An Empirical Analysis of Risk and Size Factors in Momentum Profitability at the Nairobi Stock Exchange

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A paper submitted for presentation at the Operation Research Society of East Africa (ORSEA) Conference, University of Nairobi, 2011.

Abstract

A generation ago, the intellectual dominance of the efficient markets hypothesis as the accepted asset pricing paradigm was unchallenged. By the start of the twenty-first century, however, 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. 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 continue to confound the efficient markets theory. This study sought, first, to establish whether the NSE experienced price momentum in the period covered. Next we tested whether momentum profitability could be explained by, and was compensation for, risk. Finally, we investigated any relationship between price momentum and the well documented size anomaly. We found out that the NSE experienced significant degree of price momentum in the period covered. And that this momentum profitability could not be explained by the three factor risk factors of Fama-French, and that there was no size effect to momentum.

Terms: price momentum, size effect, risk, winners, losers.

1. Introduction

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. Two possible explanations for momentum are size and market wide risk.

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), Daniel and Titman (1997), and Davis et al (2000) provide evidence that sorting stocks according to market capitalisation and book-to-market explains a big proportion of stock returns. 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. 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. To the contrary, Hameed and Kusnadi (2002) find no size influence in momentum profits in five of the six Asian markets they studied.

Other studies 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 profits¹. Using the frequency domain component method to decompose stock returns, Yao (2003) provides strong evidence that momentum is a systematic phenomenon.

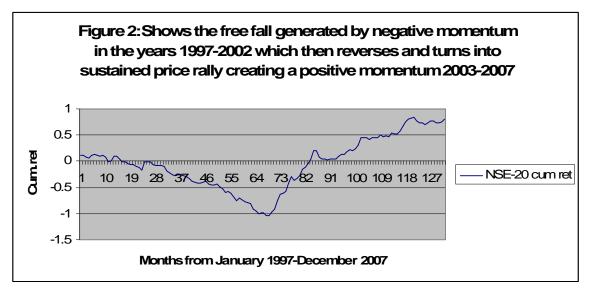
Models have been developed that are based on momentum on economic risk factors affecting investment life cycles and growth rates. Berk, Green and Naik (1999) illustrate that momentum

¹ Both Conrad and Kaul (1998), and Lewellen (2002), employ Lo and MacKinlay's (1990) statistical framework to decompose the profits of an investments strategy.

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.

Momentum strategies are part of the bigger universe of technical trading rules that posit predictability of stock returns using past trends in prices and trading volumes. Studies using the NSE data base are just beginning to trickle in. Lishenga et al. (2011) report the existence of significant price momentum at the NSE that could be the basis of profitable trading strategies. Atiti (2003) also documents evidence of price momentum in the short to medium term, while Ndungu (2005) finds the existence of a size effect at the NSE.

A scrutiny of the NSE-20 index shows trends that attest to both reversal and continuation in returns that can be predictable. 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 hhh4 to 5 years later. This is followed by an upward recovery that is also unbroken until the high of 5679 of 2007 is reached. This is clear in the Figure 2 below.



The current study builds on Lishenga (2011) and investigates the influence of two firm-level characteristics on the propensity of a stock to exhibit price momentum. We will investigate whether the market wide risk and size stories can explain the phenomenon.

The rest of the paper is arranged as follows; Section 2 reviews related literature on the momentum anomaly. Section 3 describes the data and the methodology used to test existence of momentum and how momentum is influenced by risk and size factors. Section 4 presents and discusses the results and Section 5 concludes.

2. Review of Related Literature

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 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) show that momentum strategies yield 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.

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) 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. 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.

In the event study area, it has been observed that, 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) 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 standardized unexpected earnings (SUE). The findings support the hypothesis of drift to earnings 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 evidence of underreaction. Cuttler et al. (1991) examine auto-correlation in excess returns on various indexes and generally find positive auto-correlation in excess returns of around 0.1 for stocks, and in bonds of 0.2. This autocorrelation is statistically significant and consistent with the underreaction hypothesis. Chan, Hameed, and Tong (2000) implement momentum strategies on stock markets of 23 countries and find that a great proportion of momentum profits come from price continuation in stock indices, and very little from movements in exchange rates.

A common belief noted by Chan et al. (2000) is that, 'it takes volume to move prices.' Conrad *et al.* (1994) find that high volume securities experience more price continuation, Gervais *et al.* (1998) show that individual stocks whose volumes are unusually large (small) tend to experience large (small) subsequent returns and Lee and Swaminathan (1998) illustrate that past trading volume predicts both the magnitude and persistence of future price momentum..

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. 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.

Emerging market² 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 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.

3. Data Analysis

3.1 Measuring the Returns to Momentum Strategies

This research used the causal comparative design (a.k.a. *ex-post-facto* design.).We analyzed the returns of the portfolio strategies for the period 2000 to 2007 on data from the NSE. To test the significance of momentum profitability, we first formed the relative strength portfolios as described in Jegadeesh and Titman (1993). At the end of each month t, all stocks are ranked in descending order on the basis of their past J months' returns (J = 3, 6, 9, or 12). Based on these rankings, the stocks are assigned to one of five quintile portfolios. The top quintile portfolio is called the "Winner", while the bottom quintile called the "Loser". These portfolios are equally weighted at formation, and held for K subsequent months (K=3, 6, 9, and 12).

² The data for these studies were drawn from the Emerging Markets Data Base (EMDB) of the IFC and included Argentina, Brazil, Chile, Colombia, Greece, Indonesia, India, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela and Zimbabwe.

To minimize small-sample biases and to increase the power of the test, we implement trading strategies for overlapping holding periods on a monthly frequency. Therefore, in any given month t, the strategies hold a series of portfolios that are selected in the current month as well as in the previous K-1 months. This is equivalent to a composite portfolio in which 1/K of the holding is replaced each month. To avoid the potential "survival biases", we do not require all securities included in a particular strategy in the formation period to survive up to the end of the holding period. If a security survives for less than J periods, we use a (J-j) period in calculating returns, where *j* is the period of delisting. If a security does not survive the formation period, it is dropped from the particular strategy.

Having analyzed the momentum effect for all the sixteen strategies and arrived at general conclusions, the investigation of the risk and size effects were pursued by employing the *standard* J=-6month, K=6month strategy. This is consistent with JT (1993), Rouwenhorst (1997), and Hameed and Kusnadi (2002) who focus only on this one representative strategy. This is the strategy formed on the basis of the preceding 6 month ranked returns, formed immediately at the end of the ranking period, and held for next 6 months.

3.2 Size and Momentum Profits

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 sizeneutral 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.

3.3 Risk-Adjusted Momentum Returns

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 and French (1996), Lee and Swaminathan (2000), and Grinblatt and 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 and Sadka (2004). Nevertheless, despite the burgeoning to the contrary, proponents of risk-based explanation still harbour hopes of finding a risk-based explanation for momentum profitability (Conrad and Kaul (1998) and Moskowitz and Grinblatt (1998)).

This subsection explored the relationship between the returns of momentum portfolios and risk factors. First we employed a market version of the CAPM, and secondly the broader Fama-French three factor model.

The testable version of the CAPM can be rendered in the form,

$$R_{RSS,t}-rf_{,t}=\alpha+\beta_m(R_{M,t}-rf_{,t})$$

Where,

 $R_{RSS,T}$ =Average return of momentum strategy for the month t.

- rf The risk free rate of return observed at the beginning of the month, t.
- R_{M} , Average monthly return on the overall market factor
- α 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).

Subsequently, 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) was explored. 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:

$$R_{RSS,t} - rf_{,t} = \alpha + \beta_m (R_{M,t} - rf_{,t}) + \beta_{smb} SMB_t + \beta_{hml} HML_t + \varepsilon_t$$
(3.1)

Where

 $R_{RSS,T}$ =Average return of the relative strength strategy for the month t.

rf = 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
 - α The intercept in the regression equation

 $eta_{_{SMB}}$ The sensitivity of the size factor to relative strength strategy (RSS) profits

 β_{μ} The sensitivity of RSS profits to the overall market factor

 $oldsymbol{eta}_{_{HML}}$ The sensitivity of RSS profits to the B-M factor

$\boldsymbol{\mathcal{E}}_t$ 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.

4. **Results and Discussions**

4.1 Profitability of Momentum Strategies

Table 1 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 period, buying "Winner" from a 3-month/3-month strategy earns an average return of 2.68 percent per month, 1.59 percent higher than buying "Loser" in the same strategy, which returns 1.09 percent. The excess return is significant at the 1 percent level, with a *t*-statistic of 2.36.

Formation	Portfolio	2000-2007 Holding period (K)- months					
Period (J)- months		3	6	9	12		
	Winner(W)	.0268	.0272	.0262	.025		
3	Loser(L)	.0109	.021	.0234	.028		
3	W-L	.0159	.0062	.0028	002		
	(t-stat)	2.36**	1.11*	054*	-0.46		
6	Winner(W)	.0435	.0293	.0290	.029		
	Loser(L)	.0221	.0149	.0244	.026		
	W-L	.0214	.0144	.0046	.002		
	(t-stat)	2.44**	2.58**	0.78*	0.4		
	Winner(W)	.0252	.0426	.0313	.032		
9	Loser(L)	.0221	.0230	.0081	.024		
9	W-L	.0031	.01196	.0232	.008		
	(t-stat)	0.41	2.31*	4.2**	1.42*		
12	Winner(W)	.0227	.0411	.0201	.032		
	Loser(L)	.0209	.0218	.0177	.022		
	W-L	.0018	.0193	.0024	.010		
	(t-stat)	0.24	2.26*	0.35	1.88*		

Key: J =Formation Period, K= Holding Period

The table shows average monthly profits to relative strength (or momentum) strategies (RSS) mounted at the NSE from 2000 to 2007. 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.

Significantly positive excess returns are observed at the 5 percent level for seven strategies, and at 1 percent level for six, of the sixteen strategies implemented. In all 13 out of the 16 strategies implemented are significantly profitable at or below the 5 per cent level. Specifically, the excess monthly returns of buying "Winner" over buying "Loser" range from -0.25 per cent for the 3-by-12 strategy to 2.32 percent for the 9-by-9 strategy (indeed the only negative return is the -0.25 percent of the 3 by 12 strategy). The 6-by-6 strategy that is standard for most studies registers a mean return of 1.44 percent per month which is statistically and economically significant at the 1 percent level. The average Winner-Loser return for the entire sample was 0.91 percent with a standard deviation of 0.78 percent.

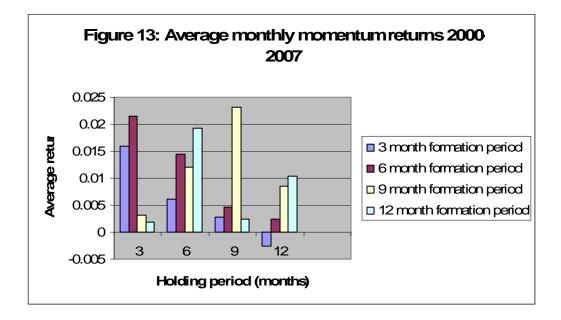


Figure 13 is a chart constructed from Table 1. During the sub-period analyzed, momentum was evidently widespread. Twelve of the sixteen strategies exhibit significant momentum (6 at the 1% level and the remaining 6 at 5 % level of significance). Average monthly returns were as high as 2.32% for the 9 by 9 strategy, with the only negative return at -0.25% (significant at 5% level) being registered in the 3 by 12 strategy.

Table 2: Momentum Returns Reported in the Literature								
	Momentu	T-Value	Sample	Weigh	Percentag			
	m			t	e			
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			
In the first column of the table, the references are listed and the second and third columns report								
the 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 16 strategies implemented, there is concrete evidence of momentum in individual stocks at the NSE. Comparing the findings of the current study with those of studies from the US (See Table 2) most of which report the existence of momentum, it is clear the NSE is in the same league. The conclusion that appears inevitable from our test findings is that a significant degree of momentum is present in stock prices at the NSE.

4.2 Size and Momentum Profits

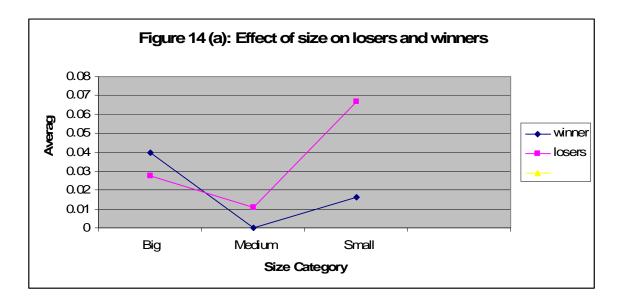
The first column in Table 4 confirms that there is significant momentum, in the full sample. A strategy that goes long in the best performing quintile and short in the worst performing quintile generates 1.44 percent per month. The next columns break the momentum effect down by size: the "Big" stocks, the "medium" stocks, and the "Small" stocks, as defined in the preceding paragraph.

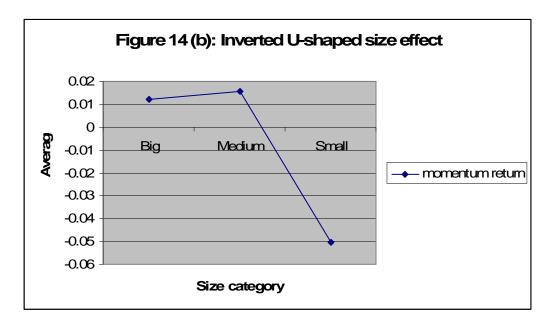
Figures 14(a) and 14(b) illustrate the results, plotting the relationship between size and the magnitude of the winner, loser and momentum effects. Figure 14(a) shows that in size extremes there is reversal in returns. Losers outperform winners in the small and the big capitalization categories; only for the medium category do continuation in returns manifest. From Figure 14(b), it is apparent that momentum profits follow a hump shape (an Inverted U-shape) with respect to size. Considering the small sub-sample with a mean capitalization of Sh.486 million, momentum effect is virtually absent: in fact it is marginally *negative*. The momentum effect reaches a peak of 1.55 percent per month among the medium cap stocks, whose mean capitalization is Sh. 2,404 million. The momentum return of the medium sub-sample is more than 3 times the return for the whole sample. The momentum effect then dissipates when one moves to the big capitalization sub-sample,

registering an average return of 1.14 percent per month. Overall, however, momentum profits reported for all three size portfolios are not significant at conventional levels.

Table 3: Returns to size-based momentum portfolios								
MOMENTUM PORTFOLIOS	SIZE CLASS							
	All stocks	Big	Medium	Small	Small <i>minus</i> Big			
$P_1^{(winners)}$	0.0293 (3.31)	0.0352 (2.57)	0.0264 (1.90)	0.0183 (1.35)	-0.0169			
P_2	0.0380 (3.33)_	0.0182 (1.51)	0.0459 (2.24)	0.0479 (2.05)	0.0297			
P_{3}	0.0246 (2.39)	0.0201 (1.65	0.0268 (1.16)	0.0250 (1.59)	0.0049			
P_4	0.0192 (2.84)	0.0172 (1.30)	0.0065 (0.83)	0.0292 (2.55)	0.0119			
$P_{5}^{(losers)}$	0.0149 (2.25)	0.0238 (1.58)	0.0111 (1.21)	0.0192 (1.06)	-0.0046			
$P_{1}^{-}P_{5}$	0.0144 (0.38)	0.0114 (0.63)	0.0155 (1.27)	-0.0008 (-0.05)	-0.01228			
$\frac{P_3 - P_5}{P_1 - P_5}$		-0.3247	1.0151	-6.9754				
Mean size (Sh. millions)		16791	2404	486				
Median (Sh. millions)		6938	1617	289				

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 asymmetric effect of size may be explained, on one hand, by the thin trading that characterizes most of the small cap stocks leading to supply shock induced reversals, while on the other hand, the decline of the momentum effect in the big cap stocks may be testament to the hypothesis that such stocks with more analyst and investor attention are subject to faster information diffusion and hence have less momentum.

Some past research³ 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*. In Table 4, 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 the big and small cap stocks are inconsistent with prior research findings⁴. Our findings (in Table 4) indicate a negative impact on momentum profitability by the big and small cap losers (-32.5% for big and -698% for small). Evidently, size extremes (be it on the high or low side) seem to dissipates the momentum effect. For the medium capitalization stocks, indeed the short position contributes the preponderance of momentum profits, i.e. 102% of the profits. In contrast, Hameed and Kusnadi (2002) find no size influence in momentum profits in five of the six Asian markets they studied.

In sum, our results fail to confirm the hypothesis that momentum is more pronounced in small stocks than in other size categories. Possible explanations could include the fact that small stocks at the NSE are closely held, are thinly traded and consequently are insulated from market forces that drive momentum.

4.3 Risk-Adjusted Momentum Returns

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

Table 4: CAPM Adjusted Excess Returns of Momentum Portfolios						
	α	$t(\alpha)$	β_m	$t(\boldsymbol{\beta}_m)$		
1996-2007	0.00	4.5**	-0.308	-5.51**		
1996-2002	0.00	0.653	-0.576	-10.01**		
2003-2007	0.00	3.83**	-0.244	-1.846		

³ 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.

⁴ Fama and French (1993) provide evidence that sorting stocks according to market capitalisation and bookto-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.

The table reports the results of regressing excess momentum returns $(R_{RSS,t}-r_{f,t})$ against the excess returns on the market portfolio $(R_{M,t}-r_{f,t})$, $R_{RSS,t}-r_{f,t}=\alpha+\beta_m(R_{M,t}-r_{f,t})$. Data was available for the test between 1995 and 2007 and the sub-samples were influenced by the perceived momentum in the NSE-20 stock index. $t(\alpha) t$ and (β_m) are t-statistics for α and β_m . ** significant at 1 percent level.

The Table 4 shows the results of the test of the ability of CAPM's beta to explain momentum returns. The findings are not reassuring. 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. 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 4 is that all the beta values, though significant are negative, implying illogically that returns and risk have a negative relationship. It is clear that risk as measured by the CAPM beta cannot be responsible for the momentum phenomenon in returns at the NSE.

	α	$t(\alpha)$	β_m	$t(\boldsymbol{\beta}_m)$	β_{SMB}	$t(\beta_{SMB})$	β_{HML}	$t(\beta_{HML})$	R ²
1996-	0.00	4.5**	-0.308	-5.51**	0.026	0.756	0.016	0.685	0.203
2007 1996- 2002	0.00	0.653	-0.576	-10.01**	0.018	0.646	0.11	0.597	0.627
2003- 2007	0.00	3.83**	-0.244	-1.846	-0.072	-1.015	-0.035	-0.467	0.082
	in exces		0		•	rench three-		$\overline{R}_m - r_F$),	
$R_{RSS,t}$ - R^2 is the	$r_{f,t} =$ ne coeff ent divid	ficient of led by its	determin	ation adjust	ted for d	-	reedom;	$t(\bullet)$ is the significant a	

We alternatively employed the broader model of Fama and French (1993, $R_{RSS,t} - rf_{,t} = \alpha + \beta_m (R_{M,t} - rf_{,t}) + \beta_{smb} SMB_t + \beta_{hml} HML_t + \varepsilon_t$

Table 5 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 (β 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 (β_{SMB}) and book-to-market factor coefficients (β_{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 some, but marginal explanatory power for momentum profits

Columns 2 and 3 of Table 5 report the alpha (α) of the various momentum portfolios as estimated by regressing the monthly excess 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. This begs the question whether or not there may be other variables with more correlation with momentum profits not specified in the three factor model.

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.

5. Conclusions

The striking finding from our test is that one can earn abnormal returns by implementing momentum-based trading strategies at the NSE. This momentum is caused by investors underreacting, trading in herds, or the limitations of the arbitrage process. Investor education, institutional, legislative, regulatory strengthening and improvement in operational efficiency could reduce the misevaluation in stocks at the bourse.

We did not find a size effect in the momentum profitability. This contrasts findings in prior studies. The discrepancies in the findings on NSE data may be the result of the differences in what constitutes small or big stocks in the different markets. For instance the typical small capitalization in NSE will be the stocks that are excluded from samples using NYSE data as being outliers that could distort results. A future study should exclude the typical small and infrequently traded stocks in the alternative segment, and concentrate only on the main segment. A size investigation confined to the main segment would reduce the operation of omitted variables and allow the size effect to stand out.

As regards the explanatory power of risk, the analysis revealed that the market wide co-variation, the book-to-market and the size factors cannot explain the out-performance of momentum stock selection strategies at the Nairobi Stock Exchange. Consistent with the findings of a majority of extant studies, our tests failed to explain momentum profits within the framework of two risk motivated models. Thus we are led to conclude that investors and markets do not react only to risk in pricing assets. We are led to conclude that, perhaps, behavioural factors and psychological biases are a major influence on the demand and supply forces at the NSE. Additionally, the restrictions on short selling and the limitations in the operation of arbitrage forces can lead to the persistence of profitable arbitrage opportunities unexploited.

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