require frequent trading in disproportionately high cost securities such that trading costs prevent profitable strategy execution. They conclude that the magnitude of the abnormal returns associated with their momentum strategies creates an illusion of profit opportunity when, in fact, none exists. Carhart (1997), notes that chasing momentum can generate high turnover and much of the potential profits from momentum strategies may be dissipated by transaction costs. Indeed, after estimating the magnitude of transaction costs, Carhart concludes that momentum is not profitably exploitable after those costs are taken into account.

Korajczyk and Sadka (2004), in contrast, investigate the effects of trading costs, including the price impact of the trades, on the profitability of momentum strategies. Specifically, they employ several trading cost models and momentum strategies and find that the estimated excess returns to some momentum strategies disappear only after US$ 4.5 to over US$ 5.0 billion (relative to the market capitalization in December 1999) is engaged by a single fund in such strategies. They conclude that momentum strategies are

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robust to transaction costs in the form of spreads as well as price impacts of trades. Grinblatt and Moskowitz (2004) note that a large part of the gains associated with momentum strategies are due to short positions in small and illiquid stocks, leading to high transaction costs. They also find that a large part of momentum profits come from short positions taken in November, anticipating tax-loss selling in December. However, they still conclude that momentum profits are large enough to be economically exploitable.

The evaluation of the usefulness of such momentum strategies requires that their profitability is measured bearing in mind that trading is by no means a free activity. In earlier studies there are several attempts to make momentum strategies less expensive with respect to transaction costs, for example by restricting the sample to large caps (e.g., see Chan et al., 1999), by excluding stocks with a share price below $5 (e.g., see Jegadeesh and Titman, 2001), or by concentrating on long and neglecting short positions (e.g., see Grinblatt and Moskowitz, 2004).

Whether momentum strategies are anomalous may ultimately depend on the answers surrounding the costs of trading the strategies. It appears evident that transactions costs when properly modelled and incorporated in the analysis have the potential to eat away into any illusory abnormal profits. The efficient markets hypothesis that has been retreating in the face of the relentless march of behavioural scientist may find here the saving grace that could make it reclaim its place in asset pricing theory.

From the analysis, we conclude that momentum strategies still remain marginally profitable and robust to incorporation of transaction costs. We acknowledge though, if the preceding basic analysis has any credibility, that momentum strategies mounted at the NSE may not be very profitable, at least not to the degree touted in developed markets.
4.2.6 Seasonality Effect

Finding

We first examined the performance of the strategy in January and non-January months to see whether the January effect applies at the NSE. We broadened the seasonality tests to investigate on the behaviour of momentum strategies for all the calendar months of the year. Earlier studies that documented the weak momentum in January had posited the hypothesis of investors' pressure to sell losing stocks in December in order to benefit from the resultant reduction in tax liability. Expanding the tests was informed by the fact that Kenyan tax regime and institutional reporting requirements (not always in tandem with the USA structures) could exhibit its own unique seasonal regularities.

Table 10 reports the average monthly momentum portfolio returns and the percentage of months with positive returns for January as well as non-January months. Column 3 in the table is the associated \( t \)-statistics. The findings of this study deviate from earlier findings in the United States market. We find that the momentum profits in January are significantly positive. Indeed January, compared to the rest of the months of the year registers a positive, though insignificant excess return of 0.157% per month. Noteworthy is the fact that momentum profitability appears more or less evenly spread across all the months of the year. In no one month is the momentum returns significantly different from the average returns for the rest of the months. When we focus on this excess returns for each month, there is quite a significant range between the worst performing and the best performing month. October appears to be the worst month to be invested in stocks while April is the best with excess returns of -0.393% and +0.377% respectively.
<table>
<thead>
<tr>
<th>Month</th>
<th>Average</th>
<th>t-statistic</th>
<th>Percent positive</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall</td>
<td>0.01179**</td>
<td>2.8209</td>
<td>68.056</td>
</tr>
<tr>
<td>January</td>
<td>0.01314*</td>
<td>1.8006</td>
<td>75</td>
</tr>
<tr>
<td>Other than January</td>
<td>0.01157**</td>
<td>4.20208</td>
<td>67.424</td>
</tr>
<tr>
<td>January-Others</td>
<td>0.00157</td>
<td>0.28469</td>
<td>58.3</td>
</tr>
<tr>
<td>February</td>
<td>0.01150*</td>
<td>1.836306</td>
<td>66.7</td>
</tr>
<tr>
<td>Other than February</td>
<td>0.01182</td>
<td>1.777546</td>
<td>67.4</td>
</tr>
<tr>
<td>February-Others</td>
<td>-0.00032</td>
<td>-0.048358</td>
<td>58.3</td>
</tr>
<tr>
<td>March</td>
<td>0.01177</td>
<td>1.534939</td>
<td>68.2</td>
</tr>
<tr>
<td>Other than March</td>
<td>0.01179*</td>
<td>1.807791</td>
<td>66.7</td>
</tr>
<tr>
<td>March-Others</td>
<td>-0.00002</td>
<td>-0.002554</td>
<td>68.2</td>
</tr>
<tr>
<td>April</td>
<td>0.01525</td>
<td>1.886365</td>
<td>67.4</td>
</tr>
<tr>
<td>Other than April</td>
<td>0.01148</td>
<td>1.77288</td>
<td>67.4</td>
</tr>
<tr>
<td>April-Others</td>
<td>0.00377</td>
<td>0.45469</td>
<td>68.9</td>
</tr>
<tr>
<td>May</td>
<td>0.01045</td>
<td>1.237661</td>
<td>66.7</td>
</tr>
<tr>
<td>Other than May</td>
<td>0.01146</td>
<td>1.780965</td>
<td>67.4</td>
</tr>
<tr>
<td>May-Others</td>
<td>-0.00102</td>
<td>-0.117696</td>
<td>68.2</td>
</tr>
<tr>
<td>June</td>
<td>0.01300</td>
<td>1.729746</td>
<td>75</td>
</tr>
<tr>
<td>Other Than June</td>
<td>0.01168</td>
<td>1.786824</td>
<td>67.4</td>
</tr>
<tr>
<td>June-Others</td>
<td>0.00132</td>
<td>0.170651</td>
<td>67.4</td>
</tr>
<tr>
<td>July</td>
<td>0.01039</td>
<td>1.571079</td>
<td>66.7</td>
</tr>
<tr>
<td>Other than July</td>
<td>0.01192*</td>
<td>1.800788</td>
<td>68.2</td>
</tr>
<tr>
<td>July-Others</td>
<td>-0.00153</td>
<td>-0.22158</td>
<td>68.2</td>
</tr>
<tr>
<td>August</td>
<td>0.01188</td>
<td>1.732725</td>
<td>58.3</td>
</tr>
<tr>
<td>Other than August</td>
<td>0.01178</td>
<td>1.785597</td>
<td>68.9</td>
</tr>
<tr>
<td>August-Others</td>
<td>0.00010</td>
<td>0.014104</td>
<td>68.9</td>
</tr>
<tr>
<td>September</td>
<td>0.01132</td>
<td>1.656042</td>
<td>66.7</td>
</tr>
<tr>
<td>Other than September</td>
<td>0.01183</td>
<td>1.79286</td>
<td>68.2</td>
</tr>
<tr>
<td>September-Others</td>
<td>-0.00051</td>
<td>-0.072251</td>
<td>68.2</td>
</tr>
<tr>
<td>October</td>
<td>0.00819</td>
<td>1.358138</td>
<td>66.7</td>
</tr>
<tr>
<td>Other than October</td>
<td>0.01212*</td>
<td>1.820085</td>
<td>68.2</td>
</tr>
<tr>
<td>October-Others</td>
<td>-0.00393</td>
<td>-0.620023</td>
<td>68.2</td>
</tr>
<tr>
<td>November</td>
<td>0.00807</td>
<td>1.28745</td>
<td>66.7</td>
</tr>
<tr>
<td>Other than November</td>
<td>0.01213*</td>
<td>1.826943</td>
<td>68.2</td>
</tr>
<tr>
<td>November-Others</td>
<td>-0.00406</td>
<td>-0.619223</td>
<td>68.2</td>
</tr>
<tr>
<td>December</td>
<td>0.01158**</td>
<td>2.121807</td>
<td>75</td>
</tr>
<tr>
<td>Other than December</td>
<td>0.01181</td>
<td>1.760738</td>
<td>67.4</td>
</tr>
<tr>
<td>December-others</td>
<td>-0.00023</td>
<td>-0.039769</td>
<td>67.4</td>
</tr>
</tbody>
</table>

This table reports the average monthly momentum portfolio returns, associated t-statistic, and the percentage of positive returns for each specific month of the year as well as the "other" months for the years 2000 to 2007 inclusive. The momentum portfolios are formed based on previous six-month returns and held for six months. The table also reports the difference between the returns of specific months as contrasted with the returns of the "other" months. *Significant at 5% level. ** Significant at 1% level.

**Discussion**

A probable explanation for NSE observations could hinge on the consumption and investment patterns of Kenyan public. A version of a residual investment policy seems to guide investment decision in NSE Equities. By this policy, the portion of wealth and income that finds its way to the NSE will only be the surplus after the investor first satisfies his other demands such as ostentatious consumption; family needs such school
fees obligation, investment in real property and insurance cover. Over the year there appears to be a cycle of peaks and troughs for this kind of expenditures. The peak occurs at the end of the year: hence October will suffer divestment from the stock exchange in readiness for the spending binge. By the end of the first quarter of the year the spending pressures will have dissipated, and the funds released thereof can now generate a surge in demand for stocks at the NSE in April. Investment activity at the stock exchange appears to oscillate through, more or less, regular swings of highs and lows, peaking in April and hitting the floor in October.

Studies of momentum seasonal have not returned consensus conclusions. Jegadeesh and Titman (1993, 2001) document a January effect in the USA, that Winners outperform the Losers in all months except January, when the Losers outperform the Winners. Grundy and Martin (2001) also report similar results in the U.S., where the momentum portfolio earns significantly negative returns in Januaries and significantly positive returns in months other than January. Contrary evidence is adduced by Wang (2008), who find no significant difference between January returns and returns of other months for the United Kingdom, Germany, and China stock markets. Our findings using NSE data are consistent with Wang (2008). Momentum returns in the month of January average 1.3%, significant at five percent level. Indeed January returns exceed average returns for the rest of the months of the year by a positive though insignificant 1.6 basis points.

Our overall findings on the whether there is a seasonal pattern to momentum profitability at the NSE is that yes, there appears to be a pattern with April showing most momentum and October the lowest. To the contrary, however, there is no semblance of a January effect. Different from earlier findings in the United States market, the momentum profits in January are significantly positive and not different from those in non-January. Wang (2008. p.15) "We think this seasonality might be simply a statistical fluke". My findings incline me into the direction of that conclusion.
4.2.7 Post-holding Period Cumulative Profits to the Momentum Strategy

Findings

In this subsection we examined the results of momentum portfolios over various holding time horizons, \((K)\), to check the behaviour of the momentum returns over the long term. This provides information on the duration of the continuation, its permanency, and reversal.

Table 11 shows the post formation period holding returns for winners and losers and for the momentum strategies for different formation periods (3, 6, 9, 12 months). For each, we documented the post-formation holding period returns spanning 60 months. From the analysis, two findings stand out.

First that the longevity and persistence of the momentum affect after the formation of strategies is positively related to the length of the formation period. Profits of strategies formed after shorter periods reverse and peter away faster than for those formed after longer periods. This is clearly demonstrated in Figure 15 where it is apparent that momentum effect for formation periods of 9 and 12 months does not reverse compared to returns of the 3 and 6 months strategies that reverse after the first 18 months of the post formation period. A logical conclusion is that one who wants to profit from momentum should be patient. Strategies based on short formation periods are ephemeral and yield low and transient returns.

The second finding is that eventually reversal sets in. This is consistent with overreaction. The overreaction and price correction hypothesis predicts that over the post-holding period, when the stock prices of the winner and loser stocks revert to their fundamental values, return differences between the winner and the loser stocks should be negative.

We examined the cumulative average return differences between the winner and the loser stocks following the initial formation date. As the theoretical models do not offer any guidance regarding the length of the relevant post-holding period over which return reversals are expected to occur, we follow Jegadeesh and Titman (2001) and use a post-
holding period of five years. Our results though not conclusive incline in the direction of overreaction.

Table 11: 60-months cumulative momentum returns for selected formation periods

<table>
<thead>
<tr>
<th>Holding period (Months)</th>
<th>Form period</th>
<th>3 month</th>
<th>6 month</th>
<th>9 month</th>
<th>12 month</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>2.57</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>1.445</td>
<td>7.07</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>2.313</td>
<td>1.026</td>
<td>0.045</td>
<td>15.471</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>-3.45</td>
<td>1.42</td>
<td>5.42</td>
<td>5.1</td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>-3.64</td>
<td>0.07</td>
<td>-1.05</td>
<td>-3.08</td>
<td></td>
</tr>
<tr>
<td>24</td>
<td>-3.28</td>
<td>-7.55</td>
<td>5.34</td>
<td>4.66</td>
<td></td>
</tr>
<tr>
<td>30</td>
<td>-6.13</td>
<td>-9.27</td>
<td>20.35</td>
<td>50.6</td>
<td></td>
</tr>
<tr>
<td>36</td>
<td>-26.2</td>
<td>-15.11</td>
<td>29.26</td>
<td>28.21</td>
<td></td>
</tr>
<tr>
<td>48</td>
<td>2.62</td>
<td>-15.57</td>
<td>32.14</td>
<td>27.87</td>
<td></td>
</tr>
<tr>
<td>54</td>
<td>-32.42</td>
<td>-40.3</td>
<td>51.49</td>
<td>47.88</td>
<td></td>
</tr>
<tr>
<td>60</td>
<td>5.61</td>
<td>-54.02</td>
<td>18.44</td>
<td>-2.12</td>
<td></td>
</tr>
</tbody>
</table>

Momentum strategies are formed by ranking stocks on the basis of their returns during selected the past months of a formation period. The portfolios are held for the subsequent months to a maximum of 60 months. The cumulative holding period returns in percentage points for the strategies, measured at various points in the 60 month period are shown in the table.
Table 11 displays cumulative returns for strategies based on various formation periods (3, 6, 9, and 12 months). The returns are depicted graphically in Figures 15. We judge the survival of momentum so long as the cumulative returns are positive, and consequently the cumulative graph is above the horizontal axis. The cumulative graph shows that for 3 month formation period, momentum dissipates within 12 months. For the 6-month formation period, the effect lasts a little longer eventually reversing after 20 months. For the 9-month and 12-month formation periods momentum is more permanent and lingers into 5th year.

It is evident that momentum reverses earlier and finally peters out for the strategies formed after shorter period (3 and 6 months). For the longer formation period strategies (9 and 12 months), momentum is maintained for up to 48 months. It thus appears that the degree of significance and duration of momentum effect is positively related to the length of the formation period.

**Discussions**

We examined the results of momentum portfolios over various holding time horizons ($K$) to check the behaviour of the momentum returns over time. This provides information on the duration of the continuation effect and the extent to which it is permanent, and if there is reversal. An examination of the performance of momentum portfolios over longer holding horizons could facilitate the distinction between the validity of three competing momentum hypotheses. The three hypotheses are market underreaction (Barberis et al. (1998)), investor overreaction and price correction (Daniel et al. (1998), and Hong and Stein (1999)), and Conrad and Kaul (1998) risk hypothesis.

It was revealed that cumulative momentum profits over a 60-month post-formation exhibited reversal of returns in the third into the fifth years. Cumulative momentum profits increase monotonically in the first two years until they reach the peak of about 24.5% in the 21st month after formation. Thereafter the cumulative returns reverse slowly but steadily to reach a level of 5% in the 60th month after formation. These findings for

Consequently, we may report that there is evidence of eventual reversal of the momentum effect: eventually winners become losers. Remarkable also is that a longer formation period results in the selection and classification of stocks into categories that are genuine winners and losers. When formation periods are short, classification into winners and losers could be a function of chance and transient factors, hence the relatively faster reversal.

4.2.8 Decomposition of the Momentum Profit Sources with WRSS

Findings

To enable us decompose momentum profits we generate them using the weighted relative strength method of Conrad and Kaul (1998). As in the section under relative strength strategies, the test period is divided into $J$-month formation period (from time $t-2$ to $t-1$) and $k$-month holding period (from time $t-1$ to $t$).

Table 12 presents the results of the contribution of time-series predictability and cross-sectional variation of stock returns over different holdings $k$ for the entire sample period, where $k$ ranges from 3 to 12 months. For brevity, we only list strategies for which the length of the formation period $J$ and the future holding period $k$ are identical. Their results are representative for other strategies with different formation and holding periods.

The columns 2-4 report $E[\pi_i(k)]$, $P(k)$, and $\sigma^2[\mu(k)]$. To facilitate evaluation of the relative importance of the profit sources, the percentage contributions of $P(k)$, and $\sigma^2[\mu(k)]$ to the total profits, $E[\pi_i(k)]$, are reported in column 5 and column 6, respectively.
There are several notable findings in Table 11. First, is $\sigma^2[\mu(k)]$ significant in all cases, given the fact that $\sigma^2(k)$ is the cross-sectional variance of $\mu_{\mu-1}$.

The $P(k)$ is negative but insignificantly different from zero. Second, The magnitude of $P(k)$ increases monotonically with time. The percentage contribution of $P(k)$ dominates that of $\sigma^2[\mu(k)]$ in nearly all strategies.

We decomposed momentum returns into two components. The first component is the time series momentum profitability while the second component is the cross-sectional variance of returns of individual stocks. We find that momentum profitability is highly predictable from the time series profitability component. The results are revealing in two ways. First, the expected profits are highly predictable for most of the trading strategies from the time-series components, since $P(k)$ contributes more of the profits than $\sigma^2[\mu(k)]$ does. This finding is different from the results by Conrad and Kaul (1998) but consistent with Jegadeesh and Titman (2001) and Liu, Strong and Xu (1999).

<table>
<thead>
<tr>
<th>Table 12: The Decomposition of Average Profits to WRSS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E[\pi_t(k)]$</td>
</tr>
<tr>
<td>---------------</td>
</tr>
<tr>
<td>3-month</td>
</tr>
<tr>
<td>(t-stat)</td>
</tr>
<tr>
<td>6-month</td>
</tr>
<tr>
<td>(t-stat)</td>
</tr>
<tr>
<td>9-month</td>
</tr>
<tr>
<td>(t-stat)</td>
</tr>
<tr>
<td>12-month</td>
</tr>
<tr>
<td>(t-stat)</td>
</tr>
</tbody>
</table>

This table reports the decomposition of average profits to trading strategies and associated t-statistics (with identical formation and holding period during its entire sample period. The decomposition is given by $E[\pi_t(k)] = P(k) + \sigma^2[\mu(k)]$, where $P(k)$ and $\sigma^2[\mu(k)]$ represent the time-series and cross-sectional predictable parts, respectively. All profit estimates are multiplied by 100. * and † denote significance at 5% and 10%, respectively.
Second, the results do not support the random walk hypothesis. Although the magnitude of $\sigma^2[\mu(k)]$ does increase with the trading horizon, the magnitude of the increase is much smaller than the random walk hypothesis indicates. In sum, these results reveal market inefficiencies.

**Discussion**

A commonly used conceptualization of the sources of momentum profits (see Conrad & Kaul, 1998; Jegadeesh & Titman, 1999; Lehman, 1990; and Lo & MacKinlay, 1990) is the decomposition of momentum profits into, and their attribution to, two sources: across-sectional, and a time-series source. The majority of studies have come to the conclusion that the profitability of momentum profits is entirely due to serial covariance in the idiosyncratic component of returns, i.e., the irrational component (see, among others, Chen & Hong, 2002; Grundy & Martin, 2001; Jegadeesh & Titman, 1993). This conclusion is disturbing because it implies that the market is not efficient. And this inefficiency is nontrivial because it takes several months for readily available public information to be incorporated in prices. Furthermore, this conclusion also suggests that the expected returns and betas of all securities are the same, thus bringing into question the foundation of asset pricing in a risk-averse world.

Other researchers have argued that momentum is basically a cross-section phenomenon (See Conrad & Kaul, 1998; Berk et al., 1999; and Chordia & Shivakumar, 2002). The proponents recognize that strategies that rely on relative strength should be expected to earn positive returns due to cross-sectional variation in expected returns of individual securities. Since, on average, stocks with relatively high (low) returns will be those with relatively high (low) expected returns, a momentum strategy should on average earn positive profits. Thus, cross-sectional variation in either unconditional or conditional mean returns should contribute to the profitability of momentum strategies. The proponents of this strand of the debate view momentum return not as an anomaly but as a perfectly rational return for bearing risk.
Evidence from the NSE weighs more in the direction of momentum profitability having a time series genesis than a cross-sectional one. Tests and analysis lead to the conclusion that on the whole rational sources contribute less, compared to irrational sources, to momentum profits. The momentum phenomenon can be interpreted as evidence that investors underreact/or overreact to new information in line with the behavioural models of Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998), and Hong and Stein (1999). We are thus inclined to support the hypothesis that behavioural factors do a better job explaining momentum profits than risk factors.
CHAPTER FIVE
CONCLUSIONS, LIMITATIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

5.1 Introduction
This chapter presents the major conclusions, recognizes the inevitable qualifying limitations, and identifies literature and research gaps that may motivate potential future academic inquiry. The objectives that guided this study were, first, to adduce empirical evidence, one way or the other, as to the existence or otherwise of the price momentum phenomenon at the NSE. Second, was to investigate the existence or otherwise, of any correlation between price continuity and individual stock characteristics i.e. size and trading volume. Thirdly, to examine whether or not the momentum profitability was illusory, or was robust to incorporation of risk factors and trading cost in our analyses. Fourthly, to investigate whether or not, there are any inter-temporal patterns in price persistence and hence opportunity for arbitrage profits i.e. January effect and long-term reversal. Lastly, decompose the momentum profits at the NSE and contribute to the debate on whether the “anomaly” is nevertheless consistent with market efficiency, or, is indeed an exemplification of “irrationality” in the economic agents and markets. We summarize our conclusions in respect of the objectives in the following section, followed by limitations and, finally recommendations for further research.

5.2 Conclusions
We set out to investigate various aspects regarding profitability or otherwise of momentum strategies at the NSE. Our conclusions mixed when considered, both in light of findings in other markets and financial theory expectations. While on some aspects our evidence was consistent with hypothesized theory, in others evidence was weak if not contradictory. The conclusions can be summed up as follows: first, raw returns from trading strategies based on price continuation were significantly material, providing prima facie evidence that the NSE was not efficient in the weak form sense. Apparently one could earn abnormal profits by constructing zero-cost portfolios that were long on winners and short on losers, for periods between 3 to 12 months.
Secondly, the effect of size on momentum profits at NSE is controversial. Against expectation we find that the momentum effect is confined to medium and big capitalization stocks with the small cap stocks exhibiting virtually no momentum. I ascribe the discrepancy to fact that the small caps at NSE are actually outliers rather than part of the regular market.

Thirdly, though we had initially hypothesized the expectation that momentum profitability would be driven by high trading activity, our analysis led us to a contrary position: that momentum profitability is a feature restricted to only those stocks that experience low to medium activity, and is absent in high volume stocks.

Fourth, our study, in line with many previous works, attempted to link momentum returns to market wide risk. Consistent with the findings of a majority of extant studies, our tests failed to explain momentum profits within the Fama-French three factor model. Thus we are led to conclude that investors and markets do not react only to risk in pricing assets: Other factors (behavioural) may be in play.

The fifth finding is that earlier evidence of abnormal profitability from momentum strategies has increasing been called into question by the realisation that such strategies call for frequent and costly trading. Though scanty and incomplete data at the NSE was such as not to allow for rigorous testing of the impact of transaction costs, our conservative estimates made us arrive at the tentative conclusion that momentum strategies profitability was not robust to transaction costs modelling. The profits may be an illusion rather than real.

Sixthly, we sought for any January in the momentum profits and found none. There was no January effect (Jegadeesh & Titman, 1993), though the month of April registered the highest average returns, which nevertheless, was not significantly different from the average profits for the other months.
In our seventh conclusion, our observation of the performance of the portfolios in the long term (60 months), revealed positive returns between 3 to 20 months followed by a reversal thereafter. This confirms that momentum is a short to medium term phenomenon.

Finally, when the momentum profits were decomposed, it was found that momentum profitability was attributable more to a time series genesis than a cross-sectional one. Tests and analysis lead to the conclusion that on the whole rational sources contribute least compared to irrational sources to momentum profits.

5.3 Limitations of the Study
The findings of this study are to be accepted albeit with some qualifications, chief among them being the following:

5.3.1 Myriad Alternative Methods and Approaches
In analysing data and forming trading strategies, literature is replete with a plethora of diverse methods and approaches. Although the momentum phenomenon has been widely documented in extensive literature in many world markets, nevertheless estimates of the magnitude of the effects differ across many publications. Some of the causes of the disparities in recorded momentum returns are to be attributable to the diversity of sample selection criteria and research methods used. Therefore it is only prudent that the findings in the current research effort be read and compared with other research findings with a pinch of caution. Caution is to be exercised in the following circumstances:

First, the incidence of momentum could be sample period specific. Some periods could exhibit this phenomenon to a higher degree than others. Jegadeesh and Titman (1993) mention that momentum is weaker in periods prior to 1941. In our analysis we found less momentum in the 1997 – 2002 sub-period than in the 2003-2007 sub-period.

Second, the size of the stocks sampled could be important. Many studies using data from the big stock exchanges exclude low priced or low market capitalization stocks.
This exclusion generally reduces the variability in portfolio returns which leads to increased statistical significance. Because of the small listing at the NSE, we used all the stocks quoted, small and big.

Third, some studies use formation periods contiguous with the holding period, while others skip a week or month between the holding and formation periods. Studies that skip a month have been found to register somewhat higher returns. Furthermore, momentum strategies with shorter investment horizons are more prone to experience difference between average momentum returns on skip and no-skip strategies (Swinkels (2004)). For reasons explained in Chapter 4, it was found unnecessary to skip some period before commencing the holding period.

Fourth, since the momentum effect is a function of two polar positions (winner-losers), the further removed they are from each other the more pronounced the effect. Therefore strategies which employ top and bottom 20 or 30 per cent of sampled stocks should generate lower average returns than decile strategies. Variation in the constitution of the winner and loser portfolio could lead to differences in reported returns. This study employed quintile strategies. Jegadeesh and Titman (1993, 2001), and Lee and Swaminathan (2001) employed deciles while Moskowitz and Grinblatt (1999) employ 30 percent in the top and bottom portfolios.

Fifth, one could employ overlapping and non-overlapping strategies. Overlapping strategies have to be rebalanced every month. Rebalancing has been shown to influence the reported excess returns on longer holding periods, leading to somewhat lower returns. This study employed overlapping strategies which were rebalanced every month.

Sixth, the weighting schemes for the strategies may differ. It has been evidenced that the use of value weighted strategies produce lower average returns than do equally weighted strategies. In this study equally weighted portfolios were used.
5.3.2 Short Sample Period

Data for the study was sourced from the Nairobi Stock Exchange data base. The data base's scope and depth of coverage was not always adequate. Consequently the sample period for the study covered a period of 11 years, going back only to 1997, which coincides with the advent of storage of data in electronic media. Furthermore, even with these data, there were gaps that further restricted some of the tests to shorter test periods. This limited coverage weakens the power of the tests and renders our conclusions somewhat tentative. With time and as more data becomes available, the validity or otherwise of the study's findings could be revisited and more conclusive inferences reached.

5.3.3 Quality of Data

The quality of data from the NSE could have been better. For instance, record of corporate events had a number of gaps, leaving the dating of some necessary data adjustments a subjective choice. Further, as is the case for many emerging markets, insider trading and manipulation of trading and prices by vested interests pose a real risk to the integrity of the data. Compounding the situation is the very small number of companies listed at the NSE, which means that some tests that require stratification of sample units cannot be conducted with any statistical validity.

5.3.4 Structural Inadequacies and Inefficiencies.

The momentum anomaly was first documented and has since been widely studied in the developed markets of Europe and America. In the developed markets such as New York Stock Exchange, the London Stock Exchange and the Tokyo stock Exchange, the trading structures are technology intensive, the volume of transactions and the number of participants are enormous, and the speed of reaction to information and news events almost instantaneous. NSE has recently taken significant leaps to the league of these giants but it is still miles behind. These structural and operational differences make unqualified one-for-one comparisons of results of studies using the NSE data with those studies based on data from developed markets tenuous.
The NSE lacks depth and width when one considers the number of instruments traded and the frequency of innovations introduced and adopted. Specifically, the derivatives market is non-existent, complicating the hedging and spanning against risk; the dealers market is still nascent compounding the incidence of non-trades and thin trading; and the total absence of short selling restricts the operation of arbitrage forces and renders the market inefficient. These fragilities have an adverse effect on the capacity of a market to impound information into prices which in turn bear on the profitability or otherwise of any trading strategies.

5.4 Recommendations for Further Research

We summarize some areas where gaps in literature exist and which in our opinion merit future research attention. First, we have enumerated in the preceding section the multiplicity of methods and criteria used by different studies studying momentum profitability. To test the robustness of the results of this study, other alternative approaches could be employed. Specifically, studies would be conducted using value-weighted strategies as opposed to equal-weights, using weekly or daily returns rather than monthly returns, using strategies that skip a month between formation and holding periods rather than non-skip strategies, and using strategies employing more extreme winner and loser portfolios (5 percent of sampled stocks) rather than quintiles and deciles.

Secondly, we have recorded results that could be considered controversial when set against conventional finance theories and empirical findings elsewhere. These areas are areas that can be revisited using out-of-sample data. One area that merit attention is the effect of transaction costs on momentum trading. Our tests in this area were less than rigorous due to unavailability data. Another issue regards the effect of size on momentum profitability; the question is whether the small capitalization stocks which form the bulk of the alternative segment should be excluded as being outliers. Finally the effect of trading activity on momentum could be revisited as time passes and more data becomes available.
Thirdly, it is to be noted that the strategies tested in this paper form only but a small sample of the population of possible strategies. We examined strategies formed and held in multiples of 3 month periods because dividing a year in quarters is appealing intuitively, but more importantly to facilitate comparisons of most other studies that take a similar approach. Further work would investigate the impact of forming strategies using 1, 2, 4, or 6 months intervals. One could even form and hold strategies at intervals of more than 12 months and study the effect on momentum profitability. In sum, varying formation and holding periods presents limitless possibilities of extending the momentum strategy testing.

Finally, there is a gap in literature on the profitability of trading strategies that target developing markets. More effort needs to be directed at testing the potential for reaping diversification benefits by including third world capital markets in constructing global portfolios.
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APPENDICES

Appendix 1

A Historical/Thematic Perspective of the Development of the Theory of Asset Pricing

I RANDOM WALK AND MARTINGALE

1900 A French mathematician, Louis Bachelier explained efficient markets in terms of a martingale.

1934 Holbrook Working concludes that stock returns behave like numbers from a lottery.

1953 Kendall analyzed 22 price-series at weekly intervals and found to his surprise that they were essential random. Also, he was first to note of the time dependence of the empirical variance (non-stationarity).

1959 Harry Roberts demonstrate that a random walk will look very much like an actual stock series.

1959 Osborne shows that the logarithm of common stock prices follows Brownian motion; and also found evidence of the square root of the time rule.

1963 Granger and Morgenstern perform spectral analysis on market prices and found that short-run movements of the series obey the simple random walk hypothesis but the long-run movements do not.

1966 Mandelbrot proved some of the first theories showing how, in competitive markets, with rational-risk neutral investor's return are unpredictable security values and prices follow a martingale.

II EFFICIENT MARKET HYPOTHESIS

1953 Milton Friedman points out that due to arbitrage, the case of the Efficient Markets Hypothesis can be made even in situations where the trading strategies by investors are correlated.

1961 Muth introduces the rational expectations hypothesis in economics.

1965 Samuelson provided the first formal economic argument for “efficient markets”. His contribution is neatly summarized by the title of his article. “Proof that property
anticipated prices facilities randomly”. He correctly focused on the concept of a martingale, rather random walk.

1965 Fama explains how the theory of random walks in stock market prices presents important challenges to both chartists and the proponents of fundamental analysis.

1967 Harry Roberts coined the term “efficient markets hypothesis” and made the distinction between weak and strong form tests, which became the classic taxonomy in Fama (1970).

1970 The definitive paper on the EMH is Eugene Fama’s first of three review papers “Efficient capital market: A review of theory and empirical work”. He was also the first to consider the “joint hypothesis problem”.

1972 Scholes studies that price effect of secondary offerings and finds that the market is efficient except for some indication of post-event price drift.

1978 Jensen famously wrote “I believe there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient markets Hypothesis”. He defined efficiency thus: “a market is efficient with respect to information set $\Theta_t$, if it is impossible to make economic profits by trading on the basis of information set $\Theta_t$.”.

1968 Michael Jensen evaluates the performance of mutual funds and concludes that “on average the funds apparently were not quite successful enough in their trading activities to recoup even brokerage expenses”.

1991 The second of Fama’s three review papers on EMH is published.

2001 Mark Rubinstein re-examines some of the most serious historical evidence against market rationally and concludes that markets are rational.

1998 In his third of three reviews, Fama concluded “market efficiency survive the challenge from the literature on long term return anomalies”.

2003 Malkiel examines the attacks on EMH and concludes that “our stock markets are far more efficient and far less predictable than some recent academic papers would have us believe”.

2003 Schwert shows that when anomalies are published, practitioners implement
strategies implied by the papers and the anomalies subsequently weaken or disappear. In
other words, research findings cause the market to become more efficient.
2005 Malkiel shows that professional investment managers do not out perform their
index benchmarks and provides evidence that by and large market prices do seem to
reflect all available information.
2006 Toth and Kertesz found evidence of increasing efficiency in the New York stock exchange

III MARKET ANOMALIES
1977 Beja showed that the efficiency of a real market is impossible.
1977 Ball wrote a survey paper which revealed consistent excess returns after public
announcement of firms’ earnings.
Value effect several authors found a value effect that returns are predicted by ratio of
market value to accounting measure such as earnings or the book value of equity (Basic).
1980 Grossman and Stiglitz showed that it is impossible for market to be perfectly
informationally efficient. Because information is costly, prices cannot perfectly reflect
information which is available, since if it did investors who spent resources obtaining and
analyzing it would receive neo compensation.
1981 Banz reported the size effect, that small (low-market value) stocks have higher
average excess returns than can be explained by the CAPM
1981 LeRoy and Porter show excess volatility and reject market efficiency.
1981 Shiller shows that stock prices move too much to be justified by subsequent
changes in dividends i.e. excess volatility.
1984 Roll examined US Orange juice futures prices and the effect of the weather. He
found excess volatility
1988 Lo and MacKinlay strongly rejected the random walk hypothesis for weekly
stock market returns using the variance ratio test.
1989 Shiller publishers *Market Volatility* a book about sources of volatility that
challenges the EMH.
1992 Fama and French drew attention to the size effect by sorting stocks by both size
and beta and showing that high beta stocks have no higher returns than low-beta stocks of
same size.

2000 Shiller publishes the first edition of Irrational Exuberance which challenges the EMH, demonstrating that markets cannot be explained historically by the movement of company earnings or dividends

IV EVENT STUDIES

1968 Ball and Brown were the first to publish an event study.

1969 Fama, Fisher, Jensen and Roll undertook the first even event study, and are results lend considerable support to the conclusion that the stock market is efficient.

V FACTOR MODELS

1993 Fama and French three factor model made up of return on a broad stock index, the excess return on a portfolio of small stock over a portfolio of large stocks, and the excess return on a portfolio of high book-to-markets stocks over a portfolio of low book-to-market stocks.

Jaganathan and Wang (1998) incorporate human capital as a component of wealth and firms that when return on human capital is included as a factor it reduces evidence against the CAPM. In similar spirit Vassalon (1999) introduces GDP forecast revisions as an additional risk factor in a cross-sectional model.

1997 Carhart augmented Fama and French three factor model to include a portfolio of stocks with high returns over the past few months.

1998 Jaganathan and Wang incorporate human capital as a component of wealth and find that when return on human capital is included as a factor it reduces evidence against the CAPM.

1999 Vassalon (1999) introduces GDP forecast revisions as an additional risk factor in a cross-sectional model and find that it strengthens the efficacy of the model.

VI TRADING STRATEGIES

1986 Fischer Black introduced the concept of noise traders, those who trade on anything other than information, and shows that noise trading is essential for the liquidity of the market.
1994 Huang and Stoll provide new evidence concerning market microstructure and stock return predictions.

1994 Lakonishok, Shleifer and Vishny provide evidence that value strategies yield higher returns because these strategies exploit the sub optimal behaviour of the typical investor and not because these strategies are fundamentally riskier.


VII MOMENTUM AND REVERSAL

1937 In the only paper published before 1960 which found significant inefficiencies, Cowles and Jones found significant evidence of serial correlation in averaged time series indices of stock prices.

1985 DeBondt and Thaler discovered that stock prices overreact, evidencing substantial weak form market inefficiency. This paper marked the start of behavioural finance.

1988 Poterba and Summers show that stock returns show positive autocorrelation over short periods and negative autocorrelations over longer horizons.

1990 Lehman finds reversals in weekly security returns and rejects the EMH.

1990 Jegadeesh documents strong evidence of predictable behaviour of security returns and rejects the random walk hypothesis.

1992 Chopra, Lakonishok and Ritter find that stocks overreact.

1993 Jegadeesh and Titman found that trading strategies that bought past winners and sold past losers realized significant abnormal returns.

1995 Haugen publishes the book *The New Finance: The case Against Efficient markets*. He emphasizes that short run overreaction (which cause momentum in prices) may lead to long term reversals (when the market recognized its error).

VIII SOURCES OF MOMENTUM PROFITS

1998 Conrad and Kaul analyze the sources of profits of a wide variety of return based trading strategies and conclude that the cross-section variation in mean returns of individual securities included in these strategies plays an important role in their profitability.
1998 Chan, Karceski, and Lakonishok evaluate the performance of various factors in capturing return comovements. Factors associated with the market size, past returns, book-to-market, and dividend yield help to explain return comovements on an out of sample basis from data in the Japanese and U.K. markets.

2002 Chordia and Shivakumar showed that profits to momentum strategies can be explained by a set of lagged macroeconomic variables and that payoffs to momentum strategies disappear once stock returns are adjusted for their predictability based on these macroeconomic factors.

2002 Jegadeesh and Titman take into account the small sample biases and demonstrate that cross-sectional differences in expected returns explain very little, if any, of the momentum profits as claimed by Conrad and Kaul (1998).

2002 Griffin, Ji, and Martin use a predictive regression framework to examine whether macroeconomic risk can explain momentum profits internationally report that that momentum profits are more related to the stock-specific components rather than macroeconomic variables.

2004 Kang and Li use a model of nesting both Chordia and Shivakumar (2002) and Grundy and Martin (2001) and applying a method free from missing factor problem conclude that virtually all momentum profits are generated by the stock specific component.

IX BEHAVIOURAL FINANCE.

1998 Lo and MacKinlay publish “A non-random walk down wall street”.

2000 Shleifer publishes “inefficient markets: An introduction to behavioural finance: which questions the assumptions of investor rationally and perfect arbitrage.
Appendix 2

TESTS OF NORMALITY


The normality of the error term is a primary econometric issue for the OLS regression equations. The Jarque-Bera statistic indicates non-normality problems. If the Jarque-Bera statistic is greater than the critical chi-squared value of 5.99 for the 5% significance level, then the error terms have a non-normal distribution (Wooldridge 2009). If the residuals don’t have a normal distribution, the T-tests and F-tests statistics for the model will not be dependable (Pindyck and Rubinfeld 1998. p. 88-89). The data sets used in this model were tested with a Jarque-Bera statistic to detect any non-normality error distribution.

One of the primary assumptions of regression of panel data is that the error terms in the many different observations are not related (Eastman 1984. p. 83-84). When serial correlation exists, the error terms of different observations across time are correlated. This problem may lead to an over-estimate or an under-estimate of the partial regression coefficients. The Durbin-Watson test is performed by comparing the calculated Durbin-Watson statistic to the upper and the lower values of the statistic in the D-W Table according to the number of observations and the number of independent variables. A value of 2 for the Durbin-Watson statistic suggests that there is no strong evidence of autocorrelation in the residuals of the estimated equation. If uncorrected, serial correlation in the residuals will lead to an incorrect estimate of the standard errors and invalid statistical inferences for the coefficients of the equation. To solve this problem, an autoregressive term was included in the OLS model, and the null hypothesis of no serial correlation was rejected according to the Durbin-Watson test statistic (Fair 1970). The autoregressive term is displayed in the table as AR(1).

The White test is conducted to test the problem of heteroskedasticity. This problem involves an irregular variance in the constant error, which is a violation of homoskedasticity (Pindyck and Rubinfeld 1998. p. 146). When the assumptions of the linear regression model are accurate, OLS provides unbiased and efficient estimates of
the set parameters. Heteroskedasticity arises when the variance of the errors fluctuates across observations. If the error terms are heteroskedastic, the OLS estimator remains unbiased but is no longer efficient. In other words, estimates of the standard errors are inconsistent, thus resulting in misleading conclusions (Long and Ervin 1998, p. 2). When the model contains $k = 9$ independent variables, the White test is based on an estimation of eighteen regressors. If the White Test statistic is smaller than the critical Chi-square value (with degrees of freedom = 18 at a 5% significance level), the model is free of the problem of heteroskedasticity.

Multicollinearity rejects the assumption that all independent variables individually affect the dependent variable. When two or more variables are correlated with one another or have the same predictive power with respect to the dependent variable, multi-collinearity exists. This makes identifying the individual effects of independent variables on the dependent variable more difficult. A correlation matrix of all the independent variables is run to detect correlation among different independent variables. If any of the off-diagonal values are bigger than 0.5, transformation of some of the independent variables is conducted to solve this problem.
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<td>Value strategies outperform growth strategies most times</td>
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