STUDIES ON THE MOMENTUM EFFECT IN THE UK STOCK MARKET

by

Jia Cao

A Thesis Submitted in Fulfilment of the Requirements for the Degree of Doctor of Philosophy of Cardiff University

Economics Section, Cardiff Business School, Cardiff University

September 2014

DECLARATION

This work has not previously been accepted in substance for any degree and is not concurrently submitted in candidature for any degree.

Signed ………………………………………………………. (candidate)

Date …………………………

STATEMENT 1

This thesis is being submitted in partial fulfilment of the requirements for the degree of …………………………(insert MCh, Md, MPhil**,** PhD etc, as appropriate)

Signed ………………………………………………………. (candidate)

Date …………………………

STATEMENT 2

This thesis is the result of my own independent work/investigation, except where otherwise stated.
Other sources are acknowledged by footnotes giving explicit references.

Signed ………………………………………………………. (candidate)

Date …………………………

STATEMENT 3

I hereby give consent for my thesis, if accepted, to be available for photocopying and for inter-library loan, and for the title and summary to be made available to outside organisations.

Signed ………………………………………………………. (candidate)

Date …………………………

ABSTRACT

This thesis studies the momentum effect in the UK stock market. The momentum effect is found to be a persistent yet not fully stable phenomenon in the UK stock market and its dynamics is at least partially conditional on the stability of the stock market. When the stock market is stable, momentum trading strategies tend to have rather reliable and good performances whereas when the stock market is in turmoil, momentum trading strategies tend to suffer losses in the near future.

We construct a threshold regression model to analyse this relationship between the momentum effect and the stock market stability. We propose that there are two regimes in the short run for shares that have had extreme past performances, the momentum and the reversal regime, and that the switch from one regime to the other is governed by the stock market volatility. Our estimation results confirm this significant role of the stock market volatility. Moreover, the stock market volatility has a negative impact on a momentum trading strategy's return in both regimes in most cases. Apart from the stock market volatility, we also find that a momentum portfolio's ranking period return has a significant inverse relationship with its holding period return in the momentum regime, i.e., the magnitude of the momentum effect during its holding period. This negative relationship suggests that the reversal can occur in the short term even in the momentum regime when the ranking period return is sufficiently large.

A new type of trading strategies is designed to take advantage of the predictability of the momentum effect dynamics, in particular, the switch between the momentum and the reversal, and our results show that they outperform momentum trading strategies with higher returns and lower risks. Indeed, following the indication of the threshold regression model, these new trading strategies can exploit not only the momentum effect but also the contrarian effect. More importantly, they are able to generate economically significant profits net of transaction costs even when momentum trading strategies fail to do so. The predictability of the dynamics of the momentum effect and the superior performance of our new trading strategies create an even bigger anomaly than the momentum effect itself in the stock market.

ACKNOWLEDGEMENT

Completing a five-year PhD programme is an enduring race and this doctoral thesis for me is a tremendous achievement. All of these would not have been possible without the help, encouragement and support of many kind people around me.

First, I would like to express my deepest gratitude to my supervisor, Professor Laurence Copeland, for his excellent guidance, invaluable advice and incredible patience. His passion and dedication in financial research is inspirational for me. No matter how tedious or challenging the work is, it becomes pleasant with him.

I would like to give my sincere appreciation to Professor Patrick Minford for giving me one of the most precious opportunities in my life to conduct this postgraduate doctoral research in Cardiff Business School. I also thank him for his constructive comments on my thesis at workshops.

My special appreciation goes to Dr Guangjie Li for his expert help and illuminating explanation of Bayesian estimation method. I shall never forget his kindness, and his willingness to offer helps.

I would like to thank Professor Kent Matthews, Dr Woon Wong, Dr Helmuts Azacis, Dr Zhirong Ou, and many others in Economics Section for sharing their academic research experiences and giving their encouragements to me. My thanks also go to my PhD colleagues, Xiaodong Chen, Kailin Zou, Hongchao Zhang, Yan yang, Wenna Lu, Yongdeng Xu, Wei Yin and many others for their precious friendship.

Lastly, I would like to thank my dearest family, my mum, Sufang Yuan, my dad, Youyuan Cao, my brother, Xiaojun Cao and my sister-in-law, Jia Xiang. They have been brilliant when I need them for support and comfort. My special thanks are given to my partner, Karl McKenzie for his love, care, support, and understanding. Without him, I could not have made it. I also would like to thank his family, his parents, Valerie Trigg and Carl Trigg. They are like another family in the UK for me and without them, my life in the UK wouldn't have been so great.

I am deeply indebted to all of people who have been there when I needed them for the last five years and no words can express how truly grateful I am.

TABLE OF CONTENTS

TABLE OF FIGURES

LIST OF TABLES

1. General Introduction

The momentum effect in the stock market refers to the tendency for a share's price to continue in the same direction. More specifically, shares that performed well in the past tend to continue performing well and shares that performed poorly in the past tend to continue performing poorly. The momentum effect implies that stock returns is predictable based on past returns to some extent. Since Jegadeesh and Titman (1993) demonstrate that momentum trading strategies that are designed to exploit the momentum effect by buying past winners and selling past losers generate significant profits in the US stock market, a great deal of research has reported the momentum effect in various stock markets, such as European stock markets (Rouwenhorse (1998), Griffin et al. (2003), Antoniou et al. (2007), Asness et al. (2013)), Asian stock markets (Chui et al. (2000), Griffin et al. (2003)), African stock markets (Griffin et al. (2003)), and Latin American emerging markets (Muga and Santamaria (2007)). Thus, there is sufficient evidence that shows the momentum effect is not an artefact of data snooping. Indeed, the momentum effect has become one of most puzzling and intriguing financial phenomena.

There has been an intense debate regarding the explanations of the nature of the momentum effect. Theoretical explanations can be categorized into the risk-oriented explanations and the behaviour-oriented explanations. According to the risk-oriented explanations, momentum payoffs reflect shares' time varying expected returns and the excess returns generated by momentum trading strategies are compensation for bearing risks. Put it more simply, momentum profits are risk premia. This argument is shared by Conrad and Kaul (1998), Berk et al. (1999), Johnson (2002), Sagi and Seasholes (2007), and so on. On the other hand, behaviourists are not convinced by the assumption of rationality and argue that investors are consistently subject to behavioural bias and psychological heuristics, for example, overconfidence, self-attribution, representativeness, and conservatism. According to their points of view, the momentum effect reflects irrationality and momentum profits are the outcome of market mispricing. Daniel et al. (1998), Baberis et al. (1998) and Hong and Stein (1999) demonstrate that the momentum effect can be generated by models that assume investors' irrational behaviour.

The momentum effect is found to be predictable based on lagged variables in the literature, of which, some are interpreted as risk factors and others are argued to be consistent with the assumption of market mispricing. Lagged variables, such as dividend yield, default spread, term spread, and yield on three-month T-bills are found to be able to explain most variation in the momentum effect and they are argued to be factors that reflect systematic risks as they are associated with business cycle. Such work includes Chordia and Shivakumar (2002), Avramov and Chordia (2006), Liu and Lu (2008) and Kim et al. (2012). Other risk factors on the list including downside risk (Ang et al. (2001)) and systematic liquidity risk (Pastor and Stambaugh (2003)) and so on. However, not all people are convinced by the explanatory power of these risk factors and many find that risk factors can at most explain only a fraction of momentum profits, for example, Lee and Swaminathan (2000), Cooper et al. (2004), Asness et al. (2013). Lagged variables that are found to be able to predict the performance of momentum trading strategies and that are more consistent with implications of behavioural models include the state of market in terms of the sign of the market return (Cooper et al. (2004), Asem and Tian (2010)) and trading volume (Lee and Swaminathan (2000), Chan et al. (2000) Glaser and Weber (2003), Daniel et al. (2012)).

The post-cost profitability of momentum trading strategies is another subject of the debate regarding the momentum effect. Although answers to this question do not shed any light on the explanations of the momentum effect, they do help with this question whether momentum profits are exploitable by arbitrage and they might help us to understand why the momentum effect has been consistent over time. As momentum trading strategies involve intensive trades and executing orders have to be done at certain point in time by the design, transaction costs might be too high for the rational arbitrage activity. Results of relevant studies are mixed. Some conclude that momentum profits are in fact illusionary and they are not exploitable when taking trading costs into account (Keim (2003), and Lesmond et al. (2004)), others suggest that there are still significant net momentum profits after transaction costs (Korajczyk and Sadka (2004), Siganos (2010)).

Given the fact that the nature of the momentum effect in the stock market is far from being fully understood and explained, and that there are conflicting findings, more research is in demand. This thesis aims to conduct more studies on the momentum effect to help to fulfil this demand. We study this phenomenon in the UK stock market and take on the following tasks. We first update the investigation of existence of the momentum effect by examining the profitability of 192 momentum trading strategies (J=3, 6, 9... 24, K=1, 2, 3... 24) in the UK stock market. [1] Based on these results, we study its dynamics. We then look for new lagged variables other than the existent ones that have predictive power on the dynamics of the momentum effect. We also design new trading strategies that take advantage of this predictability. Finally, we discuss the post-cost profitability of both momentum trading strategies and our new trading strategies.

As the literature has not yet covered the time period after 2005 for momentum study in the UK stock market, it is important to gather more evidence regarding whether the momentum effect is a long-lasting phenomenon that can survive various changes in the UK stock market over time. We examine the profitability of momentum trading strategies for the last three decades from 1979 to 2011, during which the UK stock market experiences "big shocks" associated with three big crashes in the global stock market, i.e., the stock market crash of 1987, the burst of the dot-com bubble in 2000, and the stock market crash of 2008-2009.

Our results confirm that the momentum effect presents in the UK stock market after the mid-1970s as most of momentum trading strategies in our study with both the ranking period and the holding period below 24 months make significant profits over the whole sample period and a number of momentum trading strategies achieve an average annualized buy-and-hold return (BHR) above 10% at the significance level of 1%.[2] The existence of the momentum effect is also confirmed by the high percentage of profitable observations. For example, we find that 11 momentum trading strategies make profits for above 80% of the time from 1979 to

[1] J (K) stands for the length of ranking (holding) period in terms of the number of months.

[2] For simplicity, we use BHR to refer to buy-and-hold return, and the detail of its calculation is on page 34.

2011 and these results implicate that the momentum effect is a persistent phenomenon in the UK stock market.

Apart from the verification of the persistent character of the momentum effect, our results also point out large variation in its magnitude over time in the UK stock market. In contrast with the previous conclusions that either argue an increasing (Hon and Tonks (2003)) or a decreasing trend (Galariotis et al. (2007)) in the significance of the momentum effect, we find that its dynamics is at least partially conditional on the stability of the whole stock market.

The first interesting observation that supports our argument for the conditional momentum effect lies in the performances of individual momentum trading strategies. We find that reversals occur when the whole stock market is in turmoil as all individual momentum trading strategies with various ranking and holding periods lose money almost simultaneously during market crises. The most striking example is 2008 stock crash when all momentum trading strategies in our study suffer considerable losses.

The other observation that confirms this argument is based on the change in the number of profitable momentum strategies and the change in the size of the momentum profits over time. We document that the sub-sample period from 1989 to 1998 experiences the strongest momentum effect whereas sub-sample periods from 1979 to 1988 and from 1999 to 2011 see the momentum effect being relatively weak. There are a great number of momentum trading strategies generate annualized BHRs above 20% from 1989 to 1998. In contrast, the highest annualized BHR achieved for the other two sub-sample periods is about 15%. Further, the majority of momentum trading strategies with the ranking period within 24 months are significantly profitable from1989 to 1998 compared with the fact that only momentum trading strategies with the ranking period shorter than 12 months (with a few exceptions) are profitable from 1979 to 1988 and that momentum trading strategies with the ranking period below 6 months make positive returns from 1999 to 2011. It is easy to see that a big difference regarding the three sub-sample periods is that the stock market is relatively stable from 1989 to 1998 whereas it experiences big shocks during the other two sub-sample periods.[3]

Based on the above observations and behavioural models that can generate both the momentum and the contrarian effect, we build a threshold-regression model with heteroskedasticity to analyse the dynamics of the momentum effect in the UK stock market.[4] Assuming that three market mechanisms in Daniel et al. (1998), Baberis et al. (1998) and Hong and Stein (1999) co-exist in the stock market and that investors are subject to heuristics such as overconfidence, self-attribution, representativeness and conservatism, we propose two variables to predict the dynamics of the momentum effect. The first candidate variable is the stock market volatility as it may indicate the change in investors' investment behaviour and the second candidate is the ranking period return of a momentum portfolio as it may be able to distinguish the causes of the current momentum effect, namely, under-reaction and overreaction. We test three hypotheses that are inferred from these behavioural models and our empirical findings.

The first hypothesis states that whether the momentum effect continues or reverses in the near term depends on whether the current stock market volatility lies below or above a threshold. In other words, we conjecture that there are two regimes, the momentum and the reversal regime, and that the switch between the momentum effect and the contrarian effect is governed by the stock market volatility. The second hypothesis says that the size of momentum trading strategies' returns is inversely correlated with the size of the stock market volatility. According to the first two hypotheses, market volatility not only indicates the transition between the momentum and the contrarian effect but also influence their magnitudes. In the third hypothesis, we propose that there is a negative relationship between the ranking period return of a momentum portfolio and its holding period return in the momentum regime.

---

[3]These results are consistent with those of Cooper et al. (2004), Asem and Tian (2010), Daniel and Moskowitz (2011), and Pedro and Pedro (2013), who find, respectively, that the momentum payoff is low and can be negative when market volatility is high.

[4]Contrarian effect, that is, the reversal in the momentum effect is one of the biggest challenges facing risk-based explanatory theories. We document the contrarian effect both in the short run and in the long term in the UK stock market from 1979 to 2011 and the long-run contrarian results are tabulated in Table A-**Error! Main Document Only.** and Table A-2 in the Appendix.

We test the above three hypotheses by estimating the threshold-regression model with heteroskedasticity with four different momentum trading strategies, 3x3, 6x3, 9x4 and 12x3 as they catch the momentum effect the best and the estimation results with all of these four strategies are very similar and they support our hypotheses.[5]

First of all, our estimation results confirm the two-regime model design and the switch between the momentum and the reversal regime that is determined by whether the stock market volatility lies above or below a critical value range.[6] We find that a momentum portfolio tends to make rather reliable profits when the stock market volatility during its ranking period is relatively low and that it tends to generate losses when the ranking period market volatility is large and above a threshold. Apart from being the switching variable, the stock market volatility during a momentum portfolio's ranking period is found to have a significant negative relationship with its holding period return in many cases in both regimes. In other words, an increase in the stock market volatility causes a decrease in momentum profits in the momentum regime and an increase in losses of a momentum portfolio in the reversal regime. We also obtain evidence that supports the significance of an inversely relationship between a momentum portfolio's ranking period return and its holding period return in the momentum regime and we find that this relationship is robust across various momentum trading strategies over time. In general, estimation results of parameters associated with the momentum regime are more consistent across momentum trading strategies over time than those of parameters associated with the reversal regime and the hold period return of a momentum portfolio is more predictable in the momentum regime than in the reversal regime.

To verify and to take advantage of the statistically significant predictive power of the ranking period market volatility and the ranking period return, we design trading strategies that follow the indication of the forecast of the threshold-regression model. Our new trading strategies are referred to as threshold-regression-model-guided trading strategies. Corresponding to each momentum

[5]Each of these four momentum trading strategies generates the highest annualized BHR among strategies that have the same ranking period.

[6]Our discussion focuses on the posterior distribution of the threshold since each parameter has a distribution instead of one true value according to Bayesian estimation method.

trading strategy JxK, we have a model-guided trading strategy JxK.[7] However, unlike the former strategy, it always takes long position in past winner portfolios and short position in past loser portfolios, the model-guided trading strategy implements either the momentum or the contrarian trade depending on the indication of the forecast results of the threshold regression model. When the threshold regression model forecasts significant positive momentum return, the associated model-guided trading strategy takes long position in winners and short position in losers and holds this position for the next K month. On the contrary, when the model forecasts significant negative momentum return, the model-guided trading strategy reverses the action of the momentum trading strategy by taking short position in winners and long position in losers. When this situation occurs that the model forecasts a momentum return that is insignificantly different from zero, the model-guided trading strategy takes no action. We conduct model-guided trading strategies 3x3, 6x3, 9x4 and 12x3 from 1998 to 2011 and the first prediction is generated based on data from 1969 to 1998.

The statistical significance of the threshold-regression model is confirmed as each of the four model guided trading strategies outperforms its corresponding momentum trading strategy with higher returns and less risks, which are measured by the percentage of the profitable trade and the Sharpe ratio. More importantly, the superior performance of model-guided trading strategies over momentum trading strategies are consistent over time as shown by results based on two sub-time periods, 1998 to 2005 and 1998 to 2011. For example, momentum trading strategy 9x4 generates average annualized return of 22.6% and 11.7% for the period of 1998 to 2005 and the period of 1998 to 2011 respectively. In contrast, the model-guided trading strategy 9x4 offers consistent higher annualized return, 35.8% and 34.9% for each of the two sub-periods. Model-guided trading strategies also have higher percentage of profitable trade than momentum trading strategies. The percentage of the profitable trade of the momentum trading strategy 9x4 is 72.9% for the period of 1998 to 2005 and 66.9% for the period of 1998 to 2011; whereas these two figures for the model-guided trading strategy 9x4 are 80.6% and 76.4% respectively. Further, model-guided trading strategies offer higher rewards

[7]For simplification, they are also referred to as model-guided trading strategies.

for taking the same amount of risks than momentum trading strategies. For example, from 1998 to 2005, the momentum trading strategy 9x4 has a Sharpe ratio of 0.417 whereas the figure for the model-guided trading strategy 9x4 is 0.780; and from 1998 to 2011, the Sharpe ratio of the momentum trading strategy 9x4 is 0.182 while this figure for the model-guided trading strategy 9x4 is 0.639.

These results lead us to conclude that the dynamics of the momentum effect, in particular the switch between the momentum and the reversal, is predictable to some extent and that the profitability of model-guided trading strategies that make use of the predictive power of the lagged stock market volatility and the ranking period return is greater and more reliable than that of momentum trading strategies. This predictability of momentum portfolios' occasional severe losses is also discussed in the US stock market by studies including Daniel and Moskowitz (2011), Daniel et al. (2012), and Pet. Aiming to reduce this risk, more sophisticated momentum trading strategies are proposed as well in their work. However, our research is different from theirs in many ways.

Daniel and Moskowitz (2011) find that occasional strong reversals of momentum effect, or momentum crashes in their words are predictable and they design an optimal dynamic momentum strategy, which at each point in time, is scaled up or down so to maximize the unconditional Sharpe ratio of the dynamic portfolio by using the insights from their analysis on the forecastability of both the momentum premium and the momentum volatility to generate the dynamic weights. Daniel et al. (2012) develop a variation of the two state hidden Markov regime switching model (HMM) of Hamilton (1989), where the market is "calm" in one state and "turbulent" in the other. They find that the hidden states are persistent, and can be estimated ex-ante using the switching model. Hence, they suggest a dynamic momentum strategy that avoids turbulent months. Barroso and Santa-Clara (2015) measure the risk of momentum by the realized variance of daily returns and find that it is highly predictable. They simply scale the long-short portfolio by its realized volatility in the previous 6 months, targeting a strategy with constant volatility. By doing so, they can significantly reduce momentum crash risk.

Our work is related to the above literature in term of addressing the great variation in momentum effect. However, our studies are different in nature. First, we discuss the characteristics of momentum return from different aspects. For example, Daniel et al. (2012) assume that momentum returns are drawn from a mixture of normal distribution to match the skewed and leptokurtic distribution. However, we assume that these features of the distribution of momentum returns result from investors' behavioural heuristics. Second, we do not forecast the states of market as Daniel et al. (2012) or the volatility of momentum returns as Barroso and Santa-Clara (2015). Instead, we forecast the switch between the momentum effect and the contrarian, which, in our assumption, results from investors' irrational investment behaviours. It follows that the strategies that are designed to improve the simple momentum strategies are different. Our trading strategies are designed to take advantage of the predictability of the switch and thus to exploit abnormal returns generated by not only the momentum effect but also the contrarian effect whereas trading strategies introduced in Daniel and Moskowitz (2011), Daniel et al. (2012) and Barroso and Santa-Clara (2015) mainly aim to reduce the variance of the momentum payoffs.

Finally, we discuss the post-cost profitability of both momentum trading strategies 3x3, 6x3, 9x4 and 12x3 and four associated model-guided trading strategies based on momentum portfolios' transaction costs estimated in the UK stock market in Agyei-Ampomah (2007) and li et al. (2009). Given that all of our studies are based on stocks in the UK stock market, we assess the suitability of applying their estimated transaction costs to our discussion by showing that our study share similarity with these studies in features of winner and loser portfolios that impact transaction costs.

We verify that the average firm size, measured by the market capitalization, of stocks in a momentum trading strategy' loser portfolio is always much smaller than that of stocks in this momentum trading strategy' winner portfolio. Loser portfolios overweight stocks of small firms and winner portfolios have rather even distribution among stocks of different firm size. We also show that the turnover ratio, which measures the percentage of shares in a portfolio that change hand each investment period, decreases as the ranking period increases.

Our results show that none of these four momentum trading strategies makes profits after subtracting transaction costs. However, we find that the model-guided trading strategy 12x3 still makes sizable profits even when considering the most generous estimated transaction costs. We also examine the profitability of taking the long position of both types of trading strategies as short-selling stocks especially stocks of small firms is very costly and not always available for all investors. Our results show that buying winner portfolios of momentum trading strategies 3x3, 6x3, 9x4 are not profitable after taking transaction costs into account. Although the long position of the momentum trading strategy 12x3 can make profits net of transaction costs, the net profits are not economically significant. In contrast, investing in the long side of model-guided trading strategies 6x3, 9x4 and 12x3 can generate lucrative post-cost profits. For example, the long position of the model-guided trading strategy 12x3 could generate an annualized net return that is between 14% and 30% from 1998 to 2011.

In a nutshell, our thesis has the following findings. We find that the momentum effect is a long-lasting phenomenon in the UK stock market yet it has great dynamics. In particular, it can be reversed sometimes even in short run. The dynamics of the momentum effect is predictable to some extent by the lagged stock market volatility and the ranking period return of a momentum trading portfolio. More importantly, our threshold regression model can predict the switch between the momentum effect and the contrarian effect in the short term in the UK stock market, which has never been done before. Strategies that take advantage of the predictive power of the threshold regression model consistently outperform momentum trading strategies as these new strategies are able to exploit not just the momentum effect but also the contrarian effect. We also find that our new strategies are able to make economically significant profits net of transaction costs even when momentum trading strategies aren’t.

The rest of this thesis is organized as follows. In Chapter 2, we discuss relevant literature regarding findings on the momentum effect and the performance of momentum trading strategies, theoretical arguments about the implications of the momentum effect and their corresponding empirical evidence, and the post-cost profitability of various momentum trading strategies. Chapter 3 updates studies on this financial phenomenon and examine its dynamics in the UK stock market from 1979 to 2011. We also test the explanatory power of conventional risk factors on the momentum effect. In Chapter 4, we construct the threshold regression model with heteroskedasticity and test three hypotheses by estimating this model based on Bayesian estimation method. We also design a new type of trading strategies to take advantage of the predictive power of this threshold regression model and compare the performance of our new trading strategies with those of momentum trading strategies. Chapter 5 discusses the post-cost profitability of both momentum and threshold-regression-model-guided trading strategies. Chapter 6 concludes the thesis.

2. Literature Review

2.1 The Momentum Effect and Momentum Trading Strategies

The momentum effect is first documented by Jegadeesh and Titman (1993). Inspired by the report of DeBondt and Thaler (1985) that contrarian strategies, buying part losers and selling past winners, achieve abnormal returns, Jegadeesh and Titman (1993) conjecture that trading strategies that choose stocks based on their past returns should be profitable if stock prices either overreact or underreact to news. They find that trading strategies, buying past winners and selling past losers, are profitable in the United State stock market over the 1965 to 1989 period. A trading strategy JxK in their paper is implemented as follows. At the beginning of each month, securities are ranked in ascending order on the basis of their returns in the past J months. Based on these rankings, ten decile portfolios are formed with equal weight of stocks contained in each decile. In each month, the strategy buys the winner portfolio, the bottom decile, and sells the loser portfolio, the top decile, and holds this position for K months. They apply 16 such strategies (J, K=1, 2, 3, or 4 quarters) using daily data from the CRSP. In addition, to avoid some of the bid-ask spread, price pressure, and lagged reaction effects, they also examine a second set of 16 strategies that skip one week between the portfolios formation period and the holding period. Their results show that the returns of all these 32 zero-cost strategies are positive and all profits are statistically significant except for the 3x3 strategy that does not skip a week. These strategies are known as momentum trading strategy and the phenomenon of the continuation in a stock's performance is called the momentum effect. To examine if their results are merely an artefact of data mining, Jegadeesh and Titman (2001) extend the number of observation and show that momentum trading strategies continue generate profits in the 1990s. Profitability of momentum trading strategies in the United States are also verified by many others. For example, Grundy and Martin (2001) document that the momentum trading strategy 6x1 applied to NYSE and AMEX listed stocks could have earned an average monthly return of 0.44% over period from 1926 to 1995.

The momentum effect is not confined in the U.S. stock market and an increasing number of research report this phenomenon in many other stock markets. Rouwenhorse (1998) find a similar pattern of intermediate-horizon price momentum in 12 European countries in the period 1978 to 1995.[8] Antoniou et al. (2007) find that momentum trading strategies are profitable in all three major European markets, France, Germany and the UK between January 1977 and December 2002. Chui et al. (2000) examine momentum profits in eight Asian markets and their results indicate that momentum trading strategies are highly profitable when implemented on Asian stock markets outside Japan.[9] Griffin, J.M. et al. (2003) find momentum portfolio profits are large and positive in 40 countries in Africa, America, Asia and Europe. Muga and Santamaria (2007) find that momentum trading strategies yield profits in 4 Latin American emerging markets from Jan 1994 to Jan 2005.[10] Further, the momentum effect is also found in industry, stock market index level. Moskowitz and Grinblatt (1999) document strong and persistent industry the momentum effect in United State stock market from July 1963 to July 1995 and Chan et al. (2000) show that momentum trading strategies implemented on international stock market indices are profitable. Asness et al. (2013) find consistent momentum return premia across eight diverse markets and asset classes.[11]

On one hand, the momentum effect is found to be persistent in many markets over time; on the other hand, it is full of dynamics over time, which reflected by the large variation in performance of momentum trading strategies. Conrad and Kaul (1998) implement a wide spectrum of trading strategies during the 1926-1989 period using the entire sample of available NYSE/AMEX securities and they find that momentum trading strategies usually have profits that are net positive and frequently statically significant at medium horizon; however, it is not the case during the 1926-1947 period. Grundy and Martin (2001) point out that a

[8]These 12 European countries are Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden, Switzerland, the United Kingdom.
[9]These Asian markets include Hongkong, Indonesia, Japan, Korea, Malaysia, Singapore, Taiwan and Thailand.
[10]These 4 Latin American emerging markets are Argentina, Brazil, Chile and Mexico.
[11]These markets and asset classes include individual stocks in the United States, the United Kingdom, continental Europe, and Japan; country equity index futures; government bonds; currencies; and commodity futures.

momentum trading strategy that generate profits on average does not earn arbitrage profits, and it is far from riskless. They show that a momentum trading strategy initiated in November 1942 would have accumulated a profit of $5.98 from 0 initial investment over the 633 months through July 1995; in contrast, an investor who first entered the strategy in January 1991 and continued the strategy over the 55 months through July 1995 would have lost 58 cents. Chordia and Shivakumar (2002) replicate the momentum results based on all NYSE-AMEX stocks from 1926 to 1994 and find that their momentum trading strategy has a monthly payoff of 0.27%.[12] This figure is not found to be statistically significant and the reason is that momentum payoff is an insignificant -0.61% by the pre-1951 period. In the post-1951 period, the monthly payoffs are significantly positive, 0.83% for the period Jan 1951 to June 1963 and 0.73% for the period July 1963 to December 1994. Hwang and Rubesam (2013) investigate the robustness of the momentum premium in the US over the period from 1927 to 2010 using a model that allows multiple structural breaks and they find that the risk-adjusted momentum premium is significantly positive only during certain periods, notably from the 1940s to the mid-1960s and from the mid-1970s to the late 1990s, and they argue that momentum has disappeared since the late 1990s. Most recently, Daniel and Moskowitz (2011) as well as Barroso and Santa-Clara (2015) confirm the risk of momentum as they document that the remarkable performance of momentum comes with occasional large crashes and that the most expressive momentum crashes occurred as the market rebounded following large previous declines.

There are studies suggesting that the magnitude of the momentum effect depend on market conditions. Chordia and Shivakumar (2002) find that the momentum trading strategy payoffs are positive only for the expansionary periods of a business cycle during the sample period. Later, Cooper et al. (2004) document that momentum profits depend on the state of the stock market.[13] From 1929 through 1995 in the US stock market, the momentum trading strategy 6x6 generates a significant mean monthly profit of 0.93% after three-year UP markets and an insignificant −0.37% profit after three-year DOWN markets. In the light of the

[12]In their paper, momentum trading strategy 6x6 is discussed.
[13]Two states are defined as follows in their paper. “UP” is when the lagged three-year market return is non-negative and “Down” is when the lagged three-year market return is negative.

asymmetric momentum profits following UP versus DOWN markets found by Cooper et al. (2004), Asem and Tian (2010) document more interesting results from their empirical investigation of the effects of market reversals on momentum profits. According to their findings, following UP markets, momentum profits are higher when the markets continue in the UP state than when they transition to DOWN states; following DOWN markets, there are momentum profits when the markets continue in DOWN states and large momentum losses when markets transition to UP states. Daniel et al. (2012) find that momentum strategies incur periodic but infrequent large losses. During 13 of the 1002 months in their sample period from 1927 to 2010, losses to a US equity momentum strategy exceeded 20 percent per month. They further discover that each of the 13months with losses exceeding 20 percent per month occurs during a turbulent month and that there is a joint movement of momentum returns and market returns.

In summary, the momentum effect is not an exclusive financial phenomenon of any single market; instead, it exists globally regardless of different regulations and different culture. The momentum effect also display a rather dynamic behaviour. It is persistent however not fully stable over time as momentum strategies can occasionally suffer considerable losses.

2.2 Theoretical Explanations of the Momentum Effect and Momentum Profits

There are in general two categories of theoretical explanations regarding the momentum effect, namely, rational or risk-based explanations and behavioural explanations. In the risk-based framework, the difference in shares' realized returns is because these shares have different expected returns and higher expected return is associated with higher risks. Thus, the momentum effect is simply the result of winners being riskier than losers and momentum profits are rewards for taking risks. On the contrary of risk-oriented explanation that is based on assumption of rationality, behaviourists argue that the momentum effect reflects investors' behavioural bias that is associated with psychological heuristics, such as overconfidence, self-attribution, representativeness, and conservatism. It follows that information cannot be interpreted and acted upon in a "rational" way. Thus, profits are outcomes of the market mispricing. There has been intense debates over the causes of the momentum effect for the last two decades.

2.2.1 Rational Explanations of the Momentum Effect and Momentum Profits

One of the earliest rational explanations of the momentum effect is proposed by Conrad and Kaul (1998). They attempt to determine the sources of the expected profits of the trading strategies that are based on information contained in past returns of individual securities by decomposing the profits into two parts, one that results from time-series predictability in security returns and another that arises due to cross-sectional variation in the mean returns of the securities comprising the portfolio.[14] Their results based on an empirical decomposition of the profits of the strategies suggest that the cross-sectional variation in mean returns of individual securities is an important determinant of their profitability and thus they cannot reject the hypothesis that the in-sample cross sectional variation in mean returns can explain the profitability of momentum trading strategies. They argue that the actual profits to the trading strategies implemented based on past performance

[14]In their paper, they assume mean stationarity of the returns of individual securities during the period in which the strategies are implemented.

contain a cross-sectional component would arise even if stock prices are completely unpredictable and do follow random walks.

In order to more explicitly explain the relation between the cross section of expected returns and risks, Berk et al. (1999) provide a model and use it to develop an explanation for empirical financial findings, for example, the predictive power of book-to-market, size, or past returns, based on changes in firms' systematic risks through time. Their model relates changes in risk, represented by book-to-market, size, or past returns, to firm specific variables such as valuable investment opportunities and as firms exploit those opportunities, their systematic risk changes. According to Berk et al. (1999), expected returns in a given period are positively related the past expected returns, that it, momentum effect, because the composition and systematic risk of the firm's assets are persistent and they are negatively related to past expected returns, i.e., the contrarian effect, because shocks to the composition of the firm's assets are negatively correlated with changes in systematic risk. They also demonstrate by simulations that their model can reproduce the profitability of momentum trading strategies at different horizons.

Following Berk et al. (1999) but different from connecting momentum effect to the variation in systematic risk exposure over the life-cycle of a firm's chosen investment project, Johnson (2002) demonstrate a simple, standard model of firm cash-flow discounted by an ordinary pricing kernel with stochastic expected growth rates deliver a strong positive correlation between past realized returns and current expected returns. As the log of the curvature with respect to growth rate of equity prices is convex, this means growth rate risk rises with growth rates. By assuming that exposure to this risk carries a positive price, expected returns then rises with growth rates. In their model, the momentum effect exists because winners are more likely to have positive growth rate shocks than other firms, like losers, which are more likely to have negative growth shocks. Thus, Johnson (2002) argue that the momentum effect needs not imply investor irrationality, heterogeneous information, or market friction.

More recently, Sagi and Seasholes (2007) also argue in favour of rational explanations of return autocorrelation, including both the momentum and the contrarian effect. On the basis of previous literature that shows that functional relation between the microeconomics of a firm, such as firm value and cash flow variables, is an important determinant of conditional expected returns as in Berk et al. (1999) and Johnson (2002). Sagi and Seasholes (2007) attempt to identify proxies that are empirically relevant when determining firms that might exhibit positive return auto correlation and firms that might not. By running a numerical analysis of their model firm, they show that return autocorrelation is increasing in return volatility, decreasing in costs, and increasing in the market-to-book ratio. Further, by constructing a population of model firms, they demonstrate that momentum trading strategies carried out in high revenue volatility firms, low cost firms, and high market-to-book firms all produce greater profits than a traditional Jegadeesh and Titman (1993) strategy. More interestingly, their model firms exhibit higher momentum profits in up markets than they do in down markets, which is argued in favour of behavioural explanation by Cooper et al. (2004).

In short, in the rationalists' point of view, stocks with high realized returns will be those that have high expected returns and that stocks with low realized returns will be those that have low expected returns. The momentum trading strategy's profitability is a result of cross-sectional variability in expected returns. Since high expected returns are associated with high risks assuming rationality, their arguments imply that momentum profits are rewards for bearing extra risks.

2.2.2 Behavioural Explanations of the Momentum Effect and Momentum Profits

There are four well-known behavioural models that can generate the short-run momentum effect with three of them also generating long-run contrarian effect, although each of them focuses on different types of psychological heuristics.

Daniel et al. (1998) propose a theory of securities market under- and overreactions based on two well-known psychological biases: overconfidence and self-attribution.[15] In this model, investors tend to self-attribute and this behavioural bias causes asymmetric shifts in investors' confidence as a function of their investment outcomes. As a results of self-attribution, investors become overconfident with favourable investment outcomes. Daniel et al. (1998) assume that investors are overconfident about their private information, which leads to overreacting to private information signals and underreacting to public information signals. They show that overconfidence implies negative long-lag autocorrelations, excess volatility and biased self-attribution adds positive short-lag autocorrelations, that is, the momentum effect. Based on their model, Daniel et al. (1998) argue that short-run positive return autocorrelations can be results of under-reaction as well as continuing overreaction which results in long-run correction, the contrarian effect.

Barberis et al. (1998) propose a parsimonious model of investor sentiment based on behavioural heuristics including representative and conservatism.[16] In their model, the earnings of the asset follow a random walk. However, the investor does not know that. Rather, he believes that the behaviour of a given firm's earnings moves between two "regimes". In the first regime, earnings are mean-reverting. In the second regime, they trend, i.e., are likely to rise further after an increase. When a positive earnings surprise is followed by another positive surprise, the investor raises the likelihood that he is in the trending regime, whereas when a positive surprise is followed by a negative surprise, the investor raises the likelihood that he is in the mean-reverting regime. Barberis et al. (1998) show that, for a plausible range of parameter values, their model generates both the momentum and the contrarian effect. In this framework, conservatism suggests underreaction and representativeness gives rise to overreaction.

Hong and Stein (1999) build a behavioural model that features two types of agents, "newswatchers" and "momentum traders". There is no explicit assumption of

---

[15] Overconfidence is defined as underestimation of forecast errors. Self-attribution refers to the observation that individuals too strongly attribute events that confirm the validity of their actions to high ability and events that disconfirm the action to external noise or sabotage (Berm (1965)).

[16] Representativeness is the tendency of experimental subjects to view events as typical or representative of some specific class and to ignore the laws of probability in the process. For example, people think they see patterns in truly random sequences (Tversky and Kahneman (1974)). Conservatism is a heuristics of the slow updating of beliefs in the face of new evidence. (Edwards (1968))

psychological heuristics; however, both types of agents are assumed to be bounded rational in a sense that each of them is only able to process some subset of the available public information. More specifically, the newswatchers rely exclusively on their private information; momentum traders rely exclusively on the information in past price changes. The additional assumption is that private information diffuses only gradually through the marketplace, which, as Hong and Stein (1999) show, leads to an initial underreaction of newswatchers to news. The underreaction leaves opportunities for further future profits that momentum traders will arbitrage away. Hong and Stein (1999) go on and show that momentum traders' arbitrage does not leads to market efficiency and instead the fact that momentum traders only rely on price history leads to an eventual overreaction to any news. Prices revert to their fundamental levels in the long run.

Apart from the above three behavioural models, Grinblatt and Han (2005) construct a framework where the momentum effect can be generated based on one of the most well-documented regularities in the financial markets, that is, disposition effect (Shefrin and Statman (1985))-the tendency of investors to hold on to their losing stocks too long and sell their winners too soon. The tendency of some investors to hold on to their losing stocks, driven by prospect theory and mental accounting, creates a spread between a stock's fundamental value and its equilibrium price, as well as price underreaction to information. Spread convergence, arising from the random evolution of fundamental values and updating of reference prices, generates predictable equilibrium prices that will be interpreted as possessing momentum.

Compared with the rationalists' explanations of the nature of the momentum effect, the behaviourists' argument is that the positive short-term autocorrelation and the negative long-term autocorrelation in stock returns are caused by the market mispricing as investors consistently fail to fairly value assets with available information set due to their psychological bias. The momentum effect are in effect the outcome of investors' underreaction or (and) overreaction to news.

2.3 Empirical Research on the Explanatory Power of Risk Factors and Behavioural Models

The momentum effect remains a big challenge that needs to be fully explained. Fama and French (1996) find that Fama-French-three-factor model can explain financial anomalies such as the relation between average returns on stocks and size, earnings/price, cash flow/price, book-to-market equity, or long-term past returns but the momentum effect.[17] Since Fama and French (1996), there have been an increasing number of papers that aim to empirically examine the causes of the momentum effect and to test the explanatory power of both rational and behavioural theories. There have been some progress and a number of lagged variables, either being interpreted as risk factors or as evidence of market mispricing, are found to be able to predict the dynamics of the momentum effect to some extent.

2.3.1 Empirical Research in Favour of Rational Explanations

Risk factors that are found by some researchers to be able to explain the momentum effect can be classified as systematic risks that associated with macro-economy, such as risks represented by default spread, three-month T-bills and that associated with financial market, for example downside risk and systematic liquidity risk.

Chordia and Shivakumar (2002) argue that common macroeconomic variables that are related to the business cycle can explain the profits to momentum trading strategies. They find that returns to momentum trading strategies are positive only during expansionary periods of a business cycle and that during recessions, the momentum trading strategy returns are negative, though statistically insignificant. They suggest that momentum payoffs can be explained by rational pricing theories as they show that profits to momentum trading strategies are explained by a parsimonious set of macroeconomic variables that are related to the business cycle, and that these findings provide support for the time-varying expected returns as a

[17]The incompetency of Fama-French three-factor model in term of explaining the momentum effect is confirmed by many papers, such as Moskowitz and Grinblatt (1999); Liu, Strong, and Xu (1999); Lee and Swaminathan (2000); Grundy and Martin (2001).

plausible explanation for stock momentum.[18] Chordia and Shivakumar (2002) hence conclude that profitability of momentum trading strategies represents compensation for bearing time-varying risk and hence consistent with rational pricing theories.

Avramov and Chordia (2006) develop a framework that applies to single securities to test whether asset pricing models can explain financial anomalies including the momentum effect. In their model, stock level beta is allowed to vary with firm-level size and book-to-market as well as with macroeconomic variables. When beta is allowed to vary, the size and value effects are often explained, but the explanatory power of past return remains robust. However they argue that it may be premature to discard risk-based models to explain momentum and point to the possibility that there may exist a yet undiscovered risk factor related to the business cycle that may capture the impact of momentum on the cross-section of individual stock returns based on the results that when model mispricing is allowed to vary with business-cycle variables in the first-pass regression, then this variation captures the impact of momentum on returns. The point of view in Avramov and Chordia (2006) is shared by Antoniou et al. (2007) based on evidence from three major European stock markets, France, Germany and the UK. They show that an application of the predictive regression framework of Chordia and Shivakumar (2002) cannot capture momentum profits. However, when the conditional asset pricing model of Avramov and Chordia (2006) is applied, momentum profits are found to be related to model mispricing that varies with business cycle variables. Antoniou et al. (2007) hence argue that there are business cycle patterns within momentum profits, but not all risk factors that are responsible for momentum in stock returns are identified.

Inspired by the work of Chen et al. (1986), which suggests that macro-economic variables such as the spread between long and short interest rates, expected and unexpected inflation, industrial production, and the spread between high- and low-grade bonds are significantly priced in financial market as sources of risks, Liu and Lu (2008) find that the macroeconomic risk factor, the growth rate of industrial

[18]The parsimonious set of macroeconomic variables includes lagged dividend yield, default spread, yield on three-month T-bills and term structure spread.

production, explains more than half of momentum profits by showing that winners have temporarily higher loadings on the growth rate of industrial production than losers. Combined with evidence that suggests that the expected-growth risk is priced and that the expected-growth risk increases with the expected growth, they interpret these results as suggesting that risk is an important driver of momentum.

More recently, Kim (2012) use a two-state Markov switching model with time-varying transition probabilities to evaluate the empirical relevance of rational theories of momentum profits. They find that, in the recession state, loser stocks tend to have greater loadings on conditioning macro variables than winner stocks while in the expansion state winner stocks tend to have greater loadings on these variables. They argue that these findings indicate that returns on momentum portfolios react asymmetrically to aggregate economic conditions in recession and expansion states and that the asymmetries in winner and loser stocks' risk across the states of the economy leads to strong pro cyclical time-variations in the expected momentum profits. Kim (2012) hence name momentum profit "procyclicality premium".

Apart from macroeconomic risk factors, there are other risk factors found to be able to explain at least partially the momentum effect, including "downside risk" and systematic liquidity risk in returns. "Downside risk" is defined to be the risk that an asset's return is highly correlated with the market when the market is declining. Ang et al. (2001) follow the custom of constructing and adding factors to explain deviations from the Capital Asset Pricing Model (CAPM) and they find that the profitability of the momentum trading strategies is related to downside risk. Their results suggest that some portion of momentum profits can be attributed as compensation for exposures to downside risk. Past winner stocks have high returns, in part, because during periods when the market experiences downside moves, winner stocks move down more with the market than past loser stocks. Pastor and Stambaugh (2003) investigate whether expected returns are related to systematic liquidity risk in returns. Systematic liquidity risk is measured by the equally weighted average of the liquidity measures of individual stocks on the NYSE and AMEX. They find that expected stock returns are related cross-sectional to the sensitivities of returns to fluctuations in aggregated liquidity and that a liquidity risk factor accounts for half of the profits to a momentum trading strategy over period 1966 to 1999.

2.3.2 Empirical Research in Favour of Behavioural Explanations

Although there is an increasing amount of evidence that is argued to be in favour of rational explanations of the momentum effect, some studies find that it is not convincing and that behavioural expiations are more suitable. Some aspects of the momentum effect dynamics are found hard to reconcile with rational explanations, especially the long-run reversal of the momentum effect. For example, Conrad and Kaul (1998) predict that the post-formation returns of the momentum portfolio will be positive on average in any post-ranking period as they argue that the higher returns of winners in the holding period represent their unconditional expected rates of return. However, behavioural models proposed by Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1998) predict a reversal in returns in the long run.

Jegadeesh and Titman (2001) examine the long-term returns of the winner and loser stocks in the momentum portfolio in order to test the conflicting implications of behavioural explanations and rational explanations. Their results show that for the sample period of 1965 to 1997, momentum trading strategies generate losses in months 13 to 60, which verifies the prediction of behavioural models and reject hypothesis of Conrad and Kaul (1998). The reversal in the momentum effect over long horizons is also found by Lee and Swaminathan (2000) and many others.

Another argument of Conrad and Kaul (1998) that momentum profits arise due to cross-sectional variation in the mean returns is challenged by Grundy and Martin (2001) as they find that the momentum strategy's profitability reflect momentum in the stock-specific component of returns rather that cross-sectional component. This finding echoes many previous studies, such as in Bernad (1992), La Porta (1996) and Chan, Jegadeesh and Lakonishok (1996). Moreover, Grundy and Martin (2001) lend support to the behaviourists' view as they point out that, although the theoretical models of momentum due to Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999) do not distinguish between expectations based on firm-specific information and on factor-related information, they could be extended such that only revisions in the former component give rise to momentum.

Behavioural explanations are also supported by Lee and Swaminathan (2000). They find that past trading volume predicts both the magnitude and the persistence of future price momentum. Specifically, high (low) volume winners (losers) experience faster momentum reversals. Conditional on past volume, momentum portfolios can be created that either exhibit long-horizon return reversals or long-horizon return continuations. This evidence shows that the information contained in past trading volume can be useful in reconciling intermediate horizon "under-reaction" and long-horizon "overreaction" effect. They also show that trading volume as measured by the turnover ratio is unlikely to be a liquidity proxy and is not highly correlated with firm size or relative bid-ask spread and the volume effect is independent of firm size effect. Rather, they argue that their evidence shows that the information content of trading volume is related to market misperceptions of firms' future earnings prospects. The volume effect is later confirmed by Chui et al. (2000) and Glaser and Weber (2003). Chui et al. (2000) document the volume effect in five Asian countries and they also find that momentum implemented on international stock market indices is stronger following an increase in trading volume. Weber (2003) confirm this effect in German stock market.

Cooper et al. (2004) show that a multifactor macroeconomic model of returns in Chordia and Shivakumar (2002) does not explain momentum profits and that the ability of such a model to explain momentum profits is not robust to controls for market frictions. Additionally, they find that the macroeconomic model has little predictive power over the time-series of momentum profits out-of-sample. On the other hand, they find that implementing momentum trading strategy 6x6 in the US stock market this strategy generate significant profits after three-year UP markets and insignificant losses after three-year Down markets based on data from 1929 through 1995. More interestingly, there is significant long-run reversal following both UP and Down markets, which is in general consistent with the overreaction hypothesis.

Following the direction of the relationship between market state and the momentum effect, Asem and Tian (2010) add more evidence in favour of behavioural explanation by empirically investigating the effects of reversals in market state on momentum profits. According to their findings, following UP markets, momentum profits are higher when the markets continue in the UP state than when they transition to DOWN states; following DOWN markets, there are momentum profits when the markets continue in DOWN states and large momentum losses when markets transition to UP states. Although all three models, Daniel et al. (1998) and Hong and Stein (1998), Sagi and Seasholes (2007), provide explanations for the higher momentum profits following UP markets than following DOWN markets, the evidence following DOWN markets is more consistent with the Daniel et al. (1998) model than the other two models.

2.4 Post-Cost Profitability of Momentum Trading Strategies

According to empirical research results so far, no any measure of risks can fully explain momentum profits. Meantime, there are evidence building up that tends to interpret momentum profits as the outcome of market mispricing. Since there is no convincing explanations of the nature of the momentum, it is important to answer another question that is whether momentum profits are exploitable taking transaction costs into account. The answer to this question matters as it relates to another crucial assumption in conventional finance, which says arbitrage corrects any pricing error so that market efficiency is maintained. Shleifer and Vishny (1997) emphasize the importance of discussion on limit to arbitrage and they point out that while limits to arbitrage do not explain the underlying causes for the existence of seemingly profitable momentum trading strategies, they may be sufficient for their persistence. Therefore, if momentum strategies are not profitable net of transaction costs, stock markets can still be deemed as efficient and rationality remains a valid assumption. Rubinstein (2001) even coin the terminology, minimally rational, to describe a market where costs are sufficiently large and there might not really be any excess return available to investors. Although relevant studies draw different conclusion on the post-cost profitability of momentum trading strategies, they all point to the significance impact of transaction costs on the size of momentum profits. As far as the post-cost profitability of momentum strategies is concerned, the literature gives mixed answers.

Based on a 0.5% one-way transaction cost, Berkowitz et al. (1988) and Jegadeesh and Titman (1993) report that relative strength returns exceed trading costs, and they conclude that momentum trading strategies are profitable after transaction costs. Keim (2003), however, study the actual costs of momentum-based tradesand show that the returns reported in previous studies of simulated momentum trading strategies are not sufficient to cover the costs of implementing those strategies.[19]

[19]Keim (2003) examine the trade behaviour and the costs of those trades for three distinct investor styles including momentum for 33 institutional investment managers executing trades in the U.S. and 36 other equity markets worldwide in both developed and emerging economies.

Lesmond et.al (2004) question the trading cost figure applied by Berkowitz et al. (1988), and Jegadeesh and Titman (1993) and point out that their figure for transaction costs is very likely underestimated for three reasons. First, using a NYSE trade-weighted measure is inappropriate as a benchmark for a strategy dominated by small, off-NYSE, extreme performers since transaction costs exhibit substantial cross-sectional variation. Second, they argue that a constant or single period measure is unable to capture the substantial time-series variation in trading costs. Third, their figure understates the full transaction costs facing investors as it excludes a number of important costs of trading such as bid-ask spread, taxes, short-sale costs, and holding period risk. Lesmond et al. (2004) investigate post-cost profitability of momentum trading strategy 6x6 using all NYSE/AMEX stocks over a period from January 1980 to December 1998 employing earlier limited dependent variable (LDV) procedures and conclude that the delay in price adjustment for security returns simply reflects the costs of arbitrage--creating an illusion of anomalous price behaviour and momentum trading profit opportunity when, in fact, none exists.

However, there are also authors who suggest that momentum trading strategies are still profitable after transaction costs that are estimated by various advanced methods. Korajczyk and Sadka (2004) employ several trading cost models and investigate the effect of trading costs including price impact, on the profitability of taking long position of particular momentum trading strategies based on sample that consists of all stocks included in the CRSP monthly data files from February 1967 to December 1999.[20] In particular, they estimate the size of a momentum-based fund that could be achieved before abnormal returns are either statistically insignificant or driven to zero and find that the estimated excess returns of some momentum trading strategies disappear after an initial investment of $4.5 to over $5.0 billion is engaged by a single fund in such strategies. The statistical significance of these excess returns disappears after $1.1–$2.0 billion is engaged in such strategies. Therefore, they conclude that transaction costs, in the form of

[20]Among proportional Cost Models are Effective and Quoted Spreads; Non-proportional Cost Model I is proposed by Breen et al. (2002) and Non-proportional Cost Model II is recommended in Glosten and Harris (1988).

spreads and price impacts of trades, do not fully explain the return persistence of past winner stocks exhibited in the data.

Following the approach of estimating transaction costs proposed by Lesmond et al. (1999), Agyei-Ampomah (2007) examine the post-cost profitability of momentum trading strategies in the UK over the period 1988-2003 and find that after factoring out transaction costs the profitability of the momentum trading strategy disappears for shorter horizons but remains for longer horizons and similar conclusion can be drawn to the post-cost profitability of momentum trading strategies applied for a sub-sample of relatively large and liquid stocks. Momentum trading strategies' profitability net of transaction costs in the UK stock market is also found by Li et al. (2009) and Siganos (2010). Li et al. (2009) find that the momentum trading strategy can generate post-cost abnormal returns as long as investors follow a strategy of using low transaction cost shares. Based on actual turnover, low-cost relative-strength strategies that shortlist the 10% and 20% of winners and losers with the lowest total trading costs generate positive and significant net average returns of 18.24% and 15.84%, respectively. Siganos (2010) demonstrate that an investor who invests £20,000 among 20 winners and 20 losers gains 1.78% per month after adjusting for transaction costs including commissions, stamp duty, selling-short costs, and bid-ask spread and that a relatively large number of small investors can enjoy momentum gains.

By summing up current findings in the literature, we can see that the momentum effect is a persistent and dynamic financial phenomenon; however, its implications are still in debate. The dynamics of momentum can be predicted to some extent by a number of lagged variables, nevertheless, properties of different lagged variables are argued to be consistent with two conflicting explanations of the momentum effect, some being claimed to proxy risks and others to imply market mispricing. Although there is an agreement achieved that transaction costs reduce momentum profits significantly, some argue that there is still room to exploit and that momentum trading strategies can be adjusted to be post-cost profitable by either increasing their profitability or bringing down transaction costs. Apparently, there have been great achievements made by prior research that help to understand the momentum effect, but many questions remain unsettled and more efforts are certainly needed.

3. The Momentum Effect in the UK Stock Market 1979-2011

3.1 Introduction

In this chapter, we first update the research on the momentum effect in the UK stock market and then study its dynamics by investigating the performance of momentum trading strategies over time from 1979 to 2011. At the end of this chapter, we test the explanatory power of a set of conventional risk factors in the literature.

We implement a large number of momentum trading strategies on monthly basis in order to obtain information as much as possible. In total, there are 192 momentum trading strategies with the ranking period varying from 3 months to 24 months at 3-month interval and the holding period varying from 1 to 24 month at 1-month interval. To facilitate our study on the momentum effect dynamics, we split the whole sample period into three sub-sample periods based on the stability of the whole stock market, Jan1979-Dec1988, Jan1989-Dec1998, and Jan1999-Dec2011. This is very interesting as the first sub-sample period includes the big shock of the stock market crash of 1987 and the third one contains the burst of the dot-com Bubble in 2000, and the stock market crash of 2008. In contrast, the second sub-sample period is free of big market shocks. Our study has the following findings.

First of all, we verify the presence of the momentum effect in the UK stock market over the whole sample period as the majority of our momentum trading strategies are found to be significantly profitable with many strategies reaching the average annualized return above 10% at the significance level of 1%. The performances of some momentum trading strategies are rather persistent. For example, 82% of observations of the momentum trading strategy 3x10 are profitable. We also find that winner portfolios contribute to the momentum profits much more than loser portfolios. Thus, in our study, the momentum effect is reflected in winners' outperformance instead of losers' underperformance.

Secondly, we discover great variation in the magnitude of the momentum effect. We find that the sub-sample period from 1989 to 1998 experiences the strongest momentum effect whereas sub-sample periods from 1979 to 1988 and from 1999 to 2011 see relatively weak momentum effect. The dynamics of the momentum effect is assessed by two criteria, the size of momentum profits and the number of significantly profitable strategies, respectively. There are many momentum trading strategies that are able to generate annualized BHRs above 20% with the highest annualized BHR being 27% from1989 to 1998; in contrast, the highest annualized BHR achieved for the rest of the whole sample period is about 15%. Further, the majority of momentum trading strategies with the ranking period within 24 months are significantly profitable from1989 to 1998 compared with the fact that only momentum trading strategies with the ranking period within 12 months with a few exceptions are profitable from 1979 to 1988 and that momentum trading strategies with the ranking period shorter than 6 months make positive returns from 1999 to 2011. More interestingly, we find that the momentum effect is absent from time to time. Typically, momentum trading strategies suffer large losses almost simultaneously when the whole stock market is in turmoil.

Finally, we find that the conventional risk factors are not responsible for momentum profits as the CAPM model, the Fama-French-3-Factor (FF3F) model as well as the consumption based CAPM (C-CAPM) model do rather poorly. All risk-adjusted momentum returns are still significantly positive and there is little change in terms of their size. We also find little evidence in favour of the C-CAPM model as winners outperform losers regardless the market state.

The remainder of this chapter is structured as follows. Section 3.2 specifies our motivation. Section 3.3 describes the data, the sample selection criteria and the portfolio formation method. In Section 3.4, we demonstrate the empirical findings on the profitability of momentum trading strategies. We also study the dynamics of the momentum effect by investigating the performance of momentum trading strategies during period when market is experiencing dramatic shocks. Section 3.5 tests the explanatory power of conventional risks factors associated with the CAPM model, the FF3F model, and the C-CAPM model. Section 3.6 concludes this chapter.

3.2 Motivation

The momentum effect has been documented in the UK stock market by a number of papers; however, there is no update been made yet on the performance of momentum strategies after 2005. Data after 2005, which includes the 2008-2009 stock crash, could provide valuable information on the momentum effect in the UK stock market. Moreover, there are conflicting findings among studies regarding the dynamics and the proportion of contribution by winner and loser portfolios towards the momentum profits. Thus, reinvestigation is highly necessary. Finally, improvements could be made when it comes to the calculation method of stock returns and the treatment of delisted firms.

Hon and Tonks (2003) find that momentum trading strategies are profitable in the UK stock market from 1955 to 1996. Moreover, their findings suggest that the momentum effect is a much more significant feature of the UK stock market during the sub-period from Jan 1977 to Dec1996. For the sub-period of 1955 to 1976, only 3 out of their 48 momentum trading strategies that generate statistically significant profits, whereas from 1977 to 1996, the majority of their trading strategies are significantly profitable. Thus, they conclude that the momentum effect has become stronger over time. On the contrary of the conclusion made by Hon and Tonks (2003), Galariotis et al. (2007) find that their results indicate a decrease in this effect in the UK market as the number of profitable momentum trading strategies falls from 15 for the period of 1964 to 2005 to only 4 for the period of 1975 to 2005.

When it comes to the proportion of contribution to the momentum profits from winner and loser portfolios, conclusions are contradictory. Hon and Tonks (2003) find that winner portfolios contribute more than loser portfolios do to the profits earned by a self-financing momentum trading strategy on average. However, Agyei-Ampoman (2007) find that for the momentum trading strategy in their study, returns on the zero-investment momentum portfolios are largely driven by the negative returns of the loser portfolios. Siganos (2010) draw the same conclusion as Agyei-Ampoman (2007).

There is also an issue regarding the method of calculating ranking-period returns. A number of papers on the UK stock market, such as Clare and Thomas (1995), Hon and Tonks (2003), Galariotis et al. (2007) and Siganos (2010), use continuously compounded returns (CCR), which are calculated as the first difference in the log of end of month prices. However, as Dissanaike (1994) point out, CCR is not a precise measure of return. Instead, buy-and-hold return (BHR) should be used.[21] These two different calculations affect results of stock selection and hence lead to different constituents of portfolios.

Another concern is with delisted firms. Excluding firms with missing value(s) in the holding period as in Hon and Tonks (2003) and Clare and Thomas (1995) introduces survivorship bias. Boynton and Oppenheimer (2006) illustrate that the survivorship bias together with bid-ask spreads have a substantial effect on the size of both momentum and contrarian anomalies. Another issue with the delisting that needs to be taken care of is how to treat proceeds from delisting events. There are three treatments in the literature. The first one is simply to assign the missing monthly return to zero as in Agyei-Ampoman (2007). The other two methods are suggested in Dissanaike (1994) when using the BHR. The proceeds from stocks that are delisted after the portfolio formation can either be reinvested in the market portfolio, which is employed by Galariotis et al. (2007) or in the remaining stocks in the portfolio that is adopted by Arnold and Baker (2007).

[21]To see why this is unrealistic, Dissanaike (1994) gives an example. Consider a security which displays monthly prices of 100, 50, and 80. Using continuously compounded returns, the overall return would be equal to + l0%, but buy-and-hold return is equal to - 20%. The discrepancy is likely to be greater, the greater the volatility of the series. However, log returns are generally better behaved as they tend to be closer to normal distribution. That being said, using log returns are unlikely to make any qualitative change in our main findings.

3.3 Data and Momentum Portfolio Formation Method

3.3.1 Data

The monthly stock return data are obtained from the London Share Price Data (LSPD) for the period from January 1977 to December 2011. Since 1975, the LSPD has a complete history for all UK companies quoted in London. This study includes all firms listed on the London Stock Exchange (LSE) except odd foreign mining and banking shares, shares traded on the Unlisted Securities Market (USM), the Third Market companies, and the O.T.C. companies.[22] The AIM and the OFEX are also excluded. In total, there are 4939 firms for the whole sample period. The number of firms in each month ranges from 1105 to 2064. Fama-French-3-Factor, $R_{m,t} - R_{f,t}$ SMB and HML data are taken from Xfi Centre for Finance and Investment.[23]

3.3.2 Momentum Portfolio Formation Method

In order to investigate the momentum effect, we implement momentum trading strategies and assess their profitability. A number of momentum trading strategies JxK are formed and carried out on a monthly basis starting from the end of Jan 1979. J represents the number of months for the ranking period and K indicates the number of months for the holding period. In our study, J takes values varying from 3 to 24 at 3-month interval and K has 24 values, varying from 1 to 24 at interval of 1 month. As we implement various momentum strategies every month, we obtain monthly observations for each trading strategy; in other words, we adopt overlapping momentum strategies.

Following the conventional stock selection criteria for forming momentum portfolios, we require that firms in the sample have a complete record over the

[22]The LSPD includes all investment trusts (mutual funds) listed on London Stock Exchange, therefore, investment trusts are included in our study.

[23]Data are available at: http://businessschool.exeter.ac.uk/research/areas /centres /xfi/ research/ famafrench/files/

ranking period. Therefore, any firm that has any missing value(s) during the ranking period is not considered. However, unlike some previous studies that exclude firms with missing values during holding period, our study include these firms in the sample to avoid the survivorship bias.

To implement a momentum trading strategy JxK and to assess its performance, we carry out the following steps. Before the start of the first trading day of each month (t=0), all firms in the sample are ranked according to the buy-and-hold return (BHR) on the past J months. Eq. (3.1) and Eq. (3.2) illustrate the calculation.

$$BHR_{i,0} = \prod_{t=-1}^{-J} R_{i,t} \quad (3.1)$$

Where

$$R_{i,t} = (P_{i,t} + D_{i,t})/P_{i,t-1} \quad (3.2)$$

Then, all firms are ranked in ascending order based on BHRs and ten equal deciles are formed. The loser portfolio is made up of the firms in the top decile with equal weight and the winner portfolio consists of firms in the top decile with equal weight. The momentum trading strategy is to take short position in the loser portfolio and long position in the winner portfolio. A self-financing momentum portfolio is invested one month after its formation. One month is skipped between formation and holding periods to mitigate bid-ask bias and bias induced by infrequent trading.[24] It has been shown that failing to skip a month has a substantial impact on the number of strategies that offer statistically significant profits.[25]

During each holding period, there might be firms are delisted by the London Stock Exchange or cease to trade due to various reasons. In this case, we mainly follow Arnold and Baker (2007) to remedy this problem. A stock is regarded as losing all value in the delisting month if it death type described from the LSPD as liquidity, quotations cancelled for reasons unknown, received appointed/liquidation, in administration/administrative receivership, and cancelled assumed valueless. In

[24]A self-financing momentum portfolio, or a zero-cost momentum portfolio, takes long position using capital obtained from short position of the same value. For simplicity, self-financing momentum portfolios (strategies) are referred to as momentum portfolios (strategies).

[25]For example, Jegadeesh and Titman (1995), and Galariotis et al. (2007) show that profits can be overstated as a result of non-synchronous trading and the bid-ask spread in the stock market.

other words, the BHR on this stock is 0 since the date of the death event. For a firm with the other death types (e.g. acquisition, merger, suspension) during the holding period, the money received will be reinvested equally in the other shares in its portfolio and will rebalance monthly afterwards.

Finally, at the end of the last trading day of the K^{th} holding month, the self-financing trading strategy is closed and its BHR is calculated. As momentum trading strategies are defined as long in the prior winners and short in the prior losers, the BHR for each momentum trading strategy is calculated as in Eq. (3.3). The same procedure repeats every month. The size of each investment is scaled to be unit 1.

$$BHR_p = \frac{1}{n}\sum_{i=1}^{n}\prod_{t=1}^{K} R_{i,t,W} - \frac{1}{n}\sum_{i=1}^{n}\prod_{t=1}^{K} R_{i,t,L} \quad (3.3)$$

To illustrate the overlapping momentum strategy implementation, we take the momentum trading strategy 3x3as an example. The first formation takes place at 1st Jan 1979, all shares that meet the selection criteria without any missing value during Oct, Nov, and Dec in 1978 are sorted in ascending order according to their BHRs over these three calendar months. The top 10% performers form the loser portfolio and the bottom 10% performers form the winner portfolio with equal weight. At 31 Jan 1979, a short position is taken in the loser portfolio and a long position is taken in the winner portfolio, hence, a self-financing portfolio is carried out. This self-financing portfolio's performance is tracked for 3 months from 1^{st} Feb to 30^{th} Apr of 1979 and its BHR over the three months is calculated and recorded. By doing this, we obtain the first observation for the 3x3 momentum trading strategy. The second formation takes place at 1st Feb 1979, and the same procedure is followed to obtain the second observation. This formation is repeated every month until 1^{st} Sep 2011 and in total there are 392 observations for the 3x3 trading strategy.

3.4 Empirical Findings on the Profitability of Momentum Trading Strategies

3.4.1 Testable Hypotheses

In this section, we test if the momentum effect is a significant phenomenon in the UK stock market from 1979 to 2011. Following DeBondt and Thaler (1985), the hypothesis of market efficiency can be expressed in form of mathematics as in Eq. (3.4).

$$E\left(\tilde{R}_{Kt} - E_m\left(\tilde{R}_{Kt} \middle| F_{t-1}^m\right) \middle| F_{t-1}\right) = E(\tilde{u}_{Kt}|F_{t-1}) = 0 \quad (3.4)$$

K represents either winner stocks or loser stocks. $E_m\left(\tilde{R}_{Kt} \middle| F_{t-1}^m\right)$ is the expectation of returns on stocks $\tilde{R}_{Kt}$, assessed by the market on the basis of the information set F_{t-1}^m. F_{t-1} stands for complete set of information at time t-1. Accordingly, we have the following hypotheses.

The Null hypothesis of market efficiency is expressed as in Eq. (3.5).

$$E(\tilde{u}_{Kt}|F_{t-1}) = 0 \quad (3.5)$$

And the alternative hypothesis of the momentum effect can be expressed as in Eq. (3.6) or (and) in Eq. (3.7).

$$E(\tilde{u}_{Wt}|F_{t-1}) > 0 \quad (3.6)$$

$$E(\tilde{u}_{Lt}|F_{t-1}) < 0 \quad (3.7)$$

Where W stands for winner portfolio and L for Loser portfolio.

Using self-financing momentum trading strategy, we have the Null hypothesis of market efficiency as in Eq. (3.8).

$$E(\tilde{u}_{Wt}|F_{t-1}) - E(\tilde{u}_{Lt}|F_{t-1}) = 0 \quad (3.8)$$

And the alternative hypothesis of the momentum effect as in Eq. (3.9).

$$E(\tilde{u}_{Wt}|F_{t-1}) - E(\tilde{u}_{Lt}|F_{t-1}) > 0 \quad (3.9)$$

Since we implement overlapping momentum trading strategies, each trading strategy's monthly return time series are likely to suffer serial correlation. To remedy this problem, we employ Newey-West (1987, 1994) heteroskedasticity-and-autocorrelation-consistent (HAC) estimator to estimate variances of BHRs.[26]

3.4.2 Profitability of Momentum Trading Strategies and Significance of the Momentum Effect

In this section, we are going to test hypotheses described by Eq. (3.8) and Eq. (3.9). If Eq. (3.8) holds, then there should not have any momentum trading strategy that can make significant profits; on the other hand, if there are momentum trading strategies that generate significant profits, then the null hypothesis (3.8) will not be accepted and in this case, the momentum effect is favoured. We are also going to discuss the performance of winner and loser portfolios and hence to test hypotheses described in Eq. (3.6) and Eq. (3.7). As long as there exist winner (loser) portfolios of a momentum trading strategy that generate significant positive (negative) return net of market return, then again we argue that the momentum effect exists in the UK market during the sample period.[27]

[26]Toolbox "sandwich" recommended in Zeileis (2004) is applied. The "lag" value is set equal to the number of months in ranking period of the momentum strategy under study. It is reasonable under the assumption that performances of non-overlapping momentum portfolios are independent. We conjecture that if there is autocorrelation between performances of two adjacent momentum portfolios, the occurrence of the autocorrelation is mostly likely due to the fact that two adjacent portfolios consist of a number of same stocks, which is the direct result of overlapped ranking periods. Tests are also conducted with "lag" values set automatically by the toolbox "sandwich" and results do not change our conclusion of significant momentum profits in the UK stock market.

[27]Here, winner and loser portfolios are assumed to have expected return that equal the expected market return. It is a reasonable assumption as in our study both winner and loser contains 10% of the whole shares in the market, they are fairly diversified. Under Efficient Market Hypothesis, both portfolios should replicate the whole market.

3.4.2.1 Performances of Self-Financing Momentum Trading Strategies

The performances of 192 self-financing momentum trading strategies are tabulated in Table 3-1 and the results clearly indicate rather strong momentum effect in the UK stock market from 1979 to 2011 as a large number of momentum trading strategies generate statistically significant profits during this time period. According to Table 3-1A, in total there are 91 out of 192 momentum trading strategies generate significant profits over the whole sample period at the significance level of 1%.[28] It is striking to see that all momentum strategies with ranking periods of 3 months, 6 months, and 9 months generate positive BHRs for any length of holding time within 24 months, with all of them generating profits at the significance level of 1% except two trading strategies, 9x23, which generate profits at the significance level of 5% and 9x24 at the significance level of 10%. Holding momentum portfolios with 12-month ranking period up to 14 months also gains positive BHR at the significance level of 1%, and profits from trading strategies of 12xK, K=15, 16, 17, are significant at the level of 5%. Table 3-1B reports annualized BHRs across various momentum trading strategies and the profitability of different momentum trading strategies can be compared easily. Apparently, the momentum trading strategy 9x4 is the most profitable trading strategy with an annualized return of 18%, which is followed by the 6x3 trading strategy that generates an annualized return of 17%. Momentum trading strategies that achieve an annualized return above 10% are 3xK and 6xK with K in the range of 1 to 12, 9xK with K=1 to 9, and 12xK with K=1 to 6.

Further evidence in favour of the momentum effect is that momentum trading strategies have rather reliable performances over time. We use the ratio of profitable observations to the total observations to measure the performance reliability for each momentum trading strategy. Table 3-2 shows that most profitable momentum trading strategies have rather reliable performances. All momentum trading strategies JxK in our study have ratios above 60%, and most of them, except when J=15 or K=1, have ratios above 70%. The most reliable

[28] To reduce the probability of type I error, 1% significance level is used to make statistic inference on the profitability of momentum strategies. We will only report results for momentum trading strategies that generate profits at the significance level of 1% for the rest of this chapter.

momentum trading strategy is 3x10, of which, 82% of observations are profits and the momentum trading strategy 3x1 have the least reliable performance with ratio of 62%.

Apart from the evidence in favour of the momentum effect in the UK stock market, we confirm that the momentum effect exist only in short term. First, as shown in Table 3-1A, when the ranking period exceeds 12 months, the profitability of momentum trading strategies weakens dramatically. Among 24 trading strategies with the 15-month ranking period, only 7 generate profits at the significant level of 1% and 4 at the significant level of 5%. Among 24 trading strategies with the 18-month ranking period, only 18x4 trading strategy generates significant profits at the significant level of 1%. When the ranking period extends beyond 18 months, no momentum trading strategy is profitable at the significance level of 1%. Second, all momentum trading strategies reach their highest BHRs within one year after the formation and profits start to decline afterwards. For example, the momentum trading strategy with 3-month ranking period achieves the best BHR of 11% 11 months after formation and the momentum trading strategy with 15-month ranking period reaches the best BHR, 4%, after 7-month holding period. This feature is clearer when using annualized BHRs. It is apparent that the annualized BHRs of all momentum trading strategies reach their highest levels within 12 months and then fade as shown in Table 3-1B.

Consistent with the findings in Jegadeesh and Titman (2001) and many others, we also find the reversal in the momentum effect. Table 3-1B shows that the annualized BHRs of momentum trading strategies decline after about 12 months, and that in some cases, the annualized BHRs become negative. For example, holding a self-financing momentum portfolio with 9 months ranking period for 4 months gains an average annualized BHR of 18%; however, holding it for 24 month only achieves an average annualized BHR of 2%. Another observation that confirms this reversal pattern is momentum portfolios formed on the basis of the BHR over the 15-month ranking period. Holding this portfolio for 3 month generates an average annualized BHR of 10% and holding it for 24 month generates an average annualized BHR of -2%..

Since nearly half of momentum strategies in our study are profitable at the significance level of 1%, we can comfortably conclude that our findings are in favour of the alternative hypothesis expressed in Eq. (3.9) instead of the null hypothesis in Eq. (3.8).

3.4.2.2 Performances of Long and Short Positions of Momentum Trading Strategies

We now test the significance of the momentum effect expressed in Eq. (3.5) and Eq. (3.6) by looking at the performances of long and short positions of momentum trading strategies relative to the whole UK stock market's performances. Again, results confirm the momentum effect as taking long positions of many momentum trading strategies significantly outperforms the market although there is no evidence of losers significantly underperforming the market. In other words, our findings support Eq. (3.6). It follows that profits of the momentum trading strategies are mainly contributed by winners instead of losers, which is consistent with the findings in Hon and Tonks (2003).

Table 3-3 shows that winner portfolios of all momentum trading strategies in study universally outperform the stock market.[29] Excess returns of all winner portfolios reported are significant at the significance level of 1%. Most winner portfolios offer annualized market-adjusted BHRs above 10%. Winners of the 9x4 trading strategy offer the biggest excess return above the market return. Its annualized market-adjusted return is 13%. On the contrary of the winner portfolios' significant outperformance relative to the market, loser portfolios underperform the market in some cases although results are not statistically significant. The significance of the

[29] As momentum portfolios are equally-weighted, equally-weighted market portfolios are formed for the performance comparison. Equally-weighted market returns are calculated based on FTA total returns taken from LSPD and the market-adjusted buy-and-hold return for a portfolio is calculated according to the following formula, where $p = W, L$, and $R_{t,M}$ represents the monthly market return.

$$BHR_p^{m\_adj} = \frac{1}{n}\sum_{i=1}^{n}\prod_{t=1}^{K} R_{i,t,p} - \prod_{t=1}^{K} R_{t,M}$$

outperformance of winner portfolios alone provides sufficient evidence that leads to the rejection of the null hypothesis expressed in Eq. (3.5) at the significance level of 1%.

Based on findings in Section 3.4.2, we can conclude that the momentum effect is present in the UK stock market from 1979 to 2011. In line with the literature, it is a short-term phenomenon as the profits of profitable momentum trading strategies fade after 12 months. We also document the reversal in the momentum as momentum trading strategies generate losses after held for a certain period of time. This is important as the reversal in the momentum effect is regarded as the big challenge for rational explanations and it is consistent with the predication of behavioural models. Further, the momentum effect in our study is mainly reflected by the outperformance of winner portfolios instead of the underperformance of loser portfolios relative to the whole stock market.

Table 3-1. Buy-and-Hold Returns of Momentum Trading Strategies

A self -financing momentum trading strategy JxK is formed by ranking all stocks in the descending order based on their Buy-and-Hold return from time t-J to t-1. The top decile forms the winner portfolio with equal weight and the bottom decile forms the loser portfolio with equal weight. At time t+1 (skipping month t), the self-financing momentum portfolio, shorting the loser portfolio and longing winner portfolio, is invested and is held for K months for t+1 to t+K. Such momentum trading strategy carries out every month from Jan 1979 (forms at the beginning of Jan 1979 and is invested at the beginning of Feb 1979) till K+1 months before Dec 2011. In total, there are 395-k observations for the JxK momentum trading strategy. Table 1A reports the average BHRs of the 395-k observations and t-values.

A. Buy-and-Hold Returns

J	K											
	1M	**2M**	**3M**	**4M**	**5M**	**6M**	**7M**	**8M**	**9M**	**10M**	**11M**	**12M**
3M	0.01	0.02	0.04	0.05	0.06	0.07	0.08	0.09	0.10	0.10	0.11	0.11
t-value	3.56	5.85	7.07	8.10	8.83	8.75	8.74	8.82	9.06	9.03	9.10	8.53
6M	0.01	0.03	0.04	0.06	0.07	0.08	0.09	0.10	0.11	0.11	0.11	0.10
t-value	3.60	5.78	7.08	7.60	7.64	7.72	8.05	8.37	8.41	8.12	7.64	6.98
9M	0.01	0.03	0.04	0.06	0.07	0.08	0.09	0.09	0.09	0.09	0.09	0.08
t-value	3.17	5.04	6.54	7.30	7.41	7.24	7.26	7.02	6.64	6.12	5.76	5.14
12M	0.01	0.03	0.04	0.05	0.05	0.06	0.06	0.06	0.06	0.06	0.06	0.05
t-value	3.28	4.83	5.69	5.91	5.66	5.26	5.07	4.80	4.45	4.01	3.74	3.35
15M	0.01	0.02	0.03	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03
t-value	1.77	3.18	3.67	3.84	3.56	3.23	3.06	2.78	2.55	2.40	2.28	2.05
18M	0.00	0.01	0.02	0.02	0.02	0.03	0.03	0.03	0.02	0.02	0.02	0.01
t-value	1.08	2.18	2.57	2.65	2.44	2.28	2.16	2.11	1.84	1.59	1.35	0.85
21M	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.00	-0.01	-0.02
t-value	-0.20	0.93	1.44	1.49	1.43	1.30	1.08	0.76	0.39	-0.08	-0.46	-1.08
24M	0.00	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.00	-0.01	-0.01	-0.02
t-value	0.64	1.88	2.20	2.07	1.76	1.39	0.90	0.53	0.03	-0.39	-0.71	-1.17

A. Buy-and-Hold Returns

(Continued from the previous page)

J	K											
	13M	**14M**	**15M**	**16M**	**17M**	**18M**	**19M**	**20M**	**21M**	**22M**	**23M**	**24M**
3M	0.10	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.09	0.10	0.10	0.10
t-value	7.91	6.71	5.79	5.46	5.63	5.73	5.62	5.45	5.48	5.75	5.88	5.79
6M	0.10	0.09	0.09	0.08	0.08	0.09	0.09	0.09	0.09	0.09	0.09	0.09
t-value	6.32	5.68	5.03	4.69	4.71	4.90	5.03	5.00	5.08	4.81	4.58	4.19
9M	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.06	0.06	0.05	0.04	0.04
t-value	4.56	4.00	3.76	3.72	3.66	3.70	3.56	3.33	3.06	2.55	2.11	1.68
12M	0.05	0.05	0.04	0.04	0.04	0.03	0.03	0.02	0.01	0.01	0.00	-0.01
t-value	3.01	2.70	2.50	2.22	2.06	1.92	1.52	1.18	0.74	0.34	0.04	-0.26
15M	0.03	0.02	0.02	0.01	0.00	-0.01	-0.01	-0.02	-0.02	-0.03	-0.03	-0.04
t-value	1.65	1.26	0.95	0.49	0.05	-0.31	-0.59	-0.88	-1.00	-1.27	-1.47	-1.84
18M	0.00	-0.01	-0.01	-0.02	-0.03	-0.03	-0.03	-0.04	-0.04	-0.05	-0.06	-0.07
t-value	0.25	-0.30	-0.79	-1.25	-1.58	-1.77	-1.94	-2.21	-2.43	-2.70	-2.94	-3.34
21M	-0.03	-0.03	-0.04	-0.05	-0.05	-0.05	-0.06	-0.06	-0.07	-0.07	-0.08	-0.09
t-value	-1.61	-2.03	-2.36	-2.62	-2.85	-3.01	-3.16	-3.35	-3.56	-3.83	-4.11	-4.48
24M	-0.02	-0.03	-0.04	-0.05	-0.05	-0.05	-0.06	-0.07	-0.07	-0.08	-0.09	-0.10
t-value	-1.52	-1.95	-2.28	-2.65	-2.88	-3.12	-3.50	-3.83	-4.14	-4.46	-4.81	-5.22

J= ranking period; K=holding period

Note: two-tailed tests are applied to examine the significance of BHRs. Critical values corresponding to the significance level of 1%, 5%, and 10% are 2.576, 1.96 1.645 respectively.

B. Annualized Buy-and-Hold Returns of Momentum Trading Strategies

The annualized average BHR is calculated using the conversion formula$((1 + BHR)^{1/k} - 1) * 12$.

J	K											
	1M	**2M**	**3M**	**4M**	**5M**	**6M**	**7M**	**8M**	**9M**	**10M**	**11M**	**12M**
3M	0.11	0.14	0.15	0.15	0.15	0.14	0.14	0.13	0.13	0.13	0.13	0.11
6M	0.13	0.17	0.17	0.17	0.17	0.16	0.16	0.16	0.15	0.14	0.12	0.11
9M	0.12	0.16	0.17	0.18	0.17	0.16	0.15	0.14	0.12	0.11	0.10	0.08
12M	0.13	0.15	0.15	0.14	0.13	0.12	0.11	0.10	0.08	0.07	0.06	0.05
15M	0.07	0.10	0.10	0.09	0.09	0.08	0.07	0.05	0.05	0.04	0.04	0.03
18M	0.05	0.07	0.07	0.06	0.06	0.05	0.05	0.04	0.03	0.03	0.02	0.01
21M	-0.01	0.03	0.04	0.03	0.03	0.03	0.02	0.01	0.01	0.00	-0.01	-0.02
24M	0.02	0.06	0.06	0.05	0.04	0.03	0.02	0.01	0.00	-0.01	-0.01	-0.02
	13M	**14M**	**15M**	**16M**	**17M**	**18M**	**19M**	**20M**	**21M**	**22M**	**23M**	**24M**
3M	0.10	0.08	0.07	0.07	0.06	0.06	0.06	0.05	0.05	0.05	0.05	0.05
6M	0.09	0.08	0.07	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05
9M	0.07	0.06	0.05	0.05	0.05	0.05	0.04	0.04	0.03	0.03	0.02	0.02
12M	0.05	0.04	0.04	0.03	0.03	0.02	0.02	0.01	0.01	0.00	0.00	0.00
15M	0.03	0.02	0.01	0.01	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02
18M	0.00	0.00	-0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.03	-0.03
21M	-0.02	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03	-0.04	-0.04	-0.04	-0.04	-0.04
24M	-0.02	-0.03	-0.03	-0.03	-0.03	-0.03	-0.04	-0.04	-0.04	-0.04	-0.04	-0.05

J= ranking period; K=holding period

Table 3-2. Performance Reliability of Momentum Trading Strategies

The reliability of the JxK momentum trading strategy is measured by the percentage of the number of the profitable observations to the number of the total observations, 395-K, of the JxK trading strategy. A profitable observation of the JxK trading strategy occurs when a self-financing portfolio that is formed based on the previous J-month buy-and-hold return generates positive return after being held for K months.

	K											
	1M	**2M**	**3M**	**4M**	**5M**	**6M**	**7M**	**8M**	**9M**	**10M**	**11M**	**12M**
	No. of Observations:											
J	394	393	392	391	390	389	388	387	386	385	384	383
	% of Profitable Observations											
3M	62%	74%	74%	77%	78%	79%	81%	80%	81%	82%	81%	80%
6M	66%	73%	76%	80%	80%	79%	79%	80%	81%	80%	78%	77%
9M	64%	73%	75%	75%	77%	77%	76%	78%	77%	76%	76%	76%
12M	69%	72%	72%	74%	74%	74%	74%	74%	72%	72%	70%	72%

J= ranking period; K=holding period
Note: Only results for momentum trading strategies with profits being significant at the significance level of 1% are tabulated.

Table 3-3. Market-Adjusted Performances of Loser and Winner Portfolios

The market-adjusted buy-and-hold return for a portfolio is calculated according to the following formula, $BHR_p^{m\_adj} = \frac{1}{n}\sum_{i=1}^{n}\prod_{t=1}^{K} R_{i,t,p} - \prod_{t=1}^{K} R_{t,M}$ where $p = W, L$ and represents the winner portfolio and the loser portfolio respectively; $R_{t,M}$ represents the monthly market return. The market returns are calculated based on FTA total returns taken from the LSPD. Figures reported below are annualized market-adjusted BHRs of the loser and the winner portfolio for each momentum trading strategy.

	K											
J	**1M**	**2M**	**3M**	**4M**	**5M**	**6M**	**7M**	**8M**	**9M**	**10M**	**11M**	**12M**
3M-L	-0.01	-0.04	-0.04	-0.04	-0.04	-0.03	-0.03	-0.02	-0.02	-0.01	0.00	0.00
T-value	-0.40	-1.58	-1.84	-2.03	-1.93	-1.67	-1.46	-1.24	-1.01	-0.65	-0.31	0.22
3M-W	0.10	0.10	0.10	0.10	0.11	0.10	0.10	0.10	0.11	0.11	0.11	0.11
T-value	3.95	5.03	6.18	7.09	7.97	8.30	8.49	8.88	9.40	9.86	10.18	10.18
6M-L	0	-0.04	-0.05	-0.04	-0.04	-0.03	-0.03	-0.02	-0.01	0.00	0.00	0.01
T-value	-0.10	-1.42	-1.91	-1.90	-1.72	-1.49	-1.33	-1.06	-0.75	-0.26	0.26	0.77
6M-W	0.13	0.13	0.12	0.12	0.12	0.12	0.12	0.13	0.12	0.12	0.12	0.11
T-value	5.61	6.85	7.73	8.39	9.20	10.12	10.48	10.96	11.15	11.32	11.48	11.57
9M-L	0.00	-0.04	-0.04	-0.04	-0.03	-0.03	-0.02	-0.01	0.00	0.01	0.02	0.02
T-value	-0.05	-1.15	-1.61	-1.73	-1.55	-1.24	-0.99	-0.56	-0.06	0.48	0.92	1.41
9M-W	0.12	0.12	0.13	0.13	0.13	0.13	0.12	0.12	0.11	0.11	0.11	0.10
T-value	5.13	6.63	8.20	8.90	9.79	10.30	10.64	10.78	10.75	10.63	10.70	10.51
12M-L	0.00	-0.02	-0.02	-0.02	-0.01	0.00	0.01	0.01	0.02	0.03	0.03	0.04
T-value	0.15	-0.59	-0.81	-0.74	-0.46	-0.09	0.23	0.67	1.11	1.55	1.85	2.21
12M-W	0.13	0.13	0.13	0.12	0.12	0.11	0.11	0.10	0.10	0.09	0.09	0.09
T-value	-	7.24	8.13	8.44	9.01	9.28	9.39	9.40	-	-	-	-

J= ranking period; K=holding period

Note: two-tailed tests are applied to examine the significance of BHRs. Critical values corresponding to the significance level of 1%, 5%, and 10% are 2.576, 1.96 and 1.645 respectively. Only results for momentum trading strategies with holding period not greater than 12 months and profits being significant at the significance level of 1% are tabulated as momentum does not last more than 12 months according to the results in Table 3-1.

3.4.3 Dynamics of the Momentum Effect

As Section 3.4.2 confirms the momentum effect in the UK stock market, we are now to investigate its dynamics. The prior literature shows that its magnitude varies from time to time and we have conflicting results regarding the direction of the change in the magnitude of the momentum effect in the UK stock market as Hon and Tonks (2003) conclude that it has become stronger whereas Galariotis et al. (2007) find it has weakened from 1960s to 1990s. The dynamics of the momentum effect is discussed from two perspectives. First, we analyse behaviours of individual momentum trading strategies in terms of variation in their profitability over the whole sample period. Second, we examine the performances of all momentum trading strategies for three sub-sample periods, Jan1979 to Dec1988, Jan1989 to Dec1998, and Jan1999 to Dec2011. This is very interesting as the first sub-sample period includes the big shock of the stock market crash of 1987 and the third one contains the burst of the Dot-Com Bubble in 2000, and the stock market crash of 2008. In contrast, the second sub test period is free of big market shocks.

3.4.3.1 Dynamic Performances of Individual Momentum Trading Strategies

The performances of two momentum trading strategies 3x10 and 9x4 are taken as examples for the purpose of discussion for the reason that these two momentum trading strategies catch the momentum effect the best during the sample period as the momentum trading strategy 3x10 is the most reliable strategy in terms of the percentage of profitable observations and the momentum trading strategy 9x4 is the most profitable strategy in terms of the annualized BHR. The performances of these two strategies from 1979 to 2011 are presented in Figure 3-1, where each bar represents the BHR of the corresponding strategy implemented at that point of time indicated by the horizontal axis.

Apparently, Figure 3-1 shows that these two trading strategies share a lot of similarities in terms of the performance dynamics over time even though they have very different ranking periods and holding periods.[30] First observation is that both strategies generate profits most time; however, there are occasions when both strategies suffer losses. Second feature is that the magnitude of profits and losses varies largely from time to time. For example, the momentum strategy 3x10 can generate 10-month BHRs of more than 50% and it can also generates 10-month BHRs that are just slightly above 0. Similar conclusion applies to the magnitude of losses. Further, it is striking to see that they almost always make losses at the same point in time and more importantly, the occasions when both make sizable losses are when the stock market is in crisis. The most extreme example is the stock crash of 2008 to 2009 when both momentum trading strategies suffer substantial losses.

The analysis based on individual momentum strategies provide us distinguishable observations that other studies can't. When considering profitable cases only, there is no evidence that the momentum effect either weakening or strengthening over time. These patterns displayed in Figure 3-1 indeed demonstrate both the resilient side and the uncertain side of the momentum effect.

3.4.3.2 Performances of Momentum Trading Strategies during Three Sub-Sample Periods

We further discuss the dynamics of the momentum with respect to the change in the number of profitable momentum strategies and the size of the momentum profits for three sub-sample periods of Jan1979 to Dec1988, Jan1989 to Dec1998, and Jan1999 to Dec2011. As mentioned before, the first sub-sample period includes the big shock of the Stock Market Crash of 1987, the third one contains the Burst of Dot-com Bubble in 2000, and the Stock Market Crash of 2008, and the second sub-sample period can be considered as shock-free period. Therefore, this division can help to shed a light on the impact of the stock market crisis or shocks on the momentum effect. Results are shown in Table 3-4 and they suggest large variation in the magnitude of the momentum effect over time in terms of the number of significant profitable trading strategies and the size of profits generated

[30]The other momentum trading strategies also show similar pattern and their figures are available in Appendix.

by these profitable trading strategies. It appears that the momentum effect is most profound in the sub-sample period of Jan1989 to Dec1998 judged by both criteria. For sub-sample period, Jan1979 to Dec1988, 44 momentum trading strategies can make significant profits and the number increases dramatically to 131 during Jan1989 to Dec1998, then falls substantially to only 13 during Jan1999 to Dec2011. The sub-sample period of Jan1989 to Dec1998 not only has the most profitable momentum trading strategies but also enjoys the highest profits. For example, the momentum strategy 9x4 generates an average annualized BHR of 27%. In contrast, the highest average annualized BHRs that momentum strategies can achieve for Jan1979 to Dec1988 and Jan1999 to Dec2011 are 15%.

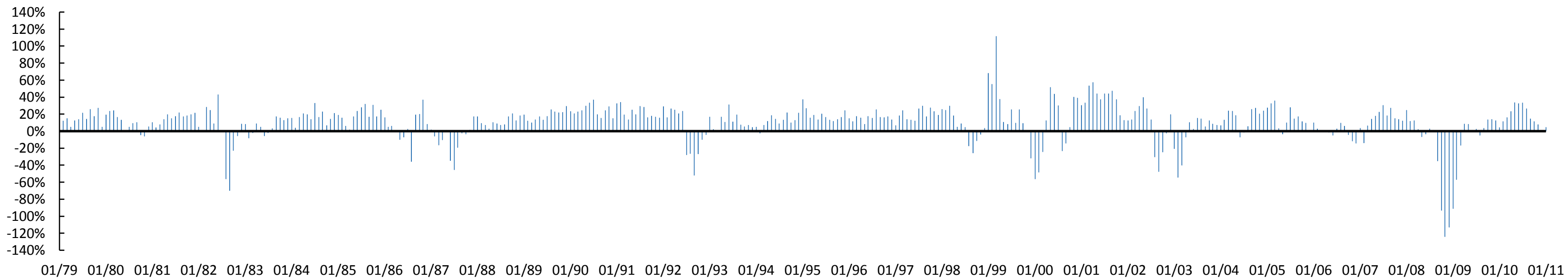
Our findings in Section 3.4.3 present a clear picture of the dynamics of the momentum effect in the UK stock market from 1979 to 2011. We find that the momentum effect does not become stronger or weaker in a monotonic fashion and that it is relatively strong and consistent when the market is stable and relatively weak and short-lived during time when market is volatile. Based on these observations, we may conclude that the dynamics of the momentum effect is associated with the stability of the whole stock market.[31]

[31]At the same time when we document this correlation between momentum effect dynamics and the stock market stability. Daniel et al. (2012) report that there are 13 months that their momentum strategy generates losses exceeding 20% per month in the sample of 978 months from 1929 to 2010 in the US stock market and that all the13 months with losses exceeding 20%/month occur during turbulent months.

Figure3-1. Performances of Momentum Trading Strategies
(J=3, K=10 and J=9, K=4)

These two figures show the performances of the most reliable and the most profitable momentum trading strategy, 3x10 and 9x4, respectively, for each month during Jan 1979 to Dec 2011 in the UK stock market. Each bar measures the return of holding the self-financing portfolio formed in that month based on stocks' performances' in the past J months for K months.

Momentum trading strategy 3x10



Momentum trading strategy 9x4

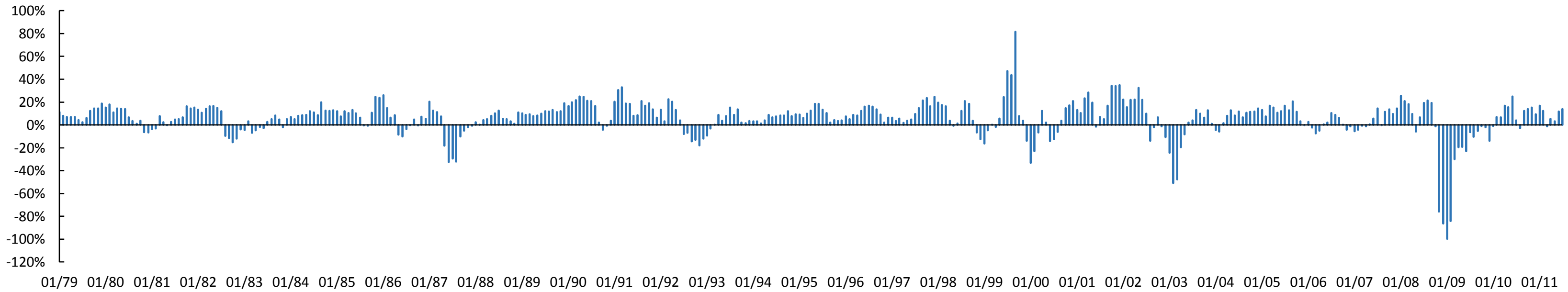


Table 3-4. Dynamics of the Momentum Effect in the UK Stock Market

The sample period between Jan 1978 and Dec 2011 is divided into three sub-sample (sub-test) periods, Jan1979-Dec1988, Jan1989-Dec1998, and Jan1999-Dec2011. Panel A, Panel B and Panel C tabulate annualized BHRs for momentum trading strategies that generate profits at the significance level of 1% for the three sub-sample periods.

Panel A: : Annualized BHRs during Jan1979-Dec1988												
J	**K**											
	1M	**2M**	**3M**	**4M**	**5M**	**6M**	**7M**	**8M**	**9M**	**10M**	**11M**	**12M**
3M	-	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.11	0.10	0.09	0.08
6M	-	0.12	0.13	0.13	0.13	0.14	0.13	0.13	0.12	0.10	0.09	0.07
9M	0.12	0.13	0.15	0.15	0.15	0.14	0.13	0.12	0.10	0.08	0.06	-
12M	0.13	0.13	0.12	0.11	0.10	0.09	0.08	0.07	-	-	-	-
15M	-	-	-	-	-	-	-	-	-	-	-	-
18M	-	-	-	-	-	-	-	-	-	-	-	-
21M	-	-	-	-	-	-	-	-	-	-	-	-
24M	-	-	-	-	-	-	-	-	-	-	-	-
	13M	**14M**	**15M**	**16M**	**17M**	**18M**	**19M**	**20M**	**21M**	**22M**	**23M**	**24M**
3M	0.07	0.05	-	-	-	-	-	-	-	-	-	-
6M	0.06	-	-	-	-	-	-	-	-	-	-	-
9M	-	-	-	-	-	-	-	-	-	-	-	-
12M	-	-	-	-	-	-	-	-	-	-	-	-
15M	-	-	-	-	-	-	-	-	-	-	-	-
18M	-	-	-	-	-	-	-	-	-	-	-	-
21M	-	-	-	-	-	-	-	-	-	-	-	-
24M	-	-	-	-	-	-	-	-	-	-	-	-

J= ranking period; K=holding period

(Table 3-4 is continued on the next page)

Table 3-4. Dynamics of the Momentum Effect in the UK Stock Market
(Continued from the previous page)

Panel B: Annualized BHRs during Jan1989-Dec1998												
J	**K**											
	1M	**2M**	**3M**	**4M**	**5M**	**6M**	**7M**	**8M**	**9M**	**10M**	**11M**	**12M**
3M	0.12	0.16	0.18	0.19	0.19	0.18	0.18	0.17	0.17	0.17	0.16	0.16
6M	0.21	0.23	0.24	0.24	0.24	0.23	0.22	0.22	0.21	0.20	0.19	0.17
9M	0.22	0.24	0.26	0.27	0.26	0.25	0.24	0.22	0.21	0.19	0.18	0.16
12M	0.23	0.25	0.26	0.25	0.24	0.22	0.20	0.19	0.18	0.16	0.15	0.14
15M	0.20	0.22	0.21	0.20	0.19	0.17	0.16	0.15	0.14	0.13	0.13	0.12
18M	-	0.15	0.16	0.15	0.15	0.14	0.14	0.13	0.12	0.12	0.11	0.10
21M	-	0.13	0.15	0.15	0.15	0.14	0.13	0.12	0.11	0.10	0.09	0.08
24M	-	0.13	0.14	0.14	0.13	0.12	0.11	0.10	0.09	0.08	0.07	0.07
	13M	**14M**	**15M**	**16M**	**17M**	**18M**	**19M**	**20M**	**21M**	**22M**	**23M**	**24M**
3M	0.15	0.13	0.12	0.11	0.11	0.11	0.10	0.10	0.09	0.09	0.09	0.09
6M	0.16	0.14	0.13	0.12	0.12	0.12	0.11	0.11	0.10	0.10	0.10	0.09
9M	0.15	0.13	0.12	0.12	0.11	0.11	0.10	0.10	0.09	0.09	0.08	0.07
12M	0.13	0.12	0.11	0.10	0.10	0.09	0.08	0.08	0.07	0.07	0.06	0.06
15M	0.11	0.10	0.09	0.08	0.07	0.07	0.06	0.06	0.06	0.05	0.05	0.04
18M	0.09	0.08	0.07	0.06	0.05	0.05	0.05	0.04	0.04	0.04	0.03	0.03
21M	0.07	0.06	0.06	0.05	0.04	0.04	0.04	0.03	-	-	-	-
24M	0.06	0.05	-	-	-	-	-	-	-	-	-	-

J= ranking period; K=holding period

(Table 3-4 is continued on the next page)

Table 3-4. Dynamics of the Momentum Effect in the UK Stock Market
(Continued from the previous page)

Panel C: Annualized BHRs during Jan1999-Dec2011												
J	**K**											
	1M	**2M**	**3M**	**4M**	**5M**	**6M**	**7M**	**8M**	**9M**	**10M**	**11M**	**12M**
3M	-	0.15	0.14	0.13	0.13	0.11	0.10	0.10	0.10	0.09	0.09	0.08
6M	-	-	0.14	0.13	-	-	-	-	-	-	-	-
9M	-	-	-	-	-	-	-	-	-	-	-	-
12M	-	-	-	-	-	-	-	-	-	-	-	-
15M	-	-	-	-	-	-	-	-	-	-	-	-
18M	-	-	-	-	-	-	-	-	-	-	-	-
21M	-	-	-	-	-	-	-	-	-	-	-	-
24M	-	-	-	-	-	-	-	-	-	-	-	-
	13M	**14M**	**15M**	**16M**	**17M**	**18M**	**19M**	**20M**	**21M**	**22M**	**23M**	**24M**
3M	-	-	-	-	-	-	-	-	-	-	-	-
6M	-	-	-	-	-	-	-	-	-	-	-	-
9M	-	-	-	-	-	-	-	-	-	-	-	-
12M	-	-	-	-	-	-	-	-	-	-	-	-
15M	-	-	-	-	-	-	-	-	-	-	-	-
18M	-	-	-	-	-	-	-	-	-	-	-	-
21M	-	-	-	-	-	-	-	-	-	-	-	-
24M	-	-	-	-	-	-	-	-	-	-	-	-

J= ranking period; K=holding period

3.5 Tests of the Explanatory Power of Risk Factors

Since Section 3.4 confirms the momentum effect in the UK stock market, this section is to test if the conventional risk factors can explain momentum returns. The most widely discussed risk factors are Beta risk in the CAPM model that is associated with market movement, and another two risk factors in the Fama and French's 3-Factor model, the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks SMB, and the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks HML. Additionally, we also investigate the C-CAPM model where the source of risk is the predicted covariance between the future consumption growth and the excess return or just the return itself on the risky asset. Consistent with the literature, we find that none of the above risk factors has significant explanatory power.

3.5.1 Tests of the Significance of CAPM-Adjusted and Fama-French-3-factor Risk-Adjusted Self-Financing Returns

We test the CAPM model by the regression Eq. (3.10):

$$R_{k,t,w} - R_{k,t,l} = \alpha_k + \beta_k\left(R_{m,t} - R_{f,t}\right) + \varepsilon_{k,t} \quad (3.10)$$

We follow the approach in Cooper et.al (2004) to form a time-series of raw profits corresponding to each month of the holding period. $R_{k,t,w} - R_{k,t,l}$ represents the return generated during the kth holding month of the holding period by a momentum portfolio in calendar month t. For the momentum trading strategy JxK, K holding month return time-series are constructed. If the market systematic risk is able to explain the profitability of any momentum trading strategy, $\alpha_k$should not be significantly different from zero. Results for momentum trading strategies are shown in Table 3-5 panel A. Since there are 60 regressions, we have 60 estimated values forα_k. We can see that 33 out of 60 are significantly larger than zero at the significance level of 1%. Therefore, we can conclude that CAPM model cannot explain returns generated by momentum trading strategies.

Fama and French (1993) argue that most abnormal returns except momentum returns, i.e., the expected return on a portfolio in excess of the risk-free rate, can be explained by the sensitivity of its return to three factors: the excess return on a broad market portfolio Rm-Rf, the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks SMB, and the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks HML. They interpret that book-to-market equity and slopes on HML proxy for relative distress. SMB explains returns to be compensated in average returns that are related to small stocks but not captured by the market return.

We test the significance of the Fama and French's 3-Factor-Adjusted self-financing profits in the same fashion as we test the significance of the CAPM-adjusted self-financing profits.[32] $R_{m,t} - R_{f,t}$, SMB and HML data are taken from Xfi Centre for Finance and Investment.[33] Again, we run 60 regressions for momentum trading strategies. The 3-factor assets pricing model takes the regression form as follows,

$$R_{k,t,w} - R_{k,t,l} = \alpha_k + \beta_{1k}\left(R_{m,t} - R_{f,t}\right) + \beta_{2k}(SMB_t) + \beta_{3k}(HML_t) + \varepsilon_{k,t} \tag{3.11}$$

Results are shown in Table 3-5 panel B. For momentum trading strategies, 41 out of 60 estimated values for α_k are significantly different from zero at the significance level of 1%. Compared with the result in CAPM model, the 3-factor model performs even worse than the CAPM does and it fails to capture the momentum returns. This results are consistent with the prior research and the Fama-French-3-factor model are found to deepen momentum profits as loadings on SMB and HML are negative.

[32]We follow the most commonly used Fama and French 3-factor model rather than the 4-factor model that includes momentum because we do not presume that momentum is a risk factor as this is an unsettled issue.

[33]Data are available at: http://businessschool.exeter.ac.uk/research/areas /centres /xfi/ research/ famafrench/files/

3.5.2 Tests of the Explanatory Power of the C-CAPM

Under the C-CAPM, the source of risk is the predicted covariance between future consumption growth and the excess return or just the return itself on the risky asset. The arguments of the C-CAPM are that, during recessions, consumption growth falls and so does the stock market, and hence stock returns; during booms, consumption growth and stock returns are high, to ensure that consumers are willing to hold a risky asset, it must have an expected return that is higher than that of the risk-free asset, which has the same return in all states of nature. Put it another way, the returns on assets that are least affected by the business cycle will have the smaller risk premium because they have a lower correlation with consumption growth. Formally, an asset is risky if for states of nature in which returns are low, the inter-temporal marginal rate of substitution in consumption is high. A risky asset is one which yields low returns in states for which consumers also have low consumption.

We assume that consumption growth rate is highly correlated with the stock market state. And we want to know whether winner portfolios are riskier in the sense that it offers poorer returns than loser portfolios do when the stock market is in the bad state. The stock market states are defined as follows. The stock market is in good state when it offers positive return; on the other hand, the stock market is in bad state when it generates loss. We classify the stock market state on monthly basis. It is shown in Section 3.4.2.2 that momentum profits are mainly contributed by winner portfolios. Therefore, it is natural to ask if winner portfolios of momentum trading strategies are riskier in the sense that they offers poorer returns than loser portfolios do when the stock market is in bad state.

Results for the performance of winner and loser portfolios in different market state are displayed in Table 3-6 Panel A and Panel B respectively. As shown in Table 3-6 Panel A, in the good stock market state both winner and loser portfolios make profits. However, in general, winner portfolios make more profits than loser portfolios. Table 3-6 Panel B shows that in the bad stock market state, both winner and loser portfolios make losses. However, in most cases, winner portfolios lose less than loser portfolios do. Our evidence apparently does not support the statement that winner portfolios are riskier than loser portfolios in bad market state and hence the C-CAPM has little power in terms of explaining momentum returns.[34]

3.5.3 Profitability of Momentum Trading Strategies Applied to Reshuffled Historical Stock Return Data

It is argued that it is possible to have the momentum effect when the stock prices follow random walk.[35] In order to examine if momentum trading strategies can generate significant profits in an efficient market environment, we apply them to samples formed by random draws from the pool of the historical monthly stock returns. We randomly draw 360 monthly returns to form a time series for a "fictional" firm and in total we create 1500 time series for 1500 "fictional" firms in the same fashion. Then, two momentum trading strategies, 3x10 and 9x4 are applied to the fictional stock market that consists of these 1500 "fictional" stocks.[36] The BHRs for 3x10 and 9x4 trading strategies are graphed in Figure 3-2 A, and B.

First of all, unlike previous results of momentum trading strategies applies to the historical data, there is no clear dominant pattern in all of these two figures based on the random sample. Secondly, on average, momentum trading strategies based on the random sample generate losses instead of profits. The size of losses in every case is very small, although seemingly statistically significant. For example, on average, 9x4 momentum trading strategies based on random sample generate a negative net return of -0.6% over 4-month holding period with t-stat -2.984, whereas the same strategy rewards a positive net return of 5.8% over 4-month holding period with t-stat 9.027.

[34]Our results seem not to support the downside risk argument (Ang et al. (2002)) either. Downside risk argument says that past winner stocks have high returns, in part, because during periods when the market experiences downside moves, winner stocks move down more with the market than past loser stocks. However, Table 3-6 Panel B reports the opposite.

[35]The case for the random walk argument is that trends can appear in patterns that are actually random. Take coin toss as an example. A coin can show heads for several consecutive tosses. Yet, for each toss, the odds of landing on heads remain a very steady 50%, regardless of how often the coin landed on heads for the previous tosses.

[36]We choose these two momentum strategies as 3x10 is the most reliable strategy and 9x4 is most profitable strategy.

Our test results based on reshuffled data confirm that patterns might occur even if data are actually random. However, the significance of these patterns based on reshuffled historical data is much weaker than that of momentum effects based on historical data. Indeed, the fact that there is a large proportion of our momentum strategies that generate positive returns with t-values comfortably above those reshuffled historical data implies that it is very unlikely that stock prices are governed by a random walk and it also suggests that it is highly unlikely for the profitability of these momentum strategies in the UK stock market to simply be a statistical artefact.

Table 3-5. Significance Tests of the CAPM and Fama-French-3-Factor Risk-Adjusted Momentum Returns

A time-series of raw profits corresponding to each event month of the holding period for the JxK trading strategy is regressed on a constant and a time series of excess market returns over risk-free interest rates. For the CAPM and the Fama-3-Factor risk model to fully explain momentum profits, α_k needs to be significantly indifferent from zero. Newey-West (1987, 1994) heteroskedasticity-and-autocorrelation-consistent (HAC) estimator is employed to estimate the variance of error term.

Panel A. $\boldsymbol{R_{k,t,w} - R_{k,t,L} = \alpha_k + \beta_K(R_{m,t} - R_{f,t}) + \varepsilon_{k,t}}$												
	K											
J	**1M**	**2M**	**3M**	**4M**	**5M**	**6M**	**7M**	**8M**	**9M**	**10M**	**11M**	**12M**
3M	0.010	0.015	0.013	0.013	0.013	0.009	0.009	0.007	0.009	0.007	0.005	-0.001
t-value	3.720	5.423	4.693	5.303	5.941	4.553	4.588	3.595	4.712	3.802	2.527	-0.534
6M	0.011	0.017	0.015	0.013	0.014	0.013	0.011	0.009	0.006	0.003	-0.001	-0.005
t-value	3.410	5.742	5.448	4.937	5.321	5.297	5.018	3.948	2.918	1.334	-0.486	-2.293
9M	0.010	0.016	0.017	0.015	0.013	0.010	0.008	0.003	0.000	-0.002	-0.001	-0.006
t-value	2.977	5.131	5.748	5.201	4.832	4.238	3.241	1.275	0.206	-0.785	-0.656	-2.901
12M	0.010	0.014	0.013	0.010	0.009	0.006	0.004	0.001	-0.001	-0.003	-0.002	-0.004
t-value	2.866	4.522	4.163	3.293	3.160	2.360	1.777	0.426	-0.239	-1.201	-0.941	-1.779
15M	-	0.011	0.008	0.007	0.005	0.003	0.002	-0.001	-	-	-	-
t-value	-	3.342	2.499	2.243	1.908	1.331	0.828	-0.264	-	-	-	-

J= ranking period; K=holding period

(Table 3-5 is continued on the next page)

Table 3-5. Significance Tests of CAPM and Fama-3-Factor Risk-Adjusted Momentum Returns (Continued from the previous page)

Panel A. $R_{k,t,w} - R_{k,t,L} = \alpha_k + \beta_{1K}(R_{m,t} - R_{f,t}) + \beta_{2K}(SMB_t) + \beta_{3K}(HML_t) + \varepsilon_{k,t}$												
	K											
J	**1M**	**2M**	**3M**	**4M**	**5M**	**6M**	**7M**	**8M**	**9M**	**10M**	**11M**	**12M**
3M	0.012	0.016	0.015	0.014	0.014	0.010	0.011	0.009	0.011	0.009	0.006	0.000
t-value	4.719	6.421	5.612	6.119	6.868	5.586	5.990	4.764	5.994	4.920	3.350	0.063
6M	0.014	0.020	0.017	0.016	0.016	0.015	0.014	0.011	0.008	0.005	0.001	-0.003
t-value	4.572	7.033	6.620	6.452	6.911	6.841	6.991	5.767	4.385	2.473	0.340	-1.733
9M	0.013	0.017	0.016	0.013	0.011	0.009	0.007	0.004	0.002	-0.001	0.000	-0.002
t-value	4.501	6.857	7.405	6.902	6.779	5.997	5.217	2.670	1.318	0.135	0.292	-2.285
12M	0.013	0.017	0.016	0.013	0.011	0.009	0.007	0.004	0.002	-0.001	0.000	-0.002
t-value	4.455	6.232	5.840	5.097	4.871	4.053	3.451	1.782	0.822	-0.277	-0.032	-1.017
15M	-	0.014	0.011	0.010	0.008	0.006	0.005	0.002	-	-	-	-
t-value	-	5.148	4.044	3.876	3.588	2.872	2.244	0.946	-	-	-	-

J= ranking period; K=holding period

Note: two-tailed tests are applied to examine the significance of α_k. Critical values corresponding to the significance level of 1%, 5%, and 10% are 2.576, 1.96, and 1.645 respectively.

Table 3-6. Performances of Loser and Winner Portfolios in the Good and the Bad Market State

The stock market is in the good (bad) state in a month when the market return is non-negative (negative) for that month. To compare the performance of loser and winner portfolios of the trading strategy JxK in the good (bad) market state, K time series of monthly returns corresponding to each of the K event months are formed for winner and loser portfolios of the self-financing JxK trading strategies. An observation from Kth time series for winners (losers) are then classified into good (bad) state observations if it occurs when the market return is positive (negative). Hence, for the trading strategy JxK, 4 time series are formed for each event month, i.e., one for the returns of winner portfolios in the good state market, one for the returns of winner portfolios in the bad state market, one for the returns of loser portfolios in the good state market, and one for the returns of loser portfolios in the bad state market.

Panel A: Loser and Winner Portfolios Monthly Returns in the Good Market State												
	K											
J	**1M**	**2M**	**3M**	**4M**	**5M**	**6M**	**7M**	**8M**	**9M**	**10M**	**11M**	**12M**
3M-L	0.039	0.032	0.032	0.032	0.033	0.034	0.034	0.035	0.034	0.035	0.038	0.04
-W	0.044	0.043	0.042	0.042	0.043	0.041	0.042	0.042	0.045	0.044	0.043	0.039
6M-L	0.041	0.032	0.031	0.033	0.032	0.033	0.033	0.035	0.036	0.038	0.04	0.042
-W	0.046	0.044	0.043	0.042	0.043	0.044	0.044	0.045	0.043	0.042	0.039	0.037
9M-L	0.041	0.032	0.031	0.032	0.033	0.034	0.034	0.037	0.038	0.039	0.04	0.042
-W	0.045	0.044	0.045	0.045	0.045	0.044	0.043	0.041	0.04	0.04	0.04	0.037
12M-L	0.041	0.034	0.033	0.034	0.036	0.036	0.036	0.038	0.038	0.041	0.04	0.041
-W	0.047	0.045	0.045	0.043	0.043	0.042	0.042	0.041	0.04	0.039	0.039	0.038
15M-L	-	0.035	0.035	0.036	0.037	0.037	0.037	0.039	-	-	-	-
-W	-	0.044	0.042	0.042	0.042	0.041	0.04	0.04	-	-	-	-

J= ranking period; K=holding period; L=loser portfolio; W=winner portfolio

(Table 3-6 is continued on the next page)

Table 3-6. Performances of Loser and Winner Portfolios in the Good and the Bad Market State (Continued from the previous page)

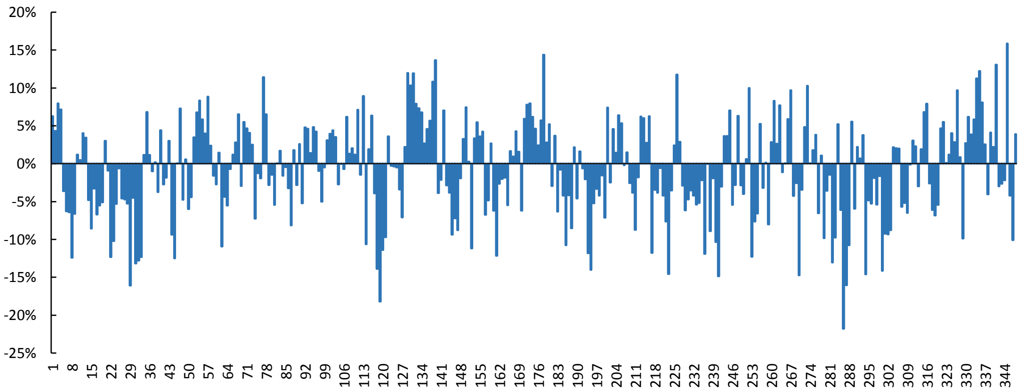
Panel B: Loser and Winner Portfolios Monthly Returns in the Bad Market State												
	K											
J	1M	2M	3M	4M	5M	6M	7M	8M	9M	10M	11M	12M
3M-L	-0.043	-0.047	-0.045	-0.044	-0.042	-0.041	-0.039	-0.037	-0.036	-0.033	-0.034	-0.032
-W	-0.026	-0.027	-0.025	-0.025	-0.026	-0.029	-0.028	-0.028	-0.027	-0.027	-0.028	-0.031
6M-L	-0.044	-0.049	-0.046	-0.045	-0.043	-0.041	-0.039	-0.036	-0.035	-0.033	-0.032	-0.031
-W	-0.021	-0.023	-0.025	-0.024	-0.025	-0.025	-0.027	-0.027	-0.03	-0.03	-0.032	-0.034
9M-L	-0.043	-0.048	-0.045	-0.045	-0.043	-0.04	-0.037	-0.035	-0.032	-0.03	-0.03	-0.029
-W	-0.022	-0.024	-0.022	-0.024	-0.027	-0.028	-0.031	-0.032	-0.032	-0.033	-0.032	-0.036
12M-L	-0.042	-0.046	-0.043	-0.043	-0.041	-0.039	-0.035	-0.032	-0.031	-0.032	-0.032	-0.03
-W	-0.023	-0.025	-0.027	-0.029	-0.029	-0.031	-0.032	-0.033	-0.033	-0.033	-0.033	-0.034
15M-L	-	-0.044	-0.041	-0.041	-0.039	-0.036	-0.035	-0.032	-	-	-	-
-W	-	-0.028	-0.029	-0.029	-0.031	-0.032	-0.032	-0.033	-	-	-	-

J= ranking period; K=holding period; L=loser portfolio; W=winner portfolio

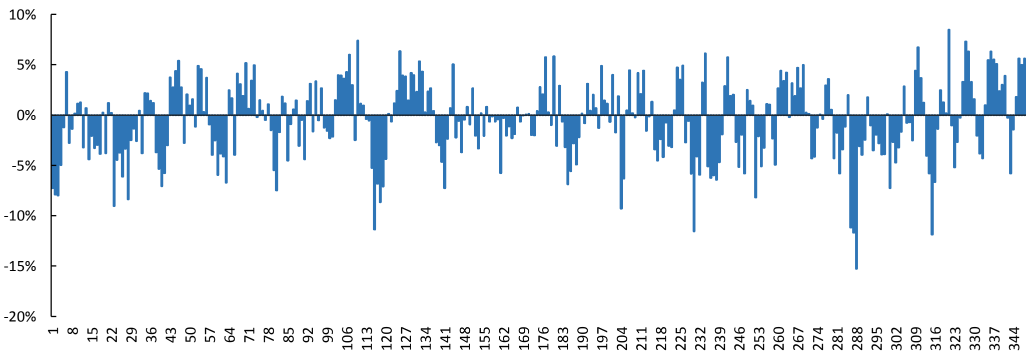
Figure3-2. Performances of Momentum Trading Strategies Applied to Random Data (J=3, K=10 and J=9, K=4)

The sample of historical monthly return data used for this study from Jan 1979 to Dec 2011in the UK stock market is treated as the population and 360 monthly return data are randomly drawn from the population and are used as a time series of return for one stock. This random draw is repeated 1500 times to form time series of return for 1500 “fictional” stocks. Figure A represents the performance of the 3x10 momentum trading strategy when it is applied to the random sample. Momentum trading strategy 3x10 generates a mean buy-and-hold return of -0.006with standard deviation of 0.039and t-value of -2.984. Figure B represents the performance of the 9x4 momentum trading strategy when it is applied to the random sample. This momentum trading strategy generates a mean buy-and-hold return of -0.008with standard deviation of 0.064and t-value of -2.430.

A. 3x10



B. 9x4



3.6 Conclusion

This Chapter adds more evidence in favour of the momentum effect in the UK stock market to the literature, and confirms that past stock returns have predictive power for the future stock returns as momentum trading strategies are highly profitable in the UK stock market based on the sample period of 1979 to 2011. During this sample time period, a number of momentum trading strategies achieve annualized BHRs above 10%. Momentum trading strategies have rather persistent performances over time, in the sense that for most profitable momentum trading strategies, there is a chance above 70% that they are going to make profits based on the historical performance. Thus, we conclude that the momentum effect is a persistent phenomenon in the UK stock market.

This chapter also demonstrates the great dynamics of the momentum effect over time and suggests that the magnitude of the momentum effect is conditional on the market stability. The momentum effect tends to be strong and reliable when the stock market is stable as in the case of sub-sample period of 1989 to 1998 and it is relatively weak when the stock market is volatile such as the two sub-sample periods of 1979 to 1988 and 1999 to 2011. More importantly, we find that the momentum effect is reversed when the stock market is extremely volatile as momentum trading strategies in our study often suffer considerable losses during stock market crises.

Our findings also confirm that there is a reversal in the momentum effect in the long run as holding momentum portfolios for too long generates negatives returns. This feature of momentum effect is important as it presents a big challenge for the rational explanations.

Finally, we confirm that the momentum effect cannot be explained by conventional risk factors as none of these risk factors including the market systematic risk, the Fama-French 3 risk factors and the C-CAPM can capture the momentum returns.

4. Threshold Regression Model Analysis of the Momentum Effect in the UK Stock Market

4.1 Introduction

Chapter 3 demonstrates that the momentum effect is a persistent and dynamic phenomenon in the UK stock market from 1979 to 2011. Most interestingly, it is found to be strong and reliable during “normal” times and to reverse during financial crises. In this chapter, we construct a model to catch its dynamics, especially the switch from momentum effect and its reversal. Unlike behavioural theories proposed by Daniel et al. (1998), Baberis et al, (1998) and Hong and Stein (1999), risk-oriented theoretical frameworks are currently not able to accommodate this particular aspect of its dynamics. Thus we start our task with assumption that financial market mechanisms described in the above three models coexist in the stock market. We construct a threshold regression model (more specifically, a two-regime switching model with heteroskedasticity) where the stock market volatility is the switching variable that governs the switch between the momentum and the reversal. We also assume that the error term has different variance in different regimes.

Three hypotheses are proposed, which are inferred from these three behavioural theories in Daniel et al. (1998), Baberis et al. (1998) and Hong and Stein (1999) and from the empirical observations in Chapter 3. The first hypothesis states that whether the momentum effect continues or reverses in the stock market depends on whether market volatility lies below or above a threshold. In other words, we conjecture that there are two regimes, the momentum regime and the reversal regime, and that the switch from one to the other is governed by the size of the stock market volatility. The second hypothesis says that the size of the stock market volatility is inversely correlated with momentum trading strategies’ returns in the near future. The third hypothesis is that there is a negative relationship between a momentum portfolio’ ranking period return and its holding period return, that is, the momentum effect during its holding period in the momentum regime.

In our threshold regression model with heteroskedasticity, the holding period return of a momentum portfolio that measures the momentum effect is the dependent variable, and the ranking period stock market volatility is the switching variable; further, in both regimes, the holding period return is regressed on both the ranking period return and the ranking period stock market volatility. The threshold regression model is estimated with four different momentum trading strategies, 3x3, 6x3, 9x4 and 12x3, using Bayesian estimation methods. In general, the estimation results of the threshold regression model are in line with our expectations and support our hypotheses. The performance of this model is robust as our estimation results are very similar across different momentum trading strategies and for different time periods.

First, estimation results confirm that the stock market volatility plays a critical role in terms of indicating the switch between the momentum and its reversal in the near future. We find that momentum trading strategies tend to make significant profits when the ranking period stock market volatility stays below a critical value range, and that they tend to make significant losses when ranking period market volatility gets extremely high and reaches above the critical value range. Second, the ranking period market volatility has a significant negative impact on the magnitude of momentum trading strategies' BHRs in many cases. That is, the higher is the ranking period stock market volatility, the lower are momentum profits in the momentum regime and the higher are losses in the reversal regime. Finally, the size of the ranking period return has a significant negative impact on the holding period return in the momentum regime. Our findings show that momentum portfolios could generate losses if ranking period returns are sufficiently large and hence the contrarian effect can occur in the short run in the momentum regime.

To double check the statistical significance of the predictability of the momentum effect dynamics based on the stock market volatility and the ranking period return of a momentum portfolio, we design a new type of trading strategies, named as the threshold-regression-model-guided trading strategy. These trading strategies follow the indication of the forecast of the threshold regression model. Our results confirm the statistical significance of the threshold regression model. We find that model-guided trading strategies can indeed exploit both the momentum effect and its reversal. They outperform momentum trading strategies with both higher returns and lower risks. Moreover, the superior performance of model-guided trading strategies over momentum trading strategies are consistent over time as shown by results based on sub-time periods of 1998-2005 and 1998-2011.

The rest of Chapter 4 is organized as follows. Section 4.2 specifies the motivation of this chapter's study and Section 4.3 discusses three testable hypotheses inferred from three behavioural models. Section 4.4 demonstrates the relationship between the ranking period market volatility and the holding period return, the relationship between the ranking period return and the holding period return based on empirical data. We show that the empirical observations are in general consistent with our hypotheses. In Section 4.5, we construct a threshold regression model with heteroskedasticity based on the three hypotheses to analyse the dynamics of the momentum effect in the UK stock market from 1969 to 2011. Section 4.6 illustrates the Bayesian estimation method and Section 4.7 reports the estimation results of parameters associated with the threshold regression model. In Section 4.8, we design threshold regression-model-guided trading strategies that make trades according to the forecast of the threshold regression model and we compare the performances of these new strategies with those of momentum trading strategies. Section 4.8 draws conclusion.

4.2 Motivation

The momentum effect currently remains an abnormal financial phenomenon under the conventional financial theoretical paradigm and the cause(s) of this effect is (are) still in debate. Although some lagged variables are found to be able to predict the moment effect to some degree, the interpretation of their predictive power is mixed. Some lagged variables are claimed to proxy risks and others are argued to be more consistent with behavioural theories. Despite an extensive amount of research has been done and we have gained more knowledge about this momentum effect, there is still lack of convincing evidence in favour of either risk-oriented or behaviour-oriented theories that are aimed to explain it. Thus, more studies are needed.

Many studies including ours in Chapter 3 have found that, in many cases, the continuation in price trend is reversed in the long run. More interestingly, we find that the momentum effect is very likely replaced by the contrarian effect even in the short run when the market is in turmoil. It has been long argued that contrarian effect makes a big challenge for rational explanations. On the other hand, there are theoretical frameworks that are based on different assumptions on investors' limited capability of interpreting news and making rational investment decision can generate both the momentum effect and the contrarian effect. Such work includes Daniel et al. (1998), Baberis et al. (1998) and Hong and Stein (1999). Thus, we intend to examine how well these models can explain our findings regarding the dynamics of the momentum effect in Chapter 3.

Our emphasis is on the switch between the momentum effect and its reversal. There has been no study dedicated to address this aspect of the momentum effect dynamics up to date and we are going to fill this gap. This is important as it can certainly help to shed light on the explanations of the momentum effect.

4.3 Hypotheses Construction

We document the reversal in the momentum effect especially when the stock market is in crises.[37] As there are models that can generate this important feature in share price, we conjecture our hypotheses based on these two behavioural theories including Daniel et al. (1998), Baberis et al. (1998) and the heterogeneous model of Hong and Stein (1999). Before we discuss three testable hypotheses, we introduce these three theoretical frameworks.

Based on assumptions that investors are subject to heuristics of overconfidence and self-attribution causes biased variations in confidence, Daniel et.al. (1998) construct a behavioural model that generate both the momentum and the contrarian effect. In their model, investors are overconfident and they overweight their own private information at the expense of ignoring publicly available information. As a result, investors overreact to private information and underreact to public information. Further, due to self-attribution, when an investor receives confirming public information, his confidence rises whereas disconfirming information causes confidence to fall only modestly. According to Daniel et.al. (1998), if an individual begins with unbiased beliefs about his ability, new public signals on average are viewed as confirming the validity of his private signal. It implicates that public information can trigger further overreaction to a preceding private signal. Such continuing overreaction causes momentum in security prices, but that such momentum is eventually reversed as further public information gradually draws the price back toward fundamentals. They demonstrate that their model reconcile short-run positive autocorrelations and long-run negative autocorrelations. Moreover, they argue that short-horizon momentum can arise either from under-reaction or from overreaction. Underreaction-induced momentum occurs only if the event is chosen in response to market mispricing. Alternatively, short-run positive autocorrelations can arise when the public event triggers a continuing overreaction. Because their model assumes that investors are overconfident only about private signals, they obtain underreaction as well as overreaction effects.

[37] We find the contrarian effect in the UK stock market and the performance of contrarian strategies are available in Appendix.

Based on another two well-documented behavioural heuristics, namely conservatism and representativeness, Baberis et al. (1998) propose a different market mechanism that can also generate both the momentum and the contrarian effect in which the earnings of the asset follow a random walk; however, the investor believes that the behaviour of a given firm's earnings moves between two 'regimes': mean-revert and trend.[38] Specifically, when a positive earnings surprise is followed by another positive surprise, the investor raises the likelihood that he is in the trending regime, whereas when a positive surprise is followed by a negative surprise, the investor raises the likelihood that he is in the mean-reverting regime. Corporate announcements such as those of earnings represent information are supposed to be of low strength but significant statistical weight. This assumption yields the prediction that stock prices underreact to earnings announcements and similar events. Their further assumption that consistent patterns of news, such as series of good earnings announcements, represent information that is of high strength and low weight. And this assumption yields a prediction that stock prices overreact to consistent patterns of good or bad news.

Different from Daniel et.al. (1998) and Baberis et.al. (1998), Hong and Stein (1999) present a framework where momentum and contrarian effect are the results of interaction of two different types of investors, 'newswatchers' and 'momentum traders'. These two groups of investors are not fully rational in a sense that they only act on subset of the available public information. More specifically, the newswatchers rely exclusively on their private information; momentum traders rely exclusively on the information in past price changes. The additional assumption is that private information diffuses only gradually through the marketplace, which, as Hong and Stein (1999) show, leads to an initial underreaction of newswatchers to news. The underreaction leaves opportunities for further future profits that

[38]Baberis et.al. (1998) explain conservatism and representativeness that seem contradictory behavioural biased can reconcile. They refer to the work of Griffin and Tversky (1992). Suppose that people update their beliefs based on the 'strength' and the 'weight' of new evidence. Strength refers to such aspects of the evidence as salience and extremity, whereas weight refers to statistical informativeness, such as sample size. According to Griffin and Tversky (1992), in revising their forecasts, people focus too much on the strength of the evidence, and too little on its weight, relative to a rational Bayesian. Conservatism would occur in the face of evidence that has high weight but low strength: people are unimpressed by the low strength and react mildly to the evidence, even though its weight calls for a larger reaction. On the other hand, when the evidence has high strength but low weight, overreaction occurs in a manner consistent with representativeness.

momentum traders will arbitrage away. Hong and Stein (1999) go on and show that momentum traders' arbitrage does not leads to market efficiency and instead the fact that momentum traders only rely on price history leads to an eventual overreaction to any news. Prices revert to their fundamental levels in the long run.

To construct our hypotheses, we assume that all of the above three market mechanisms co-exist in the stock market and that investors are subject to various behavioural heuristics such as overconfidence, self-attribution, conservatism and representativeness. We have the following candidate variables that shall affect the momentum effect.

4.3.1 Ranking Period Market Return Volatility

We propose that ranking period market return volatility can be used to predict the switch between the momentum effect and the reversal and it also has negative impact on the magnitude of momentum trading strategies' holding returns.[39]

The stock market volatility has been used as an indicator of the market participants' confidence in practice of their financial investments.[40] The lower is the stock market volatility, the more confident is the market and prolonged low stock market volatility signals market complacency and overconfidence. On the contrary, the higher is the stock market volatility, the less confident is the market and extremely high market volatility indicates market being panic and the collapse of confidence. The stock market volatility as a proxy of the market confidence has significant impact on the momentum effect according to Daniel et.al. (1998). When the stock market volatility is low, most stocks' prices are in trend. In this case, investors' investment decisions are highly likely to be proven correct and their confidence

[39]We use the market volatility over the whole ranking period instead of other options such as one, two or any other number of months prior to the holding period because market volatility at any point within the whole ranking period contains public systematic information that should have effects on stocks' performance over the ranking period.

[40]For example, VIX, a popular measure of the implied volatility of S&P 500 index options that was first developed by Brenner and Galai (1986), represents one measure of the market's expectation of stock market volatility. It is well-known and widely used as the fear index. Low VIX is associated with market complacency and high VIX indicate investors fear and worries.

rises due to self-attribution. Thus, under the framework of Daniel et.al. (1998), the momentum effect is expected to be strong when the stock market is calm. In contrast, when the stock market volatility is high, there lacks of direction in most stocks' prices. In this case, investors' confidence is challenged and may collapse in extreme cases and winner (loser) stocks are not the results of investor's overconfidence in general. Thus there should be no significant momentum effect expected in the near future.

With assumptions of conservatism and representativeness as in Baberis et al. (1998), the stock market volatility can also indicate the momentum effect in the near future. When the stock market is calm with low volatility, most news has low strength. In this case, investors tend to underreact due to conservatism bias and shares' prices will move in the same direction in near future, which leads investors to believe the market is in trend. Thus, the momentum effect carries on in the near term. On the other hand, when the stock market is turbulent, news tend to be shocking; in other words, it has great strength. In this scenario, investors overreact to news due to their representativeness bias. Such overreaction is corrected later. Thus, the reversal is likely to occur instead of the momentum effect in the near term.[41]

There are empirical research results that are consistent with our analysis. Asem and Tian (2010) find that following UP markets, momentum profits are higher when the markets continue in the UP state than when they transition to DOWN states, suggesting that the profits following UP markets are mainly due to the profits when the markets continue. Following DOWN markets, they document both large momentum profits when the markets continue in DOWN states and large losses

[41]Baberis et al. (1998) point out that it is important to develop a priori way of classifying events by their strength and weight, and to make further predictions based on such a classification. They argue that the Griffin and Tversky theory predicts that holding the weight of information constant, news with more strength would generate a bigger reaction from investors. Specifically, holding the weight of information constant, one-time strong news events should generate an overreaction. They give an example that stock prices bounced back strongly in the few weeks after the crash of 1987. One interpretation of the crash is that investors overreacted to the news of panic selling by other investors even though there was little fundamental news about security values. Thus the crash was a high-strength, low-weight news event which, according to the theory, should have caused an overreaction.

when markets transition to UP states. These findings indicate that the momentum effect is weak or reversed when market is in the stage of state transition.

Based on above discussion, we conjecture that there exist a critical value range of the stock market volatility. When the stock market volatility stays below it, confidence (overconfidence) dominates the market and news with low strength outweighs news with high strength; thus, the momentum effect should be expected. On the contrary, when market volatility shoots above it, confidence (overconfidence) collapses and news with high strength outweighs news with low strength; hence, no momentum effect should be expected and reversals might occur. Thus we have our first hypothesis.

Hypothesis one: whether there is continuation or a reverse in the momentum effect depends on whether the size of the stock market volatility stays below or above a threshold.

Further we expect there is a negative relationship between the stock market volatility and a momentum portfolio' holding period return. Since the higher is the stock market volatility, the weaker is the market confidence and weaker confidence leads to weaker momentum effect. As to news, when the stock market gets more volatile, its strength becomes higher in general which makes representativeness more likely than conservatism. Therefore we have the second hypothesis.

Hypothesis two: the stock market volatility is inversely correlated with a momentum portfolio' holding period return.

4.3.2 Ranking Period Return

The second variable that has impact on the momentum effect is the size of momentum portfolio's ranking-period return. According to Daniel et al. (1998), Baberis et al. (1998), and Hong and Stein (1999), although they have different market mechanism, they all suggest that the momentum effect can be generated either by underreaction, which leads to further momentum effect or by over-reaction, which leads to correction. It follows that a variable that is able to distinguish between underreaction and overreaction to some extent has some power to predict the momentum effect. The candidate we propose for this variable is the ranking period return of a momentum portfolio.

It is reasonable to assume that a relatively small ranking period return are likely to indicate market underreaction and thus this momentum portfolio is highly likely to generate profits during holding period as prices continue to adjust in the same direction. Conversely, a momentum portfolio that has a very high ranking-period return is more likely due to market overreaction and overreaction is to be corrected later on during its holding period; thus, weak momentum effect or even reversal occurs during holding periods. Indeed, Lee and Swaminathan (2000) provide evidence suggesting that at least a portion of the initial momentum gain is better characterized as an overreaction as they find that initial winner portfolios significantly underperform initial loser portfolios over some time. Hence, it follows the third hypothesis.

Hypothesis three: there is a negative relationship between a momentum portfolio's ranking period return and its holding period return in the momentum regime.

4.4 Evidence in Favour of the Hypotheses from Historical Data

Before the model estimation, it is worthwhile to examine if the empirical data support the hypotheses specified in Section 4.3. We take momentum trading strategy 9x4 as an example.

4.4.1 Relationship between the Stock Market Volatility and the Performance of a Momentum Trading Strategy

Figure 4-1 presents the 9-month ranking period market volatility, which is measured by the variance of the market return over the 9-month ranking period, from 1969 to 2011 and it clearly shows that the UK equity market return varies dramatically over time. According to this figure, the UK equity market is relatively stable for most time as the majority of the 9-month ranking period market volatility observations lies below 0.02. However, there are times when market becomes extremely volatile as there are several spikes in this figure. The highest figure for the 9-month ranking period market volatility has reached above 0.12 that is more than six times as large as the size of the ranking period market volatility in most cases for the whole sample period. Further, the occurrence of a dramatic surge in market volatility is always associated with a financial/economic crisis. For example the spike 9-month ranking period market volatility in 1975 is associated with the collapse of the Bretton Woods System and more recently the spike of market volatility in 2008and 2009 is corresponding to the Subprime Mortgage Crisis.

Figure 4-2 plots the performance of the momentum trading strategy 9x4 against the ranking period market volatility. The first feature that Figure 4-2 displays is the negative correlation between the 9-month ranking period market volatility and the 4-month holding period return. In general, the higher is the 9-month ranking period market volatility, the lower is the 4-month holding period return and hence the weaker is the momentum effect during the holding period. Although, the relationship is not linear by standard, a simple regression confirms the significance of this negative correlation.[42]

Another feature of this figure is that when the 9-month ranking period market volatility remains somewhere below 0.04, the 4-month holding period return clusters in the positive return territory; on the other hand, when the 9-month ranking period market volatility lies above 0.04, the 4-month holding period return is distributed mainly in the negative return area. This feature indicates the presence of the momentum effect during the holding period when the market is calm during the ranking period and the absence of the momentum effect during the holding period when the market is in turmoil during the ranking period.

It can also be observed that when the 9-month ranking market volatility is low, the size of the 4-month holding period return is relatively more contained than that when the 9-month market volatility is high. This feature hence implies that the variance of the holding period return is not constant and it is associated with the size of the ranking period market volatility.

[42] According to the simple regression with intercept, the coefficient associated with ranking period market volatility is -3.02931 and its t-stat is -10.3391. The R-square is 0.1758 and the adjusted R-square is 0.1742.

Figure 4-1. Ranking Period Market Volatilities from 1969 to 2011
(J=9, K=4)

To obtain the monthly market variance, the variance of the daily return is calculated over one month and then multiply it by 20, i.e., the number of trading days per month. Denote the market daily return at time t as r_t^M, and there are m daily observations, the sample market daily variance is $\widehat{\sigma_D^2}=\frac{1}{m-1}\sum_{i=1}^{m}(r_{t+i}^M-\mu^M)^2$, where μ^M is the sample average return. Since variance is linear in time and can be aggregated over the 9-month ranking period, it follows that monthly market variance can be calculated as $\widehat{\sigma_M^2}=\widehat{\sigma_D^2}*20$. Market volatility over the 9-month ranking period is the sum of nine monthly market volatilities. This figure presents the 9-month market volatility from 1969 to 2011.

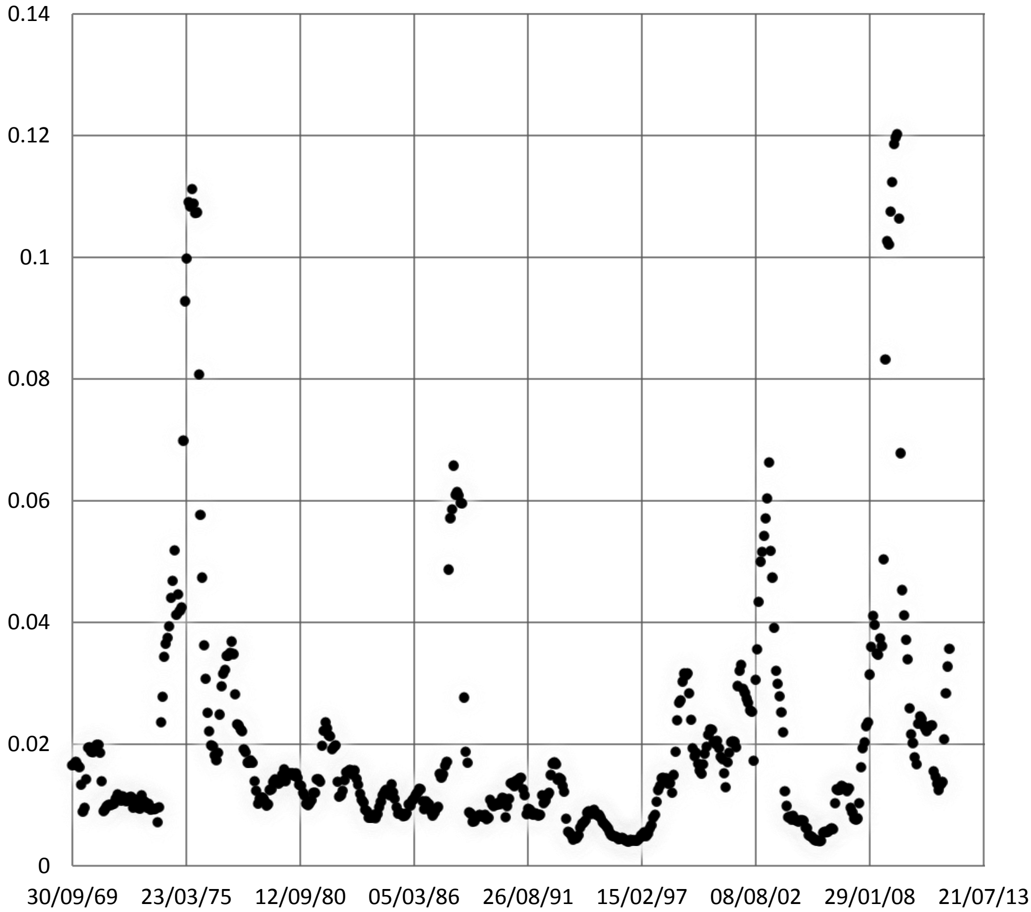
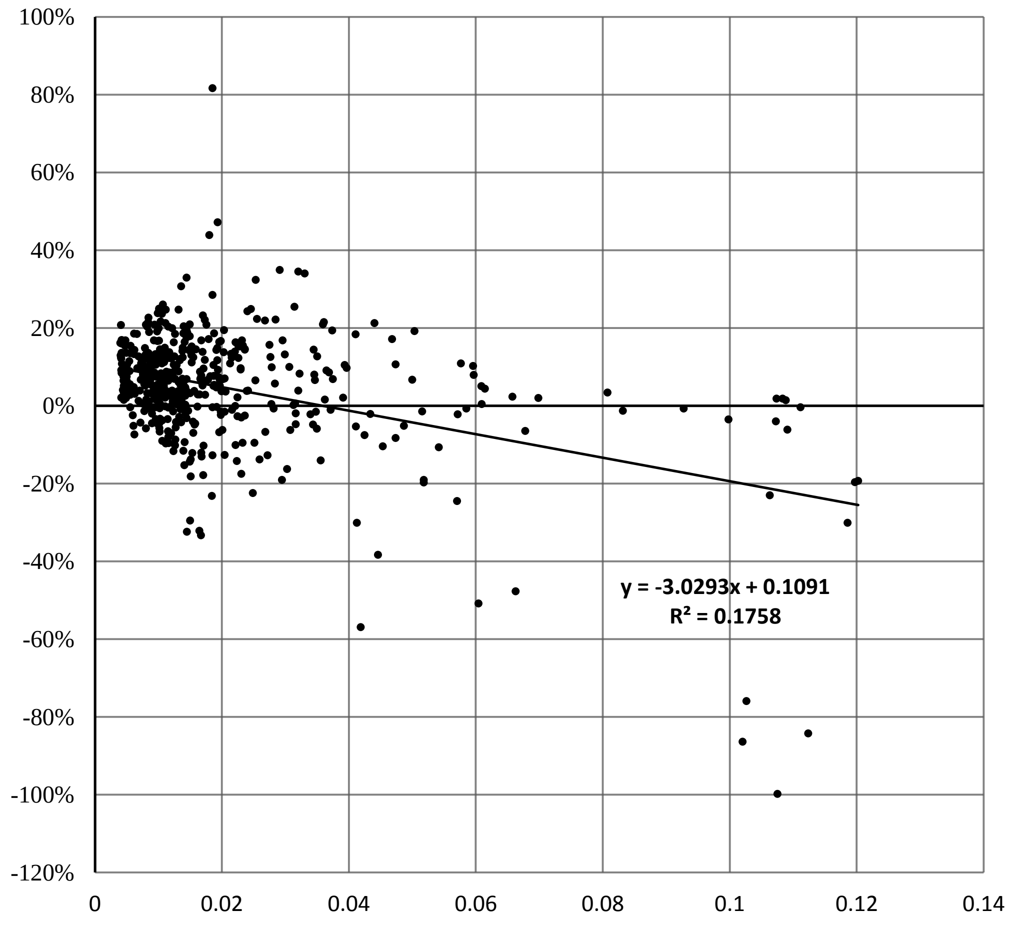


Figure 4-2. Scatter Plot between the Holding Period Return and the Ranking Period Market Volatility (J=9, K=4)

The vertical axis represents the 9x4 momentum trading strategy's buy-and-hold return over the 4-month holding period and the horizontal axis represent the market volatility over the 9-month ranking period. Each point in this figure is corresponding to a 9x4 momentum portfolio implemented at the end of a calendar month t between 1969 and 2011. Its horizontal reading is the 9-month market volatility from calendar month $t-9$ to $t-1$ and its vertical reading is its performance, that is, its 4-month buy-and-hold return from calendar month $t+1$ to $t+4$. There is a 9x4 momentum portfolio implemented each month from Sep 1969 to Aug 2011. This simple regression suggests a negative relationship between the two variables.



4.4.2 Relationship between the Ranking Period Return and the Holding Period Return of a Momentum Portfolio

The size of the 9-month ranking period return over the sample period is shown in Figure 4-3 and it can be seen that the 9-month ranking period return is far from being constant over time. On the contrary, the 9-month ranking period return fluctuates substantially over time about its mean of 138% with the lowest 9-month ranking period return being 71% and the highest 443%. In contrast with the size of the 9-month ranking period market volatility, spikes in the size of 9-month ranking period return occur more frequent. This difference implies that causes of spikes in the size of market volatility are not the same as those of spikes in the size of a momentum portfolio's ranking period return.

Figure 4-4 draws the scatter plot of the relationship between the 9-month ranking period return and the 4-month holding period return. This figure clearly shows that, in general, the 4-month holding period return becomes smaller and even turns into negative as the 9-month ranking period return increases.[43] However, there are two other observations that justify the choice of the ranking period market volatility as regime switching variable instead of the ranking period return. First, there are cases where the 4-month holding period return associated with the low 9-month ranking period return has rather large negative figure.[44] This very large negative 4-month holding period return doesn't happen with low 9-month ranking period market volatility. This difference implies that the 9-month ranking period market volatility dominates the 9-month ranking period return in term of the magnitude of impact on the momentum effect during holding period. Moreover, compared with variation in the size of the 4-month holding period return sorted by the market

[43]According to the simple regression with intercept, the coefficient associated with ranking period return is -0.0539 and its t-stat is -3.7104. The R-square is 0.0267 and the adjusted R-square is 0.0248. However, when excluding four observation with extremely high volatility, the negative relationship becomes more profound as the coefficient associated with ranking period return is -0.0692 and its t-stat is -5.7800. The R-square is 0.0623 and the adjusted R-square is 0.0611.Figure A-17 draws the scatter plot of relationship between 9-month ranking period return and 4-month holding period return when excluding 4 observation with high volatility.

[44]In general, these observations that have low ranking period return and large negative holding period return occur when the ranking period market volatility is high.

volatility, variation in the size of 4-month holding-period return doesn’t seem to get larger when the size of ranking period return gets bigger.

Based on the above discussion in this section, we can see that the historical data show patterns that are in general in favour of the relationships between the momentum effect and the ranking period market volatility, the ranking period return of a momentum strategy described by our three hypotheses.

Figure 4-3. Ranking Period Returns from 1969 to 2011 (J=9, K=4)

Each point in this figure draws a 9x4 momentum portfolio's buy-and-hold return over it 9-month ranking period. A 9x4 momentum portfolio is implemented every month starting at the end of Sep 1969. The whole figure shows the variability in the size of the 9x4 momentum portfolio's buy-and-hold return over time. The 9x4 momentum portfolio's ranking period return varies substantially over time about its mean of 138% with the lowest 9-month momentum portfolio's ranking period return being 71% and the highest 443%.

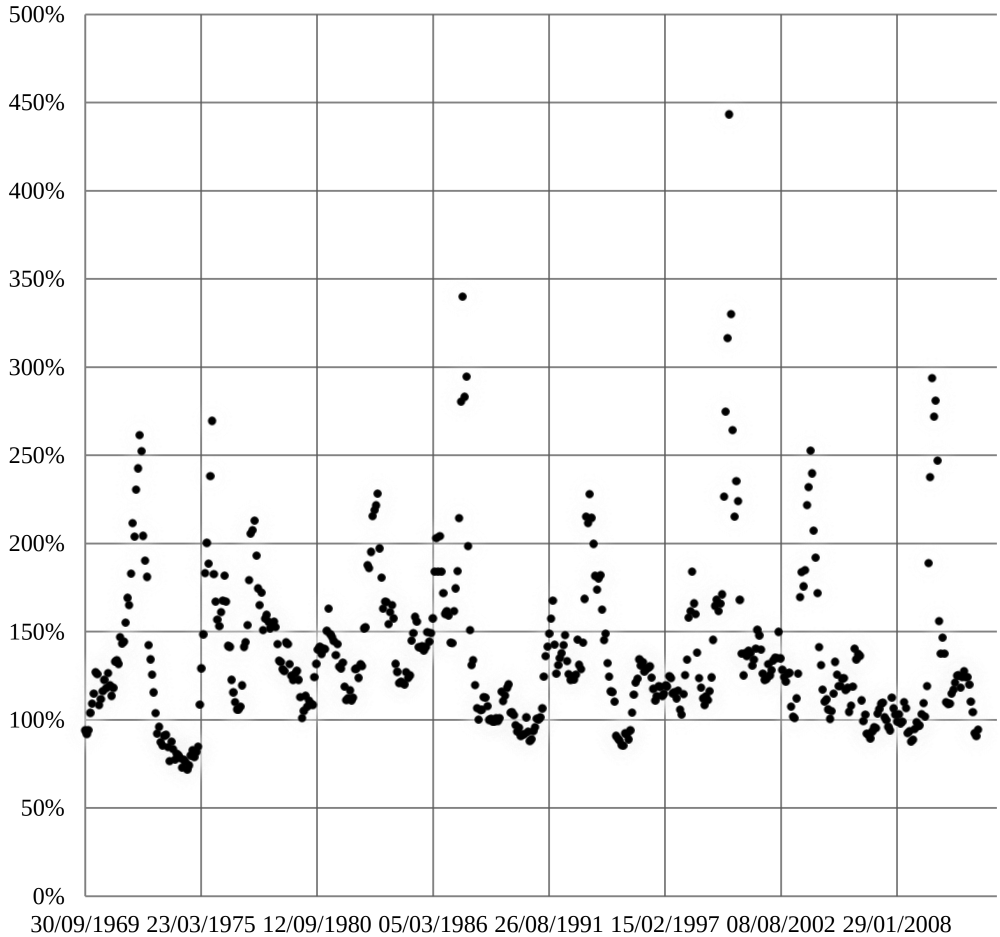
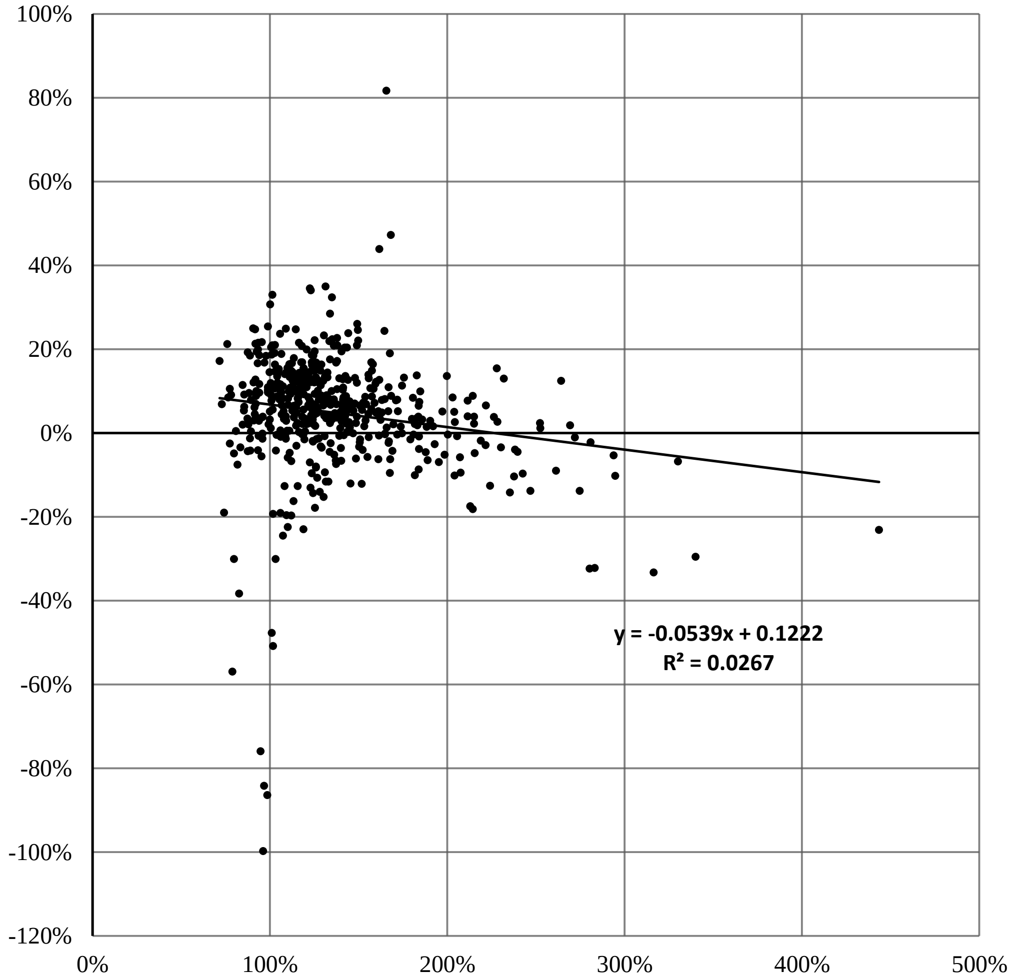


Figure 4-4. Scatter Plot between the Holding Period Return and the Ranking Period Return (J=9, K=4)

The vertical axis represents 9x4 momentum trading strategy's buy-and-hold return over 4-month holding period and the horizontal axis represent its buy-and-hold return over 9-month ranking period. Each point in this figure is corresponding to a 9x4 momentum portfolio implemented at the end of a calendar month t between 1969 and 2011. Its horizontal reading is 9-month buy-and-hold ranking period return from calendar month $t-9$ to $t-1$ and its vertical reading is its 4-month buy-and-hold holding period return from calendar month $t+1$ to$t+4$. This simple regression suggests a negative relationship between the two variables.



4.5 Threshold Regression Model (Two-Regime Switching Model) Construction

4.5.1 Threshold Regression Model with Heteroskedasticity

Based on hypotheses derived from behavioural models that provide theoretical framework for the momentum effect and on relationships between a momentum portfolio's holding period return and the ranking period market volatility, its ranking period market volatility observed from the historical data, a threshold regression (two-regime switching) model with heteroskedasticity is constructed to analyse the momentum effect. This threshold regression model with heteroskedasticity is specified as the following:

$$r_t^H = \left[1 - I_{[\tau,\infty)}(z_{t-1}^R)\right](\alpha_1 + \beta_1 z_{t-1}^R + \gamma_1 r_{t-1}^R) + I_{[\tau,\infty)}(z_{t-1}^R)(\alpha_2 + \beta_2 z_{t-1}^R + \gamma_2 r_{t-1}^R) + \varepsilon_t \quad (4.1)$$

$$Var(\varepsilon_t) = \sigma_1^2\left[1 - I_{[\tau,\infty)}(z_{t-1}^R)\right] + \sigma_2^2 I_{[\tau,\infty)}(z_{t-1}^R) \quad (4.2)$$

r_t^H represents momentum portfolio's holding-period return (buy-and-hold return over the next K months) and z_{t-1}^R is ranking period market volatility measured by the market return variance over the past J months. r_{t-1}^Rstands for ranking period return (buy-and-hold return over the last J months) and $I_{[\tau,\infty)}(z_{t-1})$ is an indicator function with τ as the threshold parameter. $I_{[\tau,\infty)}(z_{t-1})$ equals one if $z_{t-1} \in [\tau, \infty)$ and zero otherwise. When market volatility is below τ, momentum portfolio is in the momentum regime and the momentum effect is expected; otherwise, it's in the reversal regime where this effect tend to be revered.σ_1^2 denotes variance of the error term of the regression in the momentum regime and σ_2^2 is variance of the error term in the reversal regime. The first hypothesis suggests$\alpha_1 > 0$ in the momentum regime, and $\alpha_2 < 0$ or (and) $\beta_2 < 0$ or (and) $\gamma_2 < 0$ in the reversal regime as we expect reversal; the second hypothesis indicates$\beta_1 < 0$, and the third hypothesis implies $\gamma_1 < 0$. Finally, heteroskedasticity suggests $\sigma_2^2/\sigma_1^2 > 1$.

4.5.2 Data

This model is applied to four momentum trading strategies, namely, 3x3, 6x3, 9x4, 12x3, as each of them is the most profitable strategies among those with the same ranking periods in terms of average buy-and-hold return during the whole sample period in previous chapter. In order to improve the reliability of model estimation, sample period is extended from 1979 to 2011 to 1969 to 2011so that more observations associated with high market volatility and high ranking period return can be included in the estimation process.[45] Both ranking period returns and holding period returns are calculated using the same method as in Chapter 1 based on data from LSPD. Ranking period market returns are based on FTSE All index daily data from DataStream.

To calculate market return volatility, market's daily return is assumed to be independently and identically distributed, monthly market return variance is obtained simply by calculating variance in daily return over one month and multiply it by 20, the number of trading days per month.[46] Denote market daily return at time t as r_t^M, and there are m daily observations, the sample market daily variance,

$$\widehat{\sigma_D^2}=\frac{1}{m-1}\sum_{i=1}^{m}(r_{t+i}^M-\mu^M)^2 \quad (4.3)$$

μ^M is the sample average return. Since variance is linear in time and can be aggregated, it follows that monthly market variance can be calculated as

[45]FTSE All index daily data are available in DataStream from Jan 1969. The reason for that we only study the time period from 1979 to 2011 in previous chapter is that the complete sample is not available until 1979. Studying the complete sample can avoid the confusion that the variation in the magnitude of momentum effect might be caused by incomplete sample instead of other impact factors such as market volatility. In this chapter, however, we include time period with incomplete sample as our focus is more on the switch between momentum and its reversal, in other words, the sign of momentum returns. By doing this, we have more observations with negative returns, which should improve the estimation of our threshold regression model.

[46]Figlewski (1997) notes that the sample mean is an inaccurate estimate of the true mean especially for small samples; taking deviations around zero instead of the sample mean typically increases volatility forecast accuracy. We still report results with market return variance estimated by Eq. (4.3) as it is straightforward. As neither correcting for serial correlation of daily returns nor adopting the estimator recommended in Figlewski (1997) changes the main characters of ranking period market return volatility in our study significantly, our estimation results still hold using different methods of variance estimation.

$$\widehat{\sigma_M^2} = \widehat{\sigma_D^2} * 20 \quad (4.4)$$

As mentioned in Poon (2008), volatility typically does not remain constant through time, therefore it is a common practice to break one period up into smaller sub-periods if possible. Hence, in our study, market monthly variance is calculated each month in this study and ranking period market volatility for JxK trading strategy is calculated by summing monthly market volatility over J months before a momentum portfolio is formed.

4.6 Bayesian Method of Estimation

4.6.1 Bayesian Method of Estimation V.S. Classical Method of Estimation

As stated in Bauwens et al. (1999), there are marked differences between the classical and the Bayesian approaches. In a classical framework, the critical value of indicating function, τ, in the threshold regression model is determined by a grid search. As a result, inference on β gives a conditional estimator, with a fixed sample separation in the step transition case. In the Bayesian approach, on the contrary,τ is integrated out, so $E(\beta|y)$ is a marginal estimator which depends not on a single sample separation, but on the most likely and averaged sample separations.

This difference gives an advantage to Bayesian approach over classical one when making decision between threshold regression model and smooth transition model. With Bayesian approach, threshold regression model can generate rather smooth switching between regimes depending on the posterior density ofτ. The graph of the posterior density of τ in a step transition model can have direct intuition results concerning the degree of abruptness of the switching. If most of the probability appears for one value of τ this is confirmation of an abrupt change, which support the choice of threshold regression model over a smooth transition model. If on the contrary, most of the probability is scattered around one value of τ with a nice bell shape, this is evidence of a gradual transition, in this case, a smooth transition model should be considered and model comparison tests might be necessary to make a choice.

4.6.2 Posterior Probability Distributions of Parameters

According to Bauwens et al. (1999), posterior probability distribution of parameters can be obtained as follows.

Eq. (4.1) and Eq. (4.2) can be written in a compact form:

$$y_t = x_t'(\tau)\,\beta + \varepsilon_t \quad (4.5)$$

$$Var(\varepsilon_t) = \sigma^2\left[\left(1 - I_{[\tau,\infty)}(z_{t-1}^R)\right) + \phi I_{[\tau,\infty)}(z_{t-1}^R)\right] = \sigma^2 h_t(\tau,\phi) \quad (4.6)$$

Where

$$y_t = r_t^H \quad (4.7)$$

$$x_t'(\tau) = \left[1, z_{t-1}^R, r_{t-1}^R, I_{[\tau,\infty)}(z_{t-1}^R), I_{[\tau,\infty)}(z_{t-1}^R) * z_{t-1}^R, I_{[\tau,\infty)}(z_{t-1}^R) * r_{t-1}^R\right] \quad (4.8)$$

$$\beta' = [\alpha_1, \beta_1, \gamma_1, (\alpha_2 - \alpha_1), (\beta_2 - \beta_1), (\gamma_2 - \gamma_1)] \quad (4.9)$$

$$\sigma^2 = \sigma_1^2 \quad (4.10)$$

$$\phi = \frac{\sigma_2^2}{\sigma_1^2} \in (0, +\infty] \quad (4.11)$$

Define

$$y_t(\tau,\phi) = y_t / \sqrt{h_t(\tau,\phi)} \quad (4.12)$$

$$\text{and } x_t'(\tau,\phi) = x_t'(\tau) / \sqrt{h_t(\tau,\phi)} \quad (4.13)$$

Eq. (1) and Eq. (2) are transformed as:

$$y_t(\tau,\phi) = x_t'(\tau,\phi)\,\beta + \epsilon_t \quad (4.14)$$

$$\text{Where } Var(\epsilon_t) = \sigma^2 = \sigma_1^2 \quad (4.15)$$

Prior

$$\varphi(\beta, \sigma^2) \propto \sigma^{-2} \quad (4.16)$$

$$\varphi(\phi) \propto \mathrm{I}_{[\phi_L, \phi_H]}(\phi) \quad (4.17)$$

$$\varphi(\tau) \propto \mathrm{I}_{[z_L, z_H]}(\tau) \quad (4.18)$$

Values of (ϕ_L, ϕ_H) and (z_L, z_H) are chosen using the method of trial and error. In addition the number of observations per regime needs to be greater than the number of regressors.

The conditional posterior densities of β and σ^2 are given by

$$\varphi(\beta|\tau, \phi, y) = f_t(\beta|\beta_*(\tau, \phi), M_*(\tau, \phi), s_*(\tau, \phi), v) \quad (4.19)$$

$$\varphi(\sigma^2|\tau, \phi, y) \propto f_{IG2}(\sigma^2|s_*(\tau, \phi), v) \quad (4.20)$$

Where

$$M_*(\tau, \phi) = \sum_{t=1}^{T} x_t(\tau, \phi) x_t'(\tau, \phi) \quad (4.21)$$

$$\beta_*(\tau, \phi) = M_*^{-1}(\tau, \phi) \sum_{t=1}^{T} x_t(\tau, \phi) y_t(\tau, \phi) \quad (4.22)$$

$$s_*(\tau, \phi) = \sum_{t=1}^{T} y_t(\tau, \phi)^2 - \beta_*'(\tau, \phi) M_*(\tau, \phi) \beta_*(\tau, \phi) \quad (4.23)$$

$$v_* = T - K \quad (4.24)$$

The corresponding posterior density of τ, ϕ is

$$\varphi(\tau, \phi|y) \propto \left[\prod_{t=1}^{T} h_t(\tau, \phi)\right]^{-1/2} s_*(\tau, \phi)^{-v_*/2} |M_*(\tau, \phi)|^{-1/2} \varphi(\tau)\varphi(\phi) \quad (4.25)$$

The marginal posterior distributions ofϕ, τ can be obtained using one of numerical integration methods and Metropolis–Hastings algorithm with uniform distribution is employed in our estimation.

The marginal posterior densities of β and σ^2 follow with

$$\varphi(\beta|y) = \int \int \varphi(\beta|\tau, \phi, y)\ \varphi(\tau, \phi|y) d\tau d\phi \quad (4.26)$$

$$\varphi(\sigma^2|y) = \int \int \varphi(\sigma^2|\tau, \phi, y)\ \varphi(\tau, \phi|y) d\tau d\phi \quad (4.27)$$

Now that we have marginal posterior density for all parameter, we can obtain the Bayesian 90% confidence interval of each parameter as it is simply a continuous interval such that the posterior probability mass contained in that interval is 90%.

4.7 Estimation Results

We report and discuss the empirical results on the estimation of the threshold regression model with momentum trading strategy 9x4. In order to examine the robustness of our model, we also estimate this model with other three momentum trading strategies 3x3, 6x3 and 12x3. To check if this model has reliable performance over time, we estimate this model with all of the above four momentum trading strategies for three sample periods, Sep 1969 to Dec 1997, Jan 1969 to Dec 2005, and Sep 1969 to Jul 2011 respectively.

4.7.1 Discussion of Posterior Distributions of τ

For the whole sample period of Sep 1969 to Jul 2011, a uniform distribution with distribution support between 0.035 and 0.045 is assigned to τ as the prior distribution using the trial and error method.[47] Draws for $\tau's$ posterior distribution are generated by Independent Metropolis–Hastings algorithm with random walk that has uniform distribution as candidate density. The posterior probability distribution of τ is presented as in Figure 4-5A.

Apparently, the majority of the probability occurs for one value ofτ, which is between 0.04 and 0.042. This result indicates that the switch from one regime to the other is rather abrupt and it supports the choice of threshold regression model instead of smooth transition model in our study. As τ is the threshold parameter, this estimated result says that when ranking period market volatility is below (above) the range of [0.04, 0.042], momentum trading strategy 9x4 tends to make profits (losses) and thus the momentum effect tends to continue (reverse) in the stock market for the next four months.

Figure 4-5B and Figure 4-5C present the posterior density of τ for two sub samples of Jan 1969 to Dec 1997 and Sep 1969 to Jul 2005, respectively. The Trial and error method gives the same prior distribution of τ for both samples as for the whole

[47]To guarantee the reliability of regression estimation in both regimes, we choose the support for prior distribution of τ so that there are no less than 25 observations in both regimes.

sample. This same prior distribution of τ implies that the critical value of the indicating function is rather stable over time. Compared with Figure 4-5A, the posterior density of τ in Figure 4-5B and Figure 4-5C do not appear to be concentrated on a single value; instead, the posterior draws scatter in the range between 0.036 and 0.042 in both cases. We conjecture that the possible reason for this different shape of the posterior density of τ is that the number of observations falling into the prior distribution support is very small for two sub samples. Nevertheless, as most probability in Figure 4-5B and Figure 4-5C occurs around 0.04 instead of evenly distributed in the prior support of [0.035, 0.045], it is still reasonable to use threshold regression model.

4.7.2 Discussion of Posterior Distributions of ϕ

A uniform distribution with distribution support between 0.5 and 6 is employed for the prior distribution of ϕ for the whole sample period.[48] Figure 4-6A draws the posterior probability distribution of ϕ for the whole sample period and it shows that all probabilities occur for values in the range of [1, 4]. As the 90% Bayesian confidence interval of ϕ lies between [1.897, 2.490] shown in Table 4-1, it is confirmed that the variance of the error term associated with the regression in the reversal regime is significantly larger than that in the momentum regime. The same conclusion can be drawn for two sub-sample periods as the 90% Bayesian confidence interval of ϕ lies between [1.408, 2.384] and [1.323, 2.090] for two sub samples from Jan 1969 to Dec 2005 and from Sep 1969 to Jul 2011 respectively.

The estimation results ϕ clearly provide evidence in favour of the assumption that variance of the error term is different when the ranking period market volatility change from below to above the threshold range indicated by the posterior distribution of τ. The combined results of posterior distributions of τ and ϕ confirm

[48] The choice of distribution support between 0.5 and 6 is arbitrary. Since we use non-informative prior distribution, i.e., uniform distribution, the distribution support is appropriate in our study as long as it does not constrain the posterior distribution. As all posterior distributions of $\emptyset$ lie in the range between 1 and 4, this choice is appropriate.

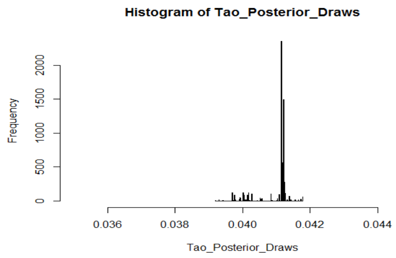
the suitability of applying a threshold regression model with heteroskedasticity to analyse the performance of the momentum trading strategy 9x4.[49]

[49]Ang and Timmerman (2011) recommend to use regime switching models to capture abrupt changes in the statistical properties of financial market variables. They demonstrate that in empirical estimates, the regime switching means, volatilities, autocorrelations, and cross-covariances of asset returns often differ across regimes, which allow regime switching models to capture the stylized behaviour of many financial series including fat tails, heteroskedasticity, skewness, and time-varying correlations. These posterior distributions of $\boldsymbol{\tau}$ and $\boldsymbol{\phi}$ are indeed consistent with the arguments of Ang and Timmerman (2011).

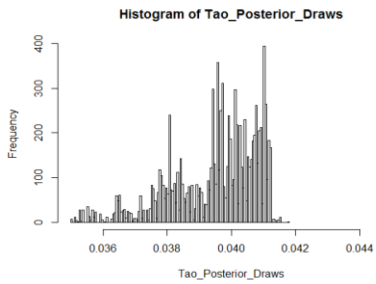
Figure 4-5. Posterior Probability Distributions of τ (J=9, K=4)

Figure A., B., and C. show the posterior probability distributions of τ for three sample periods, namely, 1969-2011, 1969-1997, and 1969-2005. A uniform distribution with distribution support between 0.035 and 0.045 is assigned to τ as the prior distribution using the trial and error method for all three sample periods. All three posterior probability distributions of τ are generated by independent Metropolis–Hastings algorithm with uniform candidate density.

A. 1969-2011



B. 1969-1997



C. 1969-2005

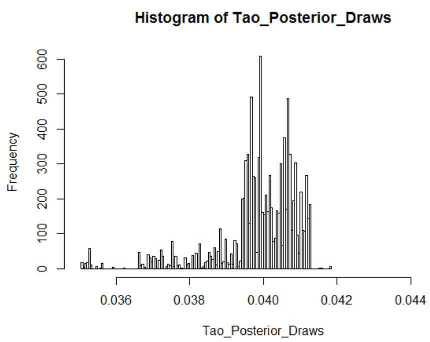
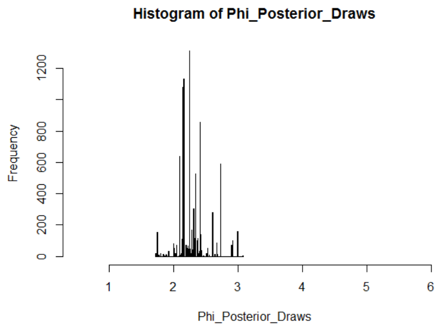


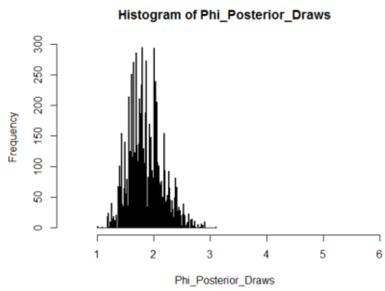
Figure 4-6. Posterior Probability Distributions of ∅ (J=9, K=4)

Figure A., B., and C. show the posterior probability distributions of ∅ for three sample periods, 1969-2011, 1969-1997 and 1969-2005 respectively. A uniform distribution with distribution support between 0.5 and 6 is assigned to τ as the prior distribution for all three sample periods. All three posterior probability distributions of τ are generated by independent Metropolis–Hastings algorithm with uniform candidate density.

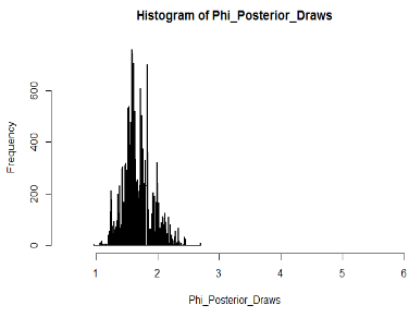
A. 1969-2011



B. 1969-1997



C. 1969-2005



4.7.3 Discussion of Posterior Distributions of $\boldsymbol{\alpha_1}, \boldsymbol{\beta_1}, \boldsymbol{\gamma_1}$

$\alpha_1, \beta_1, \gamma_1$ are parameters associated with the momentum regime when the ranking period market volatility is below the threshold τ. Based on our hypotheses, we expect that $\alpha_1 > 0$, $\beta_1 < 0$ and$\gamma_1 < 0$. Results regarding the estimation results are reported in Table 4-1.

α_1 is the constant term of the regression in the momentum regime and it measures the size of a momentum trading strategy's annualized return that can't be explained by the ranking period return and the ranking period market volatility in the regression. Table 4-1 reports the 90% Bayesian confidence interval of α_1 for momentum trading strategy 9x4 for three time periods. Based on the estimation results, α_1 is significantly positive as its 90% Bayesian confidence interval lies in positive territory for all three sample periods. The size of α_1 is quite consistent over time and centred around 0.2. The estimation results of $\alpha_1$are consistent with our first hypothesis and in general, the momentum effect is present and momentum trading strategies are profitable when the stock market is calm with relatively low volatility.

The results on the sign ofβ_1, which measures the impact of the ranking period market volatility on the size of the momentum effect, are mixed. Based on the results in Table 4-1, the significance of β_1 varies from time to time. It is significantly negative based on data as its 90% Bayesian confidence interval is [-4.258, -1.696] from 1969 to 1997 and hence suggests a negative relationship between the ranking period market volatility and the momentum portfolio's return as stated in hypothesis two. However, when sample is extended to 2005 and 2011, β_1 becomes insignificant as its 90% Bayesian confidence interval lies within the range of [-1.109, 1.050].

γ_1 is the coefficient associated with the ranking period return and it measures the effect of a momentum portfolio's ranking period return on the holding period return. In line with the hypothesis three, γ_1 is significantly below zero for all three sample periods. It can be seen from Table 4-1 that the size of γ_1 is fairly stable over time as its 90% Bayesian confidence interval for 1969 to1997, 1969 to 2005 and

1969 to 2011 is [-0.124, -0.081], [-0.116, -0.076] and [-0.112, -0.073] respectively. These results confirm that there is an inverse relationship between the ranking period return and the holding period return.

According to the results, in momentum regime when market volatility is below the thresholdτ, the magnitude of the momentum effect mainly depends on the value of α_1 and γ_1 and the size of ranking period return consideringβ_1 is insignificant most time and the size of market volatility is small in this regime. Figure 4-3 shows that in most time, the ranking period return lies below 200%, which implies that the negative impact of γ_1 is very unlikely to diminish the momentum effect. Nevertheless, ranking period return does become considerably large with the highest being 443%, which suggests that high returns of stocks during the ranking period are very likely due to overreaction. In this case, correction may happen in the holding period and the contrarian effect is possible to take place even in the momentum regime. Therefore, except the ranking period volatility, the ranking period return is also an important variable that has significant impact on moment effect during the holding period.

4.7.4 Discussion of Posterior Distributions of $\alpha_2, \beta_2, \gamma_2$

$\alpha_2, \beta_2, \gamma_2$ are parameters in the reversal regime when the stock market becomes volatile with the ranking period market volatility exceeding the threshold indicated by the value of τ. Compared with estimation results of $\alpha_1, \beta_1, \gamma_1$, there are larger variation in the posterior densities of $\alpha_2, \beta_2, \gamma_2$ over time. This is expected as we have significantly larger variance in the error term in the reversal regime based on estimated results of ϕ. According to the hypothesis one that when the market becomes volatile, the momentum effect is very likely to reverse and momentum trading strategies tend to generate losses as the large market volatility signals collapse of the market confidence and the transition of the market state. This hypothesis cannot be rejected by the estimated results as discussed below.

According to Table 4-1, α_2 is significantly negative for two sub time periods from 1969 to 1997 and 1969 to 2005 as the 90% Bayesian confidence interval is [-0.242,

-0.007] and [-0.325, -0.073] for 1969 to 1997 and 1969 to 2005 respectively. α_2 becomes insignificant as we add more data up to 2011 and the 90% Bayesian confidence interval of α_2 is [-0.258, 0.031].

In contrast with the results of $\beta_1$associated with the ranking period market volatility in the momentum regime, there is a significant negative relationship between a momentum portfolio's holding period return and the ranking period market volatility. The negative impact of the ranking period market volatility on the holding period return is consistently large. The 90% Bayesian confidence interval ofβ_2 lies in negative territory for all three sample periods and the posterior probability distribution of β_2 is far below zero. The 90% Bayesian confidence interval ofβ_2 is [-1.674, -2.535], [-2.371, -2.185] and [-5.770, -2.674] for the time periods 1969 to 1997, 1969 to 2005, 1969 to 2011, respectively.

Unlike the consistent and significant negative relationship between the ranking period return and the holding period return over time in the momentum regime, the relationship is uncertain in the reversal regime as γ_2 is not significantly different from zero for the time period of 1969 -2005 and it only becomes significantly positive when the post-2005 data is included as its 90% Bayesian confidence interval is [0.128, 0.319], as shown in Table 4-1.

The above results are in general consistent with our hypothesis that the momentum effect is very likely to reverse when the ranking market volatility is above threshold level. For the first two time periods, namely 1969 to 1997 and 1969 to 2005, given that the ranking period return has no significant impact, the negative Bayesian confidence intervals of α_2 and γ_2 indicate negative holding period return, that is, the contrarian effect during the holding period. For the whole time period of 1969 to 2011, although α_2 is not significant and γ_2 is positive, the large negative value of β_2 implies that the impact of the large ranking period market volatility is more than sufficient to cancel the positive effect of the ranking period return on the holding period return. Thus, we should expect a reversal when market volatility surges above the threshold level.

Table 4-1. 90% Bayesian Confidence Intervals of Parameters in the Threshold Regression Model (J=9, K=4)

This table reports the 90% Bayesian confidence interval for parameters in the Threshold Regression Model. A Bayesian 90% confidence interval is simply a continuous interval on α_1 such that the posterior probability mass contained in that interval is 0.9.

Parameters	**90% Bayesian Confidence interval**		
	Jan1969-Dec1997	**Jan1969-Dec2005**	**Jan1969-Jul2011**
$\boldsymbol{\alpha_1}$	[0.202, 0.271]	[0.182, 0.248]	[0.166, 0.228]
$\boldsymbol{\beta_1}$	[-4.258, -1.696]	[-1.986, 0.414]	[-1.109, 1.050]
$\boldsymbol{\gamma_1}$	[-0.124, -0.081]	[0.116, -0.076]	[-0.112, -0.073]
$\boldsymbol{\alpha_2}$	[-0.242, -0.007]	[0.325, -0.073]	[-0.258, 0.031]
$\boldsymbol{\beta_2}$	[-1.674, -2.535]	[-2.371, -2.185]	[-5.770, -2.674]
$\boldsymbol{\gamma_2}$	[-0.046, 0.151]	[-0.001, 0.219]	[0.128, 0.319]
$\emptyset$	[1.408, 2.384]	[1.323, 2.090]	[1.897, 2.490]

Note: the posterior distributions of the above parameters are available in the Appendix.

4.7.5 Robust Tests of the Performance of the Threshold Regression Model

To investigate whether the performance of the threshold regression model is robust across various momentum trading strategies, we apply this model to other three momentum trading strategies and examine results of all three momentum trading strategies for three time periods. We reports and compare estimation results of the threshold regression model applied to all momentum trading strategies including 3x3, 6x3, 12x3, and 9x4 in previous section for three different time periods, 1969 to 1997, 1969 to 2005 and 1969 to 2011.

Figure 4-7 compares the posterior probability distributions of τ for these four momentum trading strategies for the whole sample period and it shows that all posterior probabilities are highly concentrated for momentum trading strategies 12x3, 9x4 and 6x3. Hence, the performance of momentum portfolios based on these three momentum trading strategies experiences abrupt changes from profits to losses when the ranking period market volatility shifts from below to above the critical value range. The only exception is momentum trading strategy 3x3. The posterior probability distribution of τ is closer to a bell shape than that of the other three momentum trading strategies, which suggests that the switch from profits to losses is smoother when the ranking period market volatility increases. Nevertheless, the estimation results of τ for the other three momentum trading strategies have confirmed the abrupt transition between the momentum and the contrarian effect indicated by the ranking period market volatility.

Similar to the posterior distributions of ϕ for the momentum trading strategy 9x4, the posterior distribution of ϕ lies above 1 and clusters in the range between 2 and 3 for all strategies of 3x3, 6x3 and 12x3 based on data for the whole sample period according to Figure 4-8. Therefore, heteroskedasticity is a common feature of the threshold regression model for all four momentum trading strategies and the variance of the error term in the reversal regime is significantly greater than that in the momentum regime.

In terms of the posterior probability distribution of α_1, it is apparent that α_1 is significantly greater than zero over time and across all four momentum trading strategies as the 90% Bayesian confidence interval lies above zero for all cases as shown in Table 4-2 Part A. The fact that α_1 is consistent over time and cross momentum strategies provides concrete evidence of the dominance of the momentum effect in the stock market when market volatility is below the threshold. Table 4-2 Part B reports the 90% Bayesian confidence interval of β_1 across momentum trading strategies over time and it shows that β_1 is significantly smaller than zero in most cases. β_1 is not significantly different from zero only for 4 out of 12 cases, that is, the momentum strategy 3x3 based on the full sample , 6x3based on sample from 1969 to 2005, 9x4 based on sample from 1969 to 2005 and sample from 1969 to 2011. According to these results, it is reasonable to say that in general an increase in the ranking period market volatility will reduce momentum profits in the momentum regime. The negative correlation between the ranking period return and the holding period return is also robust across all four momentum trading strategies over time as the 90% Bayesian confidence interval of γ_1 lies below zero in all cases as shown in Table 4-2 Part C.

Table4-2 Part D, Part E, and Part F report 90% Bayesian confidence interval for parameters in the reversal regime. In contrast with the stability of parameters in the momentum regime, there is more variation in the significance of parameters in the reversal regime. Unlike the consistency of α_1 taking on positive values, the constant term in regime two α_2 is below zero in general; however, it is insignificant in three cases as shown in Table 4-2D. This again confirms the prevailingness of the reversal in the reversal regime. The relationship between the holding period return and the ranking period market volatility is not certain in the reversal regime. In half of the twelve cases, β_2 is found insignificant whereas it is significantly negative in the other cases according to reports of Table 4-2E. However, for the whole sample period of 1969-2011, β_2 is significantly negative for all momentum trading strategies. Results forγ_2 are quite different across momentum trading strategies. As Table 4-2F shows that for both momentum trading strategy 3x3 and 9x4, γ_2 is insignificant from 1969 to 2005 and it becomes significant when observations are extended to 2011. γ_2 is significant for both momentum trading strategies 6x3 and 12x3 for all time periods.

The above comparison of results among these four different momentum trading strategies for three different sample periods has shown that parameters in the momentum regime are rather consistent across various momentum trading strategies and reliable over time. The most impressive results are with α_1 andγ_1. The 90% Bayesian confidence interval of α_1 is in positive territory for all of our four momentum trading strategies for all three different sample periods and the 90% Bayesian confidence interval of γ_1 is in negative territory in all cases. In contrast, parameters in the reversal regime have large variation in estimated values. Although all parameters have mixed estimated results across strategies over time, the estimated values of α_2 and β_2 are negative in most cases and there is no evidence of them being significantly positive.

4.7.6 Summary of Empirical Estimation Results

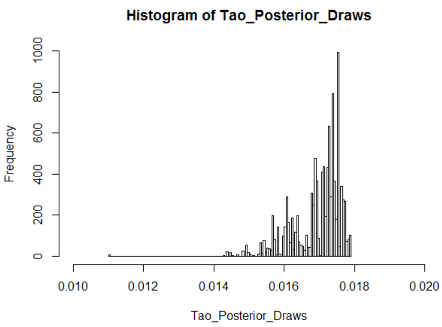
On a whole, the empirical estimation results are consistent with our expectations and the momentum effect is shown to be predictable to some extent by the lagged variables including the ranking period market volatility and the ranking period return. The performance of the threshold regression model is robust as the estimated results of all parameters are in general very similar for all of four tested momentum trading strategies with different ranking and holding periods and the results are also quite consistent over time.

Clearly, momentum portfolios have different performance in two different regimes that are governed by the ranking period market volatility. In the momentum regime when ranking period market volatility lies below the threshold, momentum trading strategies tend to make profits except the case when the ranking period return is extremely large, which is a sign of overreaction during the ranking period and indicates correction during the holding period. In the reversal regime, when the ranking period market volatility lies above the threshold, momentum trading strategies are very likely to lose money as the constant term is often negative and the ranking period market volatility has significantly large negative impact on the momentum effect in many cases.

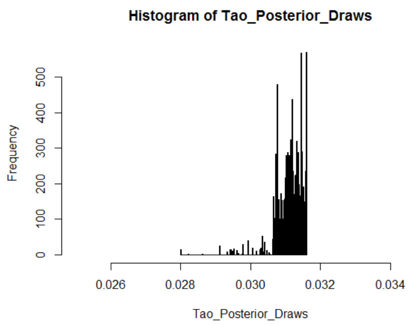
Figure 4-7. Posterior Probability Distributions of τ across Momentum Trading Strategies

Figure A., B., C., and D provide the posterior probability distributions of τ for trading strategy 3x3, 6x3, 9x4, and 12x3 for the time period 1969-2011. Using the trial and error method, the prior distribution for τ corresponding to each of the four trading strategies is a uniform distribution with the distribution support of [0.012, 0.020], [0.025, 0.035], [0.035, 0.045], and [0.040, 0.062].

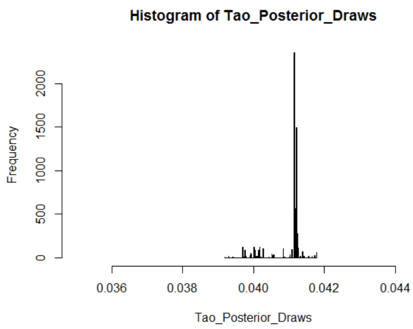
A. 3x3



B. 6x3



C. 9x4



D. 12x3

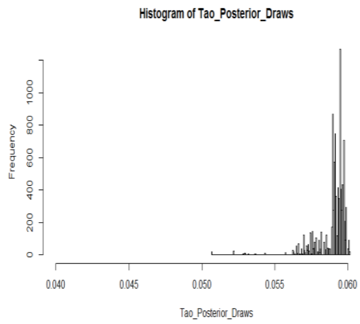
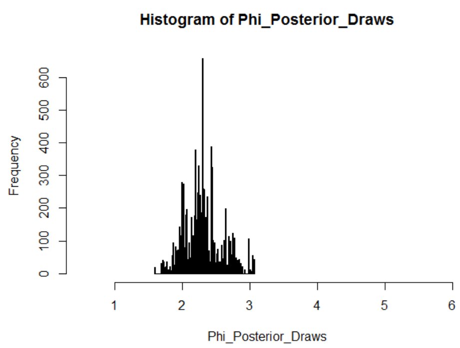


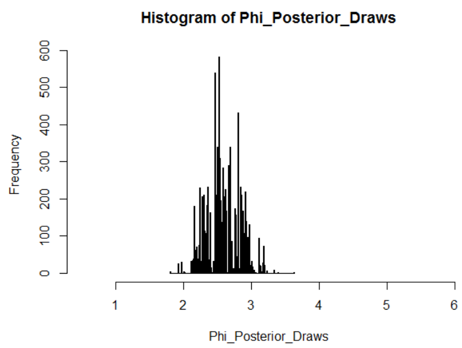
Figure 4-8. Posterior Probability Distributions of ∅ across Momentum Trading Strategies

Figure A., B., C., and D provide posterior probability distributions of ∅ for trading strategy 3x3, 6x3, 9x4, and 12x3 for the time period 1969-2011. The prior distribution for τ corresponding to each of the four trading strategies is a uniform distribution with the distribution support of [0.5, 6].

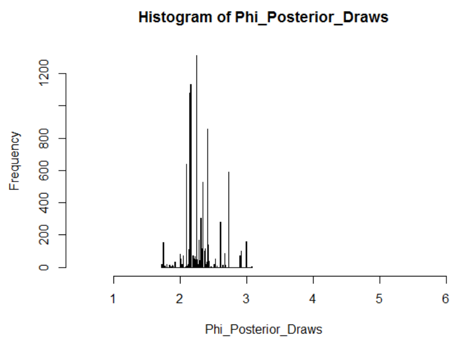
A. 3x3



B. 6x3



C. 9x4



D. 12x3

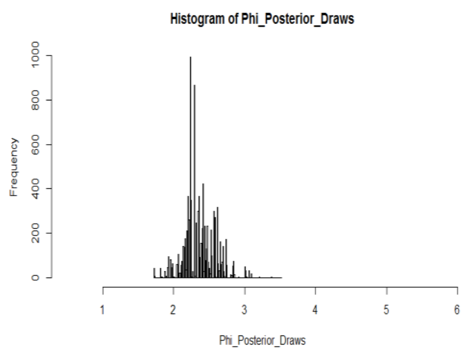


Table 4-2. 90% Bayesian Confidence Intervals of Parameters across Momentum Trading Strategies

	Jan1969-Dec1997	Jan1969-Dec2005	Jan1969-Jul2011
	Panel A. 90% Bayesian Confidence Interval of α_1		
3x3	[0.128, 0.185]	[0.121, 0.174]	[0.109, 0.161]
6x3	[0.155, 0.217]	[0.144, 0.198]	[0.129, 0.177]
9x4	[0.202, 0.271]	[0.182, 0.248]	[0.166, 0.228]
12x3	[0.183, 0.229]	[0.169, 0.211]	[0.160, 0.200]
	Panel B. 90% Bayesian Confidence Interval of β_1		
3x3	[-7.363, -3.190]	[-6.081, -1.499]	[-3.975, 0.058]
6x3	[-7.047, -2.804]	[-3.476, 0.724]	[-2.356, -0.140]
9x4	[-4.258, -1.696]	[-1.986, 0.414]	[-1.109, 1.050]
12x3	[-2.673, -1.417]	[-1.459, -0.269]	[-1.045, -0.066]
	Panel C. 90% Bayesian Confidence Interval of γ_1		
3x3	[-0.183,-0.106]	[-0.164, -0.093]	[-0.158, -0.090]
6x3	[-0.130, -0.078]	[-0.126, -0.081]	[-0.110, -0.069]
9x4	[-0.124, -0.081]	[-0.116, -0.076]	[-0.112, -0.073]
12x3	[-0.087, -0.066]	[-0.084, -0.064]	[-0.082, -0.062]
	Panel D. 90% Bayesian Confidence Interval of α_2		
3x3	[-0.220, -0.008]	[-0.195, 0.037]	[-0.176, -0.037]
6x3	[-0.240, -0.068]	[-0.186, -0.037]	[-0.250, 0.011]
9x4	[-0.242, -0.007]	[-0.325, -0.073]	[-0.258, 0.031]
12x3	[-0.243, -0.054]	[-0.344, -0.150]	[-0.338, -0.101]
	Panel E. 90% Bayesian Confidence Interval of β_2		
3x3	[-1.058, 8.101]	[-5.960, 2.508]	[-6.787,-2.644]
6x3	[-2.147, 1.196]	[-2.337, 0.388]	[-6.183, -2.620]
9x4	[-1.674, -2.535]	[-2.371, -2.185]	[-5.770, -2.674]
12x3	[-1.474, 0.680]	[-0.993, 1.264]	[-2.659, -0.692]
	Panel F. 90% Bayesian Confidence Interval of γ_2		
3x3	[-0.322, 0.093]	[-0.135, 0.286)	[0.043, 0.277]
6x3	[0.005, 0.207]	[0.046, 0.193)	[0.127, 0.325]
9x4	[-0.046, 0.151]	[-0.001, 0.219)	[0.128, 0.319]
12x3	[0.049, 0.139]	[0.063,0.154)	[0.129, 0.224]

4.8 Application of the Threshold Regression Model and the Performance Comparison between the Momentum and the Threshold-Regression-Model-Guided Trading Strategy

The estimation results in Section 4.7 imply that both the ranking period market volatility and the ranking period return have predictive power on performances of momentum trading strategies. Therefore, the threshold regression model can be used to design trading strategies that should outperform momentum trading strategies. The trading strategy based on the threshold regression model is named as the threshold-regression-model-guided trading strategy and is simply referred to as the model-guided trading strategy for simplicity.

Our new trading strategies make trades based on the forecast of the threshold regression model. If the threshold regression model has significant predictive power, then we should expect that model-guided trading strategies outperform momentum trading strategies for most time. Before we form model-guided trading strategies, we examine how good the prediction of the threshold regression model is with each of the four momentum trading strategies 3x3, 6x3, 9x4 and 12x3. For the purpose of discussion, the momentum trading strategy 9x4 is taken as an example and results are very similar among different momentum trading strategies.[50]

4.8.1 Algorithm of the Posterior Expectation of the Threshold Regression Model and Its Forecast Performance

To form the predictive density of a momentum trading strategy's return, we follow the algorithm of Lubrano (1998). According to Lubrano (1998), the posterior expectation of this model corresponds to:

$$E[g(y^*)|Data] = E_\xi\left[E_{y^*}(g(y^*)|Data,\xi)\right] = \int_\xi\left[\int_R g(y^*)p(y^*|Data,\xi)dy^*\right]\varphi(\xi|Data)\, d\xi \quad (4.22)$$

[50]Results for the other three trading strategies are available in Appendix.

Where $p(y^*|Data,\xi)$ is the density of future observations and ξ represents all the parameters of the model$\beta, \tau, \phi, \sigma^2$. For a given drawing of $\varepsilon^* = \varepsilon_{t+1}$ and conditionally onβ, τ, ϕ, generate y^* by recursion starting from:

$$y_{t+1} = \alpha_1 + \beta_1 x_t + (\alpha_2 - \alpha_1) I_{[\tau,\infty)} + (\beta_2 - \beta_1) I_{[\tau,\infty)} x_t + \varepsilon_{t+1} \quad (4.23)$$

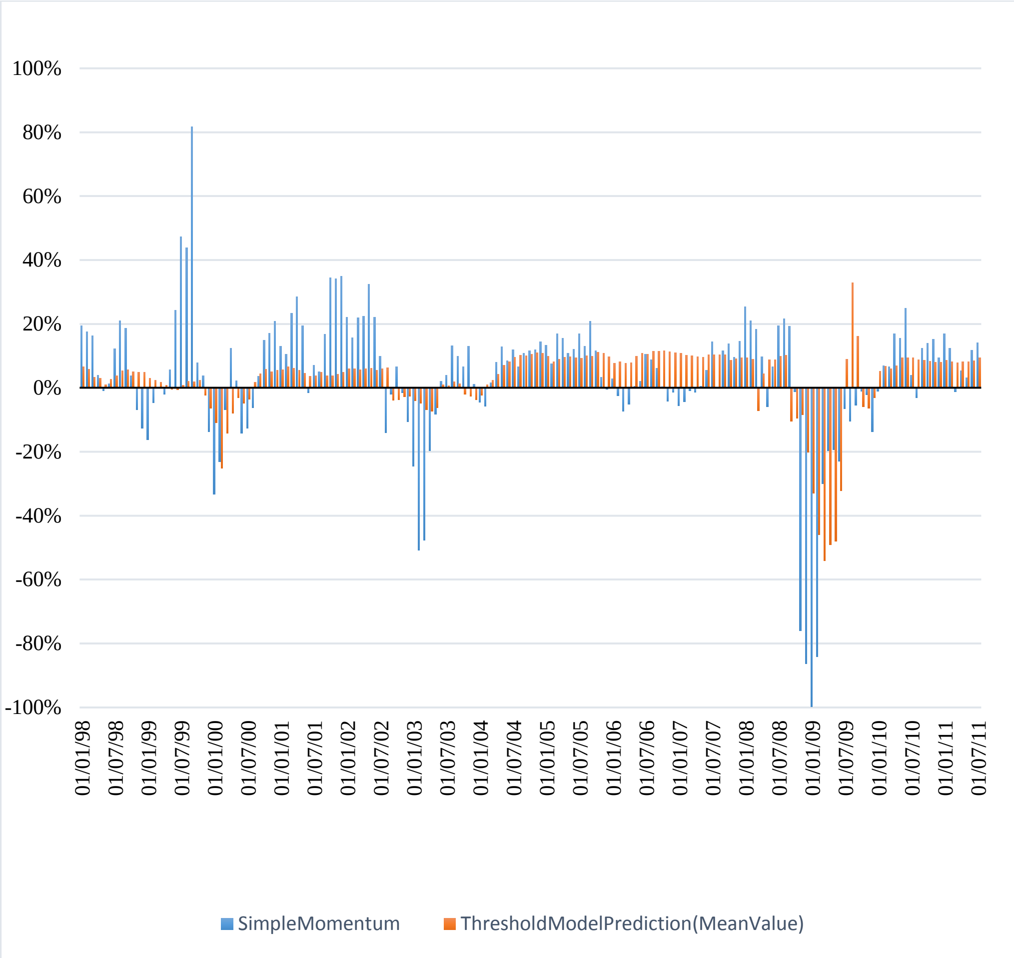
Conditional onτ, ϕ, the posterior densities of β, σ^2 are respectively Student and Inverted Gamma2. Consequently, a random drawing of βcan be obtained conditionally on σ^2 andτ, ϕ. In order to take into account of the uncertainty ofσ^2, a random drawing of ε is obtained from a Student density of T-k degrees of freedom, zero mean and scale parameters the conditional posterior mean ofσ^2. All the needed ingredients now are available to evaluate the predictive moments of y in the same numerical integration loops used for the posterior moments of the parameters.

The algorithm to generate the density of future observations is as follows. For each point on the integration grid of τ, ϕ, we compute the conditional expectation $E[\sigma^2|Data,\tau,\phi]$ and compute the conditional moments of β; draw a value for ε from a $t(0, E[\sigma^2|Data,\tau,\phi], T-k)$ and a β from its conditional Student posterior density; and then compute by recursion y^*. Finally, accumulate with the adequate weights of the Simpson rule $g(y^*)\ \varphi(\tau,\phi|Data)$.

Figure 4-9 shows predication results of the model-guided trading strategy 9x4. Apparently this threshold regression model picks up the sign of momentum portfolio's holding period return very well although this model does not do a great job in terms of predicting the size of the holding period return especially in the first half of sample period. Out of 163 months' trading results, this model can pick up signs of 135 results correctly. This prediction has a success rate as high as 82.8%. This result confirms the significant predictive power of the threshold regression model in the sense that it can forecast the switch between the momentum effect and the reversal.

Figure 4-9. Prediction Results of the Threshold Regression Model (J=9, K=4)

This figure compares the predicted performance of 9x4 momentum trading strategy by the threshold regression model with the real performance of it. Each orange bar represents the mean value of the predicted distribution of buy-and-hold holding period return of a 9x4 momentum portfolio and each blue bar measures the real buy-and-hold holding period return.



4.8.2 Threshold-Regression-Model-Guided Trading Strategies

The threshold regression model does a good job in terms of predicting the switch between the momentum and the contrarian effect and we are going to design a new type of trading strategy, named as the threshold-regression-model guided strategy, to exploit both the momentum effect and its reversal. A model-guide strategy JxK is implemented as follows.

Corresponding to each momentum trading strategy JxK, there is a model-guided trading strategy JxK. Unlike the momentum trading strategy where it always takes the long position in past winner portfolios and the short position in past loser portfolios, the model-guided trading strategy follows the indication of the threshold regression model. To implement a model-guided trading strategy, we follow the steps below.

At the beginning of month t, a momentum portfolio is formed and then the predictive density of this momentum portfolio's return over its next holding period from t+1 to t+K is generated by the threshold regression model based on available ranking period return and the ranking period market volatility data up to time t. If 95% of its distribution lies in the positive territory, we implement this momentum trading strategy by buying winner portfolio and selling loser portfolio and holding this position from month t+1 to t+K; on the other hand, if 95% of its distribution lies in the negative territory, we reverse the momentum trading strategy, in other words, we sell its winner portfolio and buy its loser portfolio and hold this position for next K months. Finally, when neither of the above is true, we take it as unclear indication and do not take any position in month t.

4.8.3 Performance Comparison between Momentum and Threshold-Regression-Model-Guided Trading Strategies

To compare the performance of model-guided trading strategies with that of momentum trading strategies, we implement model-guided trading strategies 3x3, 6x3, 9x4 and 12x3 every month from 1998 to 2011 on monthly basis. We first report trading activities of model-guided trading strategies and then make performance comparison between model-guided and momentum trading strategies.

4.8.3.1 Trading Activities of Threshold-Regression-Model-Guided Trading Strategies

Trading activities according to the prediction results are categorized into three different types, namely, the momentum trade, the contrarian trade and no trade and the number and percentage of each type of trading activity are summarised in Table 4-3 for model-guided trading strategies 3x3, 6x3, 9x4 and 12x3.

From Table 4-3, we can see that the proportion of each trade is pretty similar cross various model-guided trading strategies and over time. For all four model-guided trading strategies over both sample periods of 1998-2005 and 1998-2011, the momentum trade accounts for above 60% of all trades; whereas around 20% of time, the model indicates a significant reversal in the momentum effect and hence the contrarian trade takes place. The proportion of obscure indication, hence the decision of no position, is below 10%. The model-guided trading strategy 9x4 has the highest rate of the momentum trade, which is 74% for 1998-2005 and 76.1% for 1998-2011. The model-guided trading strategy 3x3 has the highest rate of the contrarian trade for 1998-2005, which is 28.1%, and the model-guided trading strategy 12x3 has the highest rate of the contrarian trade for 1998-2011, which is 26.8%.

Among all profitable contrarian trades, i.e., correctly predicted reversal observations, some are associated with extreme high ranking period market volatility and others are associated with extreme high ranking period return. For example, Table 4-4 lists all reversal observations for the model-guided trading strategy 9x4 that are correctly predicted by the threshold-regression model.[51] According to this table, 16 out of 27 reversal observations occur when the ranking period market volatility exceeds the critical range while the ranking period return is moderate; the other 11 reversals are associated with rather high ranking period

[51] Tables for the other three model-guided trading strategies are available in Appendix.

returns as all observations have the ranking period return above 200%. These results show that both the ranking period market volatility and the ranking period return are at work in terms of indicating the contrarian effect.[52]

4.8.3.2 Performance Comparison between Momentum and Threshold-Regression-Model-Guided Trading Strategies

The performances of model-guided trading strategies and those of simple momentum trading strategies are compared on the basis of the annualized BHR, the percentage of profitable trade and sharp ratio. The annualize BHR measures the profitability and the percentage of profitable trade and sharp ratio indicate the degree of risk. Performance comparison results are summarized in Table 4-5.

In terms of the annualized BHR, all model-guided trading strategies outperform their corresponding momentum trading strategies for both sample periods. As shown in Table 4-5 Panel A., the model-guided trading strategy 12x3 outperforms its corresponding momentum trading strategy 12x3 the most over sample period from 1998 to 2011 as the former earns an average annualized return of 33.7% and the latter 8.4%. The most profitable trading strategy is the model-guided trading strategy 9x4, which generates the average annualized BHR of 35.8% and 34.9% from time period of 1998-2005 and 1998-2011 respectively. Another noticeable difference is that the profitability of model guided strategies is more stable over time than their associated momentum trading strategies. For example, the difference in the average annualized BHR of model-guided trading strategy 9x4 between sample period of 1998 to 2005 and 1998-2011 is only 2.6% whereas the figure for the momentum trading strategy 9x4 is as much as 10.9%.

By the criteria of the performance reliability, which is measured by the percentage of profitable trade, model-guided trading strategies outperform momentum trading strategies as well. Table 4-5 Panel B shows that model guided strategies have

[52] We would like to stress the difference between the role of the ranking period market volatility and that of the ranking period return. Although both can indicate reversals, the ranking period market volatility indicate the reversal regime whereas the ranking period return indicate the reversal in the momentum regime.

higher percentage of profitable trade than momentum trading strategies with only one exception of the trading strategy 6x3 for the sample period of 1998 to 2005. Percentage of profitable trade of model-guided trading strategies in all cases is higher than 70% whereas this figure for momentum trading strategies is below 70% in general. The momentum trading strategy 12x3 has the percentage of profitable trade of 64.6% from 1998 to 2011 whereas this figure for the model guided strategy is 78.3%, which is about 14% higher than the former.

Table 4-5 Part C provides the Sharpe ratio figures that measure the risk-adjusted performance and once again results of the Sharpe ratio comparison are in favour of model-guided trading strategies. All model-guided trading strategies have higher Sharpe ratio than their corresponding momentum trading strategies according to Table 4-5 Part C. the model-guided trading strategy 12x3 offers the highest reward for taking a unit of risk as it has the highest Sharpe ratio of 0.664 and 0.564 for sample period of 1998 to 2005 and 1998-2011; whereas its corresponding momentum trading strategy 12x3 is the least beneficial for taking risk as it has the lowest Sharpe ration of 0.287 and 0.122 for 1998 to 2005 and 1998-2011.

To see the outperformance of model-guided trading strategy over its associated momentum trading strategy visually, we present the performance of the model-guided and the momentum trading strategy 9x4 in Figure 4-9 and Figure 4-10.[53]

Figure 4-9 shows the performance of both the momentum and the model-guided trading strategy 9x4 implemented every month from 1998 to 2011. It is clear that the model-guided trading strategy 9x4 has much “smoother” performance than the momentum trading strategy 9x4 in the sense that it never suffers large losses like the latter does. In fact, when the momentum trading strategy 9x4 makes huge losses, the model-guided trading strategy generate profits of the same size.

In Figure 4-10, the cumulative 4-month holding return, which is the simple sum of each month’s portfolio’s BHR starting from Jan 1998, is compared between the two trading strategies. Apparently the cumulative holding period return generated by the model-guided trading strategy 9x4 is in a clear uptrend whereas that

[53]The performance of model guided trading strategy 3x3, 6x3, and 12x3 are available in Appendix.

generated by the momentum trading strategy 9x4 suffer a couple of severe drop between 1998 and 2011. This continuous uptrend implies that implementation of the model-guided trading strategy 9x4 is not timing-dependent, meaning implementing this strategy in the UK equity market at any point in the sample time period and sticking to it should always generate profits over time. In contrast, the "bumpy" uptrend suggests that the profitability of the momentum trading strategy is more timing dependent. For example, implementing momentum trading strategy 9x4 from 2008 would suffer huge losses.

In summary, model-guided trading strategies benefit from the predictability of the switch between the momentum effect and its reversal. By exploiting both the momentum and the contrarian effect, model-guided trading strategies outperform momentum trading strategies with higher profitability and lower risks.

Figure 4-10. Buy-and-Hold Returns of the Momentum and the Threshold-Regression-Model-Guided Trading Strategy (K=9, J=4)

The threshold-regression-model-guided trading strategy follows the indication of the forecast result of the threshold regression model. At the beginning of month t, a momentum portfolio is formed and then the predictive density of momentum portfolio's return over its next holding period from t+1 to t+K is generated by the threshold regression model based on ranking period return and market volatility over time period from t-J to t-1. If 95% of its distribution lies in positive territory, we long the momentum portfolio by buying winner portfolio and selling loser portfolio and holding this position from month t+1 to t+K. On the other hand, if 95% of its distribution lies in negative territory, we reverse the momentum trading strategy, in other words, we sell past winners and buy past losers and hold this position for next K months. Finally, when neither of the above is true, it is taken as unclear indication and do not invest at month t.

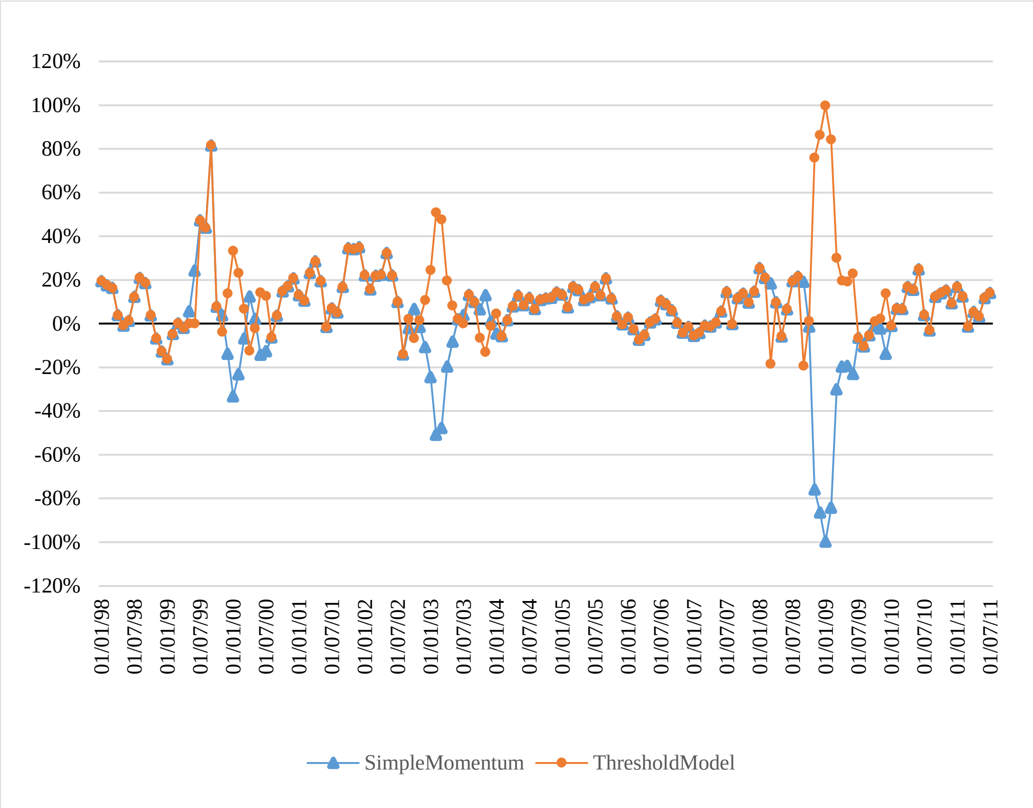


Figure 4-11. Long-Term Performance Comparison between the Momentum and the Threshold-Regression-Model-Guided Trading Strategy (J=9, K=4)

This figure compares the performance of the 9x4 momentum trading strategy and its corresponding model-guided trading strategy in terms of cumulative return, which is simple sum of a strategy's 4-month holding return over time from 1998 to 2011. Each point on a line is a simple sum of 4-month holding return generated by its strategy implemented in that month and all previous months.

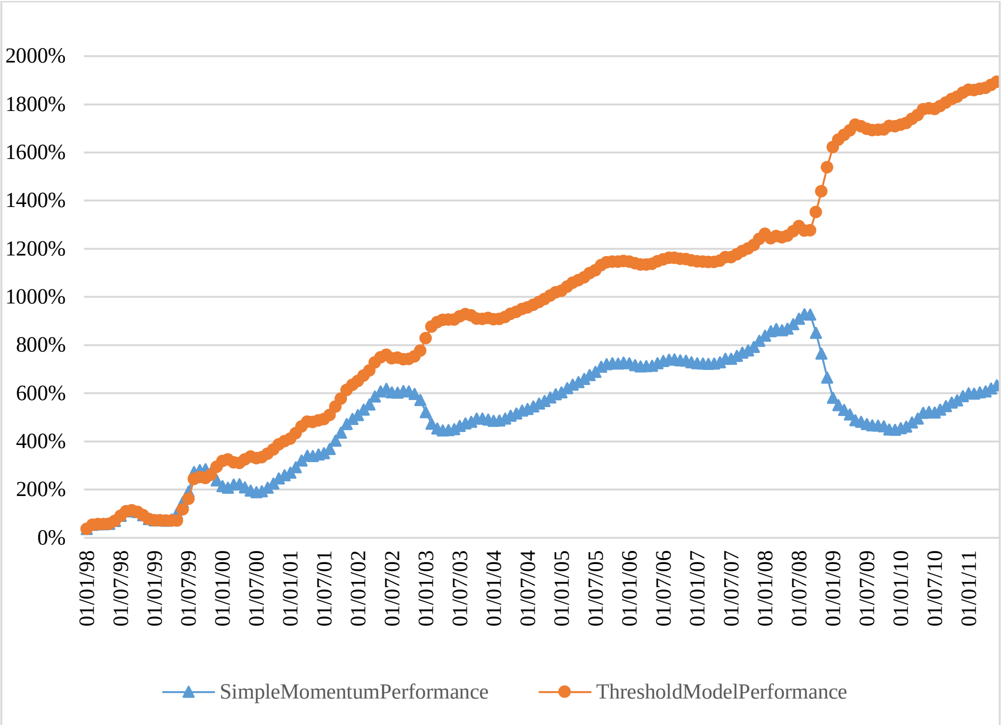


Table 4-3. Threshold-Regression-Model-Guided Trading Strategies' Trading Activities

At the beginning of each month t from 1998, a momentum portfolio is formed and then the predictive density of momentum portfolio's return over its next holding period from t+1 to t+K is generated by the threshold regression model. If 95% of its distribution lies in positive territory, momentum trading is implemented by buying winner portfolio and selling loser portfolio and holding this position from month t+1 to t+K. On the other hand, if 95% of its distribution lies in negative territory, contrarian trading occurs by selling past winners and buying past losers and hold this position for next K months. Finally, when neither of the above is true, no action is taken. Panel A records the number of each type of trading for model-guided trading strategy 3x3, 6x3, 9x4, and 12x3 for two sample periods, 1998-2005 and 1998-2011. Panel B records the percentage of each type of trading. There are 96 implementations for the time period of 1998-2005 and 164 for the time period of 1998 to 2011(163 for trading strategy 9x4).

Types of Trade	Sample Period	Trading Strategies			
		3x3	6x3	9x4	12x3
Panel A. No. of Each Type of Trade					
Momentum Trade	**1998-2005**	60	61	71	63
	1998-2011	115	120	124	113
Contrarian Trade	**1998-2005**	27	26	22	26
	1998-2011	37	32	36	44
No Trade	**1998-2005**	9	9	3	7
	1998-2011	12	12	3	7
Panel B. Percentage of Each Type of Trade					
Momentum Trade	**1998-2005**	0.625	0.635	0.740	0.656
	1998-2011	0.701	0.732	0.761	0.689
Contrarian Trade	**1998-2005**	0.281	0.271	0.229	0.271
	1998-2011	0.226	0.195	0.221	0.268
No Trade	**1998-2005**	0.094	0.094	0.031	0.073
	1998-2011	0.073	0.073	0.018	0.043

Table 4-4. Correctly Predicted Momentum Reversal Observations (J=9, K=4)

This table lists all momentum reversal observations for the momentum trading strategy 9x4 that have been correctly predicted by the threshold regression model. According to this table, 16 out of 27 momentum reversal observations occurred when the market return variance exceeds the critical range while the ranking period return is moderate. The other 11 reversals are results of rather high ranking period return as all observations have ranking period returns above 200%.

Date	Ranking Period Return	Ranking Period Market Return Variance	Holding Period Return	Ranking Period Market Return Variance >0.042
30/12/1999	2.747	0.015	-0.138	
31/01/2000	3.164	0.017	-0.333	
29/02/2000	4.433	0.018	-0.231	
31/03/2000	3.302	0.020	-0.068	
30/06/2000	2.353	0.022	-0.142	
31/07/2000	2.241	0.020	-0.126	
30/09/2002	1.243	0.043	-0.021	*
29/11/2002	1.263	0.052	-0.015	*
31/12/2002	1.266	0.054	-0.107	*
31/01/2003	1.074	0.057	-0.245	*
28/02/2003	1.017	0.060	-0.509	*
31/03/2003	1.011	0.066	-0.477	*
30/04/2003	1.120	0.052	-0.197	*
30/05/2003	1.260	0.047	-0.082	*
30/01/2004	2.397	0.010	-0.045	
31/10/2008	0.887	0.083	-0.013	*
28/11/2008	0.947	0.103	-0.760	*
31/12/2008	0.986	0.102	-0.864	*
30/01/2009	0.962	0.108	-0.998	*
27/02/2009	0.968	0.112	-0.842	*
31/03/2009	1.032	0.119	-0.301	*
30/04/2009	1.094	0.120	-0.197	*
29/05/2009	1.018	0.120	-0.193	*
30/06/2009	1.190	0.106	-0.230	*
30/10/2009	2.720	0.037	-0.011	
30/11/2009	2.809	0.034	-0.022	
31/12/2009	2.469	0.026	-0.138	

Note: an observation is marked by * if it occurs when the ranking period market return variance is above the threshold.

Table 4-5. Performance Comparison between Momentum and Threshold-Regression-Model-Guided Trading Strategies

Panel A provides mean of annualized buy-and-hold return for all trading strategies for two sample periods, 1998-2005 and 1998-2011. Annualized buy-and-hold return of trading strategy JxK is obtained by$(r_{t+1,t+K}/K)$*12. Panel B represents percentage of profitable trade for all trading strategies for two sample periods, 1998-2005 and 1998-2011 and the calculation excludes number of no action. Panel C reports the Sharpe ratio, which equals mean of sample buy-and-hold returns divided by standard deviation of all buy-and-hold returns of the same sample.

	3x3		**6x3**		**9x4**		**12x3**	
Sample period	**Momentum**	**M-Guided**	**Momentum**	**M-Guided**	**Momentum**	**M-Guided**	**Momentum**	**M-Guided**
Panel A. Average Annualized Return								
1998-2005	0.196	0.210	0.251	0.266	0.226	0.358	0.168	0.322
1998-2011	0.138	0.210	0.149	0.240	0.117	0.349	0.084	0.337
Panel B. Percentage of Profitable Trade								
1998-2005	0.688	0.770	0.760	0.736	0.729	0.806	0.677	0.787
1998-2011	0.683	0.743	0.701	0.704	0.669	0.764	0.646	0.783
Panel C. Sharpe Ratio								
1998-2005	0.385	0.442	0.486	0.543	0.417	0.780	0.287	0.664
1998-2011	0.255	0.421	0.229	0.392	0.182	0.639	0.122	0.564

M-Guided=Model-Guided

4.9 Conclusion

This chapter constructs a threshold regression model with heteroskedasticity to analyse the dynamics of the momentum effect based on the empirical results in previous chapter and three models that can generate both the momentum and the contrarian effect. We show that the dynamics of the momentum effect, more specifically, the switch between the momentum effect and its reversal in share price trend, is predictable by the threshold regression model.

We find that two lagged variables have significant role in predicting the momentum effect dynamics. This first one is the ranking period market volatility. We show that this variable has predictive power on the switch between two regimes, the momentum regime and the reversal regime. When the ranking period market volatility is below the threshold, the momentum effect dominates the stock market and when it is above this threshold, there is a reversal and the mean reverse governs the stock market. Moreover, the ranking period market volatility has a significant negative relationship with the holding period return in most cases in both the momentum regime and the reversal regime.

The ranking period return of a momentum portfolio is also a significant predictive variable in the regime where the momentum effect dominates. We find that this variable is inversely correlated with the magnitude of the momentum effect; that is, the higher (lower) is a momentum portfolio's ranking period return, the lower (higher) is the momentum effect during its holding period. With extreme high ranking period return, the holding period return can be negative. This negative relationship is consistent across momentum trading strategies and over time.

A new type of trading strategies, threshold-regression-model-guided trading strategies, is proposed to verify the statistically significant predictive power of the threshold regression model. Our results confirms there statistical conclusions. We show that the performance of the model-guided trading strategy is superior to its corresponding momentum trading strategy with higher returns and less risks. The reason is that model-guided trading strategies can exploit both the momentum effect and the contrarian effect indicated by either extreme high ranking market volatility or extreme high ranking period return.

5. Post-Cost Profitability of Momentum and Threshold-Regression-Model-Guided Trading Strategies

5.1 Introduction

This chapter discusses whether profits generated by both momentum trading strategies and model-guided trading strategies in our study can be exploited in practice; that is, whether they exceed transaction costs. There are in general three approaches to obtain transaction costs of momentum trading strategies. They can be estimated from time series data, estimated from actual momentum investment activities or taken from similar studies in the literature. We adopt the third approach and our discussion is based on transaction costs of momentum trading strategies estimated by Agyei-Ampomah (2007) and li et al. (2009), as both studies cover all stocks in the UK stock market for similar time period from mid 1980s to early 2000s.

We first compare the estimated transaction costs in both studies and show that their results share a lot of patterns that are also found in momentum trading strategies transaction costs in other stock markets. Their results show that the cost of investing a portfolio is inversely related to the average firm size of stocks in it. They also show that turnover ratio has impact on the transaction costs of a momentum trading strategy as momentum portfolios only need to be rebalanced over time. Ignoring the turnover ratio will overestimate the transaction costs of a momentum portfolio.

As the average firm size and the turnover ratio of a momentum portfolio are important factors that affect the transaction costs of momentum trading strategies, we analyse these two aspects of momentum portfolios in our study and compare them with those of momentum portfolios in Agyei-Ampomah (2007) and li et al. (2009) in order to assess the suitability of applying their estimated transaction costs in our discussion. The results of assessment are positive and we show that the costs of trading momentum portfolios in our study should be bounded in the range of estimated momentum portfolios' transaction costs in Agyei-Ampomah (2007) and li et al. (2009).

We discuss the post-cost profitability of both momentum and model-guided trading strategies 3x3, 6x3, 9x4 and 12x3. Our discussion also includes the post-cost profitability of taking long position of these two strategies as short is very costly and not available for all investors. We have the following findings.

First, implementing these four momentum trading strategies in our study cannot make profits after subtracting transaction costs; however, model-guided trading strategy 12x3 still makes profits net of transaction costs. Second, implementing the long position of the momentum trading strategy 12x3, which is, buying its winner portfolio, appears to generate net profit but the size of net profits is very small. In contrast, implementing the long position of model-guided trading strategies 6x3, 9x4 and 12x3 is post-cost profitable. The long position of the model-guided trading strategy12x3 generates double digit profits even after transaction costs. Our results show that model-guided trading strategies are able to generate economically significant post-cost profits even when momentum trading strategies aren't.

The rest of Chapter 5 is organized as follows. Section 5.2 presents the motivation and Section 5.3 introduces approaches of obtaining transaction costs in the literature and discusses the approach in our discussion. Section 5.4 summarises the estimated transaction costs of implementing momentum trading strategies in the UK stock market. In Section 5.5, we investigate the post-cost profitability of both momentum and threshold-regression-model-guided trading strategies. Finally, Section 5.6 concludes.

5.2 Motivation

We have shown that momentum trading strategies could make significant profits in the UK stock market during 1979 to 2011 in Chapter 3, and that threshold-regression-model-guided trading strategies that exploit both the momentum and the contrarian effect could have made even higher significant profits than momentum trading strategies during 1998 to 2011 in Chapter 4. As there is lack of sufficient convincing evidence in favour of either rational or behavioural explanation of the momentum effect, discussion results regarding whether trading strategies make significant profit net of transaction costs can at least help us to understand why the momentum effect has been persistent over time. In addition, it also helps to shed a light on whether arbitrage plays a role to correct "anomalies" and hence to keep the market in a "practically" efficient state. As argued by Malkiel (2003), while the stock market may not be a mathematically perfect random walk, it is important to distinguish statistical significance from economic significance.

In fact, the literature has shown that transaction costs of momentum trading strategies are too large relative to returns to be ignored as momentum trading strategies are highly trading intensive. According to the design, investors must buy the winners and short sell the losers at the end of the ranking period and reverse the action at the end of the holding period. Momentum trading strategies with short ranking and holding period involves a lot of roundtrip trades and incur high transaction costs. Further, apart from the intensive trading that increase transaction costs, studies show that momentum portfolios, especially loser portfolios, often are heavily weighted in small stocks, which are relatively more expensive to trade. Thus, transaction costs cannot be neglected when it comes to the application of momentum trading strategies in practice or the implementation of arbitrage.

While the results regarding the post-profitability of momentum trading strategies applied to the United State stock market are mixed, the results in the UK stock market suggest that momentum profits are still exploitable after transaction costs. We would like to readdress the post-cost profitability of momentum trading strategies in the UK stock market. It is worthwhile as our study has the latest data and we can add more evidence regarding whether arbitrage has done its job and has driven away “excess returns” in the UK stock market.

We are most interested in discuss whether threshold-regression-model-guided trading strategies, including the implementing the self-financing strategies and taking only the long position of these strategies, can generate significant post-costs profits. As threshold-regression-model-guided trading strategies outperform momentum trading strategies, it is possible for them to make significant profits net of transaction costs even in the case that momentum trading strategies do not. If our results show that threshold-regression-model-guided trading strategies can make significant post-costs profits, this will challenge the argument that momentum strategies’ “abnormal” returns are not exploitable due to arbitrage costs and that markets are “practically” efficient as a result.[54]

[54]It has been argued that trading costs can weaken the function of arbitrage to correct a firm’s share price so that it’s consistent with this firm’s fundamentals. If trading costs exceed expected returns, arbitrageurs, although being rational, have no interest in taking arbitrage positions and hence there are delays or friction in the price adjustment process. Discussion on limits to arbitrage can be seen in Shleifer and Vishny (1997).

5.3 Approaches of Obtaining Transaction Costs

In general, there are three ways to obtain transaction costs of momentum trading strategies in the literature. The first one is to obtain transaction costs of interested momentum trading strategies by estimation as in Lesmond et.al (2004), Korajczyk and Sadka (2004). The second method is to document the costs of implementing actual strategies as in Keim (2003). The third, which is the simplest way and widely used, is to use transaction cost figures for some components of transaction costs from the literature as in Jegadeesh and Titman (1993), Liu et al. (1999), li et al. (2009) and Siganos (2010). We employ the third method for our discussion. To ensure the reliability of our discussion results, we check the suitability of transaction costs figures available in the literature and choose those that minimise the error of our discussion.

When it comes to momentum trading strategies applied in the same stock market, there are two main factors that determine the size of annualized transaction costs. The first is the average size of firms in the winner and the loser portfolio.[55] As many studies show that shares' transaction costs are negatively related to the size of their firms, measured by market capitalization. Thus, the size distribution of winner and loser portfolio play an important role in determining annualized transaction costs of momentum trading strategies.

The second is the turnover ratio. When implementing momentum trading strategies, momentum portfolios need to rebalance after each holding period. Apparently, the higher is the turnover ratio, ceteris paribus, the higher is the annualized transaction costs. As the length of both the ranking period and the holding period affects the turnover ratio, it also affects transaction costs. Since the length of ranking period is inversely correlated with turnover ratio, it follows that the longer is the ranking period, the lower is the annualized transaction costs. Finally, the length of holding period negatively correlated with annualized

[55]As in our study, shares are equal weighted in winner and loser portfolio, hence the average firm size of a portfolio is the simple average of firm size of each stock in this portfolio.

transaction costs as because the longer is the holding period, the less frequent are transactions in a certain time period.

It is reasonable to argue that transaction costs should be more or less the same for same momentum trading strategy in different studies applied to the same stock market for the same time period when they have similar firm size distribution and turnover ratio. Out discussion of the post-cost profitability of momentum and model-guided trading strategies is based on this argument.

5.4 Momentum Transaction Costs in the UK Stock Market

There are two papers that have estimated transaction costs of various momentum trading strategies that are applied to samples similar as ours. Agyei-Ampomah (2007) examine the post-cost profitability of the momentum trading strategies in the UK over the period of 1988 to 2003 and their analysis is based on all stocks traded on the London Stock Exchange with available data on Datastream.[56] Li et al. (2009)'s study is based on data from Primark Datastream and LSPD over the period of 1985 to 2005.[57]

5.4.1 Methods of Estimating Transaction Costs

There are a vast variety of methods to estimate transaction costs and we are going to introduce methods that are used in these two papers. This first method is called spread plus commission (S+C) and it estimates transaction costs simply by calculating the sum of proportional quoted market bid-ask spread and transaction commission. This method is the easiest to conduct. This disadvantage of this method is that it cannot be used for transactions that are traded off a quoted market. In this case, "effective" trading cost estimate is proposed. This method estimates transaction costs directly from transaction records. These two methods estimate explicit components of transaction costs that are independent of trading volume and they are also called Proportional Cost Models by Korajczyk and Sadka (2004).

However, there are problems with these two direct estimators of transaction costs as pointed out by Lesmond et al. (1999). First problem is the availability of bid-ask spread data and transaction records. Second, the costs of executing a trade are often below the commission schedule of brokers; therefore, the S+C estimate can exceed the effective transaction costs. To avoid these disadvantages of the S+C estimator, alternative methods have been proposed in the literature and limited dependent

[56] Their sample excludes investment trusts, unit trusts, warrants, foreign stocks and ADRs. For simplicity, Agyei-Ampomah (2007) is referred to as AA (2007).

[57] They exclude financial companies and the lowest 5% of shares by market capitalization and companies with mid-prices that are less than 5p.

variable (LDV) is one of those techniques. The advantages of the LDV model is that a security's transaction costs can be estimated as long as its time series data is available.

The LDV is a transaction cost estimation procedure proposed by Lesmond et al. (1999). In theory, the LDV estimator reflects both the explicit components, e.g., S+C, tax, and the implicit components of transaction costs, for example, price impact. According to Lesmond et al. (1999), the LDV reflects the effect of transaction costs directly on daily security returns. The idea of the LDV model is that the marginal investor will only trade if he assesses that the value of a piece of information exceeds the costs of trading, in other words, he will only trade when his expected return is higher than transaction costs; otherwise, he will not trade, which results in a daily return of zero. It implies that the LDV estimates the marginal trader's effective transaction costs. It follows that a share with high transaction costs tends to have more zero daily returns than a share with low transaction costs. Hence, the frequency of incidence of zero returns can be used as a criterion to assess the LDV estimator.

The LDV model by Lesmond et al. (1999) assumes that the common "market model" is the correct model of security returns, but is constrained by the effect of transaction costs on security returns. The LDV model is specified as follows.

$$R_{i,t} = R^*_{i,t} - \alpha_{1,i} \text{ if } R^*_{i,t} < \alpha_{1,i} \quad (5.1)$$

$$R_{i,t} = R^*_{i,t} - \alpha_{2,i} \text{ if } R^*_{i,t} > \alpha_{2,i} \quad (5.2)$$

$$R_{i,t} = 0 \qquad \text{if } \alpha_{1,i} < R^*_{i,t} < \alpha_{2,i} \quad (5.3)$$

$R_{i,t}$ is the observed return of firm i, $R^*_{i,t} = \beta R_{i,t} + \varepsilon_{i,t}$ is the expected return of firm i based on the market model, $\alpha_{1,i} < 0$ is the trading cost on selling the stock, $\alpha_{2,i} > 0$ is the trading cost on buying the stock. With the estimates of $\alpha_{1,i}$ and$\alpha_{2,i}$, the all-in roundtrip costs, including explicit and implicit components, for firm i is given by $\alpha_{2,i} - \alpha_{1,i}$.

5.4.2 Comparison of Estimated Transaction Costs

AA (2007) investigate the post-cost profitability of 20 momentum trading strategies with J=3, 6, 9, and 12 and K=1, 3, 6, 9and 12. They estimate transaction costs by two methods, the spread (quoted or effective) plus commissions and taxes as well as the LDV model in Lesmond et al. (1999). In the first method, they apply the commission rates for private clients, which is 0.67%, and also consider the 0.5% stamp duty. [58] AA (2007) calculated transaction costs of momentum portfolios for two samples, one is all stocks available in Datastream and the other only consists of big stocks, equivalently stocks with high liquidity, whose market capitalisation exceed the top 30th percentile mark. For simplicity and being consistent with the paper, the first sample is referred to as the unrestricted sample and the second, the restricted sample.[59] The transaction costs calculated from their reports are shown in Table 5-1 Panel A.

Li et al. (2009) estimate transaction costs for 9 momentum trading strategies with J=3, 6, and 12 and K=3, 6, and 12. Transaction costs in this paper includes the bid-ask spread (estimated based on quoted spread and effective spread), commissions, stamp duties and short-selling costs. They follow Chordia et al. (2000) and measure the proportional quoted spread for a stock as 100 times the ratio of difference between the ask price and the bid price to the bid-ask midpoint and follow Lesmond et al. (2004), the proportional half effective spread is calculated as 100 times the ratio of difference between the transaction price and the bid-ask midpoint to the bid-ask midpoint.[60] Commission is measured as a percentage of the total trade value and it generally decreases as the total trade value increases. They apply the commission charges schedule from Barclays Stockbrokers for company dealing accounts.[61] They also consider the stamp duty, payable at the rate of 0.5% at the

[58]Estimates of commission charges are taken from the Survey of London Stock Exchange Transactions 2000.

[59]In the rest of this chapter, unrestricted sample and restricted sample are specifically used for unrestricted sample and restricted sample in Agyei-Ampomah (2007).

[60]Proportional quoted spread formula: $Quoted\ spread = 100\left(\frac{P_{Ait}-P_{Bit}}{P_{Mit}}\right)$ and proportional half effective spread: $half\ effective\ spread = 100\left(\frac{P_{it}-P_{Mit}}{P_{Mit}}\right)$ where P_{Ait} is the ask price and P_{Bit} is the bid price, P_{Mit} is the bid-ask midpoint and P_{it} is the transaction price for stock i on the last trading day of month t.

[61]Transaction value £0-£10,000, commission is 1.75% of trade value; £10,001-£20,000: 1.125%; £20,001-£40,000: 0.5%; £40,001-£100,000: 0.4%; £100,001+: 0.3%; (minimum £100).

time of dealing on all UK equity purchases, and short-selling costs, which is assumed to be 1.5% per year. The transaction costs calculated from their reports are shown in Table 5-1 Panel B.

There are several points worth making from Table 5-1 Panel A and Panel B regarding factors mentioned in Section 5.3, which affect the size of transaction costs. First of all, the average firm size of stocks in a momentum portfolio has a big role in determining the size of momentum portfolio' transaction costs. Momentum trading strategies applied to big-cap stocks have much lower transaction costs than those applied to small-cap stocks. Table 5-1 Panel A shows that all momentum trading strategies for the unrestricted sample have transaction costs that are more than twice as much as those for the restricted sample. For example, the momentum trading strategy 3x3 for the unrestricted sample has an annualized transaction costs of 57.2% whereas the figure for the same strategy applied to the restricted sample is 21.8%.

Second, Table 5-1 Panel B verifies the negative relationship between the turnover ratio and the transaction costs of momentum trading strategies. Assuming 100% turnover, the transaction costs for the momentum trading strategy 12x3 is estimated to be 38.39% by Li et al. (2009) while the figure reduces to 19.28% when considering the actual turnover.

Further, the annualized transaction costs decrease as holding period increases and the decline in annualized transaction costs can be substantial. Considering transaction costs of momentum strategies with 3-month ranking period. In AA (2007), transaction costs decrease from 57.2% to 15.1% when the holding period increases from 3 months to 12 months with the unrestricted sample. Similar conclusion can be made for the results of Li et al. (2009). Finally, transaction costs are negatively related to the ranking period especially in the study of AA (2007).

Compared results reported in Table 5-1 Panel A and Panel B, estimated transaction costs can be different for the same momentum trading strategy even though results of two studies do share a lot of similarity and both studies are based on samples in the UK stock market for the same time period. There are mainly two factors that are responsible for this difference. One factor is that they use different transaction costs methods and the other is that their samples are not completely the same as they exclude different types of firms. Thus it is import to check the suitability of applying figures from these papers to our study by comparing main factors that affect transaction costs between our studies and theirs.

Table 5-1. Comparison of Estimated Transaction Costs of Momentum Trading Strategies

This table reports transaction costs of various momentum trading strategies estimated in Agyei-Ampomah (2007) and in Li et al. (2009). Two transaction costs estimation methods are employed in this paper. The S+C represents transaction costs based on the quoted spread plus commissions and taxes and the limited dependent variable (LDV) procedure proposed by Lesmond et al. (1999). Transaction costs are estimated for momentum trading strategies applied to unrestricted sample and restricted sample based on both the S+C and the LDV method in Agyei-Ampomah (2007). There are two sets of estimated transaction costs in this paper with one based on the quoted spread and the other based on the quoted spread in Li et al. (2009). Further, they also calculate momentum transaction costs assuming 100% turnover ratio and using actual turnover ratio.

Panel A. Transaction Costs Estimated in Agyei-Ampomah (2007)						
	K					
J	3M		6M		12M	
	Unrestricted	Restricted	Unrestricted	Restricted	Unrestricted	Restricted
3M:						
S+C	0.572	0.218	0.302	0.108	0.151	0.055
LDV	0.498	0.192	0.249	0.101	0.111	0.051
6M:						
S+C	0.418	0.154	0.291	0.107	0.149	0.056
LDV	0.36	0.139	0.238	0.098	0.109	0.050
12M:						
S+C	0.278	0.106	0.200	0.071	0.142	0.054
LDV	0.244	0.100	0.165	0.064	0.104	0.044

J=raking period; K=holding period

(Table 5-1 is continued on the next page)

Table 5-1. Comparison of Estimated Transaction Costs of Momentum Trading Strategies
(Continued from the previous page)

Panel B. Transaction Costs Estimated in Li et al. (2009)						
	K					
J	**3M**		**6M**		**12M**	
	100% Turnover	**Actual Turnover**	**100% Turnover**	**Actual Turnover**	**100% Turnover**	**Actual Turnover**
3M:						
Quoted Spread	0.408	0.345	0.209	0.182	0.127	0.108
Effective Spread	0.392	0.330	0.200	0.174	0.125	0.106
6M:						
Quoted Spread	0.399	0.254	0.206	0.176	0.123	0.107
Effective Spread	0.383	0.243	0.200	0.171	0.119	0.103
12M:						
Quoted Spread	0.384	0.193	0.197	0.141	0.118	0.101
Effective Spread	0.373	0.187	0.193	0.138	0.114	0.098

J=raking period; K=holding period

5.5 Post-Cost Profitability of Momentum and Threshold-Regression-Guided Strategies

Before we discuss the post-cost profitability of momentum and model-guided trading strategies, we analysis the average firm size, the firm size concentration and the turnover ratio of winner and loser portfolios associated with momentum trading strategies 3x3, 6x3, 9x3 and 12x3 and compare these aspects of portfolios in our study with those in AA (2007) as they are not available in Li et al. (2009).[62]

5.5.1 Average Firm Size of Momentum Winner and Loser Portfolios

A stock's firm size is measure by the firm's market capitalization. To calculate the average firm size of a portfolio, we follow these steps. We first calculate the market capitalization mean of all constituents of winner and loser portfolios each month for a momentum trading strategy and we then calculate the average firm size of the winner and loser portfolio by taking the simple average of the market capitalization mean figures in previous step over the sample period. Results regarding average firm size are reported in Table 5-2.

The average firm size of loser portfolio corresponding to each of the four momentum trading strategies in our study lies between that based on the unrestricted sample and the restricted sample in AA (2007) according to results in Table 5-2. Taking trading strategy 9x3 as an example, the average firm size of its loser portfolio in the case of the unrestricted sample is £92.2m, which is much lower than £183m for the average firm size of the loser portfolio in our study; whereas the figure in the case of the restricted sample is £876.5m, which is above £183m. During the sample period from 1988 to 2003, the average firm size of loser portfolios in our study varies from £156.7m to £230.7m. In the case of the unrestricted sample, the smallest average size of loser portfolios is £83m and the largest average size of loser portfolios is £160.1m; whereas in the case of the

[62]We discussion transaction costs of the momentum trading strategy 9x3 instead of 9x4 because transaction costs are not available for the strategy 9x4. As transaction costs of strategy 9x3 are expected to be higher than those of the strategy 9x4, there is no risk of underestimating transaction costs of the strategy 9x4 in our later discussion.

restricted sample, the figures are £758.1m, £1096.8m respectively for loser portfolios.

Same conclusion can be drawn with respect to winner portfolios. According to Table 5-2, the average size of winner portfolios falls between £387.8m and £554.8m for the unrestricted sample and the figures are £1313.2m and £1506.2m respectively for the restricted sample. The average size of winner portfolios in our study varies from £495.5m to £635.3m. For all four trading strategies, the average size of winner portfolios in our study is between that of winner portfolios that based on the unrestricted sample and on the restricted sample. Again taking the momentum trading strategy 9x3 as an example, the average size of winner portfolios in our study is £589.5m, which is higher than £497.5m with the unrestricted sample but lower than £1420.9m with the restricted sample. Moreover, consistent with the literature, the average firm size of firms in loser portfolios is smaller than that of firms in winner portfolios in all cases in our study.

5.5.2 Firm Size Concentration

The firm size concentration is calculated based on the following steps as in AA (2007). First, divide the total sample of stocks available at month t into quintiles based on the current market capitalization. Then the proportion of stocks in a portfolio, which come from each of the size quintiles is calculated. Suppose there are 100 stocks in this portfolio at time t and suppose that 30 out of the 100stocks in the portfolio come from the first size quintile. In this case the weight of stocks from Size Quintile 1 in this portfolio is 30 % compared to 20% in the total sample. We report firm size concentration figures in Table 5-3. This report includes the firm size concentration of momentum trading strategies in our study for three different time period, 1979 to 1987, 1988 to 2003, and 2004 to 2011 so that we can examine the stability of the firm size concentration over time.

As can be observed in Table 5-3, the size distribution of winner and loser portfolios in our study is consistent with the prior literature in that loser portfolios involves larger proportion of small firms than winner portfolios. In terms of the size concentration, our results are very close to those in AA (2007) for both loser and winner portfolios. For example, for the momentum trading strategy 3x3, first quintile, that is, firms in the bottom 20% of all sample sorted ascendingly by market capitalization, on average accounts for 37.8% of constituents of loser portfolio and 19.8% of constituents of winner portfolio for sample period of 1988-2003 in the case of the unrestricted sample and the two figures are 34.8% and 20.1% respectively in our study. Largest firms that are in the top 20% of all sample account for 7.6% of constituents of loser portfolios and 16.2% of constituents of winner portfolios in study with the unrestricted sample and the two figures are 9.5% and 17% respectively in our study. Table 5-3 clearly shows that loser portfolios consist of smallest firms with largest weight and largest firms with lightest weight; in contrast, five quintiles relatively evenly distributes in winner portfolios.

Compare the firm size concentration of portfolios for different time periods and we can conclude that it is very stable over time. Loser portfolios always involves the largest number of firms from the smallest quintile and smallest number of firms from the largest quintile; in contrast, winner portfolios have much more balanced distribution among stocks of different firm sizes.

5.5.3 Turnover Ratio

The turnover ratio is calculated according to the equation % turnover = ½(% dropouts + % new), where % dropout is the proportion of stocks in the portfolio at month t-K that did not meet the eligibility criteria at month t and % new is the proportion of stocks in the portfolio at month t that were not in the portfolio at month t-K (newly eligible stocks). The % turnover is calculated each month and averaged over the sample period. Results regarding the turnover ratio are presented in Table 5-4.

Results from our study are very close to those from AA (2007) although figures in our study are slightly higher. There are two common features shared by both studies. The first common feature is that the turnover ratio of winner portfolios tends to be higher than that of loser portfolios. For the momentum trading strategy

3x3, the turnover ratio of loser and winner portfolios is 73.7% and 81.8% for the unrestricted sample, 68.3% and 71.7% for the restricted sample, and 78.6% and 86.8% in our study. The second feature is that the longer is the ranking period, the lower is the portfolio turnover ratio. For example, loser and winner portfolios of the momentum trading strategy 12x3 have much lower turnover ratios than those of the momentum trading strategy 3x3 as the former's turnover ratios are around half of those of the latter's in all three cases as shown in Table 5-4.

Table 5-2. Average Firm Size of Momentum Portfolios

Figures in columns of unrestricted sample and restricted sample are obtained from Agyei-Ampomah (2007). Size describes the average market capitalisation (in £'millions) based on data from 1988 to 2003.

Momentum Portfolio		Unrestricted Sample 1988-2003	Restricted Sample 1988-2003	Our Study 1988-2003
	Loser	160.1	1096.8	275.9
3x3	**Winner**	387.8	1313.2	495.5
	W-L	227.7	216.4	219.6
	Loser	121.2	990.6	230.7
6x3	**Winner**	440.2	1314	550.9
	W-L	319.0	323.4	320.2
	Loser	92.2	876.5	183.4
9x3	**Winner**	497.5	1420.9	589.5
	W-L	405.3	544.4	406.1
	Loser	83.0	758.1	156.7
12x3	**Winner**	554.9	1506.2	635.3
	W-L	471.9	748.1	478.6

Table 5-3. Size Concentration of Winner and Loser Portfolios

Each month stocks in the whole sample are categorized into 5 groups based on their size measured by the market capitalization. First quintile contains the 20% smallest firms and the fifth the 20% largest firms in term of the market capitalization. This table reports the proportion of stocks in the portfolio of interest, say P, which come from each of the size quintiles. Figures in columns of unrestricted sample are obtained from Agyei-Ampomah (2007) and data for restricted sample are unavailable.

Strategy	Firm Size Quintile	Unrestricted (1988-2003)		Our Study (1979-1987)		Our Study (1988-2003)		Our Study (2004-2011)	
		Loser	winner	loser	winner	loser	winner	loser	winner
3x3	1st	0.378	0.198	0.326	0.238	0.348	0.201	0.335	0.172
	2nd	0.245	0.222	0.242	0.227	0.240	0.212	0.265	0.234
	3rd	0.178	0.220	0.184	0.213	0.182	0.216	0.187	0.227
	4th	0.123	0.199	0.143	0.189	0.135	0.201	0.130	0.211
	5th	0.076	0.162	0.104	0.133	0.095	0.170	0.083	0.156
6x3	1st	0.410	0.162	0.332	0.214	0.372	0.169	0.373	0.145
	2nd	0.246	0.206	0.247	0.227	0.248	0.201	0.261	0.216
	3rd	0.175	0.233	0.180	0.218	0.178	0.222	0.184	0.241
	4th	0.113	0.221	0.139	0.202	0.124	0.216	0.113	0.224
	5th	0.057	0.179	0.102	0.142	0.078	0.179	0.068	0.173
9x3	1st	0.437	0.135	0.335	0.196	0.390	0.149	0.397	0.130
	2nd	0.249	0.193	0.252	0.215	0.251	0.194	0.265	0.204
	3rd	0.168	0.240	0.176	0.225	0.176	0.227	0.176	0.250
	4th	0.101	0.239	0.138	0.213	0.117	0.237	0.102	0.235
	5th	0.045	0.193	0.100	0.151	0.067	0.194	0.060	0.181
12x3	1st	0.457	0.116	0.335	0.175	0.405	0.134	0.420	0.116
	2nd	0.249	0.187	0.259	0.215	0.253	0.188	0.264	0.204
	3rd	0.162	0.238	0.176	0.224	0.172	0.227	0.173	0.253
	4th	0.091	0.254	0.135	0.227	0.108	0.246	0.093	0.243
	5th	0.0400	0.204	0.095	0.159	0.063	0.205	0.051	0.184

Table 5-4. Turnover Ratios of Loser and Winner Portfolios

This table shows the average turnover of winner and loser portfolios for momentum trading strategies 3x3, 6x3, 9x3 and 12x3.

Portfolio		Unrestricted Sample	Restricted Sample	Our Study	Our Study	Our Study
		1988-2003	**1988-2003**	**1979-1988**	**1988-2003**	**2003-2011**
3x3	**Loser**	0.737	0.683	0.840	0.786	0.779
	Winner	0.818	0.717	0.873	0.868	0.850
6x3	**Loser**	0.533	0.485	0.612	0.555	0.548
	Winner	0.614	0.527	0.626	0.633	0.629
9x3	**Loser**	0.436	0.385	0.575	0.527	0.519
	Winner	0.506	0.436	0.592	0.590	0.603
12x3	**Loser**	0.364	0.318	0.438	0.399	0.385
	Winner	0.428	0.364	0.439	0.449	0.455

5.5.4 Discussion of the Post-Cost Profitability of Momentum and Threshold-Regression-Guided Strategies

Based on the discussion in Section 5.5.1, Section 5.5.2 and Section 5.5.3, it is reasonable to assume that the costs of implementing each momentum trading strategy in our study should be confined within the range with upper bound being the costs of implementing the same momentum trading strategy with the unrestricted sample and the lower bound being the costs of the same momentum trading strategy with the restricted sample.

We also consider the transaction costs estimated in Li et al. (2009), although the information is limited to implementing momentum trading strategies 3x3, 6x3 and 12x3. We assume that the costs of trading the winner and loser portfolio of each momentum trading strategy in our study are confined by the costs of trading the winner and loser portfolio of the same momentum trading strategy with 100% turnover ratio and the lower bound being the costs of implementing winner and loser portfolio of the same momentum trading strategy with the actual turnover ratio in Li et al. (2009).

5.5.4.1 Post-Cost Profitability of Momentum Trading Strategies

We first discuss the post-cost profitability of self-financing momentum and model-guided strategies.[63] According to the results displayed in Table 5-7, there lacks of evidence that these four momentum trading strategies are profitable after taking transaction costs into account as there is no momentum trading strategy that has the return being positive after subtracting the estimated transaction costs based on both the S+C and the LDV from 1988 to 2003.

Taking the most profitable momentum trading strategy 6x3 before transaction costs for this sample period as an example, which can be found in Table 5-6. This momentum trading strategy generates an average annualized return of 24% from

[63] When discussing the annualize trading costs of a model-guided trading strategy JxK, we assume the transaction costs of taking long position in a winner (loser) portfolio JxK is the same as that of taking short position in this winner (loser) portfolio.

1988 to 2003; however, this “abnormal” return disappears after deducting the transaction costs estimated with the unrestricted sample based on both the S+C and the LDV method. The net annualized return lies in the range of -17.4% to 9% based on the S+C and in the range of -11.6% to 10.5% based on the LDV. The results are even worse for the other two time periods, 1979-1987 and 2004-2011 if we assume the same transaction costs. Table 5-7 shows that the momentum trading strategy 6x3 could make big losses after transaction costs as its returns are much lower during these two time periods.

The same conclusion can be drawn when we apply the transaction costs estimated by Li et al. (2009). Table 5-8 shows that no momentum trading strategy can make profits based on transaction costs estimated by assuming 100% turnover ratio. Only two cases where momentum trading strategies are profitable based on transaction costs estimated by using the actual turnover ratio. However the profits are not economically significant. The momentum trading strategy 12x3 has the best performance and it generates an annualized return of 2.5% for time period 1988 to 2003; however, it generates losses after transaction costs for the other two time periods.

5.5.4.2 Post-Cost Profitability of Threshold-Regression-Model-Guided Trading Strategies

When it comes to the post-cost profitability of model-guided trading strategies, we should expect a better performance.[64] Indeed, the results in Table 5-9 Panel A provides evidence that supports the positive net profits of model guided trading strategies as they show that model-guided trading strategies, 9x4 and 12x3 generate positive profits taking the transaction costs estimated by both estimators into account. For example, for the sample period of 1998 to 2003, the model-guided trading strategy 9x4 makes an average annualized return between 4% and 15.1%

[64]As transaction costs are not available for momentum trading strategy 9x4 in Agyei-Ampomah (2007), transaction costs for momentum trading strategy 9x3 are used instead to discuss post-cost profitability of model-guided trading strategy 9x4. As transaction costs for momentum trading strategy 9x3 are higher than those for momentum trading strategy 9x4, results will likely underestimate the net profits of model-guided trading strategy 9x4.

based on the S+C transaction costs estimation and between 8.7% and 27% based on the LDV estimation.

When considering applying the transaction costs to the time period 2004 to 2011, the model-guided trading strategy 12x3 still generate sizable post-cost profits in all cases. The annualized net return is between 3.4% and 20.6% from 1998 to 2003 based on the S+C method and between 6.8% and 21.2% based on the LDV method. The results are even better for the time period of 2004 to 2011. The model-guided trading strategy 12x3 generates an annualized return between 7.9% and 25.1% based on the S+C and between 11.3% and 25.7% based on the LDV from 2004 to 2011.

Table 5-10 reports the post-costs profits of model-guided trading strategies for two time periods 1998 to 2003 and 2004 to 2011 based on transaction costs estimated by Li et al. (2009). Assuming 100% turnover ratio, no strategies can maker post-cost profits. Considering actual turnover ratio, the model-guided trading strategy 12x3 generate above 10% annualized profits net of transaction costs regardless the estimation method.

5.5.4.3 Post-Cost Profitability of Long Positions of Momentum Trading Strategies

As taking short position is very costly and it is not always available to all investors, it is important to investigate the post-cost profitability of taking long position of each type of trading strategies. Our discussion in this section is based on the estimated transaction costs in AA (2007) only as the transaction costs for the winner and loser portfolio are only available in AA (2007). As expected, taking long position is more profitable than self-financing investment taking transaction costs into account. Table 5-7 panel B reports the relevant results.

Compared with self-financing momentum trading strategies, implementing long position of momentum trading strategies by holding winner portfolios only is post-cost profitable over sample period 1988 to 2003 for the momentum trading strategies 6x3, 9x4 and 12x3. During sample period of 1988 to 2003, buying winner portfolio of either the momentum trading strategy 9x4 or the momentum trading strategy 12x3 generates annualized post-cost return above 10%. Considering the whole sample period from 1979 to 2011, only long position of momentum trading strategy 12x3 is still post-cost profitable regardless the estimation method. However, its annualized net return is pretty small and hence not economically significant for time period 2004 to 2011. Based on the S+C method, the annualized net return is between 0.2% and 8.3%, and based on the LDV method, the figure is between 2.8% to 7.1%

5.5.4.4 Post-Cost Profitability of Long Positions of Threshold-Regression-Model-Guided Trading Strategies

Table 5-9 Panel B shows that trading long position of threshold-model-guided trading strategies only, that is, buying winner portfolio when the model predict the momentum effect for next holding period and buying loser portfolio when it indicates a reversal, generates lucrative profits net of transaction costs.

Taking long position of the model-guided trading strategies 6x3, 9x4 and 12x3 is profitable after transaction costs for the whole test time period of 1998 to 2011 based on either the S+C or the LDV estimation method. Taking model-guided trading strategy 9x4 as an example, taking long position can generate an average annualized return between 21.1% and 31.2% based on the S+C estimation and between 24.3% and 30.5% based on the LDV estimation from 1998 to 2003. For the time period of 2004-2011, this figure is between 11% and 21.1% based on the S+C estimation and between 14.2% and 20.4% based on the LDV estimation.

According to our discussion in Section 5.5.4, taking transaction costs into account weakens the profitability of momentum trading strategies substantially. In fact, no momentum trading strategy in our discussion, including self-financing and taking long position only, can make economically significant net profits. In contrast, there are some model-guided trading strategies that can still make sizable net profits, even though transaction costs hurt their profitability significantly. Thus, we can conclude that there are trading strategies that are able to make profits taking the transaction costs into account and that the best strategy in our study is to take long position of model-guide strategies as it offers double digit net annualized returns.

Table 5-5. Momentum Portfolios' Transaction Costs

This table shows the average annualized transaction costs associated with the winner, the loser and the winner-minus-loser portfolio for different momentum trading strategies. Results in columns S+C, LDV are obtained from Agyei-Ampomah (2007) and results in columns Quoted Spread and Effective Spread are from Li et al. (2009).

		S+C		LDV		Quoted Spread		Effective Spread	
		Unrestricted Sample 1988-2003	Restricted Sample 1988-2003	Unrestricted Sample 1988-2003	Restricted Sample 1988-2003	100% Turnover 1985-2005	Actual Turnover 1985-2005	100% Turnover 1985-2005	Actual Turnover 1985-2005
3x3	**Loser**	0.307	0.141	0.279	0.102	-	-	-	-
	Winner	0.265	0.077	0.219	0.090	-	-	-	-
	W-L	0.572	0.218	0.498	0.192	0.408	0.345	0.392	0.330
6x3	**Loser**	0.232	0.105	0.212	0.074	-	-	-	-
	Winner	0.186	0.049	0.148	0.065	-	-	-	-
	W-L	0.418	0.154	0.360	0.139	0.399	0.254	0.383	0.243
9x3	**Loser**	0.195	0.085	0.180	0.059	-	-	-	-
	Winner	0.144	0.043	0.112	0.050	-	-	-	-
	W-L	0.339	0.128	0.292	0.109	-	-	-	-
12x3	**Loser**	0.163	0.071	0.155	0.054	-	-	-	-
	Winner	0.115	0.034	0.089	0.046	-	-	-	-
	W-L	0.278	0.106	0.244	0.100	0.384	0.193	0.373	0.187

Table 5-6. Prior-Cost Performances of Momentum and Threshold-Regression-Model-Guided Trading Strategies

This table reports annualized BHRs for the momentum loser, winner, and winner-minus-loser (momentum) portfolio, self-financing model-guided trading strategy (M-G Trading strategy) and long position of model-guided trading strategy (M-G long position) in each row.

Strategy		Sample Period		
		1979-1988	1989-2003 (1998-2003)*	2004-2011
3x3	Loser Portfolio	0.226	0.021	0.048
	Winner Portfolio	0.335	0.210	0.146
	Momentum Portfolio	0.109	0.188	0.098
	M-G Trading Strategy	-	0.209	0.211
	M-G Long Position	-	0.202	0.204
6x3	Loser Portfolio	0.230	0.010	0.046
	Winner Portfolio	0.360	0.254	0.121
	Momentum Portfolio	0.129	0.244	0.075
	M-G Trading Strategy	-	0.264	0.222
	M-G Long Position	-	0.284	0.193
9x4	Loser Portfolio	0.209	0.025	0.065
	Winner Portfolio	0.363	0.265	0.117
	Momentum Portfolio	0.154	0.240	0.051
	M-G Trading Strategy	-	0.379	0.325
	M-G Long Position	-	0.355	0.254
12x3	Loser Portfolio	0.244	0.052	0.051
	Winner Portfolio	0.357	0.264	0.117
	Momentum Portfolio	0.113	0.212	0.065
	M-G Trading Strategy	-	0.312	0.357
	M-G Long Position	-	0.333	0.262

Note: Model guided strategies are implemented from 1998 onwards.

Table 5-7. Post-Cost Performances of Momentum Trading Strategies Based on Agyei-Ampomah (2007)

This table reports post-cost annualized returns of various momentum trading strategies based on transaction costs estimated in Agyei-Ampomah (2007). Two transaction costs estimation methods are employed in this paper. S+C represents transaction costs based on the quoted spread plus commissions and taxes and LDV the limited dependent variable (LDV) procedure proposed by Lesmond et al. (1999). Transaction costs are estimated for momentum trading strategies applied to unrestricted sample and restricted sample based on both S+C and LDV method.

Strategy	1979-1987				1988-2003				2004-2011			
	S+C		LDV		S+C		LDV		S+C		LDV	
	UnRes	Res	UnRes	Res	UnRes	Res	UnRes	Res	UnRes	Res	UnRes	Res
	Panel A. Self-Financing Momentum Trading Strategies (Winner-Loser)											
3x3	-0.463	-0.109	-0.389	-0.083	-0.384	-0.030	-0.310	-0.004	-0.474	-0.120	-0.400	-0.094
6x3	-0.289	-0.025	-0.231	-0.010	-0.174	0.090	-0.116	0.105	-0.343	-0.079	-0.285	-0.064
9x3	-0.185	0.026	-0.138	0.045	-0.099	0.112	-0.052	0.131	-0.288	-0.077	-0.241	-0.058
12x3	-0.165	0.008	-0.131	0.013	-0.066	0.107	-0.032	0.112	-0.213	-0.040	-0.179	-0.035
	Panel B. Long Winner Portfolio of Momentum Trading Strategies											
3x3	0.070	0.258	0.116	0.245	-0.055	0.133	-0.009	0.120	-0.119	0.069	-0.073	0.056
6x3	0.174	0.311	0.212	0.295	0.068	0.205	0.106	0.189	-0.065	0.072	-0.027	0.056
9x3	0.219	0.320	0.251	0.313	0.121	0.222	0.153	0.215	-0.027	0.074	0.005	0.067
12x3	0.242	0.323	0.268	0.311	0.149	0.230	0.175	0.218	0.002	0.083	0.028	0.071

UnRes=unrestricted sample; Res=restricted sample

Table 5-8. Post-Cost Performances of Momentum Trading Strategies Based on Li et al. (2009)

This table reports post-cost annualized returns of momentum trading strategies based on transaction costs estimated in Li et al. (2009). There are two sets of estimated transaction costs in this paper with one based on quoted spread and the other based on quoted spread. Further, they also calculate momentum transaction costs assuming 100% turnover ratio and using actual turnover ratio.

Trading Strategy	1979-1987				1988-2003				2004-2011			
	Quoted spread		Effective spread		Quoted spread		Effective spread		Quoted spread		Effective spread	
	100%	Actual	100%	Actual	100%	Actual	100%	Actual	100%	Actual	100%	Actual
3x3	-0.299	-0.236	-0.283	-0.221	-0.220	-0.157	-0.204	-0.142	-0.310	-0.247	-0.294	-0.232
6x3	-0.270	-0.125	-0.254	-0.114	-0.155	-0.010	-0.139	0.001	-0.324	-0.179	-0.308	-0.168
12x3	-0.271	-0.079	-0.260	-0.074	-0.172	0.020	-0.161	0.025	-0.319	-0.127	-0.308	-0.122

Table 5-9. Post-Cost Performances of Threshold-Regression-Model-Guided Trading Strategies Based on Agyei-Ampomah (2007)

This table reports post-cost annualized returns of various threshold-regression-model-guided trading strategies based on transaction costs estimated in in Agyei-Ampomah (2007). Two transaction costs estimation methods are employed in this paper. S+C represents transaction costs based on the quoted spread plus commissions and taxes and LDV the limited dependent variable (LDV) procedure proposed by Lesmond et al. (1999). Transaction costs are estimated for momentum trading strategies applied to unrestricted sample and restricted sample based on both the S+C and the LDV method.

Trading Strategy	1998-2003				2004-2011			
	S+C		LDV		S+C		LDV	
	Unrestricted Sample	Restricted Sample	Unrestricted Sample	Restricted Sample	Unrestricted Sample	Restricted Sample	Unrestricted Sample	Restricted Sample
Panel A. Self-Financing Model-Guided Trading Strategies								
3x3	-0.363	-0.009	-0.289	0.017	-0.361	-0.007	-0.287	0.019
6x3	-0.154	0.110	-0.096	0.125	-0.196	0.068	-0.138	0.083
9x4	0.040	0.251	0.087	0.270	-0.014	0.197	0.033	0.216
12x3	0.034	0.206	0.068	0.212	0.079	0.251	0.113	0.257
Panel B. Long Portfolio of Model-Guided Trading Strategies								
3x3	-0.063	0.125	-0.017	0.112	-0.061	0.127	-0.015	0.114
6x3	0.098	0.235	0.136	0.219	0.007	0.144	0.045	0.128
9x4	0.211	0.312	0.243	0.305	0.110	0.211	0.142	0.204
12x3	0.218	0.299	0.244	0.287	0.147	0.228	0.173	0.216

Table 5-10. Post-Cost Performances of Threshold-Regression-Model-Guided Trading Strategies Based on Li et al. (2009)

This table reports post-cost annualized returns of model-guide strategies based on transaction costs estimated in Li et al. (2009). There are two sets of estimated transaction costs in this paper with one based on quoted spread and the other based on quoted spread. Further, they also calculate momentum transaction costs assuming 100% turnover ratio and using actual turnover ratio.

Trading Strategy	1998-2003				2004-2011			
	Quoted spread		Effective spread		Quoted spread		Effective spread	
	100% Turnover	Actual Turnover	100% Turnover	Actual Turnover	100% Turnover	Actual Turnover	100% Turnover	Actual Turnover
3x3	-0.199	-0.136	-0.183	-0.121	-0.197	-0.134	-0.181	-0.119
6x3	-0.135	0.010	-0.119	0.021	-0.177	-0.032	-0.161	-0.021
12x3	-0.072	0.119	-0.061	0.125	-0.027	0.164	-0.016	0.170

5.6 Conclusion

This chapter examines the post-cost profitability of both momentum and model-guided trading strategies by comparing profits generated by momentum and model-guided trading strategies 3x3, 6x3, 9x4 and 12x3 to their transaction costs.

We show that momentum portfolios in our study share a lot of common features with those in the prior studies on the UK stock market. Consistent with the literature, we find that, the average firm size of stocks in loser portfolios of a momentum trading strategy is much smaller than that in winner portfolios of the same momentum trading strategy as loser portfolios overweigh small firms. In our study, loser portfolios consist of above 30% firms from the smallest quintile and less than 10% from the largest quintile in term of market capitalization, whereas winner portfolios have rather evenly distribution among different quintiles. We also find that the turnover ratio has an inverse relationship with the ranking period.

Our discussion is based on the transaction costs estimated by Agyei-Ampomah (2007) and li et al. (2009) and we justify the suitability of doing so based on the following reasons. First, all of their studies and ours cover the majority of the stocks traded in the UK stock market although we have different sources of data. Second, we compare the features of momentum portfolios, which are documented to have impact on the size of their transaction costs, and we conclude that there is a lot of similarity in these features.

Our results show that four momentum trading strategies, 3x3, 6x3, 9x4 and 12x3, cannot make profits after transaction costs, however, the model-guided trading strategy12x3 still make profits taking transaction costs into account. Investing in the winner portfolio of the momentum trading strategy 12x3 appears to generate net profit, but the size of net profits is very small. Finally, implementing the long position of model-guided trading strategies 6x3, 9x4 and 12x3 is post-cost profitable. The long position of the model-guided trading strategy12x3 generates double digit profits even after transaction costs.

Although we show that our four momentum trading strategies fail to make economically significant profits after transaction cost, we cannot make a general conclusion regarding the ability of other momentum trading strategies to exploit the momentum effect and to make significantly net profits as our discussion only covers four momentum trading strategies. Nevertheless, we have provide evidence that model-guided trading strategies, especially, taking long position of these strategies, can make sizable profits net of transaction costs even when their associated momentum trading strategies can’t.

6. General Conclusion

We update the study of the momentum effect in the UK stock market and confirm that this effect is a persistent phenomenon in the UK stock market as we find that a great deal of momentum trading strategies make highly statistically significant profits from Jan 1979 to Nov 2011. We also find a high degree of dynamics in the momentum effect. This dynamics is reflected not only by the large variation in the size of momentum returns but also by the change in the sign of momentum returns, which suggests that the momentum effect can be replaced by the contrarian effect in the short run.

The results of investigating the performances of a number of momentum strategies over time suggest that the dynamics of the momentum effect is at least partially conditional on the stability of the whole stock market. We document that momentum trading strategies with different ranking and holding periods almost simultaneously make losses during market crises. Further, the number of profitable momentum trading strategies and the size of momentum profits fluctuate substantially over time from 1979 to 2011. More specifically, there is a huge increase in the number of profitable momentum strategies and in the size of momentum profits going from the sub sample time period 1979-1988 to 1989-1998 and then a big drop in the number of profitable momentum strategies and in the size of momentum profits going from 1989-1998 to 1999-2011. The noticeable difference between the sub-sample time period of 1989-1998 and the other two sub-sample periods is that there is no big shock hitting the stock market during 1989-1998.

To predict the dynamics of the momentum effect, we turn to three behavioural models as they can generate both the momentum and the contrarian effect. Based on the empirical findings in Chapter 3 and three models in Daniel et al. (1998), Baberis et al. (1998) and Hong and Stein (1999), we conjecture that the ranking period market volatility and the ranking period return of a momentum portfolio have predictive power. We suppose that the market volatility can change and affect investors' behavioural bias including self-attribution, overconfidence, conservatism and representativeness, which are the causes of the momentum effect based on these models and therefore the market volatility should have predictive power. For example, high market volatility could destroy confidence and cause panic trading. In this case, no momentum effect should be expected and the contrarian effect might occur. We also believe that the ranking period return of a momentum effect can indicate underreaction and overreaction to some extent. This is important because both underreaction and overreaction can generate the momentum effect; however, the former leads to further momentum and the latter leads to reversal.

Based on these conjectures, we construct a threshold regression model with the ranking period market volatility being the switching variable indicating the switch between two regimes, the momentum regime and the reversal regime. In both regimes, the holding period return of a momentum portfolio that measures the momentum effect is regressed on both the ranking period market volatility and the ranking period return of the momentum portfolio.

The estimation results with momentum trading strategies 3x3, 6x3, 9x4 and 12x3, confirm that the ranking period market volatility play a significant role in terms of predicting the switch between the momentum and the reversal regime. In the momentum regime, a momentum trading strategy tend to make profits and that in the reversal regime, a momentum trading strategy tend to suffer losses. Further, the ranking period market volatility also has negative impact on the holding period return in both regimes in many cases. We also confirm that the ranking period return has a significant predictive role as it has a significant inverse relationship with the holding period return in the momentum regime. This negative relationship can lead to a reversal in the short run even in the momentum regime.

Trading strategies that are designed to follow the prediction of the threshold regression model are shown to outperform simple momentum strategies with higher returns and less risks as they can exploit the abnormal returns generated not only by the momentum effect but also by the contrarian effect in the short run. We find that among the correctly predicted reversals, some are due to extremely high ranking period market volatilities and others are associated with extremely high ranking period returns. This results seem to support our conjectures of the implications of high market volatility and high ranking period return.

Finally, we discuss the post-cost profitability of both momentum and threshold-regression-model-guided trading strategies. We find that profits of all examined momentum trading strategies 3x3, 6x3, 9x4 and 12x3disappear after transaction costs taken into account; however, the threshold-regression-model-guided trading strategy 12x3 is still able to make sizable net profits. Moreover, we find that taking long position of the momentum trading strategy 12x3 generates profits after transaction costs that are not economically significant. In contrast, taking long position of model-guided trading strategies 6x3, 9x4 and 12x3 are all post-cost profitable. The long position of the threshold-regression-model-guided trading strategy 12x3 generates an impressive annualized return around 20% from 1998 to 2011.

This thesis makes the following contributions. First, in contrast with the prior literature that conclude either a monotonic downtrend or a monotonic uptrend in the magnitude of the momentum effect in the UK stock market, we find that the momentum effect is a dynamic financial phenomenon and its dynamics is at least partially conditional on the stability of the stock market. Second, we discover new variables that have predictive power on its dynamics, especially the switch between the momentum effect and its reversal, which has never been done before. More importantly, these results seem to be consistent with behavioural models as the contrarian effect occurs even in the short run. Third, we successfully design a new type of trading strategies that is able to exploit both the momentum effect and the contrarian effect in the short run and more importantly these new strategies can make profits after transaction costs when momentum trading strategies can't. This post-cost profitability of our new trading strategies creates a new and even bigger puzzle than momentum profits and it raises a question why there are sizable profits that have not been arbitraged away.

We finish this thesis by suggesting the following possible directions for the future research. First, it is highly desirable to further test this model and hence the predictive power of the market volatility and the ranking period return in other financial markets in which the momentum effect is found as the observations in the reversal regime in our study are quite limited. Second, although the threshold regression model is good at predicting the switch between the momentum effect and its reversal, it is poor at predicting the size of the momentum effect and the degree of its reversal. Thus, there is potential to improve the predictability of the momentum effect dynamics by looking for more variables that have additional predictive power on the magnitude of the momentum effect and its reversal or by designing a more sophisticated model based on our model. Finally, the predictability of the momentum effect dynamics and the significant post-cost profits generated by our model-guided trading strategies create another financial anomaly, which challenges the market efficiency hypothesis. Although we build the threshold regression model based on behavioural theories and the estimation results seem to be consistent with behavioural explanations of the momentum effect, we do not reject the possibility of rational explanations of our findings and we leave this question open for further discussion.

REFERENCES

Agyei-Ampomah, S. 2007. The post-cost profitability of momentum Trading Strategies: further evidence from the UK. *European Financial Management* 13 (4), pp. 776–802.

Albert, J. 2009. *Bayesian computation with R.* Springer New York

Ali, A. and Trombley, M.A. 2006. Short sales constraints and momentum in stock returns. *Journal of Business Finance and Accounting* 33(3) & (4), pp.587–615.

Ang, A. et al. 2002. *Downside Risk and the Momentum Effect* [Online]. Available at http://www.nber.org/papers/w8643.pdf

Ang, A and Timmermann, A. 2012. Regime changes and financial markets. *Annual Review of Financial Economics* vol (4), pp. 313-337

Antoniou, A. 2007. Profitability of momentum strategies in international markets: The role of business cycle variables and behavioural biases. *Journal of Banking & Finance* 31(3), pp. 955–972.

Arnold, G. and Baker, R. 2007. *Return Reversal in UK Shares* [Online]. Available at SSRN: http://dx.doi.org/10.2139/ssrn.998418

Asem, E. and Tian, G.R. 2010. Market Dynamics and Momentum Profits. *Journal of Financial and Quantitative Analysis* 45(6), pp. 1549–1562.

Asness, C.S. et al. 2013. Value and momentum everywhere. *Journal of Finance* 68(3), pp. 929-985.

Avramov, D. and Chordia,T. 2006. Asset Pricing Models and Financial Market. *Review of Economic Studies* 19 (3), pp. 1001-1040.

Ball, R. and Kathari, S.P. 1989. Nonstationary expected returns: Implications for tests of market efficiency and serial correlation in returns. *Journal of Financial Economics* 25 (1), pp. 51-74.

Barberis, N. et al. 1998. A model of investor sentiment. *Journal of Financial Economics*. 49 (3), pp. 307–343.

Bauwens, L. et al. 1999. *Bayesian inference in dynamic econometric models*. Oxford University Press.

Balvers, R.J. and W, Y. 2006. Momentum and mean reversion across national equity markets. *Journal of Empirical Finance*. 13, pp. 24-48.

Berk, J.B. et al. 1999. Optimal investment, growth options, and security returns. *Journal of Finance*. 54(5), pp.1553-1608.

Boyntonm, W. and Oppenheimer, H. 2006. Anomalies in stock market pricing: problems in return measurements. *Journal of Business.*79, pp. 2617-2631.

Chan et al. 2000. Profitability of momentum strategies in the international equity markets. *Journal of Financial and Quantitative Analysis*. 35(2), pp. 153-172.

Chan, L.K.C. et al. 1996. Momentum strategies. *Journal of Finance* 51(5), pp. 1681-1714.

Chen, N.F. et al. 1986. Economic forces and the stock market. *Journal of Business* 59 (3), pp. 1681-1713.

Chordia, T. and Shivakumar, L. 2002. Momentum, business cycle and time varying expected returns. *Journal of Finance*. 57 (2), pp. 985-1019.

Chui, A. C.W. et al. 2000. *Momentum, Legal Systems and Ownership Structure: An Analysis of Asian Stock Markets* [Online]. Available at SSRN: http://dx.doi.org/10.2139/ssrn.265848

Clare, A. and Thomas, S. 1995. The overreaction hypothesis and the UK stock market. *Journal of Business Finance & Accounting* 22 (7), pp. 961–973.

Cooper, M.J. et al. 2004. Market states and Momentum. *Journal of Finance* 59 (3), pp. 1345–1365.

Conrad, J. and Kaul, G. 1998. An anatomy of trading strategies. *Review of Economic Studies* 11 (3), pp. 489-519.

Daniel, K. et al. 1998. Investor psychology and security market under- and overreactions. *Journal of Finance* 53 (6), pp. 1839–1885.

Daniel, K. et al. 2012. *Tail risk in momentum strategy returns*. [Online]. Available at http://www.columbia.edu/~kd2371/papers/unpublished/djk3.pdf

Daniel, K. and Moskowitz, T. 2011. *Momentum Crashes.* [Online]. Available at SSRN: http://ssrn.com/abstract=2371227 or http://dx.doi.org/10.2139/ssrn.2371227

De Bond, W.F.M. and Thaler, R. 1985. Does the stock market overreact? *Journal of Finance* 40 (3), pp.793–805.

De Bond, W.F.M. and Thaler, R. 1987. Further evidence on investor overreaction and stock market seasonality. *Journal of Finance* 42 (3), pp. 557–581.

Dissanaike, G. 1994. On the computation of returns in tests of the stock market overreaction hypothesis. *Journal of Banking & Finance* 18 (6), pp 1083 – 1094

Dissanaike, G. 2002. Does the size effect explain the UK winner-loser effect? *Journal of Business Finance & Accounting* 29 (1-2), pp. 139-154.

Fama, E.F. and French, K.R. 1988. Permanent and temporary components of stock prices. *Journal of Political Economy* 96 (2), pp. 246-273.

Fama, E.F. and French, K.R. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33 (1), pp.3-56.

Fama, E.F. and French, K.R. 1996. Multifactor explanations of asset pricing anomalies. *Journal of Finance* 51 (1), pp.55–84.

Figlewski, S. 1997. Forecasting volatility. *Financial Markets, Institutions and Instruments* 6 (2), pp.1-88.

Galariotis et al. 2007. Contrarian and momentum profitability revisited: Evidence from the London Stock Exchange 1964-2005. *Journal of Multinantional Financial Management* 17(5), pp. 432-447

Glaser, M. and Weber, M. 2002. *Momentum and Turnover: Evidence from the German Stock Market* [Online]. Available at SSRN: http://dx.doi.org/10.2139/ssrn.302151

Greenberg, E. 2008. *Introduction to Bayesian econometrics*. Cambridge University Press

Griffin, J.M. et al. 2003. Momentum investing and business cycle risk: evidence from pole to pole. *Journal of Finance* 58 (6), pp. 2515-2548.

Grinblatt, M. and Moskowitz, T.J. 2004. Prospect theory, mental accounting, and momentum. *Journal of Financial Economics* 78 (2), pp. 311-339.

Grundy, R.F. and Martin, S.R. 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Economic Studies* 14 (1), pp. 29-79.

Gregory,A. et al. 2013. *Constructing and testing alternative versions of the Fama–French and Carhart models in the UK*. Journal of Business Finance & Accounting. 40(1) & (2), pp. 172–214.

Hameed, A. and Kusnadi, Y. 2002. Momentum strategies: evidence from pacific basin stock markets. *Journal of Financial Research* 25 (3), pp. 383-397.

Hon, M.T. and Tonks, I. 2003. Momentum in the UK stock market. *Journal of Multinational Financial Management* 13(1), pp. 43-70.

Hong, H. and Stein, J.C. 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *Journal of Finance* 54 (6), pp. 2143-2182.

Hwang, S and Rubesam, A. 2013. The disappearance of momentum. *The European Journal of Finance* 19(10), pp. 1-24.

Jegadeeshi, N. 1990. Evidence of predictable behaviour of security returns. *Journal of Finance* 45 (3), pp. 881-898.

Jegadeeshi, N. and Titman, S. 1993. Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance* 48 (1), pp. 65-91.

Jegadeesh, N. and Titman, S. 2001. Profitability of momentum strategies: an evaluation of alternative explanations. *Journal of Finance* 56(2), pp. 699–720.

Johnson, T. C. 2002. Rational momentum effects. *Journal of Finance* 57(2), pp. 585–608.

Keim, D.B. 2003. The cost of trend chasing and the illusion of momentum profits. [Online]. Available at https://fnce.wharton.upenn.edu/files/?whdmsaction= public :main.file&fileID=7160

Kim et al. 2011. Stock return predictability and the adaptive markets hypothesis: Evidence from century-long U.S. data. *Journal of Empirical Finance* 18(5), pp 868–879.

Korajczyk, R.A. and Sadka, R. 2004. Are momentum profits robust to trading costs? *Journal of Finance* 59 (3), pp. 1039–1082.

Korenok, O. 2007. *Bayesian Methods in Nonlinear Time Series* [Online].Available at: http://www.people.vcu.edu/~okorenok/BNTpost.pdf

La Porta, R. 1996. Expectations and the cross-section of stock returns. *Journal of Finance* 51(5), pp. 1715-1742.

Lesmond, D.A. 1999. A new estimate of transaction costs. *Review of Economic Studies* 12 (5), pp. 1113-1141.

Lesmond, D. A. et al. 2004. The illusory nature of momentum profits. *Journal of Financial Economics* 71(2), pp. 349-80.

Lee, C.M.C. and Swaminathan, B. 2000. Price momentum and trading volume. *Journal of Finance* 55 (5), pp. 2017–2069.

Li, X. et al. 2008. *Low-cost momentum strategies.* Journal of Asset Management. 9 (6). pp. 366-379.

Liu, L.X. and Zhang, L. 2008. Momentum Profits, Factor Pricing, and Macroeconomic Risk. *The Review of Financial Studies* 21 (6), pp. 2417-2448.

Liu, W.M. et al. 1999. The profitability of momentum investing. *Journal of Business Finance & Accounting* 26 (9-10), pp.1043–1091.

Lo, A.W. and MacKinlay, A.C. 1990. When are contrarian profits due to stock market overreaction? *The Review of Financial Studies* 3 (2), pp. 175-205.

Lakonishok, J. et al. 1994. Contrarian Investment, Extrapolation, and Risk. *Journal of Finance* 49 (5), pp. 1541–1578

Lubrano, M. 1998. *Bayesian analysis of nonlinear time series models with a threshold* [Online]. Available at: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.54.5066

Malkiel, B.G. 2003. The efficient market hypothesis and its critics. *Journal of Economic Perspectives* 17 (1), pp. 59-82.

McKnight, P.J. and Hou, T.C.T. 2006. The determinants of momentum in the United Kingdom. *The Quarterly Review of Economics and Finance* 46 (2), pp. 227-240.

Moskowitz, T.J. and Grinblatt, M. 1999. Do industries explain momentum? *Journal of Finance*. 54(4), pp. 1249-1290.

Muga, L. and Santamaria, R. 2007. The momentum effect in Latin American emerging markets. *Emerging markets Finance and Trade* 43 (4), pp. 24-45.

Newey, W.K. and West, K.D. 1987. A simple, positive-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55 (3), pp.703-708.

Newey, W.K. and West, K.D. 1994. Automatic lag selection in covariance matrix estimation. *Review of Economic Studies* 61, pp. 631-653.

Pastor, L. and Stambaugh, R. F. 2003. Liquidity risk and expected stock returns, *The Journal of Political Economy* 111(3), pp. 642-685.

Barroso, P. and Santa-Clara, P. 2014. Momentum Has Its Moments, *Journal of Financial Economics* 116(1), pp. 111-120.

Poon, S. 2008. *Volatility Estimation* [Online].Available at: https://www.cmegroup.com/trading/fx/files/volEst.pdf

Roll, R. 1984. A simple implicit measure of the effective bid-ask spread in an efficient market. *Journal of Finance* 39 (4), pp. 1127–1139.

Rouwenhorst, K.G. 1998. International momentum strategies. *Journal of Finance* 53 (1), pp.267–284.

Sagi, J. S. and Seasholes, M. S. 2007. Firm-specific attributes and the cross section of momentum. Journal of Financial Economics 84(2), pp. 389–434.

Siganos, A. 2010. Can small investors exploit the momentum effect? *Financial Markets and Portfolio Management* 24 (2), pp. 171-192.

Shleifer, A. and Vishy, W. 1997. The limit of arbitrage. *Journal of Finance* 52 (1), pp. 35-55.

Tversky, A. and Kahneman, D. 1974. Judgment under uncertainty: heuristics and biases. *Science* 185(4157), pp.1124-1131.

Wang, K.Q. and Xu, J.G. 2009. *Market volatility and momentum* [Online]. Available at SSRN: http://ssrn.com/abstract=1342719

Zeileis, A. 2004. Econometric computing with HC and HAC covariance matrix estimators. *Journal of Statistic Software* 11(10), pp. 1–17.

APPENDIX

Table A-1. Profitability of Contrarian Trading Strategies

A self-financing portfolio of the JxK contrarian strategy is formed by ranking all stocks (without any missing value over J-month ranking period) in descending order based on their Buy-and Hold return (BHR) from time t-J to t-1. The top decile forms the winner portfolio with equal weight and the bottom decile forms the loser portfolio with equal weight. At time t+1 (skipping month t), the self-financing contrarian portfolio, shorting the winner portfolio and longing loser portfolio, is invested and is held for K months for t+1 to t+K, during which proceeds from a delisted stock is invested equally in the rest constituents of its own portfolio monthly for the rest of the holding period. Such contrarian strategy carries out every month from Jan 1979 (forms at the beginning of Jan 1979 and is invested at the beginning of Feb 1979) till K+1 months before Dec 2011. TableA-1 reports the average BHR of the 395-k observations and the annualized average BHR using the conversion formula $((1 + BHR)^{1/k} - 1) * 12$. Newey-West (1987, 1994) heteroskedasticity-and-autocorrelation-consistent (HAC) estimator is employed to estimate the variance of BHR for each JxK contrarian strategy and the corresponding T-value is also reported.

	Holding Period									
Ranking Periods	3M	6M	9M	12M	15M	18M	21M	24M	27M	30M
24M: BHR	-0.01	-0.02	0.00	0.02	0.04	0.05	0.07	0.10	0.13	0.17
Annualized BHR	-0.06	-0.03	0.00	0.02	0.03	0.03	0.04	0.05	0.06	0.06
T-value	-2.20	-1.39	-0.03	1.17	2.28	3.12	4.14	5.22	6.82	7.99
30M: BHR	0.00	0.00	0.01	0.04	0.06	0.08	0.11	0.13	0.18	0.22
Annualized BHR	0.00	0.01	0.02	0.03	0.05	0.05	0.06	0.06	0.07	0.08
T-value	-0.05	0.37	1.07	2.26	3.60	4.53	5.63	7.02	9.09	10.49
36M: BHR	0.00	0.01	0.02	0.04	0.07	0.10	0.13	0.17	0.21	0.25
Annualized BHR	0.00	0.01	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.09
T-value	-0.21	0.61	1.78	2.89	4.06	5.22	6.75	8.37	10.15	11.58
42M: BHR	0.00	0.01	0.03	0.06	0.10	0.13	0.16	0.20	0.25	0.29
Annualized BHR	0.02	0.03	0.04	0.06	0.07	0.08	0.09	0.09	0.10	0.10
T-value	0.65	1.38	2.51	3.84	5.42	6.56	8.00	9.50	11.50	12.68
48M: BHR	0.01	0.02	0.04	0.08	0.11	0.14	0.18	0.22	0.27	0.32
Annualized BHR	0.02	0.04	0.06	0.07	0.08	0.09	0.09	0.10	0.11	0.11
T-value	0.82	1.96	3.48	4.96	6.28	7.40	8.97	10.52	12.23	13.26
54M: BHR	0.02	0.04	0.06	0.09	0.12	0.16	0.19	0.23	0.27	0.31
Annualized BHR	0.06	0.07	0.08	0.09	0.09	0.10	0.10	0.10	0.11	0.11
T-value	2.47	3.34	4.26	5.48	6.80	7.95	9.01	9.87	10.86	11.61
60M: BHR	0.01	0.03	0.05	0.09	0.12	0.16	0.21	0.25	0.29	0.34
Annualized BHR	0.05	0.06	0.07	0.08	0.09	0.10	0.11	0.11	0.12	0.12
T-value	2.15	3.02	4.38	6.01	7.52	8.76	10.22	11.46	12.28	12.84

(Table A-1 is continued on the next page)

Table A-1. Profitability of Contrarian Trading Strategies
(Continued from the previous page)

	Holding Period									
Ranking Periods	33M	36M	39M	42M	45M	48M	51M	54M	57M	60M
24M: BHR	0.20	0.23	0.27	0.32	0.36	0.41	0.47	0.53	0.59	0.66
Annualized BHR	0.07	0.07	0.07	0.08	0.08	0.09	0.09	0.09	0.10	0.10
T-value	9.15	9.88	10.51	10.96	10.87	11.16	10.90	10.79	10.58	10.81
30M: BHR	0.25	0.29	0.34	0.38	0.42	0.48	0.55	0.62	0.69	0.77
Annualized BHR	0.08	0.09	0.09	0.09	0.09	0.10	0.10	0.11	0.11	0.11
T-value	11.46	12.43	13.09	12.98	12.59	12.39	12.21	11.75	11.12	11.45
36M: BHR	0.29	0.34	0.38	0.43	0.49	0.55	0.62	0.70	0.79	0.88
Annualized BHR	0.09	0.10	0.10	0.10	0.11	0.11	0.11	0.12	0.12	0.13
T-value	12.50	13.53	13.72	13.48	13.21	13.01	12.73	12.37	12.38	12.92
42M: BHR	0.34	0.39	0.45	0.51	0.58	0.66	0.75	0.85	0.95	1.06
Annualized BHR	0.11	0.11	0.12	0.12	0.12	0.13	0.13	0.14	0.14	0.14
T-value	13.45	13.83	13.93	13.85	13.52	13.13	13.48	13.56	13.19	13.61
48M: BHR	0.37	0.42	0.48	0.55	0.63	0.73	0.84	0.94	1.03	1.09
Annualized BHR	0.12	0.12	0.12	0.13	0.13	0.14	0.14	0.15	0.15	0.15
T-value	13.81	14.08	13.93	13.76	13.90	13.87	13.50	13.35	13.52	14.26
54M: BHR	0.36	0.43	0.51	0.59	0.67	0.77	0.88	0.97	1.04	1.09
Annualized BHR	0.11	0.12	0.13	0.13	0.14	0.14	0.15	0.15	0.15	0.15
T-value	12.20	13.38	14.58	14.96	15.06	14.71	14.17	14.03	14.10	14.78
60M: BHR	0.39	0.44	0.50	0.58	0.66	0.75	0.86	0.94	1.00	1.05
Annualized BHR	0.12	0.12	0.13	0.13	0.14	0.14	0.15	0.15	0.15	0.14
T-value	13.52	14.10	14.84	15.34	15.45	15.24	14.61	14.58	14.99	15.48

Note: two-tailed tests are applied to examine the significance of BHRs. Critical value corresponding to the significance level of 1%, 5%, and 10% is 2.576, 1.96 1.645 respectively.

Table A-2. Performance Reliability of Contrarian Strategies

The reliability of the JxK trading strategy is measured by the percentage of the number of profitable observations to the number of the total observations, 395-K, of the JxK trading strategy. A profitable observation of the JxK trading strategy occurs when a self-financing portfolio that is formed based on the previous J-month buy-and-hold return generates positive return after being held for K months. It can be seen that most significantly profitable trading strategies are highly reliable.

	Holding Periods																		
	6M	**9M**	**12M**	**15M**	**18M**	**21M**	**24M**	**27M**	**30M**	**33M**	**36M**	**39M**	**42M**	**45M**	**48M**	**51M**	**54M**	**57M**	**60M**
No of observations	389	386	383	380	377	374	371	368	365	362	359	356	353	350	347	344	341	338	335
% of profitable observations																			
24M	-	-	-	-	45%	48%	52%	55%	61%	63%	65%	67%	70%	72%	75%	77%	77%	76%	77%
30M	-	-	-	43%	48%	51%	57%	60%	65%	71%	73%	76%	75%	77%	78%	77%	78%	79%	81%
36M	-	-	41%	46%	53%	57%	61%	65%	71%	72%	76%	79%	79%	79%	82%	81%	83%	83%	86%
42M	-	-	45%	53%	58%	61%	65%	71%	73%	75%	78%	80%	81%	83%	85%	86%	87%	88%	88%
48M	-	42%	50%	59%	62%	66%	69%	73%	75%	78%	79%	79%	82%	85%	88%	90%	90%	90%	89%
54M	47%	51%	56%	61%	65%	67%	70%	72%	74%	78%	79%	83%	84%	86%	90%	88%	89%	89%	90%
60M	46%	52%	57%	62%	64%	66%	68%	70%	73%	77%	82%	83%	86%	89%	93%	92%	91%	92%	92%

Note: Only results for contrarian strategies with profits being significant at the significance level of 1% are tabulated.

Table A-3. Correctly Predicted Momentum Reversal Observations (J=3, K=3)

Date	Ranking Period Return	Ranking Period Market Return Variance	Holding Period Return	Ranking Period Market Return Variance >0.018
30/10/1998	0.678	-0.053	0.017	
30/11/1998	0.823	-0.012	0.016	
30/12/1998	0.875	-0.015	0.012	
29/01/1999	0.916	-0.109	0.009	
26/02/1999	0.876	-0.047	0.008	
30/12/1999	1.891	-0.074	0.004	
31/01/2000	2.180	-0.415	0.005	
29/02/2000	1.801	-0.225	0.008	
31/03/2000	1.132	-0.091	0.009	
31/05/2000	0.913	-0.016	0.010	
30/08/2002	0.745	-0.098	0.028	*
30/09/2002	0.790	-0.067	0.034	*
31/10/2002	0.845	-0.008	0.025	*
31/12/2002	1.053	-0.040	0.014	
31/01/2003	0.932	-0.165	0.010	
31/03/2003	0.753	-0.239	0.018	
30/04/2003	0.843	-0.030	0.017	
31/10/2008	0.770	-0.004	0.061	*
28/11/2008	0.801	-0.196	0.083	*
31/12/2008	0.885	-0.650	0.071	*
30/01/2009	0.970	-0.623	0.037	*
27/02/2009	1.047	-0.329	0.019	*
31/03/2009	1.203	-0.010	0.023	*

Note: an observation is marked by * if it occurs when the ranking period market return variance is above the threshold.

Table A-4. Correctly Predicted Momentum Reversal Observations
(J=6, K=3)

Date	Ranking Period Return	Ranking Period Market Return Variance	Holding Period Return	Ranking Period Market Return Variance >0.032
30/10/1998	0.828	-0.019	0.021	
30/11/1998	0.847	-0.042	0.024	
30/12/1998	0.856	-0.149	0.024	
29/01/1999	0.923	-0.117	0.027	
26/02/1999	1.127	-0.080	0.024	
30/12/1999	2.363	-0.091	0.010	
31/01/2000	2.818	-0.430	0.012	
29/02/2000	3.644	-0.248	0.013	
31/03/2000	2.808	-0.177	0.013	
31/12/2002	0.957	-0.024	0.048	*
28/02/2003	1.005	-0.289	0.032	*
30/01/2009	0.957	-1.013	0.098	*
27/02/2009	0.898	-0.708	0.102	*
31/03/2009	0.998	-0.073	0.094	*
28/08/2009	2.684	-0.140	0.026	
30/09/2009	2.561	-0.041	0.018	

Note: an observation is marked by * if it occurs when the ranking period market return variance is above the threshold.

Table A-5. Correctly Predicted Momentum Reversal Observations (J=12, K=3)

Date	Ranking Period Return	Ranking Period Market Return Variance	Holding Period Return	Ranking Period Market Return Variance >0.06
30/12/1999	4.002	-0.043	0.023	
31/01/2000	3.967	-0.340	0.022	
29/02/2000	5.032	-0.223	0.023	
31/03/2000	3.773	-0.078	0.024	
28/04/2000	3.029	-0.107	0.026	
31/07/2000	2.761	-0.175	0.027	
31/08/2000	2.801	-0.197	0.025	
29/09/2000	2.734	-0.190	0.025	
31/10/2000	2.359	-0.103	0.024	
28/02/2003	1.281	-0.294	0.063	*
31/03/2003	1.279	-0.346	0.072	*
30/04/2003	1.185	-0.288	0.074	*
30/05/2003	1.186	-0.126	0.076	*
30/06/2003	1.285	-0.162	0.073	*
31/07/2003	1.625	-0.025	0.057	
30/01/2004	2.857	-0.008	0.027	
27/02/2004	3.268	-0.016	0.023	
31/03/2004	3.089	-0.055	0.015	
28/11/2008	0.969	-0.172	0.119	*
31/12/2008	0.986	-0.756	0.122	*
30/01/2009	1.016	-0.992	0.120	*
27/02/2009	1.004	-0.753	0.122	*
31/03/2009	1.040	-0.060	0.125	*
30/04/2009	1.030	-0.117	0.129	*
29/05/2009	1.047	-0.248	0.131	*
30/06/2009	1.145	-0.248	0.131	*
31/07/2009	1.300	-0.035	0.129	*
28/08/2009	1.224	-0.044	0.128	*
30/09/2009	1.507	-0.007	0.113	*
31/12/2009	2.962	-0.052	0.049	
29/01/2010	2.834	-0.093	0.043	
26/02/2010	2.968	-0.070	0.039	
31/03/2010	2.864	-0.024	0.030	

Note: an observation is marked by * if it occurs when the ranking period market return variance is above the threshold.

Figure A-1. Buy-and-Hold Returns of the Momentum Trading Strategy (J=3, K=3)

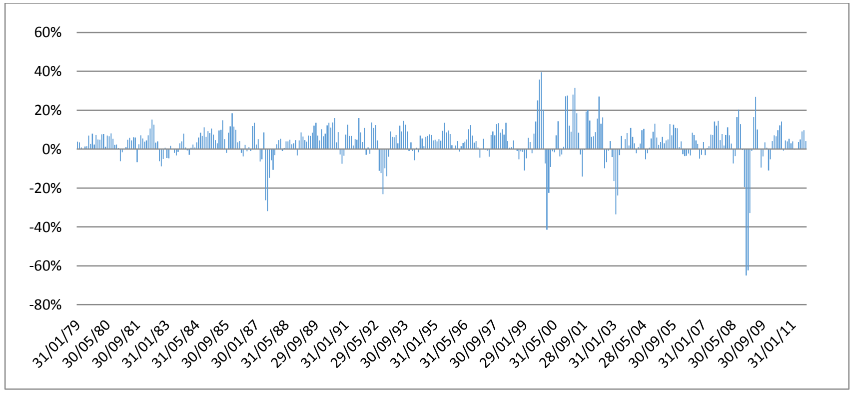


Figure A-2. Buy-and-Hold Returns of the Momentum Trading Strategy (J=3, K=6)

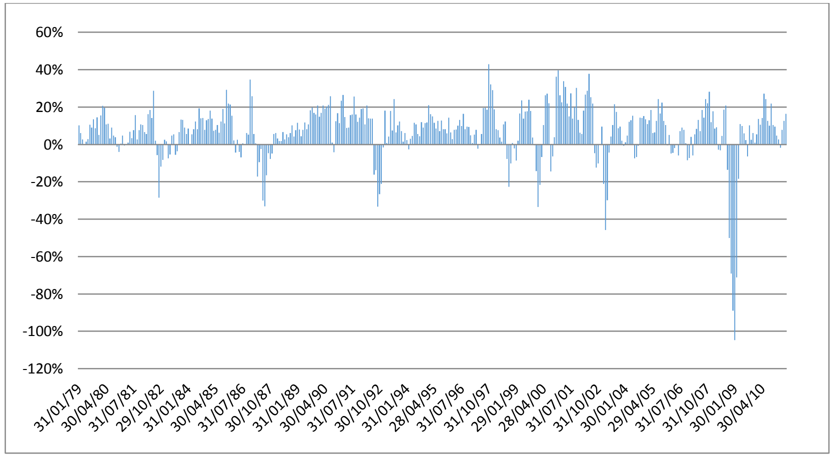


Figure A-3. Buy-and-Hold Returns of the Momentum Trading Strategy (J=3, K=9)

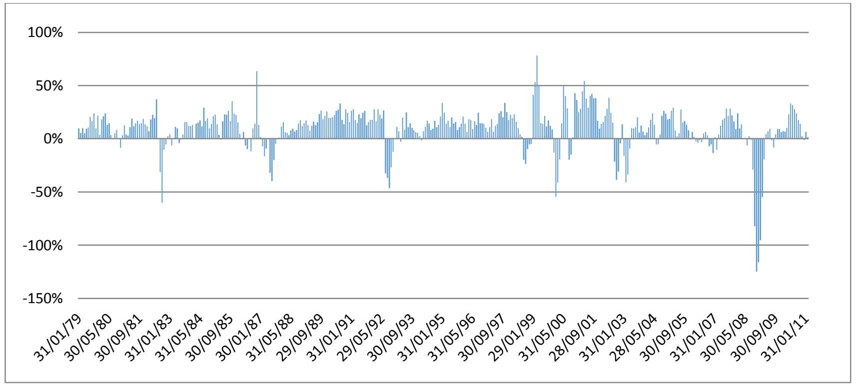


Figure A-4. Buy-and-Hold Returns of the Momentum Trading Strategy (J=3, K=12)

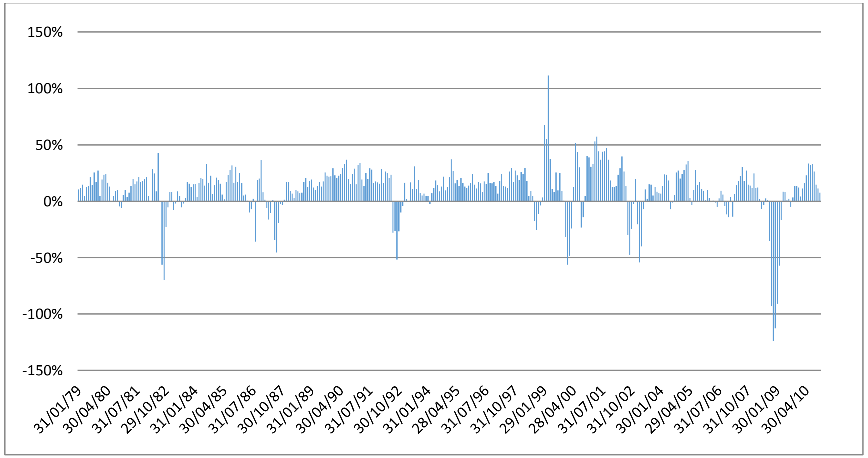


Figure A-5. Buy-and-Hold Returns of the Momentum Trading Strategy (J=6, K=3)

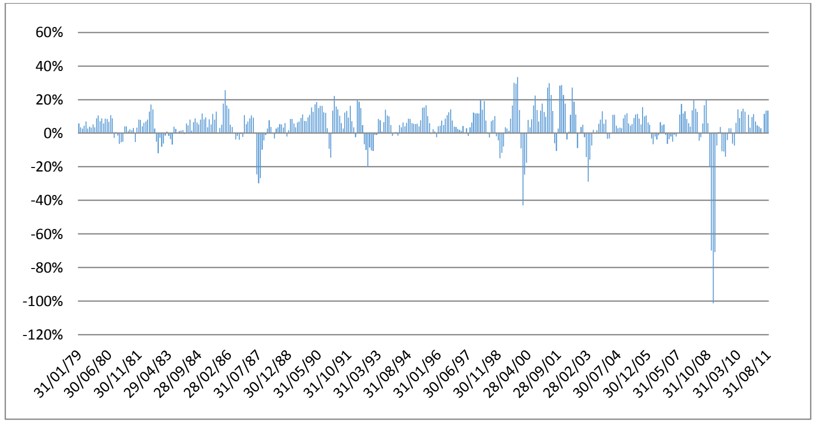


Figure A-6. Buy-and-Hold Returns of the Momentum Trading Strategy (J=6, K=6)

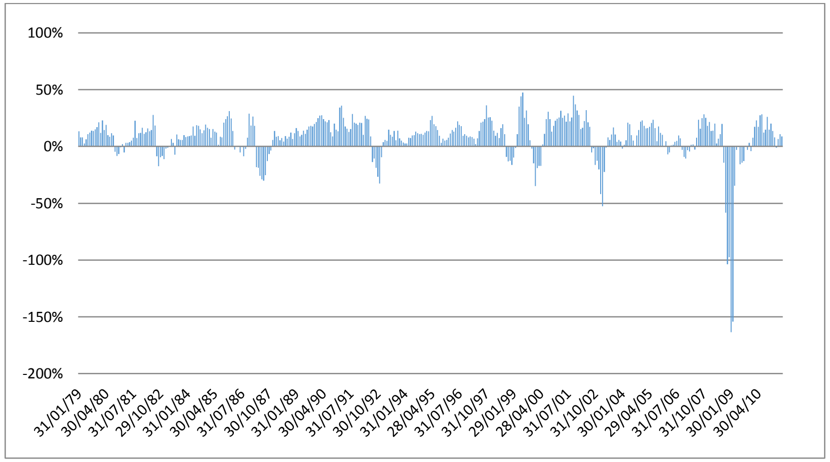


Figure A-7. Buy-and-Hold Returns of the Momentum Trading Strategy (J=6, K=9)

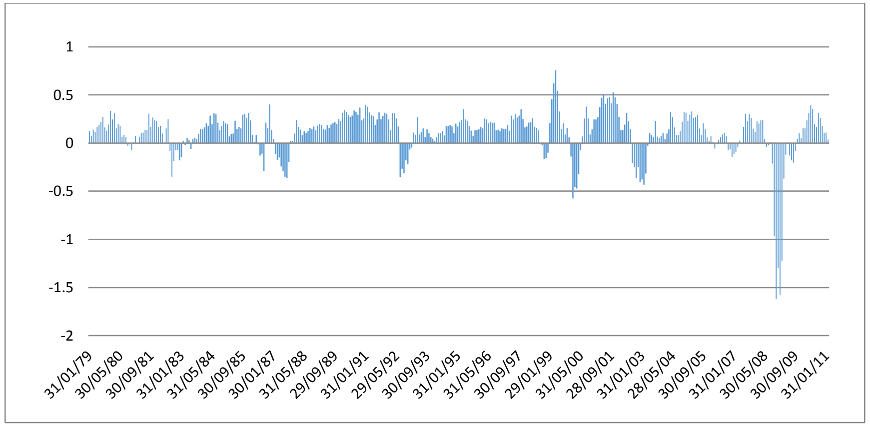


Figure A-8. Buy-and-Holds Return of the Momentum Trading Strategy (J=6, K=12)

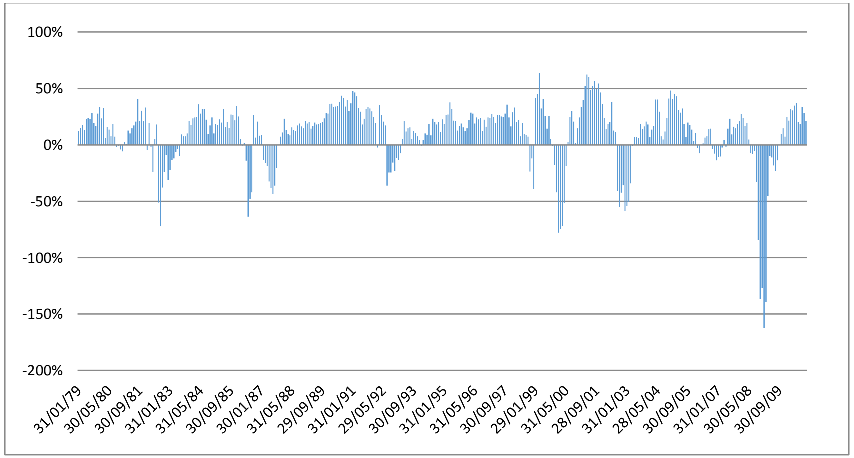


Figure A-9. Buy-and-Hold Returns of the Momentum Trading Strategy (J=9, K=3)

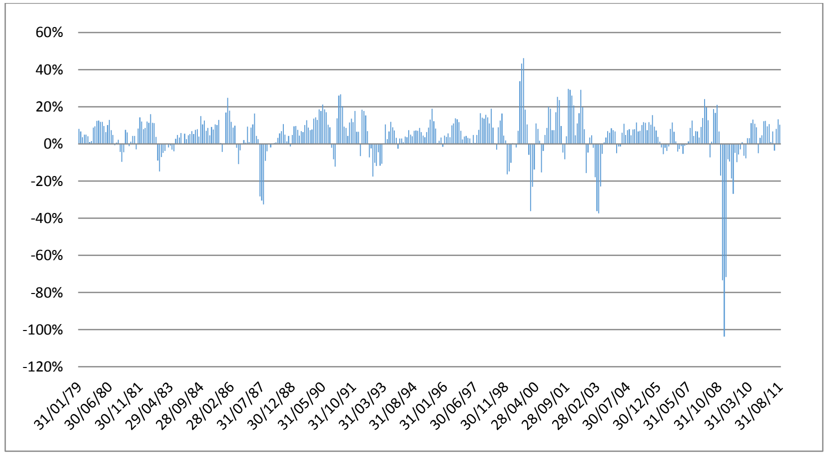


Figure A-11. Buy-and-Hold Returns of the Momentum Trading Strategy (J=9, K=9)

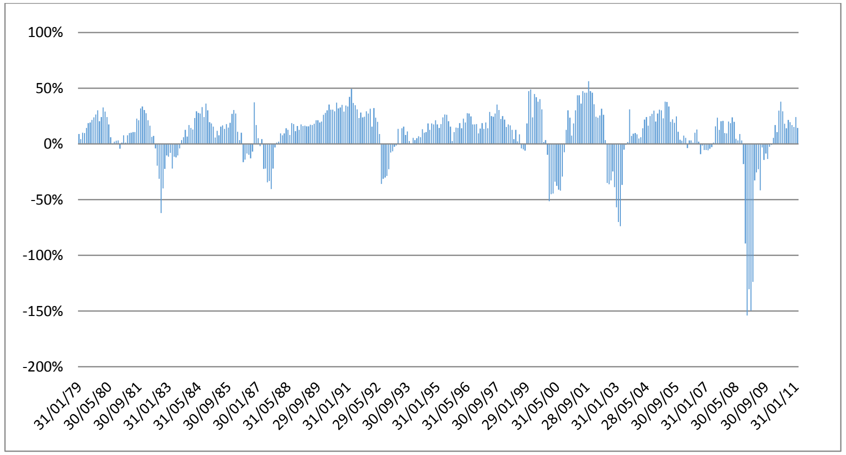


Figure A-10. Buy-and-Hold Returns of the Momentum Trading Strategy (J=9, K=6)

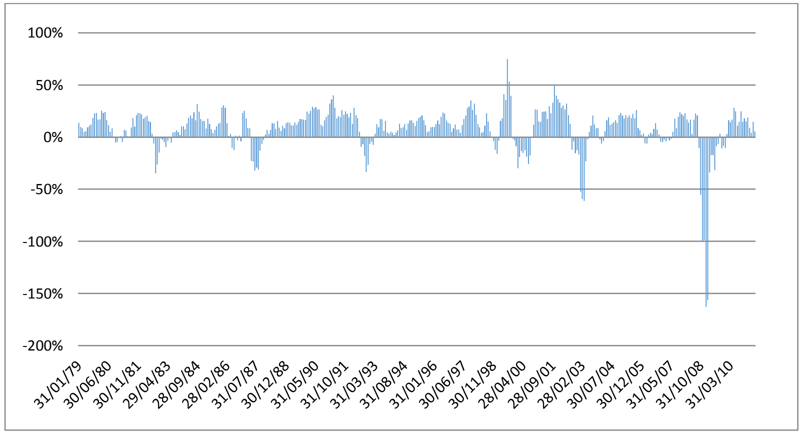


Figure A-12. Buy-and-Hold Returns of the Momentum Trading Strategy (J=9, K=12)

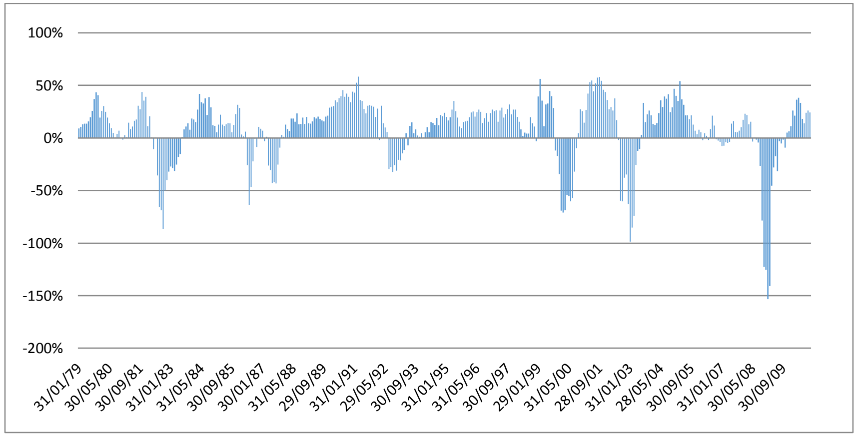


Figure A-13.Buy-and-Hold Returns of the Momentum Trading Strategy (J=12, K=3)

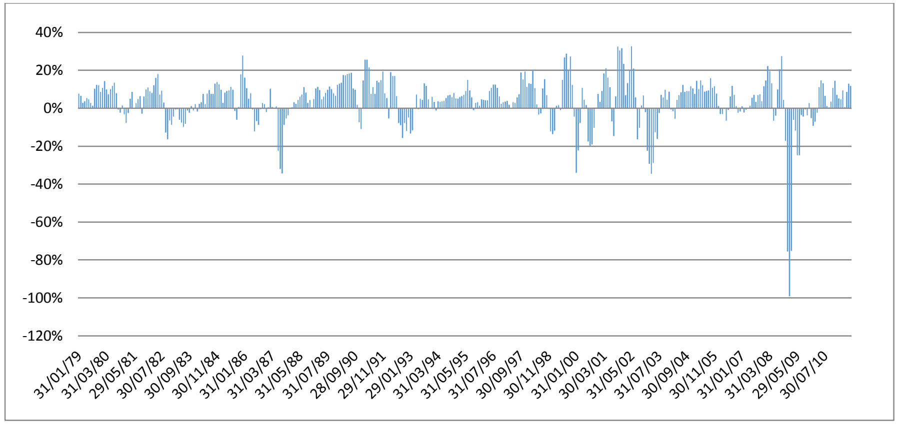


Figure A-15. Buy-and-Hold Returns of the Momentum Trading Strategy (J=12, K=9)

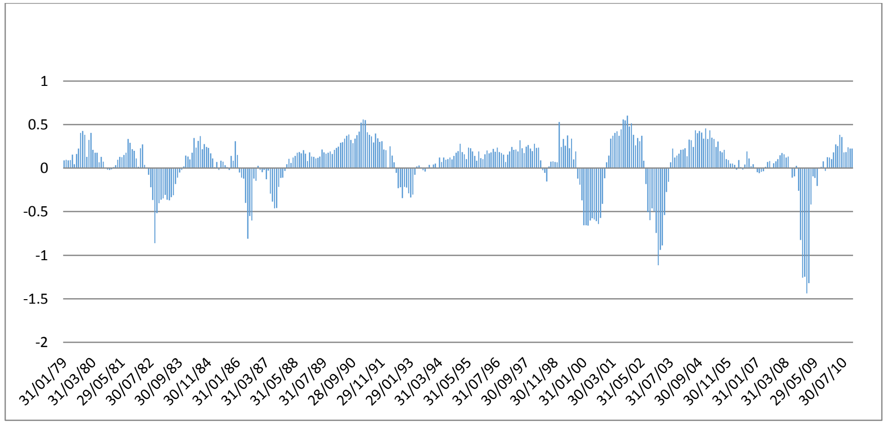


Figure A-14. Buy-and-Hold Returns of the Momentum Trading Strategy (J=12, K=6)

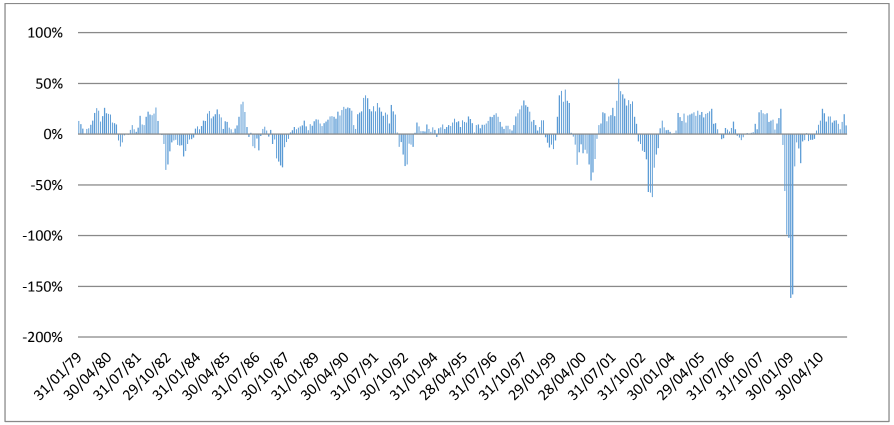


Figure A-16. Buy-and-Hold Returns of the Momentum Trading Strategy (J=12, K=12)

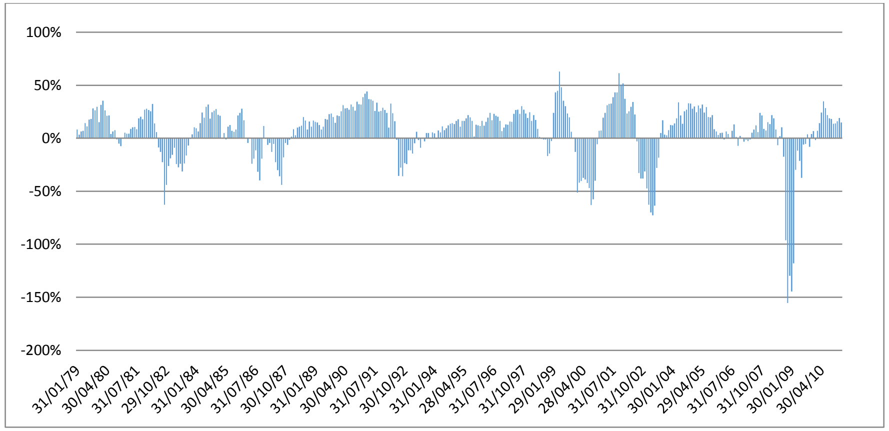


Figure A-17. Scatter Plot between the Holding Period Return and the Ranking Period Return
(J=9, K=4, Observations of 11/2008-02/2009 Excluded)

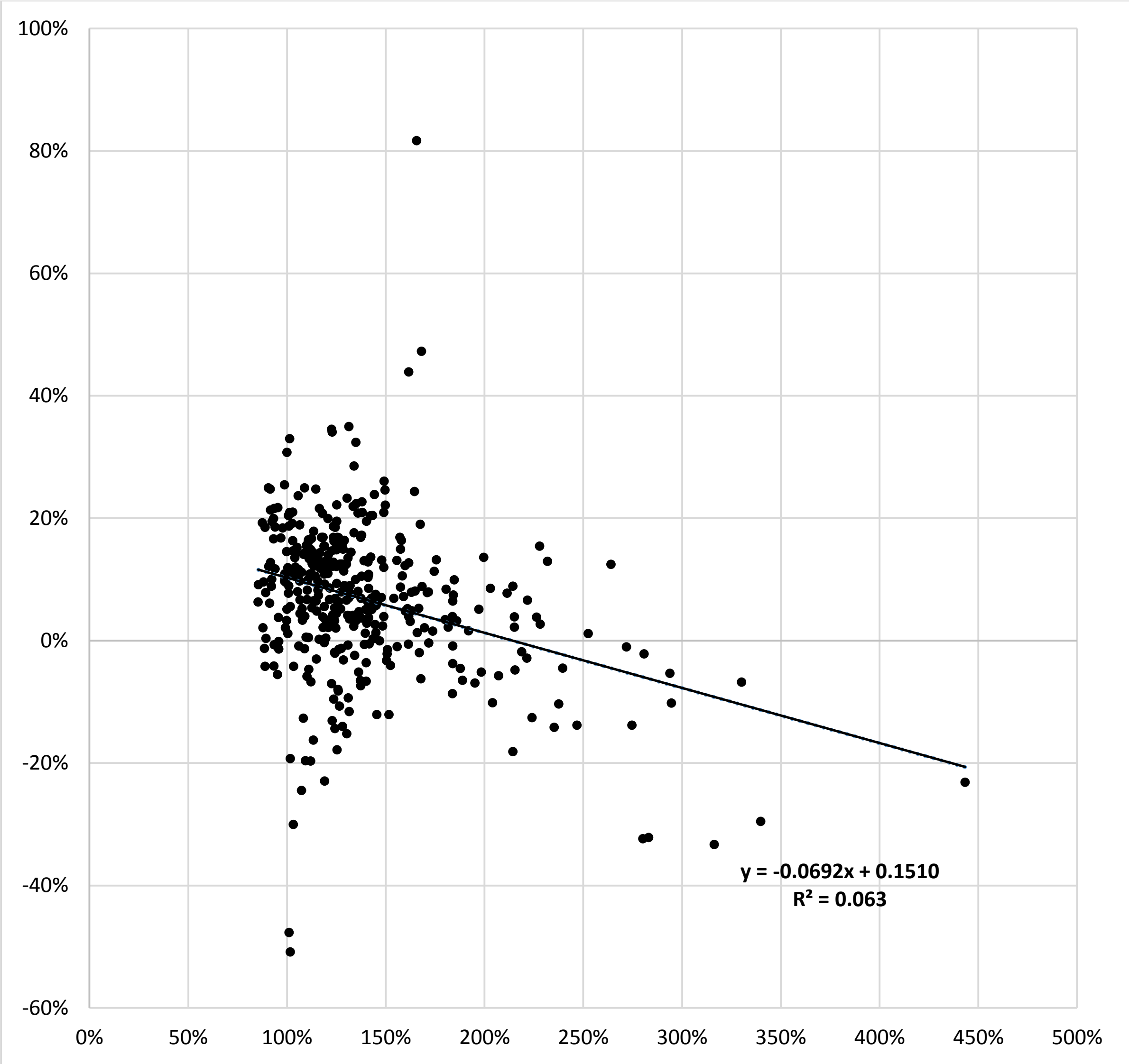


Figure A-18. Posterior Distributions of$\tau, \emptyset, \sigma_1^2, \alpha_1, \beta_1, \gamma_1 \alpha_2, \beta_2, and \gamma_2$(J=3, K=3) (1969 – 2011)

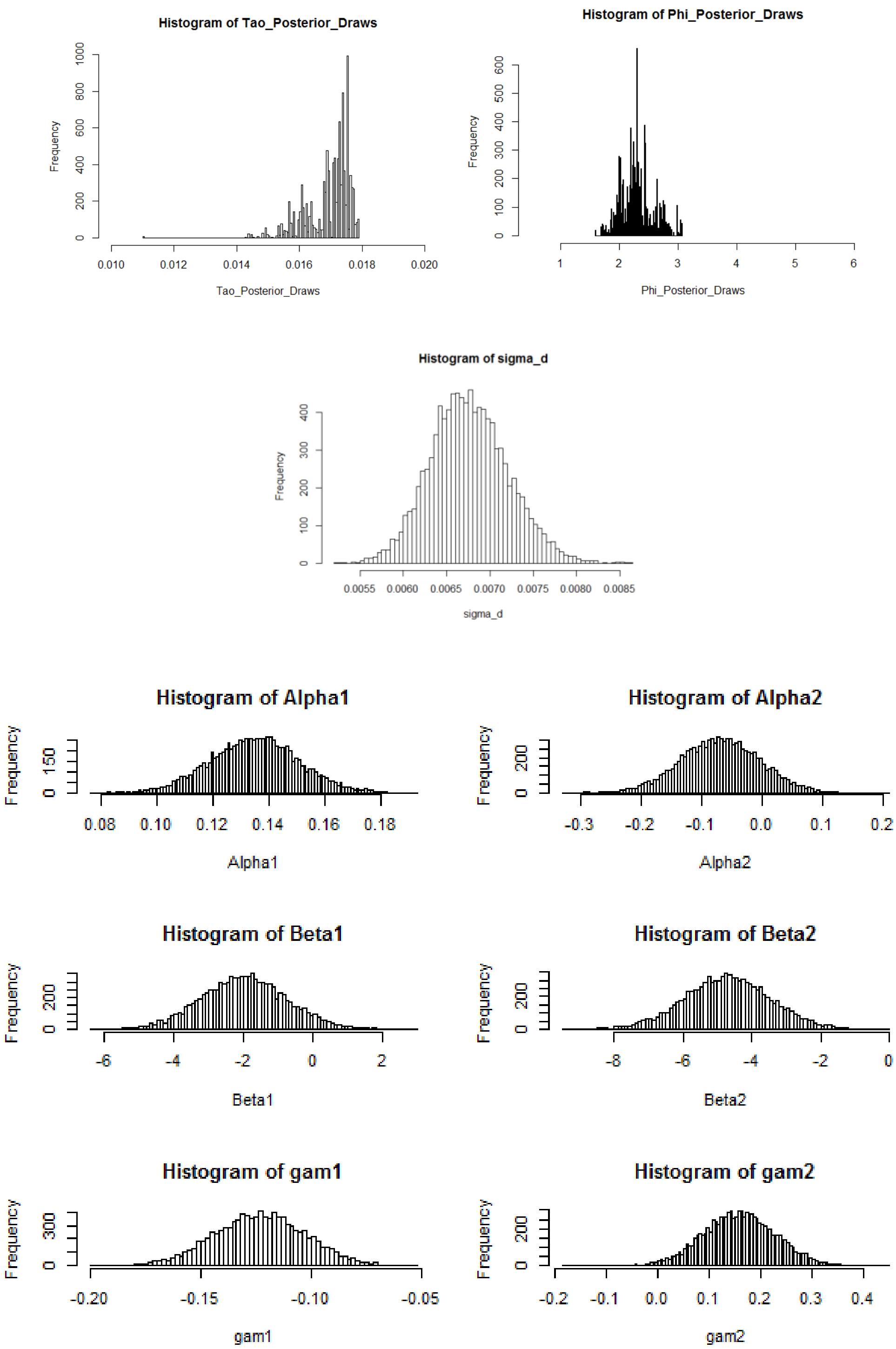


Figure A-19. Posterior Distributions of τ, $\emptyset$, σ_1^2, α_1, β_1, $\gamma_1 \alpha_2$, β_2, $and \gamma_2$ (J=6, K=3) (1969 – 2011)

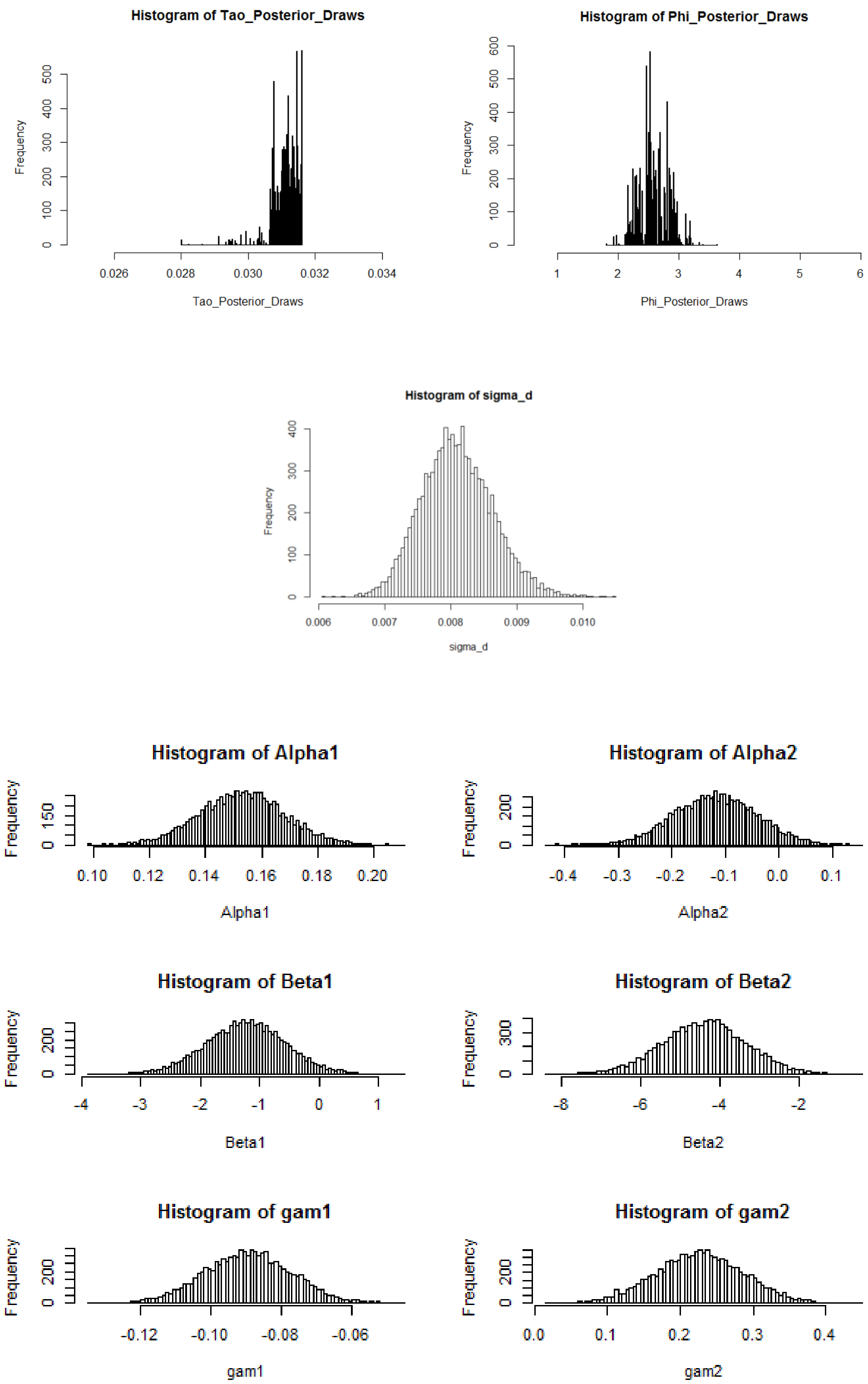


Figure A-20. Posterior Distributions of τ, $\emptyset$, σ_1^2, α_1, β_1, $\gamma_1 \alpha_2$, β_2, $and \gamma_2$ (J=9, K=4) (1969 – 2011)

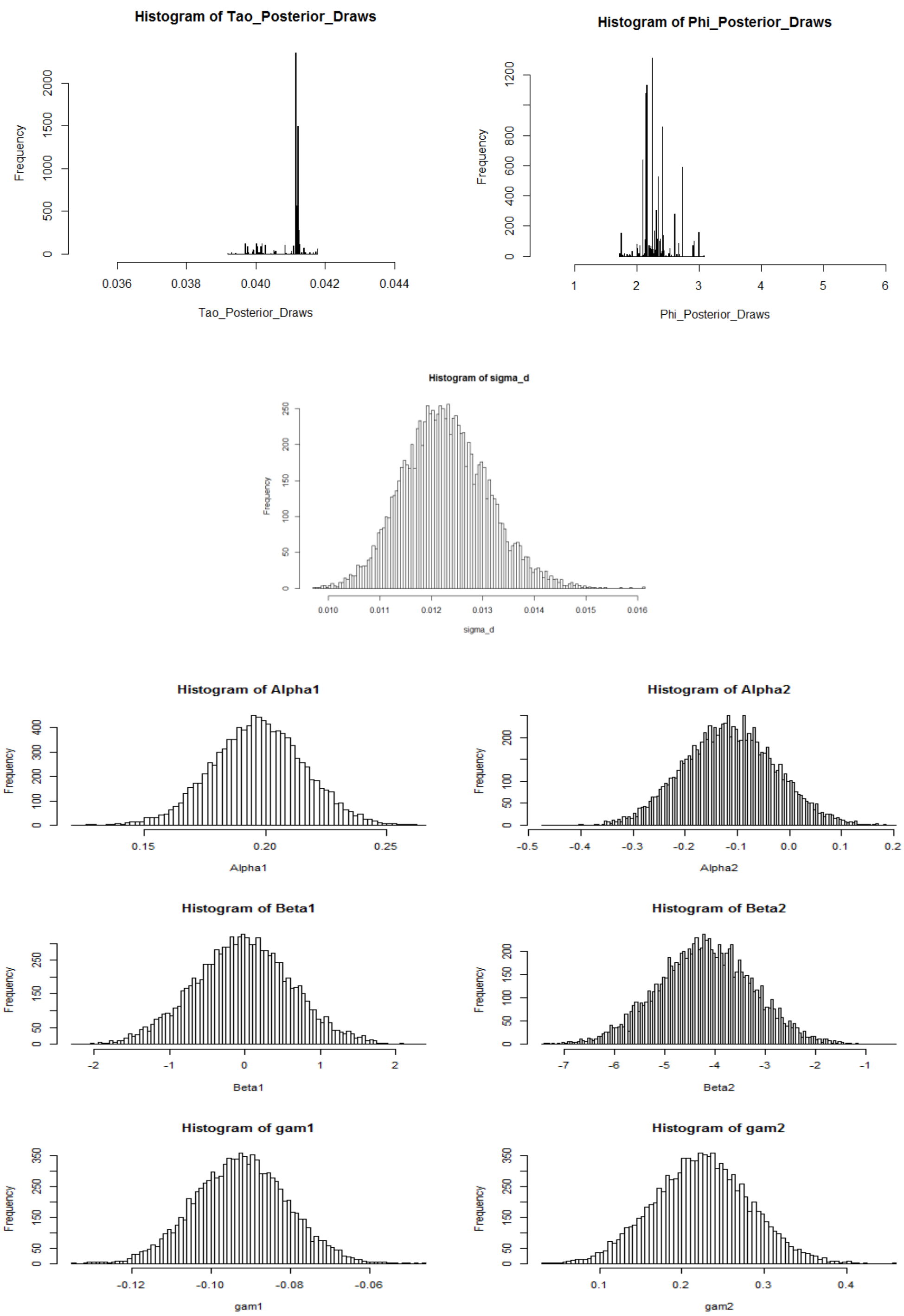


Figure A-20. Posterior Distributions of $\tau, \emptyset, \sigma_1^2, \alpha_1, \beta_1, \gamma_1 \alpha_2, \beta_2, and \gamma_2$ (J=12, K=3) (1969 -2011)

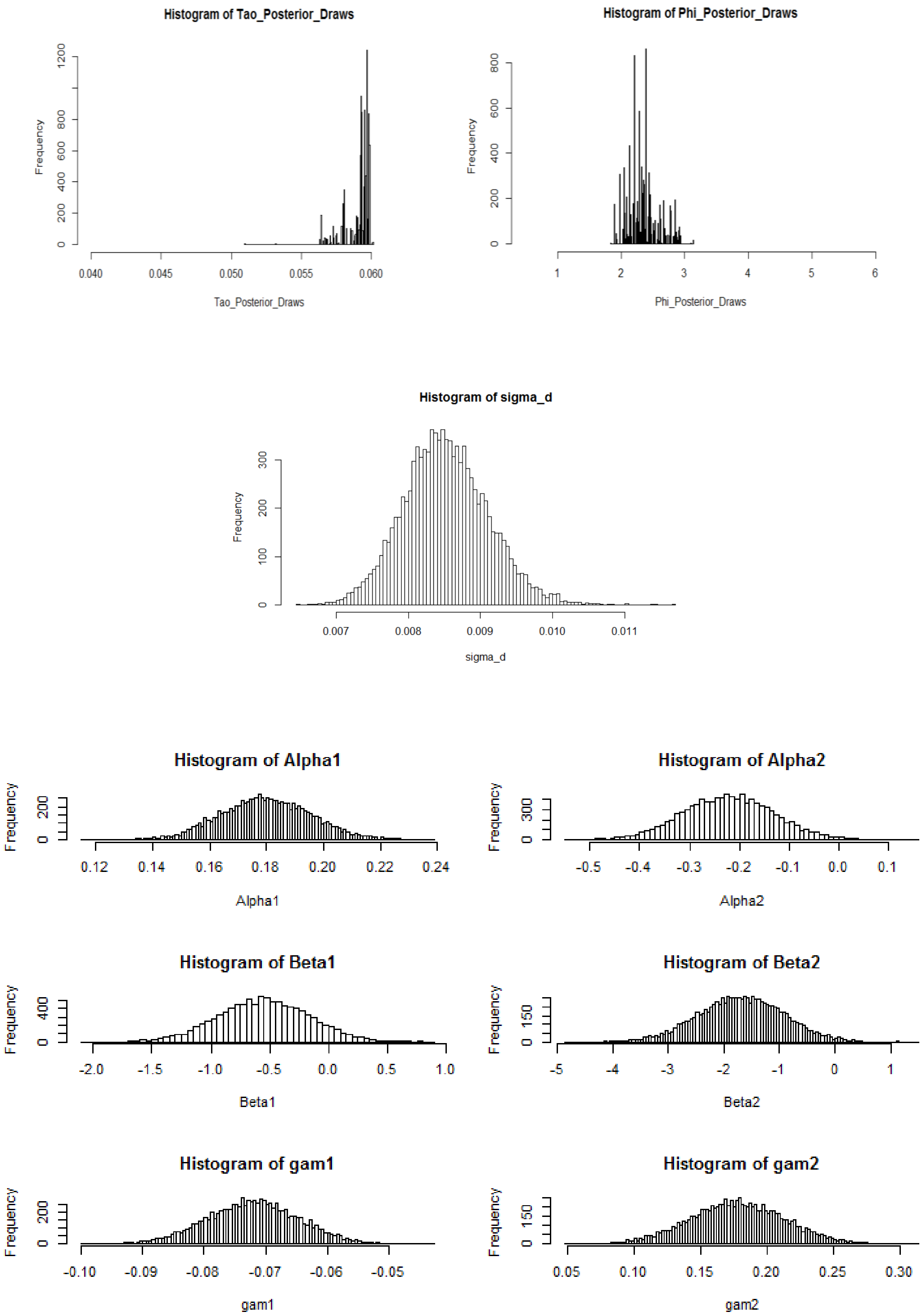


Figure A-21. Prediction Results of the Threshold Regression Model (J=3, K=3)

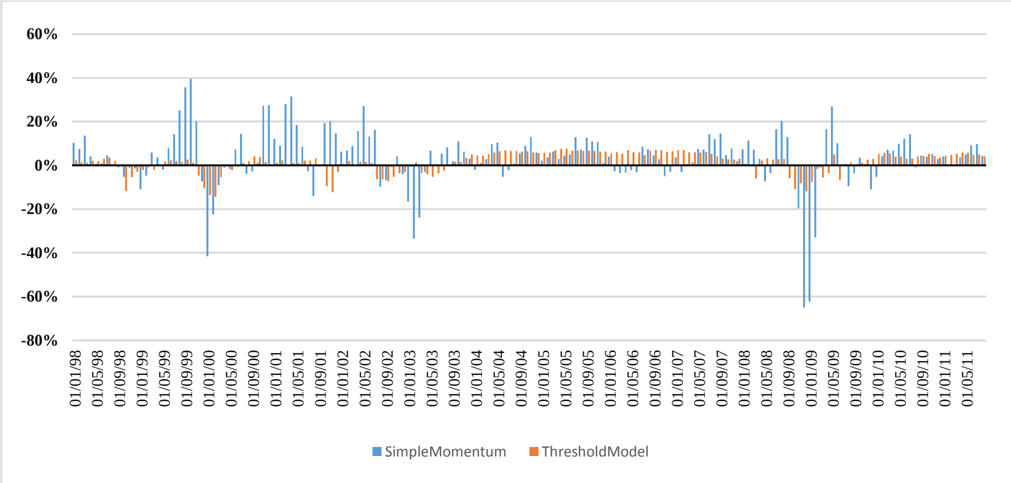


Figure A-22. Buy-and-Hold Returns of the Momentum and Threshold-Regression-Model-Guided Trading strategy (J=3, K=3)

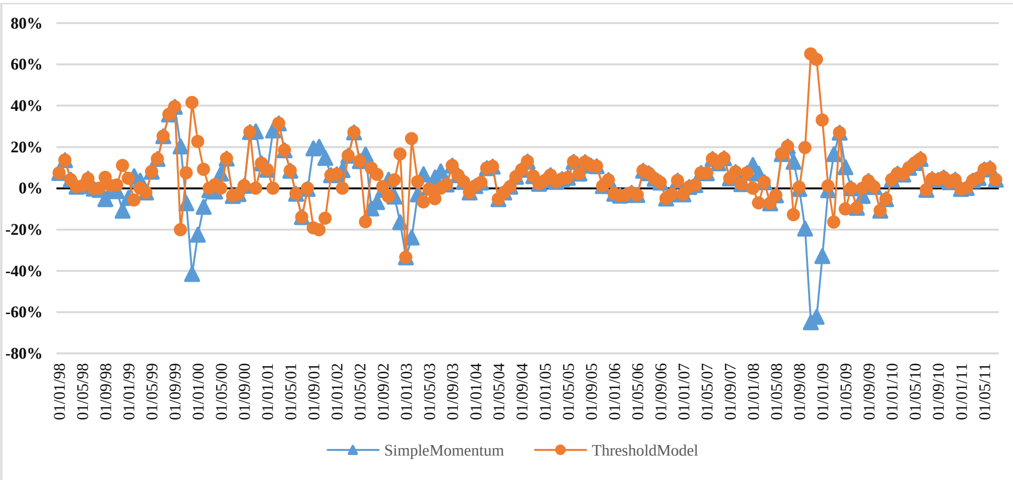


Figure A-23. Long-Term Performance Comparison between the Momentum and the Threshold-Regression-Model-Guided Trading strategy (J=3, K=3)

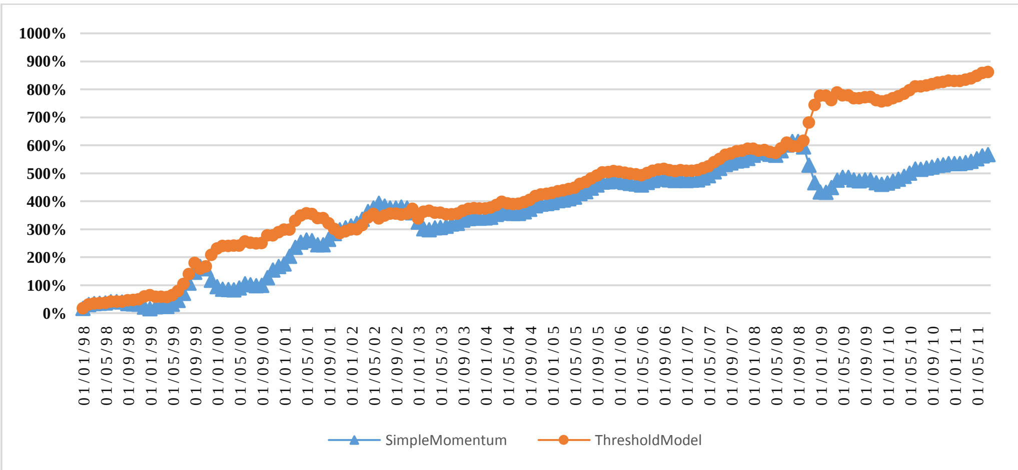


Figure A-24. Prediction Results of the Threshold Regression Model (J=6, K=3)

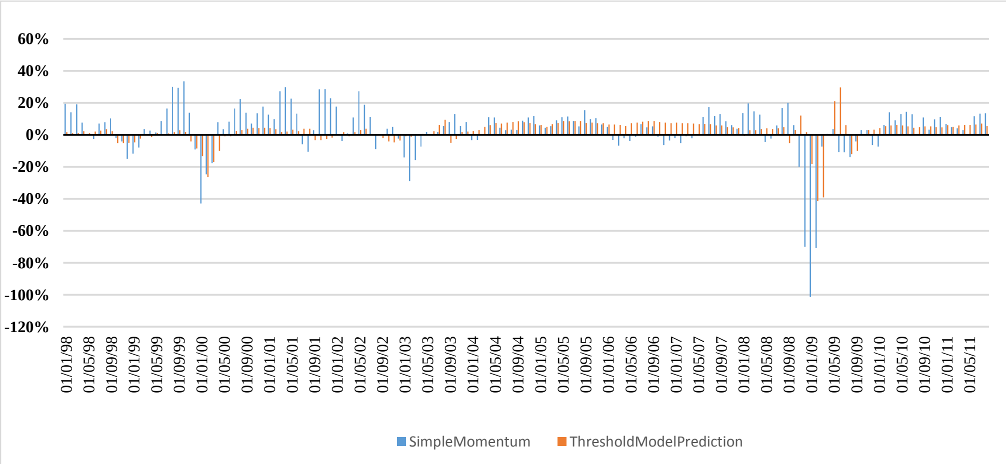


Figure A-25. Buy-and-Hold Returns of the Momentum Strategy and the Threshold-Regression-Model-Guided Trading Strategy (J=6, K=3)

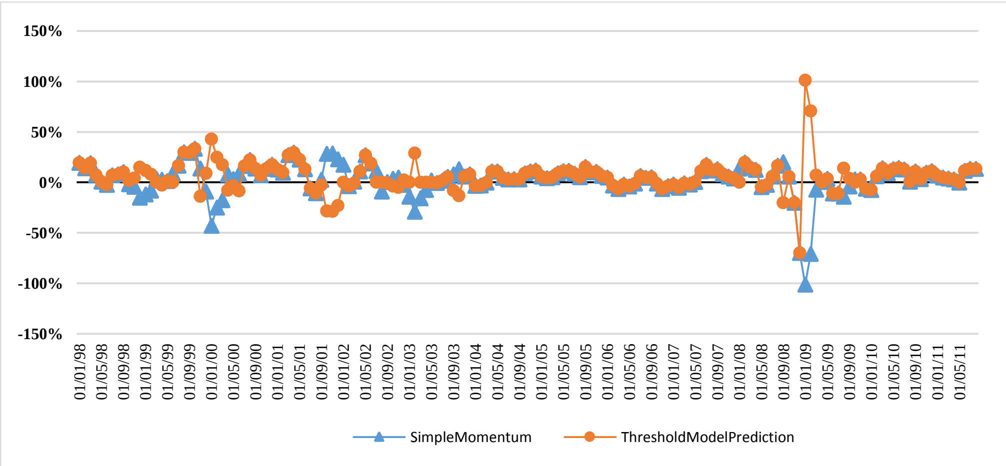


Figure A-26. Long-Term Performance Comparison between the Momentum and the Threshold-Regression-Model-Guided Trading Strategy (J=6, K=3)

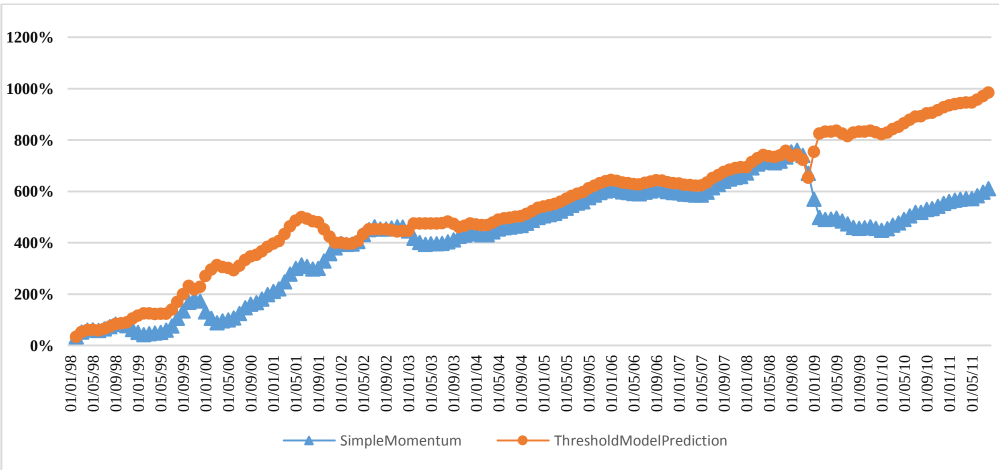


Figure A-27. Prediction Results of the Threshold Regression Model (J=12, K=3)

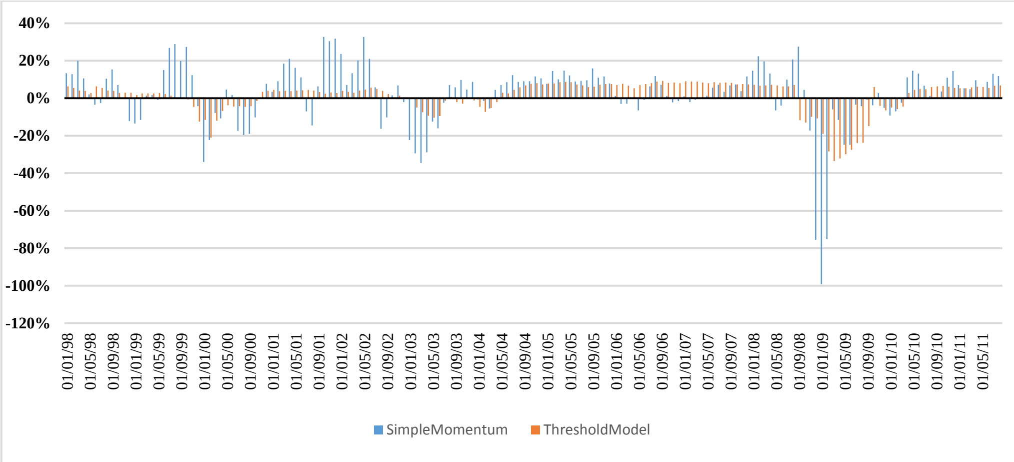


Figure A-28. Buy-and-Hold Returns of the Momentum and the Threshold-Regression-Model-Guided Trading Strategy (J=12, K=3)

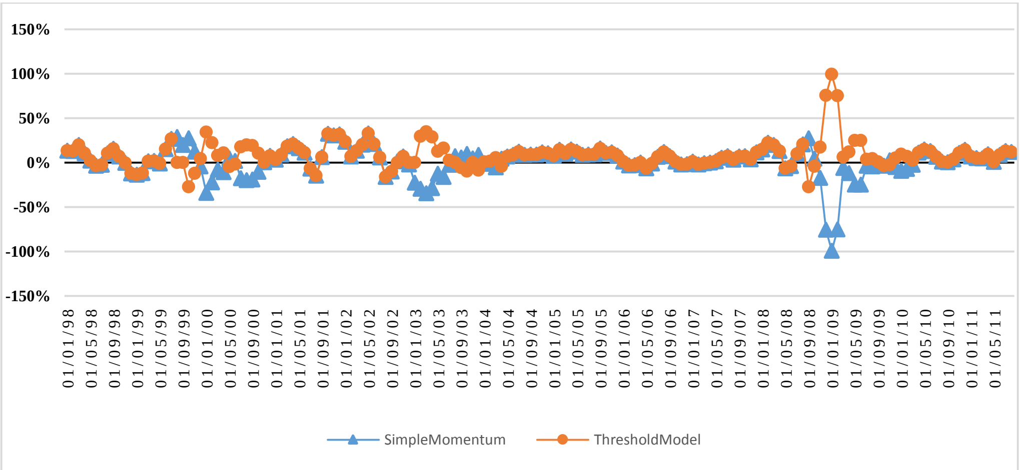


Figure A-30. Long-Term Performance Comparison between the Momentum and the Threshold-Regression-Model-Guided Trading Strategy (J=12, K=3)