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An Empirical Analysis of Momentum Profitability, Seasonality, and Reversibility at Nairobi Stock Exchange

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Abstract

In this thesis, we employed data from the NSE to investigate the existence of the price momentum effect, the profitability of momentum trading strategies, and the possibility of seasonal and reversal patterns in the profitability. We formed relative strength strategies for all stocks listed over the period (and sub-periods) 1996 to 2007. The initial unrestricted tests revealed the existence of significant momentum, which could be the basis of profitable investment strategies. When the momentum profits are analyzed further, we found; that there was absence of a calendar regularity to the profits, and that there was mild reversal of profitability in the medium term.

JEL classification numbers: G11, G12.
Keywords: Price momentum, Relative strength strategies, Seasonal effects, Reversal

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1 Introduction

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 efficient in reflecting information about individual stocks and about the stock market as a whole; that price changes followed a "random walk" and were unpredictable; and that one could not consistently outperform the market because asset prices reflected the fundamental values of the underlying assets.

From the early years of the 1970s, however, burgeoning anomalous evidence began to emerge, calling into question the faith in the belief that markets were efficient. These contradictory findings have generated sustained pressure on traditional finance so that by the start of the twenty-first century the acceptance of the efficient market hypothesis had become far less universal. Many financial economists and statisticians began to believe that stock prices are at least partially predictable. A new breed of economists emphasized psychological and behavioral elements of stock-price determination, and came to hold that future stock prices are somewhat predictable on the basis of past stock price patterns. .

On the central issue in financial economics, that of asset pricing, the dawn of the new millennium finds the finance discipline split in two camps: the efficient markets proponents who equate market prices to fundamental values; and the behavioural finance wing who hold that prices in financial markets have an element of mis-valuation. The quest for the paradigm that best explains and predicts price formation process is the pre-eminent issue in finance discipline today.

According to the efficient market 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 $E(X_{i,t+1} / \Phi_t) = 0$, where $X_{i,t+1}$ 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 Φ_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).

Fama's efficiency framework 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. 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 and Morgenstern, 1970).

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.

Behavioural finance, on the other hand, attempts to explain the what, why, and how of finance and investing, from a human perspective. Behavioural finance offers alternative explanations on the key question of why prices could deviate from their fundamental values. Behavioural finance is based on three main building pillars, namely beliefs (sentiment) and emotions, behavioural preferences, and limits to arbitrage.

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 maximizer. 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 the investor 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' decisions: 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. Being risk averse, smart money will be unwilling to take a position large enough to wipe out the mispricing. In sum, fundamental risk coupled with noise trader risk will lead to persistence in mispricing.[2] In addition, arbitrage fails to work because in many market short selling is restricted. Without short sales an arbitrage who perceives an overvaluation will be unable to correct the situation if he does not already own the asset.

These limitations in the 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.

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 strike a mortal blow at the heart of EMH. 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.

2 Literature Review

2.1 Price Momentum

Momentum in prices has been recognized as the most robust market efficiency anomaly. It is the sustained continuation of pricing movement in one direction for a period of time. The phenomenon has been documented in stock exchanges the world over and has persisted even after wide publication. Fama

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[2] Barberis and Thaler (2002) provide practical evidence of persistent mispricing that arbitrage fails to correct: There was the twin shares of Royal Dutch and Shell Transport, which despite merging, continued to trade at differential market price at the New York Stock exchange and the London Stock Exchange; and then there is the observed phenomenon that a market index inclusion of a stock causes a permanent jump of the value of the stock (Shleifer, 1986).

(1998), indeed, recognizes the momentum phenomenon as constituting the chief embarrassment to EMH.

The first and most striking 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 at the head of a 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 the past six-month' winners and shorts the past six-month' losers earns a return approximately one per cent per month over the subsequent six months. In support, 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." Further, Ryan and Overmeyer find that the profits are neither driven by differences in betas, nor attributable to size and market-to-book characteristics, nor 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 and Thomas (1989, 1990)); stock issues (Loughran and Ritter (1995) and Spiess and Affleck-Graves (1995)); repurchases, (Ikenberry, Lakonishok, and Vermaelen (1995)); dividend initiation and omissions, (Michaely, Thaler, and 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 Affeck-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 hat 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 11 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.

2.2 Seasonality Effect

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 and 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* out perform *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.

Additionally, Jegadeesh and Titman (2001), 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.

2.3 Post-holding Period Cumulative Profits to the Momentum Strategy (Reversal)

A number of hypotheses have been put forward to explain the profitability of momentum strategies. Three theories are distinguishable. 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 up date 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 and Kahneman(1974)), and "self-attribution" syndrome will make traders overconfident pushing prices of winners above there 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 a stock 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 1 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. Figure 1 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).

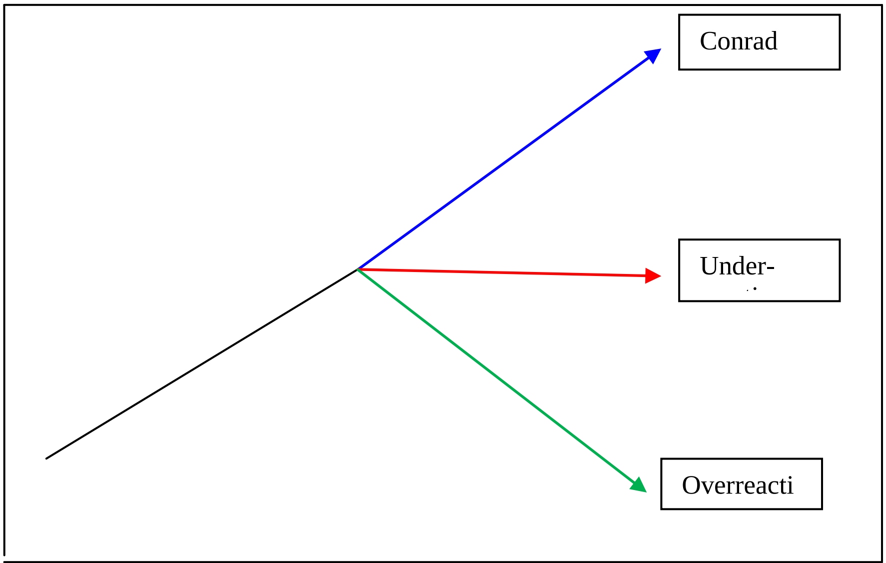

Figure 1: Long Horizon Momentum Profits under Different Alternative Hypotheses

2.4 Price Momentum Models

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. BSV attempt to explain under-reactions by conservatism and overreactions by representativeness. Inn their model, earnings follow a random walk, but investors do not realize this, rather they switch between two regimes. 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.

Daniel, Hirshleifer and Subrahmanyam (DHS) (1998) propose a theory of under and overreaction based on two psychological biases, investor overconfidence and biased self attribution, which cause asymmetric shifts in investor confidence as a function of her investment outcomes. 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. They show that short-term positive return autocorrelations can also be a result of continuing overreaction. Note that, interestingly DHS and BSV employ different psychological biases but end up with similar conclusions.

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. They conclude that with only newswatchers, there is under-reaction, but never overreaction. 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.

3 Research Methods and Data Analysis

3.1 Introduction

This research was quantitative and empirical: the nature of the quantitative research paradigm is to demonstrate that a relationship exists between variables. 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 1 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%. Table 1 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.

Table 1: Descriptive statistics of Equities in the Sample and Sub-samples

Time Period		Whole sample 1997-2007	Sub-sample 1997-2002	Sub-sample 2003-2007
Average number of stocks		48	49	45
Return on NSE-20 index R_m	Mean	0.00492	-0.01037	0.02424
	Std. Dev.	0.05408	0.04835	0.05514
Risk-free interest rate R_f	Mean	0.00968	0.01289	0.00575
	Std. Dev.	0.00751	0.00521	0.00251
Market Wide Risk $R_m - R_f$	Mean	-0.00544	-0.02497	0.01767
	Std. Dev.	0.05422	0.04688	0.05354
Size-factor R_{SMB}	Mean	-0.03133	-0.061315	0.00654
	Std. Dev.	0.40659	0.54192	0.05394
Value-factor R_{HML}	Mean	0.05526	0.09122	0.01301
	Std. Dev.	0.59618	0.80665	0.05307

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. 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.

3.2 Formation of Momentum Trading Strategies

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) show 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[3] 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

[3] There are several methods to weight the stocks making up the portfolios. The most common alternatives is to form equally weighted portfolios (e. g. Chan, Karceski, and Lakonishok (1998); to form value weighted portfolios (e.g. Fama and French (1993); and the loaded weighted portfolio approach (e.g. Asgharian and Hansson (2001). Following most previous studies on momentum, this study adopts the equally weighted approach.

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 the momentum strategies are constructed. 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, Lim and Stein (2000).

3.3 Analysis of the Returns to Momentum Strategies

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.

Table 2 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. J =Formation Period.

Table 2: Average Monthly Returns to Momentum Strategies

(J)	Portfolio	1996-2007 Holding period (K)				1996-2002 holding Period				2003-2007 holding period			
		3	6	9	12	3	6	9	12	3	6	9	12
3	Winner(W)	.01313	0.01645	0.01622	0.01597	-.01276	-.00545	-.00296	-.00129	.04981	.04783	.04371	.0407
	Loser(L)	.00456	0.01404	0.01508	0.01886	-0.01057	0.00263	.00001	.00252	.02599	.0304	..03668	.04227
	W-L	.00857	.00241	.00114	-.00288	-.00219	-.00808	-.00297	-.0038	.0238	.01743	.00691	-.00157
	(t-stat)	1.71**	.59	0.29	-.71**	-.57	-2.22**	-.93**	-1.06**	2.97**	2.87**	1.95**	-.25
6	Winner(W)	.0266	.0187	.01789	.01799	.0052	-.00261	-.00282	-.00131	.070	.04855	.04861	.04661
	Loser(L)	.0159	.0069	.0153	.06081	.0053	-.00691	.0011	.0007	.0308	.02626	.03633	.04074
	W-L	.0107	.0118	.00258	.001181	.-.0105	.0043	-.00389	-.00199	.0392	.02229	.01227	.00587
	(t-stat)	1.67*	2.82**	0.615	0.2732	-1.93*	1.082**	- 1.067**	-.556	5.73**	3.7**	1.903**	0.839**
9	Winner(W)	.01372	.02722	.01665	.0204	-.007	.01635	-.00407	-.00036	.04484	.04281	.04669	.05016
	Loser(L)	.01426	.01388	-.0005	.01589	.00155	-.00066	-.0089	.00163	.03249	.03473	.0116	.03672
	W-L	-.0005	.01307	.01719	.00433	-.00945	.01643	.00485	-.00186	.01235	.00808	.03509	.01384
	(t-stat)	-0.102	2.203**	4.18**	1.03*	-1.82**	1.98**	1.15**	-0.57	1.392*	1.18**	5.98**	1.91**
12	Winner(W)	.01174	.0268	.00088	.01927	.01172	.01814	-.0301	-.0037	.03766	.03879	.0437	.05105
	Loser(L)	.01346	.0134	.00084	.01502	.01346	-.0009	-.024.	.00218	.031	.0332	.03405	.03279
	W-L	-.0017	.0134	.00005	.00425	-.00173	.01905	-0065	-.0058	.00666	.00559	.00904	.01768
	(t-stat)	-0.31	2.18**	0.16	1.00*	-0.31	2.16**	-1.3**	-1.68**	0.68	0.78	6.23**/	2.87**

Table 2 shows 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. 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 per cent 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.

The portfolio returns of the two sub-periods are in stark contrast to each other. Figure 3 summarises the experience for the 1996-2002 sub-period while Figure 4 summarises the 2003-2007 sub-period. Evidently, in the earlier sub-period, 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 four 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).

Figure 2 below is a chart showing average monthly momentum returns for the entire Sample period, 1996 to 2007.

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 4 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.

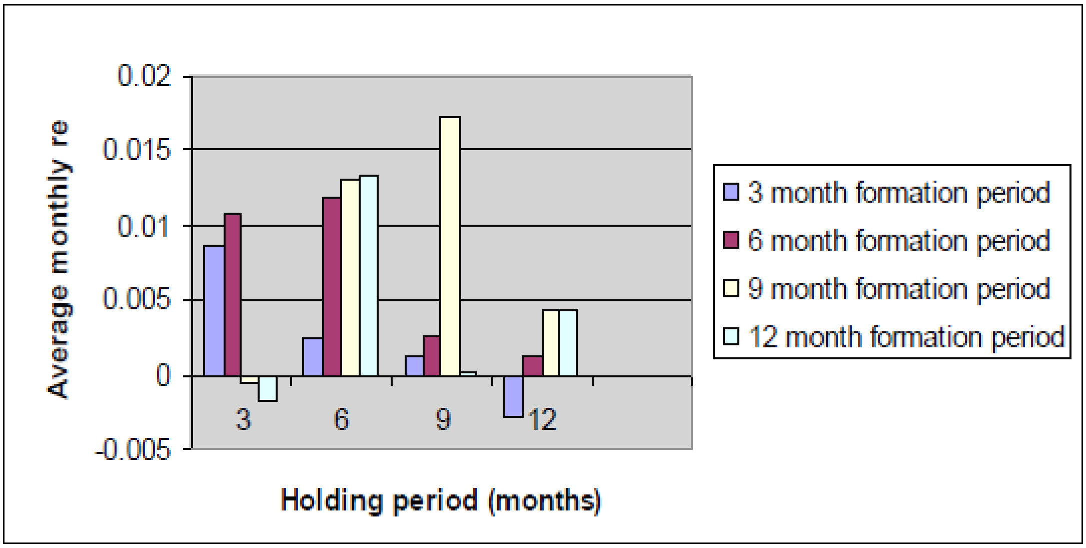

Figure 2: Average monthly momentum profits 1996-2007

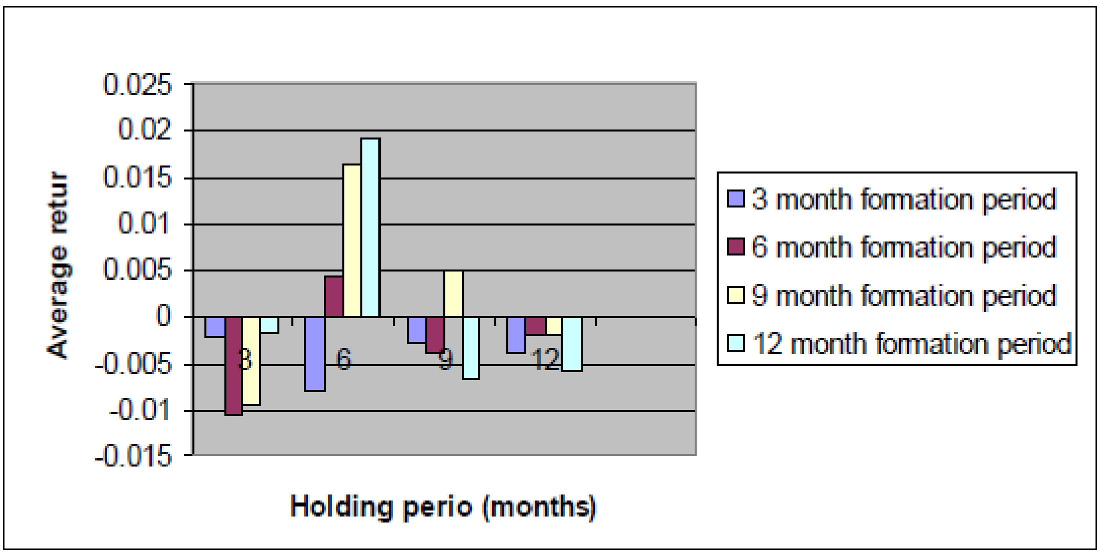

Figure 3: Average monthly momentum returns 1996-2007

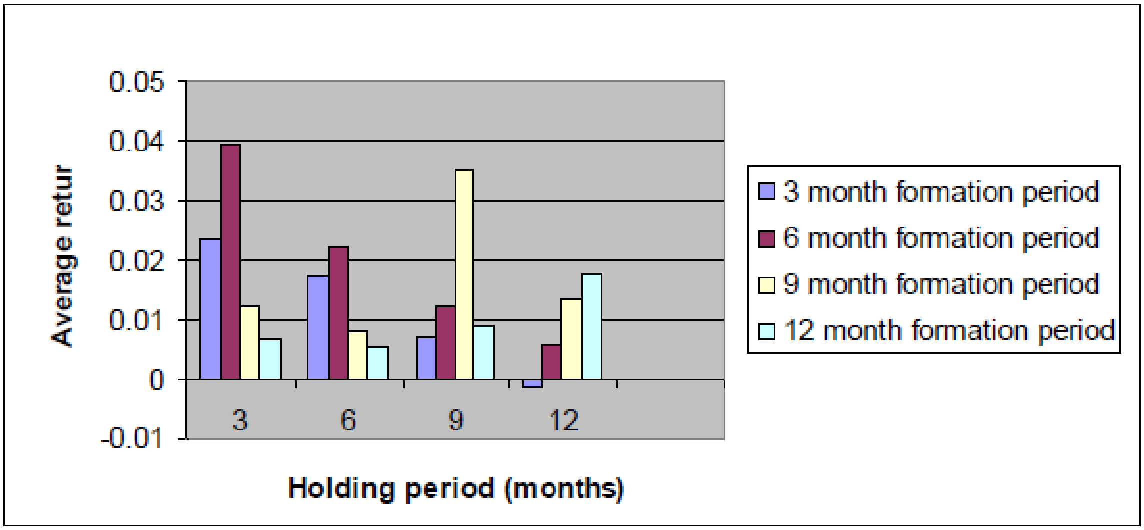

Figure 4: Average monthly momentum returns 2003-2007

Table 3 list a summary of some of the US studies that report significant momentum returns. In the first column of Table 3, 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.

Table 3: 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
Jegadeesh and Titman (2001)	1.23	6.46	1965-1998	EW	10
Chordia and Shivakumar (2002)	1.51	6.52	1963-1994	EW	10

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 3) 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 in the affirmative: Momentum exists in prices at the NSE.

3.4 Analysis of Seasonality Effect

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 the 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 4 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.[4] 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 2 shows the average monthly buy-and-hold returns on the composite portfolio strategies implemented during different periods at the NSE. For each

[4] 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. Might this seasonality be a statistical fluke?

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. 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.

A probable explanation for these observed differences 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.

Table 4 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.

Our overall findings on the whether there is a January seasonal pattern to momentum profitability at the NSE is ambivalent. 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.

Table 4: Momentum Returns by Month of The Year

Month	Average	t-statistic	Percent positive
Overall	0.01179**	2..8209	68.056
January	0.01314*	1.8006	75
Other than January	0.01157**	4,20208	67.424
January-Others	0.00157	0.28469	
February	0.01150*	1.836306	66.7
Other than February	0.01182	1.777546	67.4
February-Others	-0.00032	-0.048358	
March	0.01177	1.534939	58.3
Other than March	0.01179*	1.807791	68.2
March-Others	-.00002	-0.002554	
April	0.01525	1.886365	66.7
Other than April	0.01148	1.77288	68.2
April-Others	0.00377	-0.45469	
May	0.01045	1.237661	66.7
Other than May	0.01146	1.780965	68.2
May-Others	-0.00102	-0.117696	
June	0.01300	1.729746	75
Other Than June	0.01168	1.786824	67.4
June-Others	0.00132	0.170651	
July	0.01039	1.571079	66.7
Other than July	0.01192*	1.800788	68.2
July-Others	-0.00153	-0.22158	
August	0.01188	1.732725	58.3
Other than August	0.01178	1.785597	68.9
August-Others	0.00010	0.014104	
September	0.01132	1.656042	66.7
Other than September	0.01183	1.79286	68.2
September-Others	-0.00051	-0.072251	
October	0.00819	1.358138	66.7
Other than October	0.01212*	1.820085	68.2
October-Others	-0.00393	-0.620023	
November	0.00807	1.28745	66.7
Other than November	0.01213*	1.826943	68.2
November-Others	-0.00406	-0.619223	
December	0.01158**	2.121807	75
Other than December	0.01181	1.760738	67.4
December-others	-0.00023	-0.039769	

3.5 Analysis of Post-holding Period Cumulative Profits to the Momentum Strategy

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, its permanency, and probable reversal.

Figures 5 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 analyzed the post-formation holding period returns spanning 60 months. From the analysis, two conclusions can be supported:

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 5 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 conclusion 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.

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 attempted to differentiate between the efficacy 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 up date 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 known as "representative heuristic" (Tversky and Kahnemann (1974)), and "self-attribution" syndromes, which make traders overconfident hence pushing prices of winners above their fundamental values (and losers below 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 hypotheses was expounded by Conrad and Kaul (1998) who argue 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 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.

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 ears. Our results though not conclusive incline in the direction of overreaction.

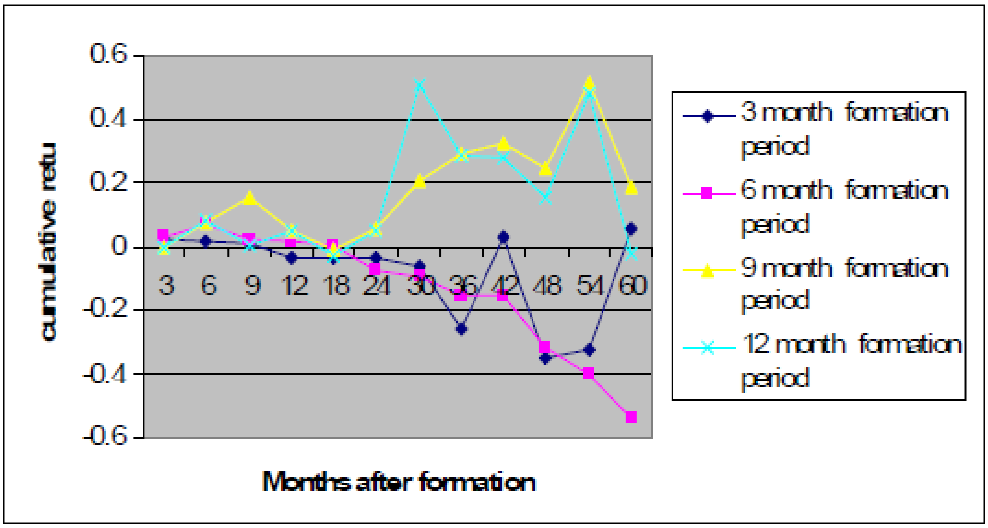

Figure 5: Cumulative momentum returns

Figure 5 graphs the behaviour of winner-loser momentum cumulative returns over a 60 month holding period analysed in accordance to the four formation periods, 3 months, 6 months, 9 months, and 12 months. The figure summarises the effect of the length of the formation period on the longevity and persistence of the return continuation. 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 appears that the degree of significance and duration of momentum effect is positively related to the length of the formation period.

Consequently, we report evidence of eventual reversal of the momentum effect. Eventually winners become losers. This confirms our hypothesis.

Remarkable also is that a longer formation period result 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 Conclusions

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 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, momentum phenomenon could be market-specific: the contrasting sub-sample results are a product of the differences in the market conditions existing in the sub-period 1997-2002 and the sub-period 2003-2007. The market and political reforms implemented in the latter sub-period resulted in more efficient transactions at the bourse and in generating a more exuberant and optimistic investor sentiment.

Our findings using NSE data show 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 finding contrasts evidence from the USA which document that the Winners outperform the Losers in all months except January, when the Losers outperform the Winners. When we extend our testing to include all the months of the year, it is found that October is the worst month, while April is the best month for momentum strategies. 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. The bottom line is that there is no January effect in momentum profitability at the NSE.

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 NSE, which are consistent with evidence documented for the US market (Jegadeesh and Titman (1993, 2000, 2001)), support the behavioural hypotheses of underreaction, overreaction and reversal in returns, rather than Conrad and Kaul (1998) risk based hypothesis.

The findings of this study are to be accepted albeit with some qualifications, chief among them being the following, other alternative methods are available, data gaps because of inadequacies in the NSE data base, and short sample period. We recommended extended testing using alternative methods and longer samples.

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