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Profitability of Momentum Strategies in the China Stock Market

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ABSTRACT

Jegadeesh and Titman (1993) first document the momentum effect, or the continuation of medium-term stock returns, in the US stock market. That is, stocks with higher returns over the past three months to one year continue to outperform stocks with lower past returns over the same period in the future. The momentum effect poses a substantial challenge to the doctrine of the efficient market hypothesis (EMH) in which Fama (1991) asserts that it is impossible to consistently outperform the market by using any information that the market already knows.

Although a large number of studies have demonstrated that the momentum effect is a general financial anomaly in developed markets, empirical evidence from emerging markets provides some elements of conflicting results and suggests that questions as to the existence of momentum, its possible sources when present, and its potential implications for market efficiency are by no means concluded. This thesis attempts to provide additional empirical evidence from one of the most important emerging markets, the China stock market, and to explore potential sources of the profitability of momentum strategies by focusing on the following three main aspects: 1) the relationship between momentum profits and the state of the market; 2) the role of short sales constraints and firm-specific characteristics in explaining momentum profits; and 3) the extension of regular momentum strategies to portfolio-based momentum strategies in style context. In sum, this study arrives at the following conclusions:

First, empirical evidence shows a degree of momentum profits in the China stock market over the period 1995 to 2006. However, a further investigation of the

momentum effect in two sub-periods shows that momentum strategies only generate significant profits over the sub-period 2001 to 2006, a relatively depressed market period, whereas momentum strategies are not profitable over the sub-period 1995 to 2000, a relatively booming market period. The results imply an inverse relationship between momentum profits and the state of the market in China. A formal test with the use of the definition of market states proposed by Cooper, Gutierrez, and Hameed (2004) confirms the inverse relationship and challenges the behavioural models of Daniel, Hirshleifer, and Subrahmangam (1998) and Hong and Stein (1999), both of which predict greater momentum profits following the market gains.

Second, an examination of the role of short sales constraints in relation to momentum shows a significantly positive relationship between momentum profits and the determinants of short sales constraints suggested by D'Avolio (2002). Extending this analysis, I find that the relationship between momentum and firm-specific characteristics in China is not consistent with that found in developed markets. For example, loser portfolios have higher beta values than winner portfolios; the large size firms always outperform the small size firms; and there is no significant difference in momentum profits between the high and low book-to-market (B/M) firms. What I do find is that, after adjusting returns of winner minus loser portfolios using a two-factor model including beta and size factors, most of momentum profits disappear.

Finally, this study contributes to the wider debate through an investigation of portfolio-based momentum strategies in style context. Empirical evidence shows that compared with regular momentum strategies, style momentum strategies based on past medium-term returns and two firm-specific characteristics (size and B/M) generate higher profits in the subsequent one year. The results have strong implication for investment management that it is likely to explore zero-cost momentum profits even after controlling for the transaction costs. In addition, the style momentum is distinct from the industry momentum. Also, the style momentum profits cannot be explained by the macroeconomic factor, the growth rate of industrial production (MP), proposed by Liu and Zhang (2008).

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CHAPTER 1

INTRODUCTION

There has been a substantial amount of work on the profitability of relative strength strategies in stock markets since Jegadeesh and Titman (1993) first document the momentum effect, or the continuation of medium-term stock returns, in the United States. Momentum refers to the tendency of stock prices to continue moving in the same direction after an initial impulse. This thesis investigates a basic form of momentum, price momentum, where the initial impulse focuses on the change in the price itself. That is, the average stock returns are related to past performance and this performance persists over the medium-term horizons: stocks with higher returns over the past three months to one year continue to outperform stocks with lower past returns over the same period in the future. Jegadeesh and Titman (1993) document that momentum strategies, which simultaneously buy stocks that have performed well and sell stocks that have performed poorly in the past three to twelve months, generate significant profits in the subsequent three to twelve months over the period 1965 to 1989. Jegadeesh and Titman (2001) find that the profitability of momentum strategies continues in the 1990s, suggesting that the original result is not due to the data mining bias.

Technically, the momentum strategy can be separated into three steps. First, in each month, all individual stocks are ranked into deciles according to their cumulative returns over the past three months to one year. Each stock is assigned into one of the ten portfolios and each portfolio contains an equal number of stocks. Second, the winner and loser portfolios are formed. The loser portfolio (D1) contains the bottom ten per cent of stocks with the lowest past returns, while the winner portfolio (D10) contains the top ten per cent of stocks with the highest past returns Finally, the momentum strategy simultaneously buys the winner portfolio and short sells the loser portfolio, and this position is held in the subsequent three months to one year. This process is repeated monthly. Therefore, the profit of the momentum strategy is computed as the mean return on the winner portfolio minus the mean return on the loser portfolio (D10 – D1). Since the approach is relatively simple and the momentum strategy is consistently profitable, Chan, Jegadeesh, and Lakonishok (1996) state that *"the popularity of this approach has grown to the extent that momentum investing constitutes a distinct, well-recognised style of investment in the United States and other equity markets"* (p. 1681).

Although numerous studies show that the momentum effect is a general financial anomaly in the United States and other developed markets (see, e.g., Conrad and Kaul (1998), Rouwenhorst (1998), Moskowitz and Grinblatt (1999), Schiereck, De Bondt, and Weber (1999), Liu, Strong, and Xu (1999), Grundy and Martin (2001), Jegadeesh and Titman (2001), Mengoli (2004), Doukas and McKnight (2006), and among others), empirical evidence from emerging markets provides some elements of conflicting results (see, e.g., Rouwenhorst (1999), Chui, Titman, and Wei (2000), Chan, Hameed, and Tong (2000), Hameed and Yuanto (2002), Wang (2004), McInish, Ding, Pyun, and Wongchoti (2008), and among others). Empirical evidence on the medium-term return predictability is among the most controversial aspects of the debate on the efficient market hypothesis (EMH). In contrast to a rich array of testable hypotheses concerning the short- and long-term reversals, there is a woeful shortage of potential explanations for the medium-term continuation. In the existing literature that has ensued, two broad explanations have emerged as the potential sources of momentum: rational risk-based theories and behavioural models, while empirical evidence proves both of them inadequate.

In relation to accounting for risk, Conrad and Kaul (1998) propose that momentum profits arise because of the cross-sectional differences in expected returns which are dominated by high return stocks in both performance ranking and portfolio holding periods, while Jegadeesh and Titman (2002) argue that the risk-based explanation suffers from a small sample bias and further point out that cross-sectional differences in expected returns explain very little, if any, of momentum profits. Moreover, Chordia and Shivakumar (2002) document that momentum profits can be entirely explained by a set of lagged macroeconomic variables that are related to the business cycle in the United States, while Griffin, Ji, and Martin (2003) question the ability of the macroeconomic model to explain momentum in the international markets. Fama and French (1996) concede that the momentum effect is the only CAPM-related anomaly that their three-factor model fails to explain.[1] Schwert (2003) concludes that momentum remains the only financial anomaly that has not faded since its discovery.

Jegadeesh and Titman (1993) also argue that *"part of the abnormal returns generated in the first year after portfolio formation dissipates in the following two years"* (p. 65), implying that the momentum effect might be a behavioural phenomenon. As a result, a host of explanations based on the behavioural biases and informational inefficiencies have been proposed. For example, Barberis et al. (1998), Daniel et al. (1998), and Hong

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[1] The Fama and French (1996) document that the Fama and French (1993) three-factor model explains the strong patterns in returns observed when portfolios are formed on earning/price, cash flow/price, and sales growth, variables recommended by Lakonishok, Shleifer, and Vishny (1994) and others, and also captures the reversal of short- and long-term returns documented by Jegadeesh (1990) and De Bondt and Thaler (1985 and 1987).

and Stein (1999) each develop behavioural models based on the idea that momentum profits could be attributed to inherent biases in the way that investors interpret information. Jegadeesh and Titman (2001) also attribute the momentum-related return patterns to an irrational response by market participants to firm-specific information. Lewellen (2002), however, finds the existence of momentum profits in size, book to market ratio (B/M), and double-sorted size-B/M portfolios and argues that *"firm-specific returns, together with the behavioural models, cannot explain a significant component of momentum"* (p. 533).

1.1 Motivations

This thesis comprehensively examines the profitability of momentum strategies in the China stock market over the period 1995 to 2006 and aims to explore the potential sources and implications. This study is motivated by the following considerations.

First, the impact of China on world affairs has risen substantially in recent years and, from a financial market perspective, has become increasingly important to global investors. An annualised growth rate in GDP of around ten per cent during the past ten years and its holding of the world's biggest foreign exchange reserves both imply enormous market potential.[2] In July 2009, China overtook Japan as the world's second largest stock market in the world.[3] With the introduction of Qualified Foreign

[2] China's annualised growth rates in GDP during recent years are 8.0 per cent (2000), 7.3 per cent (2001), 8.0 per cent (2002), 9.1 per cent (2003), 9.5 per cent (2004), 9.9 per cent (2005), 10.7 per cent (2006), 11.4 per cent (2007), 9.0 per cent (2008), and 8.2 per cent (2009). China's foreign exchange reserves reached US$ 1,528.2 billion in 2007. Sources are from the official website of National Bureau of Statistics of China. http://www.stats.gov.cn/english/

[3] Sources are from the website of Bloomberg news. The market value of the China stock market reached $3.21 trillion on 16th June 2009, exceeding Japan's $3.20 trillion.

Institutional Investors (QFII) programme into the China capital market in 2002, more foreign institutional investors are now able to access this potential.[4] Fully understanding the mechanism and behaviour of stock returns in China is therefore now of great interest to global investors.

Second, the China stock market, however, is still an emerging market: its institutional setting and trading practices are relatively new and, in part, different from and independent of those in developed markets. One important feature of the China stock market is that it is very difficulty to short sell so that the process of risk free arbitrage is likely to be a challenging venture, particularly, when it is recognised that there is no financial index futures market operating during the sample period. Additionally, the existence of A-shares and B-shares is unique and the fact that A-shares are more actively traded than B-shares and A-shares fetch a high premium over B-shares are possibly due to speculative trading rather than liquidity (Sun and Tong (2000)). Also, the China stock market is dominated by individual investors as mutual funds and pensions funds are in their infant stages of development. More institutional features are discussed in Chapter 3. The China stock market therefore provides a unique environment to investigate the equity price behaviour in an emerging market due to the presence of short sales constraints.

Finally, although the predictability of stock returns has been extensively examined in emerging markets, very little attention has been paid in the China stock market, which

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http://www.bloomberg.com/apps/news?pid=20601087&sid=a_84o9PPPGqk.

[4] On 5th November, 2002 the China Securities Regulatory Commission (CSRC) and the People's Bank of China (PBOC) introduced the QFII programme as a provision for foreign capital to access the China capital markets. http://www.csrc.gov.cn/n575458/n4001948/

remains among the most important emerging markets awaiting such investigation. The existing Chinese studies on the momentum effect make cursory research on the momentum effect and show conflicting results (see, e.g., Kang, Liu, and Ni (2002) and Wang (2004)). Both studies focusing on the sample period before 2000 suffer from the limited observations and provide no further explanations. Kang et al. (2002) argue that *"the lack of rigorous investigations on China stock returns is mainly due to both the short history of equity trading in China and the lack of material interests among global investors"* (p. 245).

1.2 Contributions

Previous studies have proposed some alternative factors that are associated with the profitability of momentum strategies, but the results are not unanimously supported by different data sample. The specifics of the operation in the China stock market lead us to conjecture that evidence of momentum needs to be examined in the light of some important market microstructure facts that have previously not been addressed. Fully examining the momentum effect in China stock market, this study intends to address the profitability of momentum strategies by exploring some factors that have previously not been identified in China. This study contributes to the financial literature in the following major aspects:

First, Chapter 4 presents the primary findings of the presence of the momentum effect in the China stock market, but further examinations show that these momentum profits are generated mainly in the depressed market conditions over the sub-period 2001 to 2006 and that no significant evidence of momentum profits is found over the period 1995 to

2000, a relatively booming period. The results imply a negative relationship between momentum profits and the state of the market. The negative relationship is robust when alternative definitions of market states proposed by Cooper, Gutierrez, and Hameed (2004) are used. The result that momentum strategies are profitable following the Down markets, rather than the Up markets contradicts the prediction of behavioural models developed by Daniel et al. (1998) and Hong and Stein (1999). The model of Daniel et al. (1998) assumes that investors are overconfident about their private information and overreact to it, while the behavioural theory developed by Hong and Stein (1999) is based on initial underreaction to information and subsequent overreaction. Both models predict that momentum profits will be greater following the market gains.

Moreover, a separate analysis of momentum profits based on the sample of stocks either on the Shanghai Stock Exchange (SHSE) or on the Shenzhen Stock Exchange (SZSE) demonstrates that stocks on the SHSE exhibit a significantly stronger momentum effect than those on the SZSE. I therefore conjecture that momentum is associated with some unique characteristics of stocks on the SHSE, such as the relatively large market capitalisation, since the mean market capitalisation of stocks on the SHSE is much larger than that of stocks on the SZSE. This new evidence firmly rejects the notion that momentum profits are related only to small size firms because they are illiquid. Empirical evidence also shows that the momentum duration is longer in China than reported elsewhere, which might be attributable to more severe short sales constraints in the China stock market.

Second, Chapter 5 in detail investigates the role of short sales constraints in explaining momentum profits. In assessing momentum in the China stock market where short sales are forbidden, this study benchmarks the momentum characteristics of a stock market in a fairly controlled environment with studies of other markets in which the role of short sales constraints is left uninvestigated. With the use of several observable firm-specific characteristics suggested by D'Avolio (2002) as proxies for short sale constraints, this study reports a significantly positive relationship between momentum and short sales constraints. Furthermore, it is loser stocks rather than winner stocks that drive this result, confirming the role of short sales constrains in explaining momentum profits.

Extending this work, I also attempt to explain whether momentum strategies are profitable in the China stock market after controlling for some firm-specific characteristics, such as beta, size, and B/M. The results are not consistent with those found in other markets. For example, loser portfolios have higher beta values than winner portfolios; big size firms always outperform small size firms; and there is no significant difference in momentum profits between high and low B/M firms. Finally, most of abnormal returns disappear, after adjusting returns of winner minus loser portfolios using a two-factor model including beta and size factors.

Finally, Chapter 6 examines whether active style momentum strategies, the combination of price momentum strategy and style investing based on the market capitalisation and B/M, can make profits in the China stock market. To the best of my knowledge, this is the first Chinese study to extend regular price momentum strategies based on individual stocks to portfolio-based momentum strategies in style context. Empirical evidence shows that compared with regular price momentum strategies, style momentum strategies generally generate much stronger profits over the same sample period. The results are robust in two sub-periods and in different market states and therefore have strong implication for investment management that it is possible to explore zero-cost momentum profits even after controlling for the transaction costs.[5] This study also investigates industry momentum and finds that style momentum is distinct from industry momentum. A final examination shows that macroeconomic risk, such as the growth rate of industry production (MP), fails to explain style momentum profits in China.

The remainder of this thesis is organised as follows. Chapter 2 presents previous empirical evidence of the momentum effect in various markets as well as the existing rational and behavioural explanations of momentum profits. Chapter 3 highlights the characteristics of the China stock market. Chapter 4 presents empirical evidence of the profitability of momentum strategies in different time periods and examines the relationship between momentum profits and market states. Chapter 5 analyses the role of short sales constraints in explaining momentum profits. Chapter 6 extends the analysis on the portfolio-based momentum strategies in style context. The final chapter concludes with a discussion of the limitations of this study and provides suggestions for future research.

[5] Several studies show that regular price momentum strategies are no longer profitable when transaction costs are taken into account. For example, Lesmond, Schill, and Zhou (2004) examine momentum strategies and find that the standard relative strength strategies require frequent trading in particularly costly stocks such that the trading costs prevent profitable execution.

CHAPTER 2

LITERATURE REVIEW

2.1 Efficient market hypothesis and return predictability

The efficient market hypothesis (EMH) has been one of the dominant themes in the financial literature for over thirty years. Fama (1970) defines an efficient capital market as one in which security prices fully and instantaneously reflect all available information. That is, the past movement or direction of the price of a stock or market cannot be used to predict the future movement. Fama (1970) states that the theory of efficient market is based on the hypotheses that *"there are no transaction costs in trading securities, all available information is costlessly available to all market participants, and all agree on the implications of current information for the current price and distributions of future price of each security"* (p. 387).

In reality, there are a lot of imperfect factors in the capital market. For example, a market is normally characterised by non-instantaneous availability and incomplete dissemination of information to all participants, which may prevent the price from incorporating the available information fully and instantaneously. In addition, there are inevitable transaction costs and other institutional constraints in the capital market. Fama (1991), therefore, argues that the earlier version of the EMH is *"surely false"* (p. 1575). Jensen (1978) develops a less stringent version of the EMH, which maintains that market efficiency holds when investors cannot follow the trading rules that display systematic profits above the transaction costs and risk premiums. Even if there are investment strategies that could achieve abnormal returns, other investors would exploit any inefficiency rapidly and the market efficiency would be re-established quickly.

A growing body of literature has raised doubts as to the efficiency of the capital market over the past twenty years. In particular, several arbitrage strategies based solely on publicly available information, such as past returns, exhibit significant profitability in the future. For example, De Bondt and Thaler (1985 and 1987) report the long-term reversal: stocks that perform well over the past three to five years tend to perform poorly over the subsequent three to five years; similarly, stocks that perform poorly over the past three to five years tend to perform well over the subsequent three to five years. Jegadeesh (1990) uncovers the short-term reversal, a significantly negative serial correlation in stock returns. That is, stocks realising the high returns over the past one week to one month tend to obtain low returns over the subsequent one week to one month, while stocks realising the low returns over the past one week to one month tend to obtain high returns over the subsequent one week to one month. Jegadeesh and Titman (1993) find the medium-term continuation effect and document that momentum strategies taking long positions in stocks which experience large positive returns in the previous three to twelve months and meanwhile taking short positions in stocks which experience large negative returns in the previous three to twelve months can make significant profits in the subsequent three to twelve months.

Empirical evidence on return predictability is among the most controversial aspects of the debate on the EMH. Accordingly, a large number of explanations have been put forward to account for the short- and long-term reversals as well as the medium-term continuation in stock returns. For example, Kaul and Nimalendran (1990) and

Jegadeesh and Titman (1995) account the short-term reversal for the bid-ask spreads, and Lo and MacKinlay (1990) also attribute the short-term contrarian profits to the lead-lag effect. Completing explanations for long-term reversals are based on either the market microstructure biases that are particularly serious for low price stocks (Conrad and Kaul (1993) and Ball, Kothari, and Shanken (1995)), or time-variation in expected returns (Ball and Kothari (1989)). Since differences across stocks in their past price performance tend to show up as differences in their B/M, the phenomenon of long-term reversals is related to the value effect discussed by Fama and French (1992), and Lakonishok et al. (1994). Zarowin (1990) associates the profitability of the long-term reversal with the size of the firm and find that the long-term profitability disappears once past winners and losers are controlled for size. Fama and French (1996) define the patterns in average returns that are not explained by the CAPM and demonstrate that the Fama and French (1993) three-factor model entirely capture both the long- and short-term reversals.

However, the situation with respect to the momentum effect is very different from the short- and long-term reversals. It has been well documented that the momentum effect is a general financial anomaly in different markets and remains one of the major unsolved puzzles in the financial literature. Numerous studies have attempted to account for the momentum effect, but without reaching a consensus. Fama and French (1996) concede momentum is the only CAPM-related anomaly that their three-factor model cannot explain. Subsequently, a number of behavioural models based on irrationality and psychological theories have been developed in attempts to explain the momentum anomaly (see, e.g., Barberis et al. (1998), Daniel et al. (1998), Hong and Stein (1999), and among others).

2.2 Empirical evidence of price momentum

2.2.1 Related evidence in developed markets

Jegadeesh and Titman (1993) analyse the relative strength trading strategies over the medium-term horizons, based on the stocks on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) over the period 1965 to 1989. They document the momentum effect that stocks with high returns over the past three to twelve months tend to continue outperforming stocks with low past returns over the following three to twelve months.

Technically, according to buying stocks with the highest past returns and short selling stocks with the lowest past returns, momentum strategies that take advantage of the continuation effect can make zero-cost, risk free profits. First, all individual stocks are ranked into deciles based on their performance in the previous three, six, nine, or twelve months. Ten portfolios containing the equal number of stocks are constructed based on the rankings. Second, D1 represents the loser portfolio containing stocks with the lowest past performance, while D10 represents the winner portfolio containing stocks with the highest past performance. Finally, momentum strategy is formed simultaneously buying the winner portfolio and selling the loser portfolio, and this position is held in the subsequent three, six, nine, or twelve months. The profit of the momentum strategy is computed as the difference of the mean return between the past winner and loser portfolios. The above procedure is repeated by skipping a week between the end of performance ranking period and the beginning of the portfolio holding period, to avoid market friction problems, such as the bid-ask spread, price pressure, and lagged reaction effect that could result in the short-term reversal reported by Jegadeesh (1990) and Lehmann (1990).

Jegadeesh and Titman (1993) find that prior winner portfolio over the past three to twelve months consistently outperform prior loser portfolio over the following three to twelve months. Almost all the winner minus loser strategies generate significant profits. In particular, the most profitable 12-3 strategy with a twelve-month performance ranking period generates a profit of 1.49 per cent per month in the subsequent three-month holding period. Grundy and Martin (2001) document the profit of more than 1.3 per cent per month using momentum strategies on the NYSE and AMEX stocks over the period 1966 to 1995. Investigating stocks on the NYSE and AMEX over the period 1926 to 1989, Conrad and Kaul (1998) also confirm the success of momentum strategies at the medium horizons.

Jegadeesh and Titman (2001) provide additional evidence confirming that momentum strategies are profitable in the US market over the period 1990 to 1998, which is subsequent to their previous period. For example, the 6-6 momentum strategy with a six-month performance ranking period and a six-month portfolio holding period generates a profit of 1.39 per cent per month, which is even higher than the profit of 0.95 per cent per month generated by the counterpart strategy over the period 1965 to 1989 examined in Jegadeesh and Titman (1993).

The concern for the data mining bias would be entirely ruled out if consistent evidence of momentum profits could be found from a variety of markets. A surge of studies on the predictability of asset returns based on historical returns confirm that the momentum effect is not confined to the United States, but robust to the international data.

Rouwenhorst (1998) examines the momentum effect in 12 developed European markets and finds that *"an internationally diversified relative strength portfolio that invests in medium-term winners and sells past medium-term losers earns approximately 1 per cent per month"* (p. 268).[6] In addition, momentum profits exist in all of the 12 European markets and last on average for about one year, but they cannot be attributed to conventional measures of risk. Doukas and McKnight (2005) reveal that momentum profits are pervasive in 13 European markets.[7] Additionally, stocks with low analyst coverage show stronger momentum profits compared with stocks with high analyst coverage. For example, stocks with low analyst coverage generate an average profit of 0.88 per cent per month, while stocks with high analyst coverage earn an average profit of 0.59 per cent per month. Furthermore, they report that momentum profits decrease monotonically with the increase of firm size. For instance, in the small size group, momentum strategies generate a profit of 1.14 per cent per month, whereas in the large size group, the momentum profit is only 0.31 per cent per month.

Liu et al. (1999) investigate the momentum effect in the UK stock market over the period 1977 to 1998. They report significant momentum profits and the results are

[6] The sample consists of 2,190 forms from 12 European markets from 1978 through 1995: Austria (60), Belgium (127), Denmark (60), France (427), Germany (228), Italy (223), Netherlands (101), Norway (71), Spain (111), Sweden (134), Switzerland (154), and the United Kingdom (494). The sample covers 60 to 90 per cent of each country's market capitalisation.

[7] The total number of firms is 3,084 covering 13 European countries, which consist of Austria (76), Belgium (86), Denmark (107), Finland (100), France (411), Germany (568), Italy (165), Netherlands (155), Norway (102), Spain (149), Sweden (216), Switzerland (160), and the United Kingdom (789).

robust across two sub-samples. Furthermore, they argue that momentum profits are not eliminated even after controlling for systematic risk, size, price, B/M, and cash earnings-to-price (E/P) ratio. Hon and Tonks (2003) test a large sample of 1,571 stocks on the London Stock Exchange (LSE) over the period 1955 to 1996. Stocks are selected based on returns over the past three to 24 months and holding periods vary from three to 24 months. They find significantly positive momentum profits over the medium horizons up to 24 months. The most profitable 12-6 strategy based on past twelve-month performance ranking period and six-month portfolio holding period earns a profit of 16.2 per cent per year. All momentum strategies with the holding periods beyond 15 months yield insignificant profits, consistent with previous conclusion that momentum investing is profitable over the medium horizons. They further examine the momentum effect in two sub-periods. The results show significant momentum profits over the sub-period 1977 to 1996, but no such evidence of profitability found over the sub-period of 1955 to 1976, suggesting that the momentum effect is not general phenomenon in the UK stock market, but only apparent over certain time period.

Schiereck et al. (1999) examine all major listed firms in the German stock market over the period 1961 to 1991 and find that momentum strategies appear to outperform a passive approach that invests in the market index. Forner and Marhuenda (2003) show that the momentum effect is present in the Spanish stock market and, in particular, that momentum strategies with a twelve-month performance ranking period yield the largest positive returns. Hurn and Pavlov (2003) establish the presence of a strong medium-term momentum effect in the Australian stock market by examining a sample limited to the top 200 stocks by market capitalisation. Mengoli (2004) observes significant momentum profits on the Italian Stock Exchange over the period 1950 to 1995 and the results hold when conditioned on different risk specifications.

In practice, momentum strategies are popularly employed by mutual fund managers as an effective investment tool to construct portfolios. Grinblatt, Titman, and Wermers (1995) examine 274 mutual funds and report that 77 per cent of the fund managers use the momentum investment tool. Investigating the persistence in equity mutual fund performance, Carhart (1997) reports that fund managers who achieve the highest (lowest) past performances over the previous year continue to perform well (disappointingly) over the following year. The best decile mutual funds outperform the worst decile mutual funds by 8 per cent per year. A four-factor model that considers the factors of market risk, size, B/M, and momentum can explain nearly half of the abnormal profits between the funds with the best and worst performances. Specifically, the best (worst) decile mutual funds are strongly positive (negative) associated with the momentum factor, suggesting that the performance of fund managers strongly rely on the momentum strategy. The manager of Standard Life's UK Equity Growth Fund, the winner of the prestigious Standard and Poor's Micropal Award in 1999, publicly presents that the continuation strategies are frequently employed to construct portfolios (Riley (1999)). Using the primary survey data, Brozynski, Menkhoff, and Schmidt (2006) state that the momentum strategy is a widely used investment tool among fund managers in Germany. Brookfield, Bangassa, and Su (2010) investigate the investment style positioning of UK equity unit trusts over the period 1987 to 2007 and attempt to reveal whether fund managers really follow their declared particular style strategies. Generally, UK unit trusts do not, in fact, consistently track declared styles in practice but select stocks mainly based on past performance.

2.2.2 Related evidence in emerging markets

Although a large number of findings demonstrate that the momentum effect is a general phenomenon in the United States and other developed markets, empirical evidence from emerging markets provides only mixed support. The conflicting results may be due to the relatively low correlation between returns on emerging markets and returns on developed markets (Harvey (1995)).

Rouwenhorst (1999) examines the cross-sectional returns in 20 emerging markets by employing return data of 1,750 individual stocks and discovers significant price momentum in 17 markets for the period spanning from the 1980s to the 1990s.[8] Examining a sample period from 1975 to 2000, Chui et al. (2000) identify that momentum strategies are highly profitable when implemented in eight Pacific Basin stock markets, excluding Japan.[9] In particular, they find significant momentum profits in stocks with small capitalisation, low B/M, and high turnover firms.

Chan et al. (2000) examine the profitability of momentum strategies implemented on the international stock market indices, and indicate evidence of significant momentum profits.[10] They *"also find higher profits for momentum portfolios implemented on*

[8] 1,750 firms in 20 emerging markets are examined in his sample, including Argentina, Brazil, Chile, Colombia, Greece, India, Indonesia, Jordan, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, South Korea, Taiwan, Turkey, Venezuela, and Zimbabwe.

[9] They examine the profitability of momentum strategies in eight Asian markets: Hong Kong, Indonesia, Japan, Malaysia, Singapore, South Korea, Taiwan, and Thailand.

[10] In the 23 sample markets, nine are from the Asia-Pacific (Australia, Hong Kong, Indonesia, Japan, Malaysia, Singapore, South Korea, Taiwan, and Thailand); 11 are from Europe (Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Norway, Spain, Switzerland, and the United Kingdom); two are from North America (Canada and the United States); and one is from Africa (South Africa).

markets with higher volume in the previous period, indicting that return continuation is stronger following an increase in trading volume. This result confirms the informational role of volume and its applicability in technical analysis" (p. 153). Hameed and Yuanto (2002) investigate the profitability of momentum strategies in six Asian stock markets, but find no evidence of price momentum effect. They report that a diversified country-neutral strategy generates an insignificant profit of 0.37 per cent per month over the period 1981 to 1994.[11] Their results suggest that country factor is important in the winner minus loser returns in the six Asian stock markets and that the country-neutral profits disappear after controlling for size and turnover factors.

McInish et al. (2008) test the profitability of short-term contrarian and medium-term momentum strategies in seven Asian markets over the period 1990 to 2000. They find that winner (loser) portfolios experience subsequent momentum (reversal) only in the Taiwanese and South Korean markets and that momentum profits are persistent and statistically significant only in Japan and Hong Kong.[12]

2.2.3 Related evidence in the China stock market

Few studies have been conducted on the momentum effect in China mainly due to the short history of the stock market and the lack of investment opportunities for global investors (Kang et al. (2002)). Based on data on A-shares in the China stock market over the period 1993 to 2000, Kang et al. (2002) investigate various short-term

[11] The markets included in the analysis are: Hong Kong (201 firms), Malaysia (244 firms), Singapore (103 firms), South Korea (309 firms), Taiwan (92 firms), and Thailand (59 firms).

[12] The seven Pacific Basin capital markets include Hong Kong, Japan, Malaysia, Singapore, South Korea, Taiwan, and Thailand.

contrarian and medium-term momentum strategies and find significant abnormal profits for momentum strategies. In particular, they find that in the case of value-weighted portfolio strategies, momentum profits are more distinct compared with those in the case of equal-weighted portfolio strategies, and attribute this result to the unique lead-lag structure in China, *"in that the lead stocks lead the lag stocks negatively and that large firms lead small firms in short horizons, whereas small firms lead large firms in relatively longer horizons"* (p. 264).

The evidence of the profitability of momentum strategies in China found by Kang et al. (2002) apparently differs from that found in other emerging market studies. In order to uncover the stock return behaviour over the medium and long horizons in the China stock market, Wang (2004) examines the individual stocks based on the SHSE and the SZSE over the period 1994 to 2000. The study of Wang (2004) differs from Kang et al. (2002) in several ways. First, the data sample of Wang (2004) is much larger than that examined by Kang et al. (2002). In addition, Wang (2004) focuses on return predictability over three- to 24-month horizons, whereas Kang at al. (2002) investigate return behaviour over a relatively short horizon of up to six months. Wang (2004) finds a negative average return to a relative strength strategy over a horizon of six months to two years. Finally, Wang (2004) conducts a risk analysis according to the Fama and French (1993) three-factor model, whereas Kang et al. (2002) only consider the market risk. Wang (2004) documents that firm size, B/M, and beta risks are qualitatively similar to those in the United States, and argue that *"after accounting for risk, predictable patterns in returns disappear, and therefore, our evidence on stock return predictability is not inconsistent with rational risk-based pricing models"* (p. 162).

Naughton et al. (2008) investigate the profitability of momentum investment strategies for firms listed on the SHSE, and find evidence of substantial momentum profits over the period 1995 to 2005. Their findings suggest that it is likely for investors to earn superior returns by following strategies unrelated to market movements. A further investigation shows that past trading volume plays a weak role in explaining momentum profits.

2.3 Empirical evidence of momentum in different contexts

The momentum effect documented by Jegadeesh and Titman (1993) refers to as the individual stocks-based price momentum in the finance literature. Recently, the price momentum has been refined and extended in different contexts by a large number of subsequent studies.

2.3.1 Style momentum

Although the price momentum has been well documented in the financial markets, the style momentum is considered to be a new empirical finding challenging the EMH. Barberis and Shleifer (2003) demonstrate that investors generally classify assets into different styles based on the market capitalisation, B/M, and/or dividend yield. They state that style investing is particularly attractive for institutional investors since it enables them to effectively make their portfolio allocation decisions, and helps them to simply evaluate the performance of professional managers relative to the standardised style benchmarks.

Several possible characteristics momentum strategies have been explored to investigate whether style cycle information can improve returns. Chen (2003) shows that portfolios formed by firm characteristics such as size, B/M, and/or dividend yield can be used to determine investment style dominance. Chen (2003) confirms that stocks with in-favour characteristics continuously outperform stocks with out-of-favour characteristics. Characteristic momentum strategies, which buy stocks with persistent in-favour characteristics and sell stocks with persistent out-of-favour characteristics, generate significantly positive profits in the future. In addition, Chen (2003) shows that characteristics momentum is distinct from price and industry momentum. Furthermore, compared with the price and industry momentum, characteristics momentum has longer effect in predicting future returns.

Chen (2003) attributes the existence of such characteristics momentum profits to the consistent firm characteristics over a short horizon. *"As a result, trend-chasing investors can confidently allocate more resources to styles with strong prior records and further inflate the price of stocks with an in-favour style. At the same time, trend-chasing investors can finance a shift into successful styles by withdrawing resources from poorer-performing ones, and further depress the price of stocks with out-of-favour styles"* (p. 138). Lewellen (2002) explores the profitability of portfolio-based momentum strategies and finds that size and B/M portfolios are well diversified and momentum in these portfolios is as strong as momentum in individual stocks or industries. Moreover, size or B/M momentum is distinct from industry momentum in that neither subsumes the other.

A study of Chen and De Bondt (2004) examines the style momentum strategies based on annual dividend yields, market value of equity, and B/M for large US firms contained in the S&P 500 Index over the period 1976 to 2000. On 31st December of each year, they divide the whole sample into ten style portfolios and each of them comprises stocks with similar characteristics. Stocks that do not pay dividends in past year are placed in one independent portfolio. The remaining stocks are allocated to three equal-sized size groups and three equal-sized B/M groups based on their year-end market capitalisation and B/M. Which portfolio at the intersection of size and B/M groups a stock belongs to and whether the stock is a member of the S&P 500 Index are checked once a year. They report that investors who buy past winner style portfolios and sell past loser style portfolios could favourably perform for a period of one year (and even more) ahead. They report that 11 out of 16 style strategies generate reliable positive returns. The most successful 12-6 strategy that selects portfolios based on their past twelve month returns and holds them for the following six months yields a profit of 0.5 per cent per month. They also show that style momentum differs from price momentum and industry momentum.

Aarts and Lehnert (2005) empirically investigate the profitability of style momentum strategies in the UK stock market, based on all stocks included in the FTSE 350 Index over the period 1992 to 2002. Nine style portfolios based on size and B/M are formed. Unlike the result reported in the US stock market by Chen and De Bondt (2004), empirical evidence suggests that style momentum strategies do not add value to the UK investors. In addition, style momentum strategies based on the FTSE 350 Index are less profitable and more risky compared with regular price momentum strategies.

2.3.2 Industry momentum

Moskowitz and Grinblatt (1999) attribute the observed medium-term momentum profits to industry momentum. That is, investment strategies that buy previous winner industry portfolios and meanwhile sell previous loser industry portfolios can generate significant returns in the medium-term horizons. Over the period 1963 to 1995, Moskowitz and Grinblatt (1999) divide all available US stocks into 20 industries by two-digit Standard Industrial Classification (SIC) codes. They form winner and loser portfolios on the basis of the returns on the industries over the past period. The winner portfolio contains the top three industries from the lag period, and the loser portfolio contains the bottom three industries. The winner minus loser portfolios are constructed by taking long position on past winner industry portfolios and taking short position on past loser industry portfolios in the subsequent holding period. At the end of the holding period, the portfolios are liquidated and rebalance on the basis of the most recent lag period ranking. This procedure is repeated for the whole 33-year sample period. The performance of such an investment strategy is the difference of returns between the winner and loser industry portfolios. The 6-6 strategy with a six-month lag period and a six-month holding period generates an average profit of 0.43 per cent per month (t-stat = 4.24). Alternative strategies with varying lag and holding periods generate similar profits. For example, the 6-12 strategy with a six-month lag period and a twelve-month holding period yields a profit of 0.40 per cent per month, and the 12-6 strategy with a twelve-month lag period and a 6-month holding period yield a profit of 0.53 per cent per month. Moskowitz and Grinblatt (1999) further identify what portion of the return comes from the overperformance of the winner industry portfolio and what portion comes from the underperformance of the loser industry portfolio. For example, of the

0.43 per cent per month for the 6-6 strategy, 0.37 per cent comes from the overperformance of the winner portfolio and the remaining 0.06 per cent comes from the underperformance of the loser portfolio.

Moskowitz and Grinblatt (1999) conclude that the industry momentum effect is strong and persistent even after controlling for size, B/M and market microstructure influences, and that the profitability of price momentum strategies can be fully captured by industry momentum. Moskowitz and Grinblatt (1999) argue that industry momentum is not due to the Fama and French (1993) three-factor risk but due to the industry-specific idiosyncratic risk. Lewellen (2002) also documents that the Fama and French (1993) three-factor model explains very little of industry momentum. Grundy and Martin (2001), however, argue that the industry momentum strategies employed by Moskowitz and Grinblatt (1999) do not skip a month between the performance ranking and portfolio holding periods. They provide evidence that individual stock momentum can be explained by the firm-specific component of returns and is different from industry momentum. Chordia and Shivakumar (2002) attribute industry momentum to macroeconomic variations rather than industry-specific returns. They show that industry momentum and individual stock momentum are distinct and independent effects, with each strategy being profitable on its own.

2.3.3 Momentum in other contexts

Based on past earnings, Chan et al. (1996) find that earnings momentum strategies tend to be smaller and persistent for a shorter time period than price momentum strategies. Using a two-way analysis, they find that both past returns and earning surprises contribute to some improved predictive power for future returns. The result indicates that earnings momentum and price momentum reflect different pieces of information and cannot subsume each other. Chan et al. (1996) also show that the profitability of momentum strategies is not a compensation for risk, but driven by an underreaction of stock prices to the information in past returns and earnings.

Lee and Swaminathan (2000) investigate the informational role of the interaction between past stock prices and trading volume in predicting future price changes. They find that the momentum effect appears to be more pronounced among high volume stocks than among low volume stocks. However, the intriguing findings do not appear to fit into any existing theoretical framework. A better understanding of this issue could benefit from more out-of-sample evidence. For example, Glaser and Weber (2003) extend the study in various dimensions and provide an additional test of the results in the German stock market. They find that high turnover winner portfolios exhibit higher returns than low turnover winner portfolios. Their results are robust after controlling for size, B/M, and industry factors. Using a sample of all A-shares on the SHSE and SZSE over the period July 1994 to December 2000, Wang and Chin (2004) examine the interaction between return predictability and trading volume over the medium horizons. They report that low volume stocks outperform high volume stocks, that volume discounts are more pronounced for past winner portfolios than for past loser portfolios, that low volume stocks instead of high volume stocks experience return continuations, and that high volume winner portfolios exhibit return reversals.[13] The results are robust to analysis based on the sub-samples in different stock exchanges or only containing

[13] Volume discount is the difference in mean returns between high and low volume stocks.

large size stocks, and to risk adjustments relative to the Fama and French (1993) three-factor model.

Moreover, Hong, Lim, and Stein (2000) find that momentum strategies perform better among stocks with low analyst coverage than among stocks with high analyst coverage. Lesmond et al. (2004) show that momentum in stock returns is related to share price and the frequency of zero-return days, which are considered to be proxies for the transaction costs. Zhan and Robert (2004) present that momentum strategies formed with high priced stocks earn statistically significant profits for any holding period in the first three to four years. Zhang (2006) reports that momentum profits are higher among firms with higher information uncertainty across six proxies: firm size, firm age, analyst coverage, dispersion in analyst forecasts, return volatility, and cash flow volatility. Avramov, Chordia, Jostova, and Philipov (2007) show that momentum profits are large and significant among firms with low grade credit ratings but are nonexistent among firms with high grade credit ratings.

2.4 Potential explanations of momentum profits

Based on the general evidence of the profitability of momentum strategies, more studies attempt to explain the financial anomaly by identifying different potential factors and employing alternative methodologies. Two broad explanations have emerged as possible sources of momentum profits, first, that accounting for risk through traditional measures, such as the CAPM or the Fama and French (1993) three-factor model, has proved inadequate; and second, that momentum-related return patterns show an irrational response by market participants to information.

2.4.1 Risk-based theories

A number of studies attempt to rationalise the abnormal profits generated by momentum strategies in terms of risk. However, Fama and French (1996) concede that although the Fama and French (1993) three-factor model successfully explains the long- and short-term reversals of stock returns (see, e.g., De Bondt and Thaler (1985 and 1987) and Jegadeesh (1990)), it fails to explain the medium-term continuation. Liu et al. (1999) confirm the failure of the Fama and French (1993) three-factor model in explaining the momentum effect in the UK stock market. The monthly risk-adjusted abnormal returns of the winner portfolio remain significantly higher than those of the loser portfolio.

Conrad and Kaul (1998) document that momentum profits arise because of the cross-sectional differences in expected returns which are dominated by high return stocks in both the performance ranking and portfolio holding periods. However, Grundy and Martin (2001) argue that the profitability of momentum strategies cannot entirely be explained by the cross-sectional variability in expected returns. Jegadeesh and Titman (2002) also argue that Conrad and Kaul (1998) ignore small sample biases in their tests and further conclude that the cross-sectional differences in expected returns explain very little, if any, of momentum profits.

Chordia and Shivakumar (2002), using information from the National Bureau of Economic Research (NBER) to define the position of the business cycle, document that the magnitude of momentum profits is influenced by the stage of the business cycle. They report an economically and statistically significant difference of momentum profits, 1.25 per cent per month, between the expansionary and recessionary periods.

Chordia and Shivakumar (2002) further document that in the US stock market momentum profits can be entirely explained by a set of lagged macroeconomic variables that are related to the business cycle.[14] They attribute the profitability of momentum strategies to the compensation for bearing business cycle risk. However, to examine the robustness of the conditional forecasting model, Griffin et al. (2003) find no relationship between momentum macroeconomic factors in 39 international markets.[15] A possible explanation is that variables included in the macroeconomic model of Chordia and Shivakumar (2002) are more related to the bond market, which is not mature in emerging markets, resulting in this model not working internationally.

Munira and Muradoglu (2010) establish a link between momentum, credit ratings, and business cycles. They divide credit-rated stocks into three categories: investment-grade, speculative grade, and default-grade. Investment-grade stocks have lower credit risks and thus lower uncertainty, while speculative-grade stocks have higher credit risks and thus higher uncertainty. They find that momentum profits occur primarily during contractions and attribute the result to speculative-grade stocks. In addition, they report

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[14] There are four macro variables in the model of Chordia and Shivakumar (2002), where *YLD* represents the yield on the three-month T-bill; *DIV* represents the dividend yield on the market; *DEF* represents the default spread; and *TERM* represents the term spread. Momentum profits disappear once stock returns are adjusted for their predictability based on these macroeconomic variables.

[15] The sample includes 1,930 firms listed on NYSE and AMEX with available from CRSP. Non-US countries have at least 50 firms and all available firms from these 39 markets include: Egypt (54) and South Africa (226) from Africa; Argentina (66), Brazil (87), Canada (843), Chile (92), Mexico (74), and Peru (71) from Americas (ex. U.S.); Australia (509), China (253), Hong Kong (179), India (375), Indonesia (97), Japan (1,898), Malaysia (190), New Zealand (80), Pakistan (117), Philippines (63), Singapore (112), South Korea (588), Taiwan (164),and Thailand (155) from Asia; Austria (51), Belgium (129), Denmark (153), Finland (54), France (571), Germany (502), Greece (62), Ireland (55), Italy (184), Netherlands (197), Norway (88), Portugal (89), Spain (100), Sweden (160), Switzerland (183), Turkey (72), and the United Kingdom (1,404) from Europe.

the non-existence of momentum among investment-grade stocks during expansions. For example, in speculative-grade stocks momentum returns are 1.71 per cent per month during expansions and 4.12 per cent per month during contractions. In investment-grade stocks, momentum returns of 1.62 per cent per month occur during contractions. Higher momentum returns during contractions can be explained by macroeconomic variables.

Consistent with Zhang (2006), momentum is related to high uncertainty due to the increased credit risk of stocks and the state of the economy. Zhang (2006) assumes that greater information uncertainty should produce relatively higher expected returns following good news and relatively lower expected returns following bas news. Using ex post returns as a proxy for expected returns, Zhang (2006) finds consistent results across six proxies for information uncertainty: firm size, firm age, analyst coverage, dispersion in analyst forecasts, return volatility, and cash flow volatility.

Griffin et al. (2003) further demonstrate that the number of stock markets experiencing positive persistence during the period of negative GDP growth is the same as that showing positive persistence during the period of positive GDP growth. They also show that the model of Chen, Roll, and Ross (1986) does not *"provide any evidence that macroeconomic risk variables can explain momentum"* (p. 2515). Cooper et al. (2004) also argue that the macroeconomic variables proposed by Chordia and Shivakumar (2002) do not capture the asymmetry in momentum profits, since *"the ability of such a model to explain momentum profits is not robust to controls for market frictions, specifically, a price screen and skip-month returns"* (p. 1364). Cooper et al. (2004) develop an alternative definition of an Up (Down) market as one in which the lagged three-year market return is non-negative (negative). Examining the US data over the period 1929 to 1995, they report that momentum profits tend to be stronger following the Up markets. For example, the 6-6 momentum strategy generates a profit of 0.93 per cent per month following the Up markets and a profit of –0.37 per cent per month following the Down markets. Griffin et al. (2003), however, provide more mixed results in the international markets. For example, the momentum profitability following bear (bull) markets is 1.53 (1.27) per cent per month in Africa, 0.77 (0.73) per cent per month in America, 0.55 (–0.10) per cent per month in Asia, 0.68 (0.76) per cent per month in Europe, and 1.04 (0.31) per cent per month in the United States. Using data from the Swiss market, Rey and Schmid (2007) also find that momentum profits are stronger in a sub-period where a bear market is present. Muga and Santamaria (2007), however, find that the momentum effect appears in the wake of both Up and Down markets in the Spanish stock market.

2.4.2 Behavioural models

In terms of irrational responses to market information, Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999) each present models based on the idea that momentum profits could be attributed to inherent biases in the way that investors interpret information. That is, cognitive biases lead investors to either underreact to information or follow positive feedback strategies that lead to a delayed overreaction to information. De Long, Shleifer, Summers, and Waldmann (1990) propose a model of positive feedback trading based on the extrapolative expectations where investors assume that future stock prices will follow past prices. Therefore, investors buy stocks with prices rising and sell stocks with prices falling, resulting in momentum profits.

The behavioural model developed by Barberis et al. (1998) is motivated by two important psychological biases: conservatism and representativeness heuristic. Conservatism bias leads investors to change their beliefs insufficiently when news arrives and underweight the new information. As a result, investors tend to underreact to firm-specific news, producing a momentum effect. The representativeness heuristic bias leads investors to misestimate future growth of firms since they use past history as the representativeness of an underlying earnings growth potential. As a result, investors tend to overvalue stocks with a record of good news and undervalue stocks with a record of bad news.

Another behavioural model to reconcile the long-term reversal and medium-term momentum is developed by Daniel et al. (1998). Their model is based on two psychological biases: overconfidence and self-attribution. Overconfidence leads investors to overestimate their ability when assessing information and underestimate their forecast error. The overweight of the private signals will result in overreaction, while the underweight of the public signals will cause underreaction. If investors trade on private information, self-attribution bias leads their confidence to increase when public information confirms their beliefs. Therefore, increasing overconfidence further accelerates the initial overreaction to the past private signal and continuing correction causes prices changes to be positively correlated to the public signal. This suggests that momentum arises because public news pushes a continuing underreaction to the public signal and causes market mispricing. However, momentum will eventually reverse as further public information slowly drags the price back towards its true value.

The behavioural model developed by Hong and Stein (1999) is based on two different trading groups: news watchers and momentum traders. They assume that private information diffuses gradually across the news watchers who trade on private signals about future fundamentals rather than past prices. As a result, prices adjust slowly to new information and generate momentum profits. Trading based on past price movements, momentum traders explore momentum profits by pushing up medium-term prices of past winners. Therefore, prices will overshoot their fundamentals, when more and more momentum traders enter the market to chase the profits.

For momentum investing, behavioural models imply that the abnormal returns arise because of a delayed overreaction to information that pushes the prices of winners (losers) above (below) their long-term values. Consequently, these models conjecture that the post-holding period returns of the momentum portfolio should be negative when investors realise that the observed returns are abnormal. This result is conditioned on the state of the market so that investors have some phenomena to irrationally respond to. Cooper et al. (2004) find that medium-term momentum profits exclusively follow the Up states, which is defined as the lagged market return is non-negative. Empirical evidence supporting behavioural theories has been presented in Lee and Swaminathan (2000), Jegadeesh and Titman (2001), and Cooper et al. (2004)). On the other hand, some recent studies provide conflicting empirical evidence (see, e.g., Rey and Schmid (2007) and Muga and Santamaria (2007)).

Hong, Lim, and Stein (2000) use the firm size and analyst coverage as proxies for information diffusion speed and find that higher momentum profits are limited to smaller size stocks with lower analyst coverage. The small size stocks with low analyst coverage exhibit higher momentum, consistent with the model of Hong and Stein (1999). However, Lesmond et al. (2004) argue that the results are due to the fact that the proxies for the information diffusion ignore the trading costs. After taking the trading costs into account, analyst coverage provides a little explanatory power for the momentum returns. Sadka (2006) also argues that although small size stocks with low analyst coverage earn high momentum returns, these returns cannot be exploited because small stocks have a low level of liquidity and higher liquidity costs.

George and Hwang (2004) also develop a behavioural model to explain the momentum effect. They introduce a new momentum strategy called the 52-week high strategy. Buying stocks that are near their 52-week high and meanwhile short selling stocks that are far from their 52-week high, investors can generate approximately double the profitability of the regular price momentum strategy of Jegadeesh and Titman (1993) and the industry momentum strategy of Moskowitz and Grinblatt (1999). They explain this finding as follows: investors expect that stock prices that are close to the 52-week high will decline in the future, even though public information can promise further increases in stock prices. The information finally prevails, generating a delayed increase in stock prices.

Grinblatt and Han (2005) present a relatively simple theory in which momentum is driven by the disposition effect. Intuitively, if disposition-prone investors are holding a stock for which good news is revealed, they will sell their shares as prices rise, decreasing any upward pressure on the stock price. Similarly, if disposition-prone investors are holding a stock for which bad news is revealed, they will hold their shares rather than sell, again decreasing any downward pressure on the stock price. If any rational investors trading against the disposition-prone investors do not fully adjust their demands for stocks to account for the disposition bias, prices will take a relatively long time to converge to the equilibrium level following large shocks. Therefore, there is a positive spread between prices and their fundamental values for winners and a negative spread for losers, resulting in momentum profits.

2.4.3 Other explanations

Re-examining momentum strategies in the time period subsequent to their original study, Jegadeesh and Titman (2001) find that past winners continue to outperform past losers by the similar magnitude as in the earlier period. Apart from evidence shown in the US stock market, a number of studies have discovered that the momentum effect exists in the international stock markets (Rouwenhorst (1998)), foreign currency markets (Okunev and White (2003)), and commodity futures markets (Miffre and Rallis (2007)), totally ruling out the concern that the momentum effect is merely due to the data mining bias.

Moskowitz and Grinblatt (1999) claim that the industry effect is almost entirely responsible for the momentum effect in the United States. However, there is still a debate on the significance of the industry factor in explaining the momentum effect, since the results are not replicated when using different data sets. For example, Chordia and Shivakumar (2002) exclude NASDAQ stocks from the sample employed by Moskowitz and Grinblatt (1999), and examine an alternative breakdown to construct the winner and loser portfolios. They argue that in this circumstance, the individual stocks-based momentum strategy experiences significant positive profits. In addition, Nijman, Swinkeis, and Verbeek (2002) report that industries have a relatively weak role in explaining the profitability of momentum strategies in European stock markets. Industry-based strategies can explain only 30 per cent of momentum profitability compared with 60 per cent achieved for individual stocks.

Trading volume is also reported as having a strong ability to predict future price momentum. Lee and Swarninathan (2000) find that past low volume stocks earn higher future returns than past high volume stocks. Additionally, trading volume provides an important link to reconcile the long-term price reversal and the medium-term price momentum. Although they highlight the significance of trading volume in explaining some of the magnitude of momentum profits, trading volume cannot subsume the momentum effect. Stocks with low trading volume still experience positive profits due to the momentum strategy.

The transaction costs are regarded as another most important factor in explaining momentum profits. Carhart (1997) argues that the apparent profitability of momentum strategies in mutual funds is due to the ignorance of the transaction costs. Grundy and Martin (2001) confirm that the level of round-trip transaction costs will offset the returns of momentum strategies. Lesmond et al. (2004) find that the momentum returns are mainly produced by stocks with the characteristics of small size, high beta, and low liquidity, which have large trading costs. After controlling for the trading costs, momentum returns cannot be exploited by arbitrageurs. Ellis and Thomas (2004), however, estimate a cost of 5.8 per cent for a momentum strategy over a twelve-month holding period for stocks contained in the FTSE 350 Index. They find that momentum profits are still significant in their sample after accounting for the transaction costs.

Korajczyk and Sadka (2004) also discover that momentum strategies remain profitable after controlling for the transaction costs. However, after considering price impact costs, the profitability of equally-weighted momentum strategies is eliminated whereas value-weighted momentum strategies earn substantial abnormal returns until the market value of the investment is slightly less than $1 billion. An alternative finding of Hanna and Ready (2005) shows that both equally-weighted and value-weighted momentum strategies earn significantly excess returns after considering trading costs.

In sum, although most findings highlight the robustness of the momentum effect in various markets, explanations of the profitability of momentum profits appear to be the most intriguing issue in the literature. The alternative explanations of the momentum effect are not unanimously supported by different data sets and methodologies. Neither risk-based theories nor behavioural models appear able to account for the momentum effect.

CHAPTER 3

CHARACTERISTICS OF THE CHINA STOCK MARKET

3.1 Introduction

Following China's economic reform, which started in 1978 to shift China from the central planning economy to the market-oriented economy, the Shanghai Stock Exchange (SHSE) was opened in 1990 followed by the Shenzhen Stock Exchange (SZSE) in 1991. The primary objective of developing stock markets in China is to help state owned enterprises (SOEs) to relax external financing constraints and to support the privatisation of SOEs (Green (2003)).

The China Securities Regulatory Commission (CSRC) and the State Council Securities Committee (SCSC) were set up in 1992 and 1993, respectively, as the body to monitor and regulate the securities market. They consolidated in 1998 and the CSRC is now the regulator of the securities industry. In March 2000, the China Securities Depositary and Clearing Company (CSDCC) was established as the central securities clearing company. In June 2004, a Small and Medium Enterprises (SMEs) board, similar to the NASDAQ system, was launched in the SZSE to provide a direct financing channel for the growing SMEs with well defined core business and hi-tech contents. The SHSE now plays the role of the main board for blue chips. The re-organisation is considered the important foundation to construct a multi-layer capital market and further to create a unified China stock market in the near future.

Table 3.1: Summary statistics

Figures report statistics at the end of December over the period January 1995 to December 2006. The annual average returns on the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) are the returns of the A-share Index of the two stock exchanges, respectively. The annual average returns of the whole market are the value-weighted return of the A-share Index of the two stock exchanges. The market capitalisation is the total market value of firms in the sample. B/M is the average book-to-market ratio of all available firms in the sample. The annual cumulative abnormal return of the market is presented in percentage and the market capitalisation is displayed in millions of RMB, or Chinese Yuan.

	The annual cumulative abnormal return			Average B/M			The total market capitalisation		
Year	SHSE	SZSE	Whole	SHSE	SZSE	Whole	SHSE	SZSE	Whole
1995	−13.86	−18.58	−17.01	0.412	0.726	0.505	226,392.1	72,893.2	299,285.3
1996	66.03	192.10	133.99	0.340	0.250	0.312	457,813.9	276,415.2	734,229.1
1997	31.78	18.91	25.02	0.341	0.272	0.317	806,134.4	672,077.0	1,478,211.5
1998	−3.09	−8.94	−6.28	0.322	0.343	0.329	917,471.3	714,387.5	1,631,858.8
1999	19.04	16.67	17.73	0.262	0.275	0.268	1,261,052.2	945,294.1	2,206,346.3
2000	51.00	58.07	54.78	0.182	0.189	0.185	2,286,810.9	1,712,928.1	3,999,739.0
2001	−21.89	−26.84	−24.65	0.257	0.264	0.260	2,432,566.9	1,266,148.5	3,698,715.4
2002	−17.13	−17.91	−17.57	0.335	0.352	0.342	2,409,876.4	1,098,071.6	3,507,948.0
2003	10.57	−4.02	2.14	0.407	0.428	0.415	2,772,430.0	999,112.4	3,771,542.3
2004	−15.23	−16.46	−15.93	0.518	0.529	0.522	2,455,589.3	910,988.4	3,366,577.7
2005	−8.21	−11.75	−10.27	0.666	0.662	0.665	2,166,266.6	749,340.3	2,915,606.9
2006	130.57	96.36	106.02	0.483	0.450	0.470	6,538,600.8	1,517,465.1	8,056,065.9

Moving in tandem with the overall China economy, the China stock market has grown very rapidly. The total market capitalisation of sample firms in the two stock exchanges increased from RMB299.3 billion at the end of 1995 to RMB8,056.1 billion at the end of 2006. By the end of 2006, the SHSE had RMB6,538.6 billion (81.2 per cent) total market capitalisation, while the SZSE had RMB1,517.5 billion (18.8 per cent) total market capitalisation. The number of listed firms on both exchanges increased from 53 at the end of 1995 to 1,287 at the end of 2006. The number of investors increased from 2.17 million in 1995 to 70.25 million in 2006.

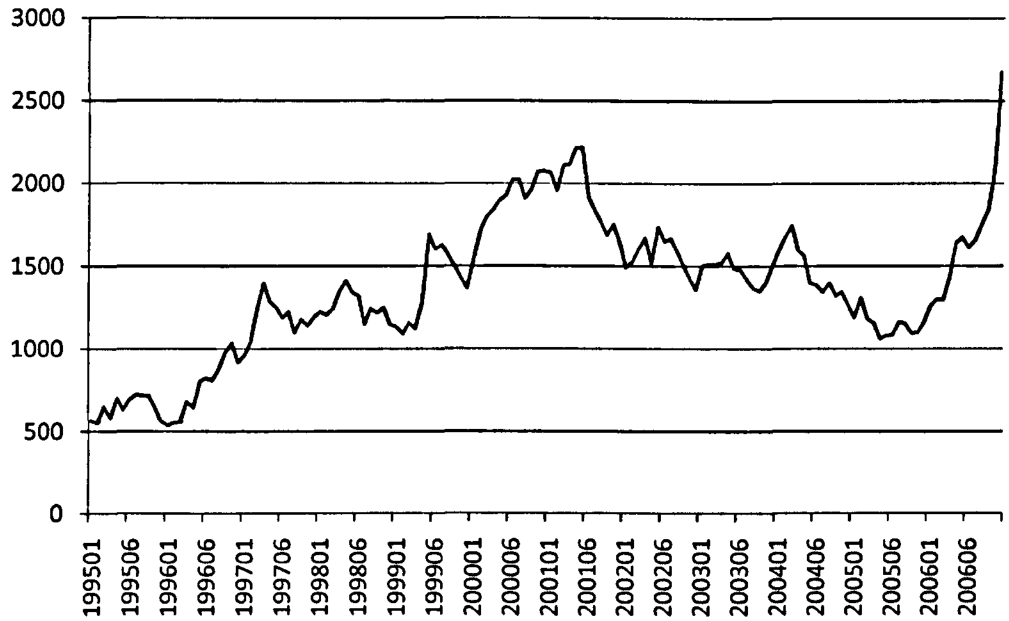

Figure 3.1: The SHSE Composite Index over the period 1995 to 2006

The annual average returns of the A-share Index of the two exchanges are both positive over the period 1995 to 2000 except for 1995 and 1998, and both negative over the period 2001 to 2006 except for 2003 and 2006. The highest annual average returns of the whole market (a value-weighted return of the SHSE and SZSE A-share Indices) is 133.99 per cent in 1996, while the lowest annual average return is –24.65 per cent in 2001. Table 3.1 also shows that during the depressed period 2001 to 2005, the average market capitalisation of firms in China decreased from RMB 3,686.0 million to RMB 2,116.7 million and the average B/M increased from 0.260 to 0.665. The market capitalisation data indicate clearly the dominance of stocks on the SHSE. During the initial stage, the role of institutional investors in this market is very limited and the composition of investors is dominated by private, small-scale individuals, because foreign institutional investors are strictly forbidden to access the A-share market and only can access to the B-share market. By 2000, individual investors overwhelmingly dominated the A-share market, holding over 99.5 per cent of the accounts, with less than 0.5 per cent held by institutional investors. After November 2002, the CSRC and the central bank introduced the QFII programme into the China capital market, more foreign institutional investors are now able to access this potential.

With more capital running into stock market for good future, it is reasonable for investors to believe that the stock market performance will be an effective indictor for macro economy. However, the opposite performance of stock market before and after June 2001 is inconsistent with the constant growth rate of China macro economy in recent ten years (see Footnote 2, p. 13). Men and Li (2006) argue that there is no Granger causality relationship between stock market performance and GDP growth rate and that there is no long run equilibrium relationship between GDP and stock index in China.

There could be many possible reasons to explain the seeming abnormal relationship between stock market performance and the national economy in China. First, the composition of GDP is inconsistent with the structure of the stock market. Most of listed firms in China are SOEs, as the purpose for listing SOEs is to get out of distress for these firms. Stock market performance of the listed firms in China can hardly reflect the real economic competency. In recent years, private sector has been playing an important role in contributing to the GDP growth in China. For example, the local private economy accounts for 49.7 per cent of the GDP in 2005 (Men and Li (2006). However, as for private economy sector financing, around 90 percent of the capital depends on self-financing, 4 percent is supported by bank loan, and even less financing could be acquired from stock market. In addition, the short-term fluctuation of domestic real estate investments has a significant impact on GDP. An increase of 1 per cent in residential investments will cause an increase of 0.16 per cent in Chinese GDP (Zhang, Wang, and Zhu (2010). The growth rate of GDP might not really reflect the national economy in China. Finally, unlike in developed market finance provided by bank and by stock market accounts for almost the same amount, most of Chinese financing is supported by commercial bank loans. For example, the capital raised from the stock market is RMB151.1 billions in 2004, while the total bank loan is RMB26,672.1 billions (Men and Li (2006)). The total capital raised from stock market only accounts for 0.6 per cent of the total bank loan in the same period. Hence, the unbalanced financial structure could explain at least partly why Chinese finance market is not playing an important role in the development of the national economy.

3.2 Ownership structure

The ownership structure of Chinese listed firms has some unique features not found in developed markets and represents a distinctive feature of the Chinese stock market. New issues in China reflect only a small proportion of total outstanding shares, with the majority of shares owned by the government and other legal entities, since most listed firms are SEOs. In China, for the government to have an effective control over state assets of SOEs, ordinary shares of a typical listed firm can be generally classified by ownership structure into two broad categories: tradable shares and non-tradable shares. With reference to SOEs, 37 per cent and 27 per cent of the shares of the listed firms are non-tradable and held by the state (government) and legal persons (enterprises and institutions), respectively. Tradable public shares comprise only 35 per cent of the outstanding shares.

3.2.1 Tradable shares

Tradable shares include A-shares, B-shares, H-shares, and N-shares, etc. A-shares and B-shares are traded on the SHSE or SZSE, while H-shares and N-shares are the shares of Chinese firms traded on the Hong Kong Stock Exchange (HKSE) and the NYSE, respectively. To attract foreign investors, some SOEs also issue foreign shares. B-shares are issued and traded in the two Chinese stock exchanges. Both the SHSE and SZSE have two strictly segmented sections: namely A-share and B-share sections. With the exception of a few firms recently listed on the SMEs board that do not involve state ownership, all Chinese listed firms are restructured SOEs and are dominated by non-tradable shares, including state shares, legal person shares, and employee shares. State shares are those owned by the central or local government. Legal entity shares are those held by domestic legal entities (institutions), such as listed firms, SOEs, and banks, etc. Employee shares are held by employees and initially prohibited from trading for a certain period of time until they become tradable A-shares.

It is required that A-shares should account for no less than 25 per cent of total outstanding shares when a firm makes its IPO.[16] Also for firms that issue both A and B shares, A shares account for less than 25 per cent. Thus, it is impossible for A-share investors to become major shareholders of most listed firms. The top ten shareholders are normally the state and legal persons. Even if some individual A- shares holders are

[16] Although the company ordinance stipulates that public offers should not be less than 25 per cent of total equities, this regulation was not followed in the early periods (Mok (1995)).

among the top ten, their holdings are normally below 0.5 per cent, much smaller than those of state and legal persons.

A-shares are denominated in Chinese currency (RMB, or Chinese Yuan) and issued to (and traded only by) Chinese citizens, since the Chinese currency is not convertible under the capital account. B-shares are exclusively allocated for foreign investors and denominated in US dollars on the SHSE or HK dollars on the SZSE. B shares can only be subscribed for, owned by, and traded amongst foreigners and people from Hong Kong, Macao, and Taiwan. There is no difference in shareholders' rights and obligations between A-shares and B-shares, although A-share prices are substantially higher than B-share prices, A-shares are much more actively traded than B-shares, and the scale of the A-share market far exceeds that of the B-share market. By the end of 2006, there were 746 A shares and 54 B shares listed on the SHSE and 489 A shares and 57 B shares listed on the SZSE. Until 31st December, 2006, 87 firms were dual listed in A and B shares. These 87 paired A- and B-share firms have similar or even identical business and operating performance. On average, foreign shares account for less than 2.5% of the total shares of all listed firms but for those firms that have actually issued foreign shares, the average is about 35 per cent. In addition, there are not many foreign share block holders. Therefore, foreign investors, like local investors, are too insignificant to influence a firm's management. As a result, trading is traditionally light in the B-share market, and both B-share and H-share prices are deeply discounted relative to their A-share counterparts and show a large A- to B-share price premium (see, e.g., Bailey (1994) and Sun and Tong (2000)).

Since February 2001, the CSRC has allowed Chinese citizens who hold foreign currencies to trade B-shares and the B-share IPO has been suspended. As the information came out in March 2001, the SHSE and SZSE B-share Indices have risen, respectively, two- and three-fold since then. This discount effect in the China stock market is contrary to the experience in other countries, where foreign shares typically trade at a premium. [17] The substantial price difference can be explained by the information problems faced by foreign investors. As Chen, Lee, and Rui (2001) report, overseas investors face language barriers and have to cope with different accounting standard, and it hard to get reliable information about the local economy and companies.

3.2.2 Non-tradable shares

The existence of state shares in China is to designate holdings in the SOEs by the central government, local governments, or solely government-owned enterprises. To preserve the economy's socialist structure, SOEs have to issue shares to the government when going public and the proportion is substantial, representing over 30 per cent of total shares on average. It is arguable that state ownership plays a positive role so that partial privatisation is better than complete privatisation. First, there can be a signalling effect for continued state ownership. Mok and Hui (1998) argue that high equity retention by the state lowers the ex-ante uncertainty of domestic investors (and IPO underpricing) because investors interpret that as a sign of the government's confidence

[17] Different models are proposed to explain the discount phenomenon include: a demand differential model (Chen et al. (2001) and Sun and Tong (2000)); information asymmetry model (Chakravarty, Sarkar, and Wu (1998), Chui and Kwok (1998), Su and Fleisher (1998), Sun and Tong (2000), Chen, et al. (2001), Karolyi and Li (2003), and Yang (2003)); a liquidity differential model (Bailey (1994), Chen, et al. (2001), Bergstrom and Tang (2001), and Karolyi and Li (2003)); and a risk differential model (Bailey (1994), Su (1999), Chen, et al. (2001), and Fernald and Rogers (2002)).

in the list firms. Second, Jefferson (1998) argues that SOEs are regarded as public goods and that a quick and complete privatisation is not desirable. In the absence of a well functioning property rights market, full privatisation can result in the transfer of public assets to private agents who do not use them more efficiently than under state ownership. On the other hand, partial state ownership helps to monitor managers in China's share issuing privatisation. As Stiglitz (1997) points out, there are *"special problems facing developing and transition economies, in which markets are lacking; the markets that do exist may function less effectively, and information problems are more severe than in industrial countries simply because of the rapid change in the economic environment"* (p. 15). Indeed, in China the managerial labour market is not well established, the product market does not function well, and the takeover market for firms does not exist at all. There is no significant independent shareholder in China who can provide effective monitoring of management. As a result, managers tend to be opportunistic and seek personal benefit rather than the success of the listed firm.

Legal person shares are owned by domestic institutions, most of which are partially owned by the central or local government. There can be several legal-person shareholders in a listed firm. Legal persons are typically business agencies or enterprises of local governments that are helpful in starting up the public company either by giving permission to operate or by allowing resources under their control to be used for the start up. Legal person and state shares are similar, not only because both of them are non-tradable, but also because many legal persons are actually controlled by the state. Although legal person shares cannot be traded, they are transferable to domestic institutions upon approval from the CSRC. In addition, the state shares are owned by a provincial branch of the state asset management bureau (SAMB), which represents the state in many other companies. A legal person, however, can be more effective in monitoring as it is typically a large block holder in only one or a few companies. Xu and Wang (1999) argue that legal persons, like institutional investors in the market economies, are active in monitoring managers and enhance the firm's performance. Their findings show that legal person ownership has a positive impact on the firm, while state ownership has no such impact. Qi, Wu, and Zhang (2000) also argue that the representatives of legal persons have incentives and expertise to monitor and control actions taken by managers. Legal persons can nominate board members, who in turn appoint corporate officials independently. Consequently, the board members are elected from different institutions, have diverse professional backgrounds, and could act to promote the best interest of the legal persons they represent.

Employee shares are offered to workers and managers of a listed company, usually at a substantial discount. However, employee shares are limited in quantity and not all companies issue employee shares. After a holding period of six to twelve months, the company can file with the CSRC to allow its employees to sell their shares on the open market. Once sold on the market, employee shares become A-shares. On average, employee shares account for less than two per cent of the total shares and act purely as an incentive scheme rather than providing ownership control of any kind.

3.3 Other characteristics

Furthermore, there are a lot of other unique regulations in China to protect the young stock market from potential risk. For example, since 16th December 1996, an increase ceiling and decrease floor of ten per cent applies to every stock during one-day trading.

This practice says that the maximum stock price during a trading day is 110 per cent of the previous closing price; the minimum stock price is 90 per cent of the previous closing price. A-shares apply a $T + 1$ settlement policy, while B-shares apply a $T + 3$ settlement policy.

For every trade of A-shares, the minimum investment is 100 shares. The actual number of shares purchased for every trading is the integer times 100 shares. When the investment is less than RMB30 million, the maximum number of shares traded is less than 100,000 shares. When the investment is more than RMB30 million and less than RMB100 million, the maximum number of shares traded is less than 200,000 shares. For every trade of B-shares, the minimum investment is 1,000 shares. The actual number of shares purchased for every trading is the integer times 1,000 shares. There is no maximum investment limit for B-shares.

For A-shares, the commission is smaller than or equal to 0.3 per cent of the stock value, and the minimum is RMB5. The stamp tax is 0.2 per cent of the stock value. There is a stock transaction fee, which is equal to 0.1 per cent of the stock value. For B-shares, the commission fee is smaller than or equal to 0.3 per cent of the stock value, and the minimum is $1 dollar. The stamp tax is 0.2 per cent of the stock value. There is a settlement fee, which is equal to 0.05 per cent of the stock value. For both A and B shares, there is no income tax, such as a capital gains tax.

Before 2000, one important role of the CSRC was to determine the pricing and timing of IPOs. In August 2004, investment banks were allowed to price IPOs on the grounds that they were more likely to better reflect market appetite for any particular IPO. Prior to the launch of the two stock exchanges, a number of firms issued shares by private placement to employees and local public, without the participation of underwriters and with few intermediaries. In the early life of the market, the IPO procedure of selling a limited number of subscription warrants was widely used, but was soon replaced by unlimited subscription warrants in 1992. After 1994, a fixed price procedure was introduced and became the major offering method from 1996 to 2002. In addition to the fixed price mechanism, an auction-like mechanism was also launched in mid-1994. In 1999, the book-building mechanism was first applied to IPOs and after 2005 this approach was generally used for all IPOs.[18]

[18] More details on the relevant IPO allocation procedures employed in China are summarised in Ma and Faff (2007) and Su, Bangassa, and Brookfield (2010).

CHAPTER 4

MOMENTUM AND MARKET STATES

4.1 Introduction

The success of momentum strategies documented by Jegadeesh and Titman (1993) has been challenging the central theme of the EMH that past stock returns cannot be used in predicting future returns. Although the profitability of momentum strategies is well documented in various markets, there has been considerable controversy in the literature about the sources and interpretations of the apparent profits. Several recent studies investigate the relationship between momentum profits and macroeconomic factors.[19] For example, Griffin et al. (2003) report that momentum profits are stronger following the bear markets at 1.53, 0.77, 0.55, 0.68, and 1.04 per cent per month in Africa, America, Asia, Europe and the United States, respectively, while momentum profits following the bull markets tend to be relatively lower, at 1.27, 0.73, –0.10, 0.76, and 0.31 per cent per month, respectively, in the same international markets. However, Cooper et al. (2004) who re-examine the US data alone over the period 1929 to 1995 arrive at the opposite result. For example, the momentum profit that follows the Up markets is 0.93 per cent per month and the continuation gain that follows the Down markets is –0.37 per cent per month. Both Griffin et al. (2003) and Cooper et al. (2004) employ monthly share returns of all NYSE and AMEX stocks from the Centre for Research in Security Prices (CRSP) and define the bull and bear markets based on the

[19] Previous studies find a great deal of empirical evidence showing that the state of the market has important impacts on stock returns. For example, Arsad and Coutts (1997) report a stronger weekend effect in the Down markets, while Butler and Joaquin (2002) document that the benefit of international diversification is weaker in the Down markets.

market performance. But they address different conclusions, which pose an interesting query that requires further examination on the role of market state in explaining the profitability of momentum strategies.

In this chapter, I first examine the profitability of momentum strategies in the China stock market over the period 1995 to 2006. According to a comparison of the profitability of momentum strategies in two sub-periods, this study finds that momentum strategies are highly profitable over the sub-period 2001 to 2006, a relatively depressed period, but no evidence of momentum profits found over the sub-period 1995 to 2000, a relatively booming period. I therefore conjecture that momentum profits are associated with the state of the market in the sub-periods and further conduct a formal investigation of the relationship between momentum profits and market states using the definitions of Cooper et al. (2004). Empirical evidence confirms that momentum profits are more pronounced following the Down markets instead of the Up markets. The results challenge the prediction of behavioural models of Daneil et al. (1998) and Hong and Stein (1999). Both theories propose that overreaction is the source of momentum profits and predict that momentum profits will be greater following market gains. I attribute the result that stronger momentum profits following the Down market to the disposition effect, which states that investors tend to sell winner portfolios and hold loser portfolios, in particular, following the Down markets (Grinblatt and Han (2005)). Therefore, a positive spread between prices and their fundamental values for winner portfolios and a negative spread for loser portfolios result in the profitability of the winner minus loser strategies.

In addition, I conduct an investigation into the profitability of momentum strategies based on two sub-samples with stocks listed either on the SHSE or on the SZSE and find that momentum strategies show much stronger profits on the SHSE. I attribute this result to the large market capitalisation of stocks on the SHSE. Finally, I find that momentum duration is longer in China than reported elsewhere, which is also inconsistent with another prediction of the behavioural theory that momentum profits will reverse in the long run as the market eventually corrects the mispricing. I conjecture that the longer duration is due to the severe short sales constraints in the China stock market. The role of short sales constraints will be examined in detail in Chapter 5.

4.2 Data and Methodology

4.2.1 Data and sample selection

The sample data for this study consists of all A-share firms listed on the SHSE or SZSE over the period January 1995 to December 2006. B-share firms are excluded from this study because of two reasons. First, B-shares are exclusively issued to (and traded only by) foreign investors before February 2001. Second, the number of B-share firms is far fewer than that of A-share firms and the B-share market is much less liquid than the A-share market. The sample period starts from 1995 because of the excessive speculation in the China stock market during the first several years after both exchanges were set up. After the SHSE and SZSE were set up in 1991, stock prices were often pushed up several hundred per cent and quickly corrected later on. During the period December 1990 to December 1993, for example, the SHSE Composite Index increased from 100 to 834. But in the following seven months, it dropped back to 334. In addition, during the early stage of the China stock market, the number of listed firms is too small to construct reliable momentum strategies. For example, there are only eight firms listed in the SHSE in 1991. To be included in the sample, a firm must have available information on the total shares outstanding and relevant accounting data (e.g. B/M) in DataStream. Firms that listed no more than six months prior to the formation period are also eliminated to avoid the influence of severe short run underpricing of Chinese IPOs.[20] Firms with a negative B/M or with a share price below RMB2.00 at the time of portfolio formation are excluded to avoid the influence of small and illiquid stocks. The sample includes all delisted firms to ensure that the study is free of survivorship bias. This screening process yields a total number of 1,184 A-share firms with an average of 757 stocks per year, and the data consist of 576 weekly observations.[21] The number of firms in the sample ranges from 238 at the end of 1995 to 1,184 at the end of 2006. For all eligible stocks, I collect data of weekly total return index for each of them, if available, from the first Wednesday of 1995 to the last Wednesday of 2006 to avoid the weekend effect.[22]

[20] Mok and Hui (1998) report an average underpricing of 289 per cent for a sample of 87 IPOs listed on the SHSE from 1990 to 1993. Chan, Wang, and Wei (2004) report an average A-share IPO initial return of 178 per cent in China from 1993 to 1998. More information on the short run underpricing are presented in Chi and Padgett (2005), Su et al. (2010), and among others.

[21] Observations over the period 1995 to 2006 range from 432 weeks (48-96 strategy) to 552 weeks (12-12 strategy).

[22] The weekend effect is a phenomenon that stock returns on Mondays are often significantly lower than those of the immediately preceding Friday. Board and Sutcliffe (1988), using the FTSE All Share Index over the period 1962 to 1986, demonstrate that the weekend anomaly persists in the UK stock market. They show that an investor, who short sells one million pounds' worth of shares on a Friday and buys back the equities on a Monday, would have achieved an average profit of three thousand pounds. Some theories that explain the effect attribute the tendency for companies to release bad news on Friday after the markets close to depressed stock

Weekly prices of stocks collected from DataStream are adjusted for stock splits, stock dividends, and rights offerings. Weekly returns are computed as the natural log of the formation day adjusted price divided by the previous week's adjusted price:

$$R_{i,t} = ln(RI_{i,t}/RI_{i,t-1}), \tag{4.1}$$

where $R_{i,t}$ represents the natural log return for firm i on week t; $RI_{i,t}$ represents the adjusted price for firm i on week t; and $RI_{i,t-1}$ represents the adjusted price for firm i on week $t-1$.

4.2.2 Methodology

To analyse the profitability of regular momentum strategies, this study follows the methodology of Jegadeesh and Titman (1993). At the Wednesday of each week t, all stocks are ranked into deciles based on their past F-week average returns (F equals 12, 24, 36, or 48) and assigned to one of ten portfolios. Each portfolio contains the same number of stocks.[23] D1 represents the loser portfolio containing stocks with the lowest past performance, while D10 represents the winner portfolio containing stocks with the highest past performance. These portfolios are equally weighted at performance ranking periods and held for the subsequent H weeks (H equals 12, 24, 36, 48, 60, 72, 84, or 96). This gives a total of 32 winner minus loser strategies. The profit of a winner minus loser

prices on Monday. Others state that the weekend effect might be linked to short selling, which would affect stocks with high short interest positions. Alternatively, the effect could simply be a result of traders' fading optimism between Friday and Monday.

[23] Over the period 1995 to 2006, the average trading day per year is 241.

portfolio (D10 – D1) is equal to the difference between the mean weekly return on the past winner portfolio (D10) and the mean weekly return on the past loser portfolio (D1).

For example, an *F-H* strategy means that a momentum strategy simultaneously buys the winner portfolio and sells the loser portfolio according to past *F*-week performance, and holds this position for the subsequent *H* weeks. The momentum portfolio (D10 – D1) represents the zero-cost risk free winner minus loser portfolio. The payoff generated by the momentum strategy is equivalent to the return of portfolios with an initial net investment of zero. Therefore, if there is evidence of the momentum effect in the China stock market, the winner minus loser portfolios will indicate significant abnormal profits. To mitigate the potential short-term reversal that may impact the measurement of returns on both the performance ranking and portfolio holding periods,[24] I also examine a second set of 32 momentum strategies by skipping four weeks between the end of the performance ranking period and the beginning of the holding period.

4.3 Empirical results

4.3.1 Momentum over the period 1995 to 2006

Table 4.1 presents average weekly returns on momentum strategies in the China stock market over the period 1995 to 2006. Generally, I find that medium-term momentum strategies generate relatively small and insignificantly positive momentum profits over the sample period. The winner minus loser portfolios in Panel A of Table 4.1 are formed

[24] Conrad and Kaul (1998) document the significant negative profits of the momentum effect over a weekly interval in the US stock market, while Jegadeesh (1990) records a –0.092 serial correlation on security returns over a one month interval.

immediately at the end of performance ranking periods. Results in Panel A show that when the holding periods are less than one year (from 12- to 48-week), 14 out of 16 momentum strategies generate positive returns except for the 12-12 and 48-48 strategies, but only three of them are statistically significant. The three significant momentum profits are from the 24-24, 24-36, and 36-24 strategies, which generate profits of 0.094 per cent per week (t-stat = 1.98), 0.086 per cent per week (t-stat = 2.23), and 0.102 per cent per week (t-stat = 2.15), respectively. The average profit of these strategies is 0.094 per cent per week, or 4.88 per cent per year, much lower compared with the magnitude of momentum profits in the US stock market. Jegadeesh and Titman (1993) report that the momentum strategy with six-month performance ranking periods produces significant return of about 1.10 per cent per month regardless of the holding periods.

The winner minus loser portfolios in Panel B of Table 4.1 are formed with a four-week gap between the end of the performance ranking period and the beginning of the portfolio holding period. Three significant momentum profits are still from the 24-24, 24-36, and 36-24 strategies, which generate profits of 0.112 per cent per week (t-stat = 2.36), 0.093 per cent per week (t-stat = 2.42), and 0.107 per cent per week (t-stat = 2.26), respectively. The average profit is 0.104 per cent per week, or 5.41 per cent per year, 0.53 per cent per year higher than that without a four-week skip between the performance ranking and portfolio holding periods. Note that even with a four-week delay of the portfolio formation, all momentum strategies yield similar returns, but the magnitude is slightly higher than that presented in Panel A of Table 4.1. Consistent with evidence found in Jegadeesh and Titman (1993), this outcome suggests that the bid-ask effect is likely to be small and has no significant influence on the profitability of the relative strength strategies.

Table 4.1: Weekly returns on momentum strategies over the period January 1995 to December 2006

The winner minus loser portfolios are formed based on past *F*-week returns and held for *H* weeks over the period January 1995 to December 2006. The values of *F* and *H* for the different strategies are indicated in the first column and row, respectively. The stocks are ranked in ascending order on the basis of past *F*-week returns and an equally weighted portfolio of stocks in the lowest past return decile is the loser portfolio (D1) and an equally weighted portfolio of the stocks in the highest return decile is the winner portfolio (D10). The average weekly returns of these portfolios are presented as percentages. The winner minus loser portfolios presented in Panel A are formed immediately after performance ranking periods, while the winner minus loser portfolios presented in Panel B are formed with a four-week skip between performance ranking and portfolio holding periods. The *t*-statistics are reported in parentheses.

F		H = 12	24	36	48	60	72	84	96
Panel A: No skip between performance ranking and portfolio holding periods									
	Loser	0.1509	0.0634	0.0611	0.0570	0.0687	0.0681	0.0526	0.0482
12	Winner	0.0514	0.0903	0.0856	0.0938	0.0640	0.0496	0.0305	0.0133
	Winner – Loser	–0.0995	0.0269	0.0244	0.0369	–0.0048	–0.0185	–0.0220	–0.0349
	t-stat	(–1.41)	(0.57)	(0.62)	(1.05)	(–0.14)	(–0.59)	(–0.75)	(–1.24)
	Loser	0.0462	0.0213	0.0386	0.0495	0.0552	0.0507	0.0385	0.0316
24	Winner	0.1026	0.1153	0.1244	0.0984	0.0615	0.0360	0.0070	–0.0110
	Winner – Loser	0.0564	0.0940	0.0858	0.0490	0.0063	–0.0146	–0.0315	–0.0426
	t-stat	(0.79)	(1.98)[a]	(2.23)[a]	(1.41)	(0.19)	(–0.47)	(–1.09)	(–1.55)
	Loser	0.0433	0.0393	0.0594	0.0613	0.0564	0.0450	0.0291	0.0248
36	Winner	0.1060	0.1412	0.1169	0.0747	0.0345	–0.0019	–0.0278	–0.0499
	Winner – Loser	0.0627	0.1020	0.0575	0.0135	–0.0219	–0.0469	–0.0569	–0.0747
	t-stat	(0.87)	(2.15)[a]	(1.47)	(0.38)	(–0.66)	(–1.52)	(–2.00)[a]	(–2.78)[b]
	Loser	0.0831	0.0769	0.0762	0.0674	0.0525	0.0401	0.0273	0.0293
48	Winner	0.1733	0.1460	0.1017	0.0535	–0.0020	–0.0357	–0.0652	–0.0808
	Winner – Loser	0.0901	0.0691	0.0256	–0.0139	–0.0545	–0.0758	–0.0925	–0.1101
	t-stat	(1.25)	(1.42)	(0.63)	(–0.38)	(–1.63)	(–2.44)[a]	(–3.26)[b]	(–4.04)[b]
Panel B: A four-week skip between performance ranking and portfolio holding periods									
	Loser	0.1069	0.0427	0.0505	0.0495	0.0663	0.0622	0.0472	0.0433
12	Winner	0.0712	0.0991	0.0920	0.0952	0.0622	0.0490	0.0271	0.0109
	Winner – Loser	–0.0357	0.0564	0.0415	0.0457	–0.0041	–0.0132	–0.0201	–0.0325
	t-stat	(–0.51)	(1.18)	(1.06)	(1.30)	(–0.12)	(–0.42)	(–0.69)	(–1.16)
	Loser	0.0108	0.0108	0.0343	0.0480	0.0543	0.0468	0.0357	0.0291
24	Winner	0.1206	0.1232	0.1274	0.0955	0.0581	0.0311	0.0024	–0.0161
	Winner – Loser	0.1098	0.1123	0.0931	0.0475	0.0038	–0.0157	–0.0333	–0.0453
	t-stat	(1.56)	(2.36)[a]	(2.42)[a]	(1.37)	(0.11)	(–0.50)	(–1.15)	(–1.65)
	Loser	0.0299	0.0377	0.0621	0.0610	0.0560	0.0438	0.0278	0.0251
36	Winner	0.1242	0.1446	0.1133	0.0687	0.0271	–0.0086	–0.0347	–0.0554
	Winner – Loser	0.0944	0.1070	0.0512	0.0077	–0.0289	–0.0523	–0.0625	–0.0805
	t-stat	(1.32)	(2.26)[a]	(1.30)	(0.22)	(–0.87)	(–1.69)	(–2.20)[a]	(–2.99)[b]
	Loser	0.0707	0.0736	0.0741	0.0644	0.0511	0.0373	0.0264	0.0288
48	Winner	0.1861	0.1406	0.0932	0.0433	–0.0125	–0.0450	–0.0726	–0.0868
	Winner – Loser	0.1154	0.0670	0.0191	–0.0211	–0.0636	–0.0823	–0.0990	–0.1157
	t-stat	(1.61)	(1.37)	(0.46)	(–0.58)	(–1.90)	(–2.66)[b]	(–3.48)[b]	(–4.23)[b]

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

4.3.2 Momentum over the period 1995 to 2000

The SHSE Composite Index increased from 512.80 points on 19th January 1996 to a historical high point of 2,245.42 on 14th June 2001, and then fell to a low point 998.23 on 6th June 2005. I, therefore, use this as the basis to define an Up or Down market period in that, when the stock market earns more than the risk free rate in a certain time period, it is categorised as Up and, when less than the risk free rate, it is categorised as Down. The three-month household deposit interest rate is used as the risk free rate. I therefore divide the whole sample period into an Up market for the period January 1995 to December 2000 and a Down market for the period January 2001 to December 2006.[25] To investigate whether there is any difference in the effectiveness of momentum strategies in the opposite market conditions, I examine returns of momentum strategies for the two sub-periods.

Table 4.2 reports the returns of winner minus loser portfolios for the first sub-period from 1995 to 2000. Panel A of Table 4.2 shows that only eight out of 32 strategies generate positive returns, and none of them is statistically significant. The 24-24, 24-36, and 36-24 strategies generate profits of 0.040 per cent per week (t-stat = 0.54), 0.008 per cent per week (t-stat = 0.15), and 0.009 per cent per week (t-stat = 0.12), respectively. The average profit is only 0.019 per cent per week, or around 1.00 per cent per year, much lower than the profit of counterparts from 1995 to 2006 shown in Panel A of Table 4.1. Similar results are found in Panel B of Table 4.2 when momentum

[25] Excluding 2006, during which the China stock market experienced a big bounce, I re-examine whether momentum strategies show significantly profitable during the longest depressed period June 2001 to June 2005. Additional unreported results supports the conclusion. For example, the 36-24 strategy yields a higher and more significant profit of 0.379 per cent per week, or 19.7 per cent per year (t-stat = 6.43).

strategies are lagged by four weeks between performance ranking period and portfolio holding period. The 24-24, 24-36, and 36-24 strategies generate profits of 0.041 per cent per week (t-stat = 0.55), 0.013 per cent per week (t-stat = 0.23), and 0.004 per cent per week (t-stat = 0.06), respectively.

The non-existence of the momentum effect over the period 1995 to 2000 is comparable to Wang (2004), who examines relative strength strategies over the July 1994 to December 2000 interval in the China stock market. Wang (2004) also finds that during the market booming period the average return is negative for all of the relative strength strategies of buying past winners and selling past losers, with a few exceptions. For example, the 24-9 strategy with a performance ranking period of 24 months and a portfolio holding period of nine months yields the largest return in absolute terms, an average return of –0.85 per cent per month (t-stat = –2.56). For the symmetric strategies with the same performance ranking and portfolio holding periods, the returns to these relative strength strategies are negative and significant except for the 3-3 strategy (positive but insignificant) and the 6-6 strategy.

Table 4.2: Weekly returns on momentum strategies over the period January 1995 to December 2000

The winner minus loser portfolios are formed based on past F-week returns and held for H weeks over the period January 1995 to December 2000. The values of F and H for the different strategies are indicated in the first column and row, respectively. The stocks are ranked in ascending order on the basis of past F-week returns and an equally weighted portfolio of stocks in the lowest past return decile is the loser portfolio (D1) and an equally weighted portfolio of the stocks in the highest return decile is the winner portfolio (D10). The average weekly returns of these portfolios are presented as percentages. The winner minus loser portfolios presented in Panel A are formed immediately after performance ranking periods, while the winner minus loser portfolios presented in Panel B are formed with a four-week skip between performance ranking and portfolio holding periods. The t-statistics are reported in parentheses.

F		H = 12	24	36	48	60	72	84	96
Panel A: No skip between performance ranking and portfolio holding periods									
	Loser	0.4523	0.3736	0.4396	0.4463	0.4737	0.4910	0.4772	0.4641
12	Winner	0.4159	0.4291	0.3937	0.4559	0.4264	0.4154	0.4050	0.3751
	Winner – Loser	–0.0364	0.0555	–0.0459	0.0096	–0.0473	–0.0756	–0.0721	–0.0890
	t-stat	(–0.33)	(0.77)	(–0.80)	(0.21)	(–1.14)	(–2.02)[a]	(–2.18)[a]	(–2.88)[b]
	Loser	0.2992	0.3553	0.4203	0.4457	0.4626	0.4660	0.4584	0.4403
24	Winner	0.4008	0.3953	0.4288	0.4543	0.4175	0.3915	0.3681	0.3343
	Winner – Loser	0.1016	0.0401	0.0084	0.0087	–0.0451	–0.0745	–0.0903	–0.1060
	t-stat	(0.88)	(0.54)	(0.15)	(0.18)	(–1.06)	(–1.91)	(–2.60)[b]	(–3.30)[b]
	Loser	0.3844	0.4285	0.4848	0.4911	0.4870	0.4737	0.4557	0.4434
36	Winner	0.3582	0.4373	0.4311	0.4250	0.3803	0.3379	0.3174	0.2661
	Winner – Loser	–0.0262	0.0087	–0.0537	–0.0661	–0.1067	–0.1358	–0.1383	–0.1773
	t-stat	(–0.22)	(0.12)	(–0.97)	(–1.38)	(–2.47)[a]	(–3.56)[b]	(–4.09)[b]	(–5.95)[b]
	Loser	0.4729	0.5150	0.5323	0.5222	0.4933	0.4759	0.4665	0.4721
48	Winner	0.5157	0.4895	0.4447	0.4253	0.3456	0.3023	0.2656	0.2320
	Winner – Loser	0.0428	–0.0255	–0.0876	–0.0969	–0.1477	–0.1736	–0.2009	–0.2401
	t-stat	(0.36)	(–0.35)	(–1.49)	(–1.88)	(–3.33)[b]	(–4.38)[b]	(–5.91)[b]	(–7.75)[b]
Panel B: A four-week skip between performance ranking and portfolio holding periods									
	Loser	0.4104	0.3608	0.4333	0.4420	0.4805	0.4880	0.4773	0.4611
12	Winner	0.4140	0.4298	0.3997	0.4586	0.4236	0.4167	0.3989	0.3717
	Winner – Loser	0.0036	0.0691	–0.0336	0.0166	–0.0569	–0.0712	–0.0784	–0.0894
	t-stat	(0.03)	(0.95)	(–0.59)	(0.36)	(–1.38)	(–1.89)	(–2.35)[a]	(–2.88)[b]
	Loser	0.2721	0.3600	0.4239	0.4529	0.4693	0.4664	0.4605	0.4419
24	Winner	0.4040	0.4009	0.4368	0.4537	0.4151	0.3875	0.3638	0.3254
	Winner – Loser	0.1319	0.0409	0.0129	0.0009	–0.0542	–0.0789	–0.0966	–0.1165
	t-stat	(1.15)	(0.55)	(0.23)	(0.02)	(–1.28)	(–2.04)[a]	(–2.79)[b]	(–3.73)[b]
	Loser	0.3890	0.4401	0.4998	0.4962	0.4921	0.4757	0.4583	0.4484
36	Winner	0.3741	0.4443	0.4327	0.4236	0.3750	0.3343	0.3088	0.2603
	Winner – Loser	–0.0149	0.0042	–0.0671	–0.0726	–0.1171	–0.1414	–0.1495	–0.1881
	t-stat	(–0.13)	(0.06)	(–1.20)	(–1.49)	(–2.74)[b]	(–3.70)[b]	(–4.50)[b]	(–6.41)[b]
	Loser	0.4761	0.5240	0.5369	0.5226	0.4951	0.4744	0.4705	0.4766
48	Winner	0.5305	0.4835	0.4381	0.4139	0.3331	0.2891	0.2561	0.2247
	Winner – Loser	0.0544	–0.0404	–0.0988	–0.1087	–0.1620	–0.1853	–0.2144	–0.2519
	t-stat	(0.46)	(–0.55)	(–1.65)	(–2.12)[a]	(–3.64)[b]	(–4.75)[b]	(–6.33)[b]	(–8.14)[b]

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

4.3.3 Momentum over the period 2001 to 2006

Panel A of Table 4.3 shows that over the period 2001 to 2006, 30 out of 32 strategies generate positive returns and most of them are statistically significant. The maximum return is from the 36-24 strategy, which generates a profit of 0.213 per cent per week (*t*-stat = 3.61), or 11.10 per cent per year. The 24-24 and 24-36 strategies generate profits of 0.142 per cent per week (*t*-stat = 2.36) and 0.179 per cent per week (*t*-stat = 3.83), respectively. The average return of the 24-24, 24-36, and 36-24 strategies is 0.178 per cent per week, or 9.27 per cent per year.

Panel B of Table 4.3 shows similar evidence. The maximum return is also from the 36-24 strategy, which generates a profit of 0.234 per cent per week (*t*-stat = 3.97), or 12.10 per cent per year. The 24-24 and 24-36 strategies generate profit of 0.180 per cent per week (*t*-stat = 3.01) and 0.195 per cent per week (*t*-stat = 4.17), respectively. The average return of the 24-24, 24-36, and 36-24 strategies is 0.203 per cent per week, or 10.57 per cent per year. The magnitude is close to that in the US stock market, where the most successful zero-cost strategy selecting stocks based on their returns over the previous 12 months and then holding the portfolio for three months yields 1.31 per cent per month when there is no time lag between the portfolio ranking and holding periods. The 12-3 momentum strategy generates a profit of 1.49 per cent per month when there is one-week lag between the portfolio ranking and holding periods (Jegadeesh and Titman (1993)). More important, it is loser portfolios instead of winner portfolios that drive the momentum effect because loser portfolios lose much more than do winner portfolios during the Down period. For example, for the 24-24 strategy, the loser portfolios generate a profit of –0.266 per cent per week, while the winner portfolios generate a profit of –0.086 per cent per week.

In sum, according to a comparison of the momentum effect in two opposite sub-periods, I confirm that momentum strategies are profitable in the depressed period rather than the booming period, which challenges the prediction of the behavioural theories. However, the result is consistent with the finding of Munira and Muradoglu (2010). Zhang (2006) measures ambiguity with the arrival of public information and shows momentum profits in high information, ambiguous stocks remain unexplained. Avramov et al. (2007) also argue that momentum returns are higher during recessionary periods when credit risk is high. Munira and Muradoglu (2010) show that momentum is due to uncertainty revealed in credit risk and can be explained by macroeconomic variables.They demonstrate that momentum returns result mainly from speculative-grade stocks during economic contractions. Momentum returns from speculative-grade stocks disappear after controlling for macroeconomic risk factors. Momentum returns provide compensation for uncertainties imposed on investors on investors due to high credit risk in individual firms and uncertainties imposed by economy. In addition, Lasfer, Muradoglu, and Lin (2008) analyse the stock price behaviour of A-shares and B-shares following a period of stock market stress in China. The prices of A-shares are relatively random in the short-term windows, while those of B-shares carry on increasing significantly following both positive and negative shocks. The trend is more pronounced for large stocks with high liquidity, in contrast to the efficient market hypotheses expectations. They relate this result to the high level of optimism foreign investors. A formal test and discussion with the definition of market states proposed by Cooper et al. (2004) will be conducted in Section 4.4.

Table 4.3: Weekly returns on momentum strategies over the period January 2001 to December 2006

The winner minus loser portfolios are formed based on past F-week returns and held for H weeks over the period January 2001 to December 2006. The values of F and H for the different strategies are indicated in the first column and row, respectively. The stocks are ranked in ascending order on the basis of past F-week returns and an equally weighted portfolio of stocks in the lowest past return decile is the loser portfolio (D1) and an equally weighted portfolio of the stocks in the highest return decile is the winner portfolio (D10). The average weekly returns of these portfolios are presented in percentage in this table. The winner minus loser portfolios presented in Panel A are formed immediately after performance ranking periods, while the winner minus loser portfolios presented in Panel B are formed with a four-week skip between performance ranking and portfolio holding periods. The t-statistics are reported in parentheses.

F		H = 12	24	36	48	60	72	84	96
Panel A: No skip between performance ranking and portfolio holding periods									
	Loser	–0.1541	–0.2383	–0.2743	–0.2913	–0.3056	–0.3248	–0.3565	–0.3611
12	Winner	–0.3054	–0.2413	–0.1984	–0.2064	–0.2537	–0.2777	–0.3081	–0.3286
	Winner – Loser	–0.1512	–0.0029	0.0759	0.0850	0.0519	0.0471	0.0484	0.0325
	t-stat	(–1.74)	(–0.05)	(1.59)	(2.13)[a]	(1.46)	(1.47)	(1.88)	(1.43)
	Loser	–0.1819	–0.2474	–0.2605	–0.2751	–0.2975	–0.3194	–0.3420	–0.3557
24	Winner	–0.1696	–0.1053	–0.0813	–0.1396	–0.1998	–0.2342	–0.2698	–0.2955
	Winner – Loser	0.0123	0.1421	0.1792	0.1355	0.0978	0.0852	0.0722	0.0602
	t-stat	(0.14)	(2.36)[a]	(3.83)[b]	(3.36)[b]	(2.67)[b]	(2.52)[a]	(2.69)[b]	(2.47)[a]
	Loser	–0.1921	–0.2256	–0.2400	–0.2637	–0.2947	–0.3093	–0.3424	–0.3555
36	Winner	–0.0453	–0.0124	–0.0383	–0.1122	–0.1783	–0.2186	–0.2571	–0.2811
	Winner – Loser	0.1468	0.2133	0.2017	0.1516	0.1164	0.0907	0.0852	0.0744
	t-stat	(1.64)	(3.61)[b]	(4.21)[b]	(3.64)[b]	(3.00)[b]	(2.61)[b]	(3.00)[b]	(2.83)[b]
	Loser	–0.1511	–0.2109	–0.2395	–0.2728	–0.2903	–0.3132	–0.3406	–0.3512
48	Winner	0.0019	–0.0201	–0.0594	–0.1333	–0.1968	–0.2380	–0.2752	–0.2979
	Winner – Loser	0.1530	0.1908	0.1800	0.1395	0.0935	0.0753	0.0654	0.0532
	t-stat	(1.68)	(3.06)[b]	(3.53)[b]	(3.12)[b]	(2.27))[a]	(2.02)[a]	(2.11)[a]	(1.85)
Panel B: A four-week skip between performance ranking and portfolio holding periods									
	Loser	–0.2043	–0.2640	–0.2866	–0.2991	–0.3115	–0.3321	–0.3624	–0.3643
12	Winner	–0.2660	–0.2205	–0.1842	–0.1975	–0.2501	–0.2757	–0.3073	–0.3278
	Winner – Loser	–0.0617	0.0435	0.1024	0.1015	0.0614	0.0565	0.0551	0.0365
	t-stat	(–0.71)	(0.73)	(2.13)[a]	(2.53)[a]	(1.73)	(1.74)	(2.13)[a]	(1.59)
	Loser	–0.2166	–0.2661	–0.2654	–0.2792	–0.3023	–0.3722	–0.3444	–0.3579
24	Winner	–0.1266	–0.0861	–0.0708	–0.1377	–0.1994	–0.2352	–0.2722	–0.2955
	Winner – Loser	0.0900	0.1800	0.1947	0.1415	0.1030	0.0880	0.0722	0.0623
	t-stat	(1.02)	(3.01)[b]	(4.17)[b]	(3.49)[b]	(2.79)[b]	(2.59)[b]	(2.67)[b]	(2.54)[a]
	Loser	–0.2208	–0.2341	–0.2435	–0.2689	–0.2972	–0.3121	–0.3442	–0.3562
36	Winner	–0.0158	–0.0004	–0.0406	–0.1180	–0.1841	–0.2252	–0.2621	–0.2862
	Winner – Loser	0.2051	0.2337	0.2030	0.1508	0.1131	0.0868	0.0821	0.0700
	t-stat	(2.31)[a]	(3.97)[b]	(4.19)[b]	(3.57)[b]	(2.88)[b]	(2.47)[a]	(2.85)[b]	(2.61)[b]
	Loser	–0.1680	–0.2208	–0.2465	–0.2760	–0.2916	–0.3148	–0.3406	–0.3512
48	Winner	0.0263	–0.0199	–0.0666	–0.1408	–0.2057	–0.2444	–0.2820	–0.3029
	Winner – Loser	0.1943	0.2010	0.1799	0.1352	0.0858	0.0704	0.0586	0.0483
	t-stat	(2.14)[a]	(3.22)[b]	(3.49)[b]	(3.00)[b]	(2.05)[a]	(1.86)	(1.86)	(1.66)

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

4.3.4 Momentum in the SHSE and SZSE

However, the finding that the medium-term momentum effect in the China market from 1995 to 2006 is positive, but statistically insignificant, seems to be inconsistent with that found by Naughton et al. (2008), whose analysis is based on the very similar sample period. They find evidence of significant momentum profits from 1995 to 2005, while their sample only contains stocks on the SHSE. In seeking to explore this difference, I conjecture that firms listed on the two stock exchanges may contain different characteristics and therefore exhibit different momentum effects. I therefore examine momentum strategies with firms listed on the two stock exchanges separately.

However, Panel A of Table 4.4 also shows that all momentum strategies on the SZSE yield insignificantly negative returns over the period 1995 to 2006. Panel B of Table 4.4 reports that during the period 1995 to 2000, momentum on the SZSE shows a strong reversal: eight out of 16 momentum strategies generate significantly negative profits. In Panel C of Table 4.4, I find that although 13 out of 16 momentum strategies on the SZSE yield positive returns during the depressed period 2001 to 2006, and eight of them are statistically significant, the magnitude of momentum profits is much lower than that on the SHSE.

In sum, empirical evidence of the momentum effect based on two sub-samples show that momentum is related to the market capitalisation in the China stock market. The larger the market capitalisation, the stronger the momentum effect, the evidence inconsistent with previous reported small size effect.

Table 4.4: Weekly returns on momentum strategies in SHSE and SZSE

The winner minus loser portfolios are formed based on past F-week returns and held for H weeks. The values of F and H for the different strategies are indicated in the first column and row, respectively. The stocks are ranked in ascending order on the basis of past F-week returns and an equally weighted portfolio of stocks in the lowest past return decile is the loser portfolio (D1) and an equally weighted portfolio of the stocks in the highest return decile is the winner portfolio (D10). The average weekly returns of these portfolios are presented as percentages. The winner minus loser portfolios are formed immediately after performance ranking periods containing stocks on the SHSE and SZSE, respectively. The winner minus loser portfolios presented in Panel A, Panel B, and Panel C are examined over the period January 1995 to December 2006, January 1995 to December 2000, and January 2001 to December 2006, respectively. The t-statistics are reported in parentheses.

		The SHSE				The SZSE			
F		**H = 12**	**24**	**36**	**48**	**H = 12**	**24**	**36**	**48**
Panel A: January 1995 to December 2006									
	Loser	0.1411	0.1205	0.0335	0.0264	0.2237	0.1434	0.1479	0.1243
12	Winner	0.0181	0.0752	0.0867	0.0940	0.0778	0.1039	0.0974	0.1137
	Winner – Loser	–0.1230	0.0215	0.0532	0.0677	–0.1459	–0.0394	–0.0505	–0.0106
	t-stat	(–1.81)	(0.47)	(1.48)	(2.13)[a]	(–1.88)	(–0.70)	(–1.04)	(–0.24)
	Loser	0.0157	–0.0188	–0.0162	–0.0121	0.1621	0.1534	0.1524	0.1408
24	Winner	0.0712	0.1057	0.1256	0.1015	0.1258	0.1222	0.1395	0.1218
	Winner – Loser	0.0555	0.1244	0.1417	0.1137	–0.0364	–0.0311	–0.0129	–0.0191
	t-stat	(0.83)	(2.80)[b]	(4.10)[b]	(3.73)[b]	(–0.45)	(–0.54)	(–0.27)	(–0.43)
	Loser	0.0083	–0.0175	–0.0133	–0.0091	0.2026	0.1772	0.1751	0.1556
36	Winner	0.0919	0.1456	0.1261	0.0860	0.1273	0.1528	0.1407	0.0985
	Winner – Loser	0.0836	0.1631	0.1394	0.0952	–0.0753	–0.0244	–0.0343	–0.0571
	t-stat	(1.21)	(3.69)[b]	(3.98)[b]	(3.08)[b]	(–0.93)	(–0.42)	(–0.69)	(–1.28)
	Loser	0.0224	–0.0050	–0.0079	–0.0089	0.2297	0.1955	0.1778	0.1492
48	Winner	0.1647	0.1464	0.1130	0.0677	0.1708	0.1624	0.1165	0.0652
	Winner – Loser	0.1423	0.1513	0.1209	0.0767	–0.0589	–0.0331	–0.0613	–0.0840
	t-stat	(2.09)[a]	(3.38)[b]	(3.37)[b]	(2.40)[a]	(–0.73)	(–0.57)	(–1.23)	(–1.89)
Panel B: January 1995 to December 2000									
	Loser	0.4041	0.3334	0.3563	0.3552	0.6082	0.5488	0.6384	0.6143
12	Winner	0.3395	0.3782	0.3715	0.4313	0.4958	0.5007	0.4703	0.5469
	Winner – Loser	–0.0646	0.0448	0.0152	0.0761	–0.1124	–0.0481	–0.1680	–0.0673
	t-stat	(–0.60)	(0.66)	(0.31)	(1.94)	(–0.90)	(–0.53)	(–2.18)[a]	(–1.00)
	Loser	0.2099	0.2438	0.2706	0.2738	0.5451	0.6479	0.6860	0.6732
24	Winner	0.3133	0.3326	0.3964	0.4322	0.4986	0.4736	0.5145	0.5531
	Winner – Loser	0.1034	0.0888	0.1258	0.1584	–0.0465	–0.1742	–0.1715	–0.1201
	t-stat	(0.95)	(1.29)	(2.63)[b]	(4.22)[b]	(–0.35)	(–1.82)	(–2.20)[a]	(–1.74)
36	Loser	0.2820	0.2803	0.2932	0.3049	0.7215	0.7304	0.7537	0.7191
	Winner	0.2978	0.4076	0.4285	0.4324	0.4794	0.5344	0.5378	0.5205
	Winner – Loser	0.0158	0.1273	0.1353	0.1275	–0.2421	–0.1960	–0.2159	–0.1986
	t-stat	(0.14)	(1.93)	(2.92)[b]	(3.50)[b]	(–1.78)	(–2.05)[a]	(–2.71)[b]	(–2.80)[b]
48	Loser	0.3099	0.3029	0.3129	0.3179	0.7986	0.7903	0.7794	0.7306
	Winner	0.4586	0.4665	0.4578	0.4487	0.5827	0.5740	0.5098	0.4770
	Winner – Loser	0.1487	0.1637	0.1450	0.1308	–0.2159	–0.2163	–0.2696	–0.2536
	t-stat	(1.35)	(2.53)[a]	(3.14)[b]	(3.56)[b]	(–1.57)	(–2.28)[a]	(–3.36)[b]	(–3.57)[b]

continued

Table 4.4 (continued)

Panel C: January 2001 to December 2006									
12	Loser	−0.1298	−0.2252	−0.2604	−0.2798	−0.1540	−0.2345	−0.2724	−0.2941
	Winner	−0.2953	−0.2210	−0.1709	−0.1828	−0.3265	−0.2803	−0.2452	−0.2445
	Winner − Loser	−0.1655	0.0041	0.0896	0.0970	−0.1725	−0.0458	0.0272	0.0496
	t-stat	(−1.97)	(0.07)	(1.88)	(2.40)[a]	(−1.90)	(−0.74)	(0.55)	(1.21)
24	Loser	−0.1695	−0.2398	−0.2540	−0.2650	−0.1679	−0.2351	−0.2500	−0.2742
	Winner	−0.1546	−0.0694	−0.0479	−0.1133	−0.2016	−0.1566	−0.1266	−0.1760
	Winner − Loser	0.0149	0.1705	0.2061	0.1517	−0.0337	0.0785	0.1234	0.0982
	t-stat	(0.17)	(2.85)[b]	(4.37)[b]	(3.68)[b]	(−0.36)	(1.27)	(2.57)[b]	(2.38)[a]
36	Loser	−0.1811	−0.2267	−0.2370	−0.2621	−0.1686	−0.1984	−0.2235	−0.2500
	Winner	−0.0206	0.0188	−0.0173	−0.0934	−0.1112	−0.0736	−0.0840	−0.1493
	Winner − Loser	0.1605	0.2455	0.2197	0.1688	0.0573	0.1248	0.1395	0.1007
	t-stat	(1.84)	(4.15)[b]	(4.53)[b]	(3.94)[b]	(0.61)	(2.06)[a]	(2.84)[b]	(2.41)[a]
48	Loser	−0.1509	−0.2134	−0.2448	−0.2785	−0.1321	−0.1916	−0.2217	−0.2570
	Winner	0.0298	−0.0007	−0.0449	−0.1193	−0.0624	−0.0630	−0.0912	−0.1614
	Winner − Loser	0.1807	0.2127	0.1999	0.1592	0.0696	0.1286	0.1305	0.0956
	t-stat	(2.00)[a]	(3.36)[b]	(3.82)[b]	(3.43)[b]	(0.74)	(2.03)[a]	(2.51)[a]	(2.12)[a]

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

The result is consistent with that of Kang et al. (2002). They find that in the case of value-weighted portfolio strategies, momentum profits are more distinct compared with those in the case of equal-weighted portfolio strategies. I attribute this big size effect to the unique lead-lag structure in China, since the large firms lead small firms in short horizons, whereas small firms lead large firms in relatively longer horizons. The lead-lag effect is stronger for high trading volume stocks. The momentum profits found for high volume stocks mostly represent the lead-lag effect. A more detailed examination of the large size effect will be conducted in Chapter 5.

4.3.5 Momentum duration

A central prediction of the behavioural theory is that the momentum profits will reverse in the long run once investors observe future news and realise their errors. Based on initial underreaction to information and subsequent overreaction, the behavioural models of both Daniel et al. (1998) and Hong and Stein (1999) predict that overconfidence results in medium-term momentum and eventually leads to stock price reversal in the long run.

The collapse of momentum investing over the long horizons has been documented in previous literature. Conrad and Kaul (1998), for example, with the use of the US data, study the performance of momentum strategy within eight holding periods varying in length from one week to 36 months. They find that when the holding period goes beyond twelve months, the momentum strategy is unable to achieve a positive profit. Mengoli (2004) also shows that in the Italian stock market the profitability of momentum investing is weakened when a holding period moves from one year to three years. In short, previous studies record the negative average monthly returns when the holding period goes beyond one year, but this study demonstrates that the average monthly return on the winner minus loser portfolio is still significantly positive up to two years. The finding of the longer duration indicates that the momentum effect not only works over medium-term intervals but is also able to produce profits over the relatively long horizons in the China stock market.

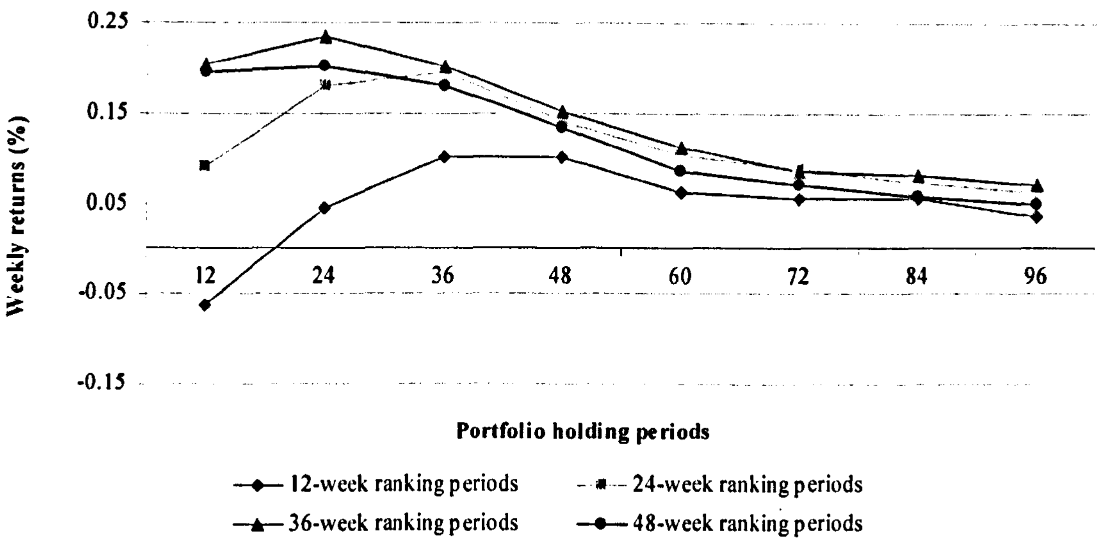

Figure 4.1: Weekly profits of momentum strategies in the depressed periods (January 2001 to December 2006)

As can be seen from Figure 4.1, each of the strategies based on past twelve- to 48-week returns exhibit a peak at around the 24- to 36-week holding periods with subsequent returns tailing off in the longer holding periods over the period 2001 to 2006.[26] The magnitude of abnormal returns maintains a downward tendency but still statistically significant as progressing from 60- to 96-week holding periods. For example, the momentum strategy with a 36-week ranking period generates significant profits of 0.116 per cent per week (*t*-stat = 3.00) and 0.074 per cent per week (*t*-stat = 2.83) in the following 60- and 96-week holding periods, respectively. This data suggests that momentum profits in the China stock market remain in longer post-holding periods compared with those in developed markets.

[26] There is a four-week lag between performance ranking and portfolio holding periods in all momentum strategies shown in Figure 4.1.

Table 4.5 presents the monthly returns of momentum strategies (with a six-month performance ranking period) in the following 12- and 24-month portfolio holding periods in different markets. I observe that in the 24-month holding period all momentum profits in developed markets are either negative or insignificantly positive. As I predict, the 24-96 strategy with a 24-week (or six-month) ranking period still generates a significantly positive profit of 0.060 per cent per week (t-stat = 2.47) in the subsequent 96-week (or 24-month) holding period in the China stock market. I attribute the longer momentum duration to the lack of the short sales opportunities in the China stock market. In particular, in the depressed market, investors tend to sell winners and hold losers to avoid the direct capital loss. A detailed examination of the role of short sales constraints in explaining momentum profits will be carried out in Chapter 5.

4.4 Momentum and market states

4.4.1 Definition of market states developed by Cooper et al. (2004)

A formal test is conducted in this section to examine whether conditioning on the state of the market is important to the profitability of momentum strategies. Following the definitions proposed by Cooper et al. (2004), I define two opposite states: 1), the *Up* market, when the lagged three-year market return is non-negative, and 2), the *Down* market, when the lagged three-year market return is negative. The equally weighted return on the SHSE and SZSE A-share Indices is used to calculate the market return of the China stock market.

Table 4.5: Comparison of momentum profits in the 12- and 24-month holding periods

All momentum strategies are based on a six-month ranking period and 12- and 24-month holding periods. The weekly returns of 24-48 and 24-96 strategies over the period 2001 to 2006 in the China stock market are converted into average monthly returns. All returns are presented as percentages and the *t*-statistics are reported in parentheses.

Sample	Portfolio holding periods			
	12-month		24-month	
	Mean	*t*-stat	Mean	*t*-stat
The China stock market (2001-2006)	0.54	(3.36)[b]	0.24	(2.47)[a]
NYSE, AMEX, and Nasdaq (1965-1981)[c]	1.07	(4.33)[b]	–0.38	(–2.33)[a]
NYSE, AMEX, and Nasdaq (1982-1998)[c]	1.16	(6.41)[b]	–0.23	(–1.70)
NYSE, AMEX, and Nasdaq (1965-1998)[c]	1.11	(7.28)[b]	–0.31	(–2.87)[b]
NYSE and AMEX (1996-1995)[d]	0.88	(4.18)[b]	–0.09	(–0.66)
NYSE, AMEX, and Nasdaq (1963-1995)[e]	0.40	(5.01)[b]	0.04	(0.67)
The U.K. stock market (1955-1996)[f]	0.70	(3.85)[b]	0. 29	(1.51)
The U.K. stock market (1955-1976)[f]	0.37	(1.50)	0.12	(0.47)
The U.K. stock market (1977-1996)[f]	1.11	(4.21)[b]	0.50	(1.73)

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

[c]: Jegadeesh and Titman (2001)

[d]: Lee and Swaminathan (2000)

[e]: Moskowitz and Grinblatt (1999)

[f]: Hon and Tonks (2003)

The following analysis concentrates on the 24-24 and 36-36 momentum strategies. Panel A of Table 4.6 shows that following the Up markets, both 24-24 and 36-36 strategies generate insignificantly negative profits, –0.143 per cent per week (*t*-stat = –0.25) and –0.062 per cent per week (*t*-stat = –1.39), respectively. While, Panel B of Table 4.6 shows that following the Down markets, momentum profits of 24-24 and 36-36 strategies are both positive and statistically significant, 0.245 per cent per week (*t*-stat = 3.44) and 0.218 per cent per week (*t*-stat = 3.72). The magnitude is very close to previous finding presented in Table 4.3. Panel C of Table 4.6 further shows that the momentum profits of both 24-24 and 36-36 strategies are statistically greater following the Down markets than following the Up markets (*t*-stat = 7.69, 10.33).

Table 4.6: Average weekly profits following three-year Up and Down states

An Up (Down) market is defined as the equally weighted return of the SHSE and SZSE A-share Indices over past three years are non-negative (negative). Reported below are the mean weekly profits of the 24-24 and 36-36 strategies over the period January 1995 to December 2006. Panel A and Panel B report the profits following Up and Down markets, respectively. Panel C reports the *t*-statistics for the test of the equality of profits between Up and Down markets. The average weekly returns of these portfolios are presented as percentages. The *t*-statistics are reported in parenthesis.

	24-24 strategy	**36-36 strategy**
Panel A: Average weekly profits following lagged three-year Up markets		
Loser	0.0793	0.0696
Winner	0.0650	0.0079
Winner – Loser	–0.0143	–0.0617
t-stat	(–0.25)	(–1.39)
Panel B: Average weekly profits following lagged three-year Down markets		
Loser	–0.2558	–0.2307
Winner	–0.0106	–0.0129
Winner – Loser	0.2452	0.2179
t-stat	(3.44)[b]	(3.72)[b]
Panel C: Test for equality		
Down – Up = 0	(7.69)[b]	(10.33)[b]

[b] indicates statistical significance at the 1 percent level.

Cooper et al. (2004) argue that the longer horizons should capture greater differences in market states, but the longer horizons also yield fewer observations of Down states. I plot the number of Down weeks in each year for the lagged one-year market return and for the lagged three-year market return as well. Figure 4.2 shows that the number of Down states decreases dramatically as the number of years defining market states increases. In particular, the one-year market definition produces 271 Down weeks (47.05 per cent of the sample period) and the one-year Down markets are more dispersed across the sample period. While the three-year market definition produces 183 Down weeks (31.77 per cent of the sample period), they are mainly contained with the period from 2002 to 2006.

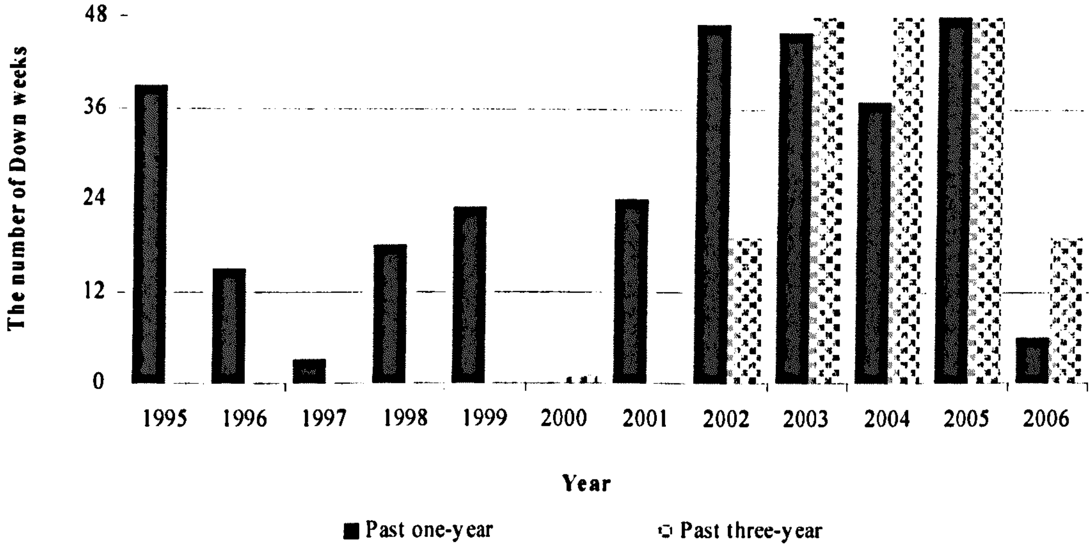

Figure 4.2: The number of lagged one- and three-year Down states (January 1995 to December 2006)

I next use lagged one- and two-year market returns to define the state of the market. Table 4.7 shows that the previous findings are robust to these alternative definitions. Both 24-24 and 36-36 strategies generate significantly positive momentum profits following the Down markets and insignificant profits following the Up markets. Moreover, momentum profits between Up and Down markets are also significantly different using both alternative state proxies.

Table 4.7: Average weekly profits following with the use of alternative definitions of market states

An Up (Down) market is defined as the equally weighted return of the SHSE and SZSE A-share Indices over past one or two years are non-negative (negative). Reported below are the mean weekly profits of the 24-24 and 36-36 strategies over the period January 1995 to December 2006. Panel A and Panel B report the profits following Up and Down markets, respectively. Panel C reports the t-statistics for the test of the equality of profits across Up and Down markets. The average weekly returns of these portfolios are presented as percentages. The t-statistics are reported in parenthesis.

	Lagged one-year market return		Lagged two-year market return	
	24-24 strategy	36-36 strategy	24-24 strategy	36-36 strategy
Panel A: Average weekly profits following Up states				
Loser	0.1085	0.1456	0.0878	0.1256
Winner	0.1500	0.1046	0.1248	0.0751
Winner – Loser	0.0415	–0.0409	0.0370	–0.0504
t-stat	(0.60)	(–0.69)	(0.55)	(–0.95)
Panel B: Average weekly profits following Down states				
Loser	–0.0790	–0.0128	–0.0257	–0.0189
Winner	0.0985	0.1211	0.1927	0.1540
Winner – Loser	0.1775	0.1339	0.2183	0.1729
t-stat	$(2.72)^{b}$	$(2.55)^{a}$	$(3.15)^{b}$	$(2.90)^{b}$
Panel C: Test for equality				
Down – Up = 0	$(3.79)^{b}$	$(5.80)^{b}$	$(5.05)^{b}$	$(7.71)^{b}$

^{a} and ^{b} indicate statistical significance at the 5 percent and 1 percent levels, respectively.

4.4.2 The State of the market as a continuous variable

To test the robustness of the result based on the definitions proposed by Cooper et al. (2004), I further examine the relation between momentum profits and lagged market return using the market return as a continuous variable. I attempt to confirm whether momentum increases monotonically with the decline of the lagged market return, and whether momentum profits are greatest when the lagged market return is lowest. To address this, I regress momentum profits on lagged market returns (*Lagmkt*) and the square of lagged market returns (*Lagmkt*^{2}). I report the results using the lagged two-year market return as the state proxy. The regression model is shown as follows:

$$R_p - R_f = \alpha + \beta_1 \times Lagmkt + \beta_2 \times Lagmkt^2 + \varepsilon, \qquad (4.2)$$

where R_p represents the weekly return on the winner minus loser portfolio; R_f represents the risk free return, measured by the weekly three-month household deposit interest rate; *Lagmkt* represents the lagged two-year market return.

As shown in Panel A of Table 4.8, momentum profits for the 24-24 and 36-36 strategies are both significantly negatively related to lagged market return, confirming the negative relation between momentum profits and market states in China: momentum strategies generate high (low) profits when lagged market return is low (high). The fact that momentum profits are positively related to the square of lagged market returns suggests that profits do not decrease linearly with lagged market returns. Panel B of Table 4.8 reports momentum profits by ranking the market's two-year lagged returns into quintiles (from highest to lowest market return). I find that momentum strategies are not profitable in quintiles 1 (highest) and 2, then increase dramatically at the median levels of lagged market return, and peak at quintile 4.[27] In sum, the results using the definitions of Cooper et al. (2004) support previous conclusion that momentum profits in China are related to depressed market conditions.

4.4.3 Implications of behavioural theories

Since the risk-based asset pricing models like the CAPM and the Fama and French (1993) three-factor model do not explain momentum returns, an extensive range of literature turns to behavioural theories. Daniel et al. (1998) and Hong and Stein (1999)

[27] The results are robust when the lagged one- or two-year market returns are used as the state proxies.

each employ different behavioural or cognitive biases to explain momentum profits and attribute these returns to investors' overreaction to information. For example, Daniel et al. (1998) assume that investors are overconfident about their private information and overreact to it. Their theory can be extended to predict differences in momentum profits across different market states. If overconfidence is in fact higher following market increases, then the overreactions will be stronger following these Up markets and generates greater momentum profits. Hong and Stein (1999) also predict relative changes in price dynamics depending on the state of the market that momentum profits will be greater following market gains.

However, empirical evidence that momentum profits *exclusively* follow Down periods in the China stock market is opposite to the behavioural prediction of Daniel et al. (1998) and Hong and Stein (1999). I attribute the large magnitude of momentum profits following the Down markets to the disposition effect (Grinblatt and Han (2005)). Following a relatively depressed market, investors generally tend to sell winner portfolios immediately and hold the loser portfolios. Since in a market without the permission of the short sales, the only way for investors with loser portfolios to avoid the direct capital loss is to hold and wait until the market becomes booming again. Therefore, following the Down market, past loser stocks appear to keep the momentum in returns, while prior winner stocks tend not to display significant continuation in prices, consistent with the evidence that momentum strategies are profitable mainly because loser portfolios lose more than winner portfolios. There will be a positive spread between prices and their fundamental values for winners and a negative spread for losers, resulting in the profitability of momentum strategies.

Table 4.8: The state of the market as a continuous variable

The momentum profits of the 24-24 and 36-36 strategies are regressed on an intercept, lagged two-year market return (*Lagmkt*), and lagged two-year market return squared (*Lagmkt²*). Panel A provides the weekly regression coefficients and *t*-statistics. In Panel B, momentum profits are allocated each week *t* into quintiles based on the full sample of lagged two-year market returns. The average weekly returns of these portfolios are presented as percentages. The *t*-statistics are reported in parenthesis.

	24-24 strategy				36-36 strategy			
Panel A: Lagged two-year market return								
	Intercept	Lagmkt	Lagmkt²	Adj. R²	Intercept	Lagmkt	Lagmkt²	Adj. R²
Mean	0.115	−0.356	18.071	0.061	0.094	−0.396	9.000	0.142
t-stat	(2.27)[a]	(−1.92)	(0.48)		(2.31)[a]	(−2.80)[b]	(0.33)	
Panel B: Momentum profits by quintiles of lagged two-year market states								
	High	2	3	4	Low	High	2	3	4	Low
Mean	0.005	0.001	−0.050	0.261	0.211	−0.109	−0.085	0.008	0.271	0.143
t-stat	(0.05)	(0.01)	(−0.50)	(2.85)[b]	(2.03)[a]	(−1.60)	(−1.03)	(0.09)	(3.18)[b]	(1.91)

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

4.5 Summary of findings

I find no significant evidence of momentum profits over the period 1995 to 2000, while momentum strategies exhibit significant profits over the period 2001 to 2006 such that a relatively depressed market is associated with a strong momentum effect in the China stock market. A further study with the use of definition of market states proposed by Cooper et al. (2004) confirms the result that profits to momentum strategies depend critically on the state of the market. A six-month momentum portfolio is profitable only following periods of Down market states, inconsistent with the behavioural models of Daniel et al. (1998) and Hong and Stein (1999). The momentum duration is longer, since the lack of short sales opportunities in the China stock market. In the absence of both short sales and derivative markets in China, one prediction I offer and explore is that profitable momentum holding periods are likely to be longer than those reported elsewhere.

In addition, momentum strategies with firms listed on the SHSE generate significantly positive profits in different sample periods; momentum strategies with firms listed on SZSE only yield significantly positive momentum profits during the depressed time period 2001 to 2006, and even significantly negative returns in the bull market 1995 to 2000. I take this to imply potentially different characteristic between the stocks quoted on the two stock exchanges as one reflection of a large size effect I investigate.

Appendix 4.1 The calculation of *t*-statistics

Frequent replications with overlapping test periods increase the power of the statistical tests. However, autocorrelation of stock returns is inevitable because the *H*-week holding returns have a great deal of overlapping from week to week. In addition, a lot of stocks contained in the winner (loser) portfolio will remain as winner (loser) in the next week. As a result, it is invalid to use the simple *t*-statistic to evaluate the significance of the average return in the whole sample. The following approach is employed to rule out the concern for autocorrelation. In each week t, a winner stock, based on the past *F*-week returns, is considered a winner in week $t + 1$, $t + 2$, ..., and $t + \mathrm{H}$, even if it perform very poor from the week $t + 1$ to the week $t + \mathrm{H}$. In each week t, I compute the average returns for all stocks labelled as winner, no matter they get their winner name in week $t - 1$, $t - 2$, ..., or $t - \mathrm{H}$. If a stock is considered a winner in the week $t - \mathrm{H} - 1$, it is not necessarily included in the winner group any more. This technique avoids the issue of overlapping and allows us to use a simple t-statistic for weekly returns. The winner-loser portfolio test statistic is calculated as:[28]

$$t - stat = \frac{R_{winner} - R_{loser}}{\sqrt{\frac{\sigma^2_{winner}}{N_{winner}} + \frac{\sigma^2_{loser}}{N_{loser}}}}, \tag{5.3}$$

where R_{winner} represents the mean weekly return on the winner portfolio; R_{loser} represents the mean weekly return on the loser portfolio; σ^2_{winner} represents the variance of the winner portfolio; σ^2_{loser} represents the variance of the loser portfolio; N_{winner} represents the number of observations in the winner portfolio; and N_{loser} represents the number of observations in the loser portfolio.

[28] Notice that transaction costs that investors face in stock markets are ignored. As in the majority of studies in the field (see, e. g., Liu et al. (1999) and Hon and Tonks (2003)), it is assumed that momentum profits are high enough to cover transaction costs. A cost of the magnitude of around 2 per cent cannot outweigh the momentum profitability, considering that momentum strategies are not transaction-intensive, and so the trading frequency is limited.

CHAPTER 5

MOMENTUM AND SHORT SALES CONSTRAINTS

5.1 Introduction

This chapter begins with an investigation of the role of a fully short sale constrained environment in relation to momentum in China. Unlike the direct transaction cost, which can be measured by bid-ask spread and commission fees, the cost of short sales is not readily available. I therefore employ a series of observable stock characteristics suggested by D'Avolio (2002), such as firm size, share turnover, volatility, IPO status, and B/M, as proxies for short sales constraints. Further, I combine these determinants of short sales constraints into an aggregate measure called *Prob*, using a modified model developed by D'Avolio (2002). *Prob* represents the magnitude of aggregate short sales constraints for a stock.

I find that short sales constraints play an important role in explaining momentum in the China stock market. Momentum profits are positively related to the determinants of short sales constraints over the period 2001 to 2006. Specifically, momentum profit over the first 24 weeks (six months) is –0.056 per cent per week for the 20 per cent of stocks with lowest *Prob*. In contrast, momentum profit is 0.201 per cent per week for the 20 per cent of stocks with highest *Prob*. Further evidence confirms that loser stocks rather than winner stocks drive momentum profits. Of the 0.262 per cent per week in momentum returns between the two groups, 0.212 per cent is due to stocks that are prior losers, suggesting that the difference in momentum returns is driven almost entirely by loser stocks. I also find that the momentum returns of stocks in the highest short sales constraints group exceed the momentum returns of stocks in the lowest short sales constraint group for 193 of the 204 portfolio formation weeks over the period 2001 to 2006.

This study makes the following contribution to the literature. First, it is possible to construct a reliable index of unobservable short sales constraints using observable stock characteristics in the China stock market and that *Prob* is a good proxy for short sales constraints. In addition, the results suggest that short sale constraints constitute a coherent explanation for the well documented patterns in momentum profits. This study shows that momentum strategies in the China stock market remain nominally profitable at least in part due to the existence of short sales constraints.

Furthermore, I examine whether the firm-specific characteristics play a major role in explaining momentum profits in the China stock market. I find some new empirical evidence that is inconsistent with that shown in developed markets. For example, the large size portfolios always outperform the small size portfolios in explaining momentum profits in contradiction to previous evidence regarding small firms and momentum, and which firmly rejects the notion that momentum profits are related only to small firms because they are illiquid stocks. In addition, loser portfolios have higher beta values than winner portfolios and there is no significant difference in momentum profits between high and low B/M firms. Finally, an enhanced risk-adjusted returns framework that includes a large firm/liquidity premium can account for most of the momentum effect in the China stock market.

5.2 Methodology

D'Avolio (2002) identifies several variables as proxies for the short sales constraints. In general, these variables capture heterogeneity of investor beliefs or uncertainty about valuations. For example, a high level of trading of a firm's stocks indicates heterogeneity of beliefs, so stocks with high turnover and high historical return volatility are more likely to have high short selling demand. A wide dispersion in analysts' earnings forecasts indicates the disagreement among market participants, increasing the short selling demand. Low (or negative) cash flows are likely to complicate valuation calculations and lead to disagreement about valuation among market participants, resulting in high short selling demand. Internet firms and firms with recent IPOs are likely to be more difficult to value accurately because of their short track records, resulting in greater heterogeneity of beliefs and more short selling demand by pessimistic investors. A high level of interest in a stock among unsophisticated individual investors may be an indicator of optimistic beliefs impounded in prices, making the stock more attractive as a short selling target. D'Avolio (2002) counts Yahoo! message board postings to measure interest by such investors. Finally, short selling is likely to be greater for glamour stocks and stocks with recent price declines, increasing borrowing demand for stocks in these categories. D'Avolio (2002) also identifies two variables that measure the supply of stock available to short sellers. These supply-side drivers are the size of the firm, measured by market value of equity, and institutional ownership, which indicates the percentage of shares outstanding held by one group of potential lenders.[29]

Given the differences of market mechanism and structure between the US and the China capital markets, I examine the influence of five factors associated with short sales constraints suggested by D'Avolio (2002) and follow his definitions as closely as possible. *Size* is the market capitalisation as of the week prior to the portfolio formation date, calculated as price per share multiplied by shares outstanding according to weekly return data in DataStream; *Turn* (turnover) is the percentage of shares traded during the week prior to the portfolio formation date, calculated as weekly trading volume divided by the number of shares outstanding; *IPO* is a dummy variable set to 1 if the return series begin within one year prior to the portfolio formation date; *Sig* (volatility) is the standard deviation of the trailing 24 weeks of daily returns; *Glam* (glamour) is a dummy variable set to 1 if the stock is in the lowest 30 per cent of B/M, where B/M is calculated as being the inverse of the market-to-book ratio obtained from DataStream; and finally, *Prob*, a comprehensive measure of short sales constraints, is a combination of the above measures derived using the mean regression coefficients in D'Avolio (2002):

$$Prob = e^{\hat{y}}/(1 + e^{\hat{y}}), \qquad (5.1)$$

where:

[29] More details on the determinants of short sales constraints are presented in Table 6 of D'Avolio (2002) (p. 293).

$$\hat{y} = (0.46 \times Size) + (1.59 \times Turn) + (0.86 \times IPO) - (0.06 \times Sig) + (0.41 \times Glam)\,. \tag{5.2}$$

The coefficient estimates are based on the analysis of the US stock market using D'Avolio's (2002) model, which includes six additional variables unused in this analysis due to the lack of significance or the data unavailability in China.[30] Therefore, two potential concerns for the use of these variables and coefficient estimates are inevitably raised. First, whether D'Avolio's (2002) model that works in the US stock market is also appropriate for analysing short sales constraints in China; and second, whether the six unused variables will affect the regression. To address these concerns, I follow the methodology employed by Ali and Trombley (2006) to separately consider each of the five determinants as an individual proxy for short sales constraints. This approach does not utilise the magnitude of a coefficient estimate but its sign, which anticipates the direction of the relation between momentum profits and each variable. Additionally, I examine an alternative aggregate measure of short sales constraints, *Prob1*, which uses the same component variables as *Prob*, but with equal weights and using standardised variables. A variable is standardised by subtracting its mean and then dividing by its standard deviation. *Prob1* is a linear combination of these standardised variables used in *Prob* with the signs from Eq. (5.2). Thus, *Prob1* considers variables

[30] Ali and Trombley (2006) examine six determinants of short sales constraints, excluding five insignificant variables in D'Avolio (2002). In this study, I drop six variables that are either unavailable to collect data or not suitable for analysis in the China stock market, such as *IO* (institutional ownership), *Disperz* (dispersion in analyst forecasts), *Authors* (the number of contributions to the stock's Yahoo! Finance message board), *CF* (cash flow), *Internet* (a type dummy variable), and *Loser* (a momentum dummy variable).

nominated by D'Avolio (2002) without using his precise suggested weights, which might be probably inappropriate for China.

Table 5.1 reports both Pearson and Spearman correlations among the determinants of short sales constraints. The Pearson correlation coefficients among the five determinants are small (coefficients range from –0.069 to 0.186), implying that each of variables could possibly be capturing a different aspect of short sales constraints. I also notice that the Pearson correlation coefficients of the five determinant variables with *Prob* and with *Prob1* are high, and *Prob* and *Prob1* are also highly correlated with each other (correlation coefficient is 0.684). Spearman correlations show similar results.

Table 5.1: Correlations among the determinants of short sales constraints

Pearson (below the diagonal) and Spearman (above the diagonal) correlation coefficients are calculated and averaged over the 204 weeks from 2001 to 2006. *Size* is the market capitalisation as of the week prior to the portfolio formation date, calculated as price per share multiplied by shares outstanding according to DataStream weekly data; *Turn* (turnover) is the percentage of shares outstanding traded during the week prior to the portfolio formation date, calculated as weekly trading volume divided by the number of shares outstanding; *IPO* is a dummy variable set to 1 if the return series begins within one year prior to the portfolio formation date; *Sig* (volatility) is the standard deviation of the trailing 24 weeks of daily returns; *Glam* (glamour) is a dummy variable set to 1 if the stock is in the lowest 30 per cent of B/M, where B/M is calculated as being the reverse of the variable of market-to-book ratio obtained from DataStream; and finally, *Prob*, the comprehensive measure of short sales constraints, is a combination of the above measures derived using the mean regression coefficients in Table 6 of D'Avolio (2002). *Prob1* is a linear combination of the variables used in *Prob* after standardization of each of the variables by subtracting their mean and dividing by their standard deviation, with signs from the Eq. (5.2).

	Size	Turn	IPO	Sig	Glam	Prob	Prob1
Size		−0.1104	−0.0343	0.0080	0.0946	0.8036	0.4172
Turn	−0.0691		0.1910	0.1920	0.0999	0.0563	0.6862
IPO	−0.0161	0.1855		0.0978	0.0397	0.3028	0.2840
Sig	0.1100	0.1600	0.0960		0.1220	0.2817	0.2482
Glam	0.1212	0.1142	0.0397	0.1606		0.3671	0.3151
Prob	0.6845	0.1315	0.5410	0.3747	0.4792		0.6744
Prob1	0.3361	0.6567	0.3955	0.2806	0.3911	0.6840	

5.3 Empirical Results

5.3.1 Momentum profits based on the determinants of short sales constraints

Following the methodology of Hong et al. (2000), I form portfolios of stocks with all available stocks on the SHSE and SZSE as of each Wednesday from January 2001 to December 2006, during which momentum strategies generate significant profits. The data employed in this analysis is the same as the data discussed in Chapter 4 and this study focuses on the 24-24 strategy. As of each portfolio formation date, the stocks with the lowest 30 per cent prior 24-week returns are assigned to the group P1 and stocks with highest 30 per cent prior 24-week returns are assigned to the group P3. I then assign all stocks into quintiles based on each of the five determinants of short sales constraints. For each of these portfolios, I report the average returns over the 24 weeks following the portfolio formation date. Over the period 2001 to 2006, the average difference between returns for groups P1 and P3 is 0.128 per cent per week (*t*-stat = 2.13), suggesting again the presence of momentum profits in the China stock market. The result is a little smaller than that obtained using the methodology of Jegadeesh and Titman (1993) (see Table 4.3), possibly because I use the top 30 per cent winners minus bottom 30 per cent losers instead of top 10 per cent winners minus bottom 10 per cent losers to construct momentum portfolios.[31]

To document the relation between momentum profits and short sales constraints, I examine the relation between the cross-sectional variations in momentum returns and the proxies of short sales constraints. In Panel A of Table 5.2, P3 – P1 returns for the smallest *Size* quintile is –0.038 per cent per week (*t*-stat = –0.58), compared to P3 – P1 returns of 0.219 per cent per week (*t*-stat = 4.00) for the largest *Size* quintile. The difference between the P3 – P1 returns of the two extreme *Size* quintiles, Q5 – Q1, is 0.256 per cent per week (*t*-stat = 7.97). The results in Panel A further demonstrate that the momentum effect is driven primarily by the loser portfolio P1. The difference in P1 returns between the two extreme *Size* quintiles groups, Q5 – Q1, is significant, –0.169 per cent per week (*t*-stat = –2.61), while the corresponding difference of the P3 group is insignificant, 0.087 per cent per week (*t*-stat = 1.06). Given that *Size* proxies for short sales constraints, the results suggest that a greater amount of momentum profits of losers remains unexploited for stocks with higher share turnover, a result I explore further below. The insignificant result of P3 group is consistent with the short sales constraints not being relevant for the arbitrage of momentum returns of winners. The asymmetric result for the winner and loser portfolios also suggests that the relation

[31] The results are also robust for the analysis on the 36-36 strategy.

between momentum profits and *Size* is possibly driven by the greater liquidity associated with larger firms. I will examine the big size effect in detail in the next section.

Panels B and C of Table 5.2 report the results for other two determinants, *Sig* (volatility) and *Turn* (turnover), which have the same pattern as the results in Panel A. Specifically, the differences in the extreme groups of *Sig* and *Turn* quintiles, Q5 – Q1, of P3 – P1 returns are 0.229 per cent per week (*t*-stat = 9.02) and 0.256 per cent per week (*t*-stat = 4.30), respectively. Moreover, it is also the loser stocks that drive the results: the difference of Q5 – Q1 of P1 returns of *Sig* and *Turn* are –0.142 per cent per week (*t*-stat = –2.16) and –0.134 per cent per week (*t*-stat = –2.06), respectively. And the corresponding differences of P3 return of the two quintiles are also insignificant. The results are consistent with a greater amount of momentum profits of losers remaining unexploited for stocks with large impact from short sales constraints. Similar results obtained from two dummy variables, *IPO* (initial public offering) and *Glam* (glamour) are presented in Panels D and E of Table 5.2.

Table 5.2: Momentum profits and determinants of short sales constraints

Portfolios are formed as of each Wednesday from January 2001 to December 2006. I examine the 24-24 strategy. As of each portfolio formation date, stocks in the lowest 30 per cent of prior 24-week return are assigned to group P1, and stocks in the highest 30 per cent of prior 24-week return are assigned to group P3. Stocks are then independently assigned to quintiles based on each of the five determinants of short sales constraints from Table 6 of D'Avolio (2002): *Size* is the market capitalisation as of the week prior to the portfolio formation date, calculated as price per share multiplied by shares outstanding according to DataStream weekly data; ***Turn*** (turnover) is the percentage of shares outstanding traded during the week prior to the portfolio formation date, calculated as weekly trading volume divided by the number of shares outstanding; *IPO* is a dummy variable set to 1 if the return series begins within one year prior to the portfolio formation date; *Sig* (volatility) is the standard deviation of the trailing 24 weeks of daily returns; *Glam* (glamour) is a dummy variable set to 1 if the stock is in the lowest 30 per cent of B/M, where B/M is calculated as being the reverse of the variable of market-to-book ratio obtained from DataStream. The average weekly returns of these portfolios are presented in percentage in this table. The *t*-statistics for differences in returns are based on the standard error of the time series of weekly estimates, corrected for serial correlation caused by overlapping measurement periods of returns, using the approach described in Newey and West (1987). The *t*-statistics are reported in parenthesis.

	All	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	*t*-stat
Panel A: Size Quintiles								
P1 Loser	–0.2553	–0.1545	–0.2598	–0.2614	–0.2371	–0.3237	–0.1692	(–2.61)[b]
P3 Winner	–0.1278	–0.1922	–0.2115	–0.1644	–0.1102	–0.1051	0.0871	(1.06)
P3 – P1	0.1275	–0.0377	0.0483	0.0970	0.1270	0.2186	0.2563	(7.97)[b]
t-stat	(2.13)[a]	(–0.58)	(0.75)	(1.54)	(2.09)[a]	(4.00)[b]		
Panel B: Sig Quintiles								
P1 Loser	–0.2553	–0.1737	–0.2431	–0.2351	–0.2482	–0.3159	–0.1422	(–2.16)[a]
P3 Winner	–0.1278	–0.1799	–0.1849	–0.1504	–0.1545	–0.0936	0.0862	(1.55)
P3 – P1	0.1275	–0.0062	0.0582	0.0846	0.0936	0.2223	0.2285	(9.02)[b]
t-stat	(2.13)[a]	(–0.10)	(0.95)	(1.39)	(1.51)	(3.74)[b]		
Panel C: Turn Quintiles								
P1 Loser	–0.2553	–0.1741	–0.2467	–0.2395	–0.2175	–0.3084	–0.1343	(–2.06)[a]
P3 Winner	–0.1278	–0.1301	–0.1462	–0.1434	–0.1348	–0.1787	–0.0486	(–0.88)
P3 – P1	0.1275	0.0440	0.1004	0.0961	0.0827	0.1297	0.0857	(4.30)[b]
t-stat	(2.13)[a]	(0.78)	(1.65)	(1.56)	(1.34)	(2.01)[a]		
Panel D: Glam Groups								
	All		***Glam* = 0**		***Glam* = 1**		**1 – 0**	***t*-stat**
P1 Loser	–0.2553		–0.2356		–0.5143		–0.2787	(–3.52)[b]
P3 Winner	–0.1278		–0.0965		–0.1802		–0.0837	(–1.44)
P3 – P1	0.1275		0.1392		0.3341		0.1949	(4.76)[b]
t-stat	(2.13)[a]		(2.32)[a]		(4.30)[b]			
Panel E: IPO Groups								
	All		***IPO* = 0**		***IPO* = 1**		**1 – 0**	***t*-stat**
P1 Loser	–0.2553		–0.1930		–0.3145		–0.1215	(–2.08)[a]
P3 Winner	–0.1278		–0.0596		–0.0364		0.0232	(0.40)
P3 – P1	0.1275		0.1334		0.2781		0.1446	(3.61)[b]
t-stat	(2.13)[a]		(2.21)[a]		(4.25)[b]			

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

Table 5.3 : Momentum profits and aggregate measure of short sales constraints

Portfolios are formed as of each Wednesday from January 2001 to December 2006. I examine the 24-24 strategy. As of each portfolio formation date, stocks in the lowest 30 per cent of prior 24-week return are assigned to group P1, and stocks in the highest 30 per cent of prior 24-week return are assigned to group P3. Stocks are then independently assigned to quintiles based on *Prob* (*Prob1*), where *Prob* is the combination of above measures derived using the mean regression coefficients in Table 6 of D'Avolio (2002) and *Prob1* is a linear combination of the variables used in *Prob*, after standardization of each of the variables by subtracting their mean and dividing by their standard deviation, with signs from the Eq. (5.2). The average weekly returns of these portfolios are presented in percentage in this table. The *t*-statistics for differences in returns are based on the standard error of the time series of weekly estimates, corrected for serial correlation caused by overlapping measurement periods of returns, using the approach described in Newey and West (1987). The *t*-statistics are reported in parenthesis.

	All	Q1	Q2	Q3	Q4	Q5	Q5 − Q1	*t*-stat
Panel A: *Prob* Quintiles								
P1 Loser	−0.2553	−0.0921	−0.2385	−0.2480	−0.2336	−0.3041	−0.2120	(−3.21)[b]
P3 Winner	−0.1278	−0.1485	−0.2224	−0.1286	−0.0653	−0.0986	0.0500	(0.90)
P3 − P1	0.1275	−0.0564	0.0161	0.1194	0.1683	0.2055	0.2620	(9.05)[b]
t-stat	(2.13)[a]	(−0.88)	(0.25)	(1.93)	(2.83)[b]	(3.59)[b]		
Panel B: *Prob1* Quintiles								
P1 Loser	−0.2553	−0.1807	−0.2519	−0.3058	−0.2766	−0.3330	−0.1523	(−2.21)[a]
P3 Winner	−0.1278	−0.1690	−0.1586	−0.1932	−0.1446	−0.1147	0.0543	(0.93)
P3 − P1	0.1275	0.0117	0.0933	0.1125	0.1320	0.2183	0.2065	(8.97)[b]
t-stat	(2.13)[a]	(0.19)	(1.53)	(1.83)	(2.16)[a]	(3.36)[b]		

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

5.3.2 Momentum profits based on aggregate short sales constraints

Panel A of Table 5.3 reports results for *Prob*, the aggregate measure of short sales constraints. These results are consistent with the results for individual determinant of short sales constraints. The P3 – P1 return increases monotonically from –0.056 per cent per week (*t*-stat = –0.88) for the lowest *Prob* quintile, Q1, to 0.206 per cent per week (*t*-stat = 3.59) for the highest *Prob* quintile, Q5. The difference in momentum profits between the two extreme *Prob* quintiles Q5 – Q1 of P3 – P1 is 0.262 per cent per week (*t*-stat = 9.05). As expected, the difference is greater than the corresponding difference for each of the individual determinants of short sales constraints shown in Table 5.2. The insignificant result of P3 group further shows that the effect of *Prob* on momentum profits is driven primarily by the loser portfolio P1. The difference of Q5 – Q1 of P1 return is –0.212 per cent per week (t-stat = –3.21), while the corresponding difference of Q5 – Q1 of P3 return is 0.050 per cent per week (t-stat = 0.90).

Panel B of Table 5.3 reports results for *Prob1*, the alternative aggregate measure of short sales constraints. The measure uses the same component variables as *Prob*, except that it does not use the magnitude but just the signs of Eq. (5.2). I assign equal weights to each variable such that it explains the same variation in *Prob1*. Results with *Prob1* are very similar to the results with *Prob*. For example, the difference of Q5 – Q1 of P1 return is –0.152 per cent per week (t-stat = –2.21), while the corresponding difference of P3 return is 0.054 per cent per week (t-stat = 0.93). The difference in momentum profits between two extreme *Prob1* quintiles is 0.207 per cent per week (t-stat = 8.97).

Following Hong et al. (2000), I repeat the analysis in Table 5.3 with a beta-adjusted return measure, instead of the raw return measure. Panel A of Table 5.4 shows that this adjustment does not alter the conclusions. The P3–P1 return increases monotonically from –0.013 per cent per week (t-stat = –0.52) for the lowest *Prob* quintile, Q1, to 0.187 per cent (t-stat = 10.46) for the highest quintile, Q5. The difference of Q5 – Q1 of P3 – P1 return is significant as before, 0.200 per cent per week (t-stat = 9.22). The loser stocks still drive the results. The Q5 – Q1 difference in P1 return is –0.168 per cent (t-stat = –7.24) while the corresponding of P3 return is insignificant 0.032 per cent (t-stat =1.61). Panel B of Table 5.4 presents similar results of the beta-adjusted momentum profits using *Prob1*.

Table 5.4: Beta-adjusted momentum profits and aggregate measure of short sales constraints

Portfolios are formed as of each Wednesday from January 2001 to December 2006. I examine the 24-24 strategy. As of each portfolio formation date, stocks in the lowest 30 per cent of prior 24-week return are assigned to group P1, and stocks in the highest 30 per cent of prior 24-week return are assigned to group P3. Stocks are then independently assigned to quintiles based on *Prob* (*ProbI*), where *Prob* is the combination of above measures derived using the mean regression coefficients in Table 6 of D'Avolio (2002) and *ProbI* is a linear combination of the variables used in *Prob*, after standardization of each of the variables by subtracting their mean and dividing by their standard deviation, with signs from the Eq. (5.2). The average weekly beta-adjusted returns of these portfolios are presented in percentage in this table. The *t*-statistics for differences in returns are based on the standard error of the time series of weekly estimates, corrected for serial correlation caused by overlapping measurement periods of returns, using the approach described in Newey and West (1987). The *t*-statistics are reported in parenthesis.

	All	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	*t*-stat
Panel A: *Prob* Quintiles								
P1 Loser	–0.2264	–0.1634	–0.2552	–0.2384	–0.2482	–0.3316	–0.1682	(–7.24)[b]
P3 Winner	–0.1102	–0.1763	–0.1509	–0.1277	–0.0961	–0.1445	0.0318	(1.61)
P3 – P1	0.1162	–0.0130	0.1043	0.1107	0.1522	0.1870	0.2000	(9.22)[b]
t-stat	(2.89)[b]	(–0.53)	(5.47))[b]	(5.06))[b]	(8.65))[b]	(10.46))[b]		
Panel B: *ProbI* Quintiles								
P1 Loser	–0.2264	–0.1776	–0.2406	–0.2189	–0.2091	–0.2899	–0.1123	(–4.70)[b]
P3 Winner	–0.1102	–0.1249	–0.1346	–0.0913	–0.0875	–0.1572	–0.0323	(-1.61)
P3 – P1	0.1162	0.0527	0.1059	0.1276	0.1216	0.1328	0.0800	(3.73)[b]
t-stat	(2.89)[b]	(2.26)[a]	(5.48)[b]	(7.03)[b]	(6.87)[b]	(6.41) [b]		

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

Since Table 5.4 provides only summary results for the sample period, I plot results for each of the 204 sample weeks over the period 2001 to 2006 in Figure 5.1. Specifically, I plot the difference in momentum profit P3 – P1 between *Prob* groups Q5 and Q1. The figure shows that the difference is positive in almost all of the weeks (193 out of 204). Moreover, whenever the difference is negative, the magnitude tends to be relatively small. Thus, the results reported in Table 5.4 are not driven by a few sample weeks. Figure 5.1 also shows that there is no noticeable trend over time.

5.3.3 OLS regression analysis

Finally, I run a multiple ordinary least squares (OLS) regression with all the previously identified determinants of short sales constraints being considered:

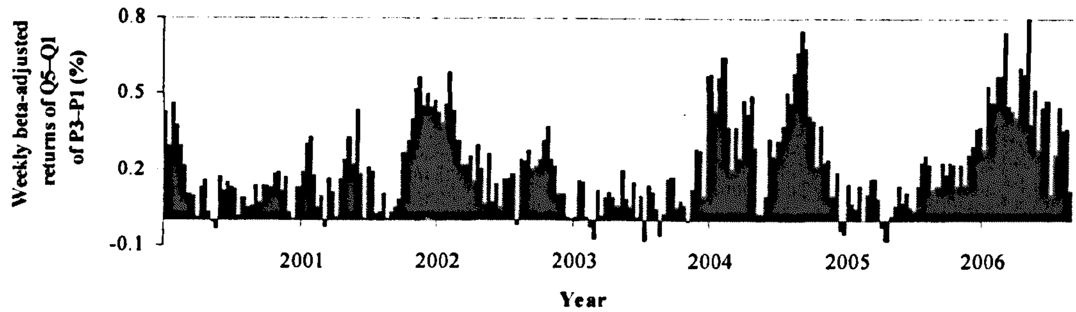

Figure 5.1: Differences in weekly beta-adjusted momentum profits in the extreme quintile groups based on an aggregate measure of short sales constraints (January 2001 to December 2006)

$$Return = \alpha_0 + \alpha_1 Past_{ret} + \alpha_2 Past_{ret} \times (1 - Prob) + \alpha_3 \times (1 - Prob) + \alpha_4 Past_{ret} \times Size + \alpha_5 Past_{ret} \times Sig + \alpha_6 Past_{ret} \times (1 - Turn) + \alpha_7 Size + \alpha_8 Sig + \alpha_9 (1 - Turn) + \varepsilon, \quad (5.3)$$

where *Return* represents the average weekly return for the 24 weeks following the measurement date and $Past_{ret}$ represents the 24 weeks return prior to that date. *Size* represents the market capitalisation as of the week prior to the portfolio formation date, calculated as price per share multiplied by shares outstanding according to weekly return data in DataStream; *Turn* represents the percentage of shares traded during the week prior to the portfolio formation date, calculated as weekly trading volume divided by the number of shares outstanding; *Sig* represents the standard deviation of the trailing 24 weeks of daily returns; *Prob* represents a comprehensive measure of short sales constraints, a combination of the above measures derived using the mean regression coefficients in D'Avolio (2002).

Table 5.5: OLS regression of the relation between momentum profits and short sales constraints

Weekly regression coefficients of Eq. (5.3) are average for the period January 2001 to December 2006. The dependent variable *Return* is the average weekly return for the 24 weeks following the measurement date; $Past_{ret}$ is the 24 weeks return prior to that date. *Size* is the market capitalisation as of the week prior to the portfolio formation date, calculated as price per share multiplied by shares outstanding according to DataStream weekly data; *Turn* (turnover) is the percentage of shares outstanding traded during the week prior to the portfolio formation date, calculated as weekly trading volume divided by the number of shares outstanding; *Sig* (volatility) is the standard deviation of the trailing 24 weeks of daily returns; *Prob*, the comprehensive measure of short sales constraints, is a combination of *Size*, *Sig*, *Turn*, *IPO*, and *Glam* using the mean regression coefficients in Eq. (5.3). The average weekly beta-adjusted returns of these portfolios are presented in percentage in this table. The *t*-statistics for differences in returns are based on the standard error of the time series of weekly estimates, corrected for serial correlation caused by overlapping measurement periods of returns, using the approach described in Newey and West (1987). The *t*-statistics are reported in parenthesis.

	Coefficient	*t*-stat
Intercept	0.1081	(2.00)[a]
$Past_{ret}$	0.9971	(2.16)[a]
$Past_{ret} \times (1 - Prob)$	-3.3992	(-2.00)[a]
$1 - Prob$	0.0363	(1.96)[a]
$Past_{ret} \times Size$	0.3792	(2.46)[a]
$Past_{ret} \times Sig$	0.0098	(0.29)
$Past_{ret} \times (1 - Turn)$	-8.4431	(-1.98)[a]
Size	0.0042	(2.94)[b]
Sig	-0.0005	(-0.78)
$1 - Turn$	-0.1289	(-2.34)[a]
Adj. R^2	0.083	

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

The coefficients on the interaction terms in Eq. (5.3) capture how momentum returns vary cross-sectionally with short sales constraints represented by *Prob*, and with other factors such as firm size, volatility, and share turnover. In the regression I include *1 – Prob, 1 – Turn* instead of *Prob* and *Turn* because the coefficients on both interaction terms have a negative expected sign. All the variables in the interactions are also included by themselves in the model to capture their main effect on future returns to prevent the coefficients on the interaction term from biasing.

Regression results are presented in Table 5.5. The coefficient on $Past_{ret}$ is significantly positive, 0.997 (*t*-stat = 2.16), indicating the existence of the momentum effect in China. The coefficient on $Past_{ret} \times (1 - Prob)$ is significantly negative, –3.399 (*t*-stat = –2.00), suggesting that momentum profits increase with the increase in short sales constraints. The significantly positive coefficient on *Size* also implies a big size effect in China, which will be examined further in the next section. In conclusion, the results appear to be consistent with a strong positive relationship between momentum profits and the measure of short sales constraints. As expected, the strength and significance of the relationship is consistent with the fully short sales constrained environment observed in the China stock market.

5.4 Firm-specific characteristics and momentum

5.4.1 CAPM beta and momentum profits

Results from the previous section indicate that returns on loser portfolios generally lose more than winner portfolios gain: specifically, the absolute value of loser returns is larger than that of winner returns. Because more risky assets are known to generate higher returns than less risky assets, momentum profits might be due to the presence of riskier stocks in the portfolio.

To investigate whether beta risk explains the phenomenon observed, an OLS estimator of the slope coefficient in the market model is used to derive the respective portfolio betas:[32]

[32] This model is based on the Sharpe-Lintner CAPM: $R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + e_{it}$. In this paper, I transpose the α_i as $[\alpha_i - R_{ft}(\beta_i - 1)]$ instead of the usual Jensen performance index.

Table 5.6: OLS portfolio regressions of test period returns on betas

Ordinary Least Squares (OLS) estimator of the slope coefficient in the market model is used to estimate the respective betas for the period January 2001 to December 2006: $R_{it} = \alpha_i + \beta_i R_{mt} + e_{it}$, where R_{it} is the realized natural log return of portfolio i at time t, R_{mt} is the realized natural log return of the market portfolio at time t, and e_{it} is the zero mean disturbance term. I obtain the beta of the respective portfolios by regressing the return on market portfolio on the mean return of portfolio i at time t. The t-statistics are reported in parentheses.

	α_i	t-stat	β_i	t-stat	$Adj. R^2$
Panel A: The 24-24 strategy					
D1 Loser	−0.1991	(−10.15)[b]	1.0186	(33.88)[b]	0.828
D2	−0.1923	(−11.04)[b]	0.9961	(37.70)[b]	0.856
D3	−0.1869	(−12.70)[b]	1.0008	(44.81)[b]	0.894
D4	−0.1888	(−13.12)[b]	0.9665	(44.30)[b]	0.891
D5	−0.1850	(−14.89)[b]	0.9559	(50.72)[b]	0.915
D6	−0.1869	(−15.77)[b]	0.9433	(52.50)[b]	0.920
D7	−0.1829	(−17.58)[b]	0.9141	(57.91)[b]	0.933
D8	−0.1731	(−19.14)[b]	0.8971	(65.38)[b]	0.947
D9	−0.1382	(−15.57)[b]	0.8584	(63.78)[b]	0.945
D10 Winner	−0.0595	(−5.05)[b]	0.8430	(47.15)[b]	0.903
D10 − D1	**0.1396**	**(5.78)[b]**	**−0.1756**	**(−4.79)[b]**	**0.088**
Panel B: The 36-36 strategy					
D1 Loser	−0.2341	(−18.88)[b]	0.9682	(43.65)[b]	0.889
D2	−0.2262	(−20.34)[b]	0.9653	(48.54)[b]	0.908
D3	−0.2174	(−21.76)[b]	0.9403	(52.64)[b]	0.921
D4	−0.2218	(−24.96)[b]	0.9310	(58.57)[b]	0.935
D5	−0.2109	(−24.94)[b]	0.8891	(58.80)[b]	0.935
D6	−0.2020	(−23.99)[b]	0.8686	(57.67)[b]	0.933
D7	−0.1871	(−24.25)[b]	0.8575	(62.14)[b]	0.942
D8	−0.1613	(−25.49)[b]	0.8595	(75.96)[b]	0.960
D9	−0.1374	(−22.03)[b]	0.8692	(77.93)[b]	0.962
D10 Winner	−0.0334	(−4.60)[b]	0.8187	(63.14)[b]	0.943
D10 − D1	**0.2008**	**(13.20)[b]**	**−0.1495**	**(−5.50)[b]**	**0.112**

[b] indicates statistical significance at the 1 percent level.

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}\,, \tag{5.4}$$

where R_i represents the realized natural log return of portfolio i at time t, R_{mt} represents the realized natural log return of the market portfolio at time t, and e_{it} represents the zero mean disturbance term.

I use the equally weighted return of the SHSE and SZSE A-share Indices as a broad-based benchmark for the market portfolio. The alpha and beta of each of the respective decile portfolios are obtained using this regression method. For simplicity and comparison with previous research, I concentrate on two representative 24-24 and 36-36 strategies.[33]

In the final row of the Table 5.6, I report the results of a *t*-statistic on the difference in the betas of the winner minus loser portfolios: the evidence indicates that the betas of the winner deciles (D10) are significantly smaller than that of loser deciles (D1). The loser portfolios have higher beta estimates than do the winner portfolios and, hence, the beta of the zero-cost winner minus loser portfolios is negative. Loser portfolios have lower returns than winner portfolios because they have larger betas and, in the depressed market conditions, their returns fall more sharply. The alpha value, however, shows that even after controlling for beta risk, the 24-24 and 36-36 strategies still make significant profits of 0.140 per cent per week (*t*-stat = 5.78) and 0.201 per cent per week (*t*-stat = 13.2), respectively.

5.4.2 Size and momentum profits

The market capitalisation (*Size*) is defined as the current share price multiplied by the number of common shares outstanding. The size effect was first observed by Banz (1981) who reports that firms with lower market capitalisation tend to have higher mean returns. Examining the NYSE over the period 1931 to 1975, Banz (1981) demonstrates that the fifty smallest firms outperform the fifty largest firms by an average of 1 per cent per month. Fama and French (1992) confirm the small firm effect with findings of

[33] The 24-24 and 36-36 strategies examined in this section have no lag between portfolio ranking and holding periods because of no significant bid-ask effect found in the previous section.

smaller firms generating higher returns than larger firms do in the US stock market. De Bondt and Thaler (1987) and Zarowin (1990) both find, however, that the winner minus loser effect is primarily not a small size effect, and that the size of loser portfolios is usually smaller than the size of winner portfolios based on a three-year sample period.

The profitability related to this size anomaly is also strong using non-US data. For example, small companies tend to generate significantly higher performances than large firms in the Belgium market (Hawanini et al. (1989)), in the Japanese market (Hawanini (1991)), in the Mexico stock market (Herrera and Lockwood (1994)), and in the Korean equity market (Cheung et al. (1994)). Both Banz (1985) and Dimson and Marsh (1984), examining the UK return data from 1955 to 1983 and from 1977 to 1983, respectively, find that the small size stocks outperform the large size firms. Banz (1985) finds that the compound annual return on the smallest portfolio exceed that of the largest one by 27 per cent, while Dimson and Marsh (1984) report that the percentage is about 23 per cent. However, not all research supports the existence of the small size effect. Dimson et al. (2001) argue that the small size effect does not apply when recent data are analysed in the UK stock market. They show that over the period 1989 to 2000, the large size firms outperform the small size firms by 4.3 per cent per year.

This study attempts to answer the question of whether the systematically better performance of winner minus loser portfolios is actually due to the average smaller size of stocks in the winner portfolios. To check whether the results are affected by the size effect, at each week *t*, I first rank all the stocks on the basis of their market capitalisation. Second, I form two groups: one group comprising firms with big market capitalisation (Big) firms and the other one comprising firms with small market capitalisation (Small) firms. I divide all firms listed on the two stock exchanges by the median size of stocks. Thirdly, I create the 24-24, and 36-36 strategies with stocks in each size group. In this case I form quintile portfolios instead of decile portfolios to make the number of stocks in each portfolio comparable with that in the previous analysis. Finally, I build a size-neutral winner (loser) portfolio picking stocks contained in the winner (loser) quintile from each size group. Using this methodology, both winner and loser portfolios end up containing the same number of stocks from each size group and are in that sense approximately size-neutral.

Table 5.7 shows that the size-neutral portfolio of the 24-24 strategy generates an insignificant return of 0.074 per cent per week (t-stat = 1.26). Compared with the return generated by previous 24-24 strategy, 0.142 per cent per week (t-stat = 2.36), approximately half momentum profits disappear after adjusting for size. A similar result is obtained from the 36-36 strategy, 0.123 per cent per week (t-stat = 1.58), which is insignificant, and the magnitude is much weaker compared with the profit of 0.202 per cent per week (t-stat = 4.21) generated by previous 36-36 strategy in Table 4.3. The finding implies that the momentum effect may be a reflection of the size effect.

Table 5.7: Weekly momentum profits divided by size

Stocks are sorted into Big and Small size groups by the median size of stocks quoted on the SHSE and SZSE. In each group I form the 24-24 and 36-36 strategies. In this case I form five quintile portfolios instead of ten decile portfolios. Finally, I build a size-neutral winner (loser) portfolio picking stocks contained in the winner (loser) quintile from each size group. The average weekly returns of these portfolios are presented in percentage. The *t*-statistics are reported in parentheses.

		Big	Small	Size-neutral	*t*-stat
24-24 strategy	Mean	0. 162	−0. 020	0. 074	(7.20)[b]
	t-stat	(2.87)[b]	(−0.27)	(1.26)	
36-36 strategy	Mean	0. 195	0. 050	0. 123	(8.84)[b]
	t-stat	(4.28)[b]	(0.94)	(1.58)	

[b] indicates statistical significance at the 1 percent level.

Following a different approach, Table 5.7 shows that the momentum effect is not a phenomenon typical of the small size effect, but the big size effect. Table 5.7 shows that the average return of the 24-24 strategy in the small size group is −0.020 per cent per week (*t*-stat = −0.27), while 0.162 per cent per week (*t*-stat = 2.87) in the big size group. A similar result is found in the 36-36 strategy. The average return of the 36-36 strategy in the small size group is 0.050 per cent per week (*t*-stat = 0.94), while 0.195 per cent per week (*t*-stat = 4.28) in the big size group. In particular, the zero-cost portfolio returns between the two size groups are significantly different from zero with high *t*-statistics, 7.20 (8.84). In summary, results from Table 5.7 strongly suggest that the momentum effect in the China stock market is likely to be a reflection of a big size effect.

In seeking to confirm the results, I compare the market capitalisations of ten deciles portfolios. As before, I rank all firms listed on the SHSE and SZSE exchanges based on their 12-week to 48-week historical returns. The stocks are then sorted into ten equally weighted deciles in ascending order, that is, the top decile (D1) represents the loser portfolio and the bottom decile (D10) represents the winner portfolio. The market capitalisation of each decile is computed by the median size of stocks in the decile portfolio in the following one-year portfolio holding periods and during the corresponding performance ranking periods, respectively.

Panel A of Table 5.8 shows that the median size of a portfolio in the following one-year holding periods increases as I move from the loser decile (D1) to the winner decile (D10). The longer the performance ranking periods are, the larger the difference in median size between the winner and loser portfolios. The market capitalisation of loser portfolios is significantly smaller than that of winner portfolios. The result of significant difference between the winner and loser groups is shown in parenthesis in the last row of Panel A. The same significant results of the median size of a decile portfolio during the corresponding portfolio ranking periods can be found in Panel B of Table 5.8.

Table 5.8: The median market capitalisation based on past 12- to 48-week returns

Using weekly market capitalisation data from DataStream, I first rank all stocks quoted on the SHSE and SZSE based on their historical returns on each portfolio ranking period. Stocks are further sorted into ten equally weighted deciles in ascending order; that is, the top decile (D1) represents the loser portfolio and the bottom decile (D10) represents the winner portfolio. I report the median market capitalisation in the following one-year holding periods and during their ranking periods (12-, 24-, 36-, and 48-week) for each decile portfolio, respectively. The market capitalisation is displayed in millions of RMB, or Chinese Yuan. The t-statistics for the differences between the winner and loser groups are reported in parentheses.

	F = 12	**24**	**36**	**48**
Panel A: The median capitalisation in the following one-year holding periods				
D1 Loser	2,643.6	2,246.6	1,896.0	1,754.3
D2	2,598.3	2,234.6	1,965.4	1,823.6
D3	2,553.9	2,319.5	2,089.5	1,924.4
D4	2,510.1	2,328.4	2,214.8	2,047.1
D5	2,576.2	2,453.2	2,376.5	2,244.0
D6	2,699.1	2,594.3	2,589.0	2,514.0
D7	2,912.8	2,911.8	2,935.9	2,940.1
D8	3,272.6	3,373.4	3,372.5	3,371.0
D9	3,608.3	3,896.0	4,014.1	4,042.6
D10 Winner	4,247.0	4,828.1	5,351.4	5,735.1
D10–D1	**1,603.4**	**2,581.5**	**3,455.4**	**3,980.8**
***t*-stat**	**(14.09)[b]**	**(23.27)[b]**	**(36.15)[b]**	**(39.35)[b]**
Panel B: The median capitalisation during past 12- to 48-week ranking periods				
D1 Loser	3,162.6	2,958.8	2,747.5	2,633.2
D2	2,942.3	2,675.7	2,495.4	2,393.3
D3	2,936.7	2,696.6	2,512.0	2,404.4
D4	2,775.7	2,648.7	2,565.1	2,452.0
D5	2,776.1	2,712.9	2,676.1	2,586.9
D6	2,900.8	2,794.9	2,799.7	2,793.7
D7	3,052.2	3,054.8	3,071.3	3,076.9
D8	3,360.9	3,429.8	3,417.5	3,384.2
D9	3,591.4	3,743.4	3,829.2	3,867.1
D10 Winner	3,995.0	4,246.2	4,490.6	4,690.0
D10–D1	**832.4**	**1,287.4**	**1,743.2**	**2,056.8**
***t*-stat**	**(7.12)[b]**	**(11.98)[b]**	**(18.85)[b]**	**(20.53)[b]**

[b] indicates statistical significance at the 1 percent level.

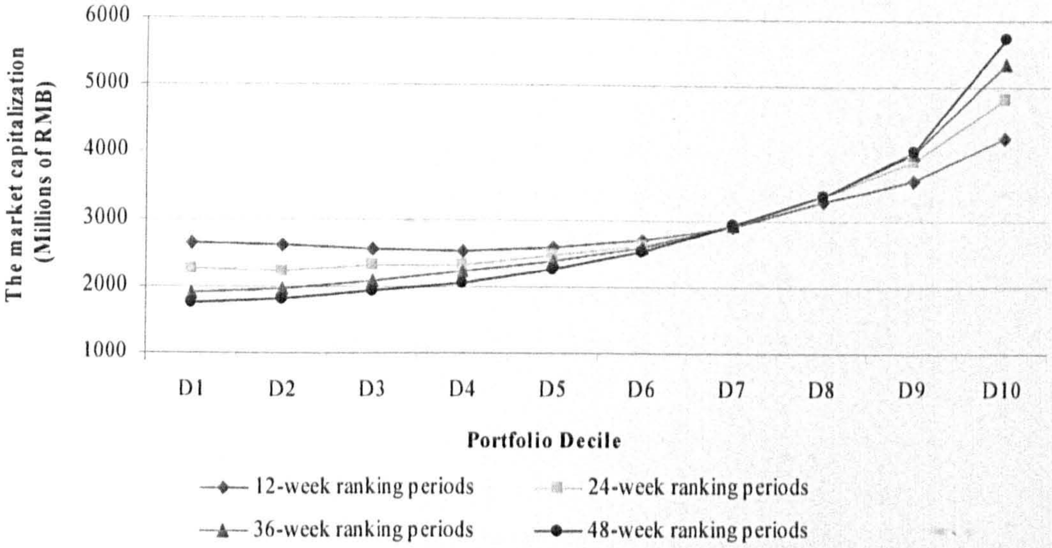

Figure 5.2: The median market capitalisation based on past 12- to 48-week returns in the following one-year holding periods (January 2001 to December 2006)

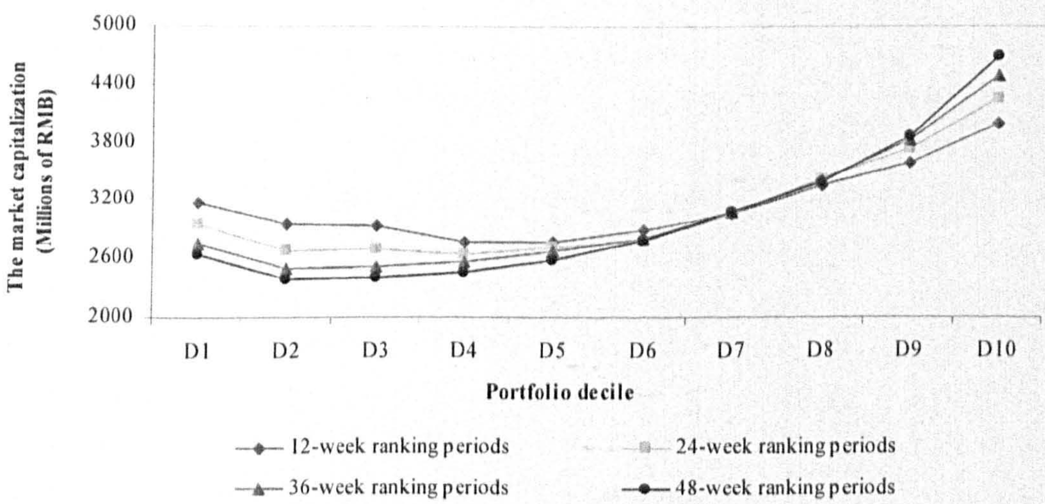

Figure 5.3: The median market capitalisation based on past 12- to 48-week returns during the corresponding portfolio ranking periods (January 2001 to December 2006)

From Figure 5.2, I observe an increase of the median size of ten deciles portfolios in the one-year holding periods when moving from the loser portfolio (D1) to the winner portfolio (D10). Figure 5.3 plots a very similar figure when analyzing the median size of ten deciles portfolios during the corresponding 12- to 48-week performance ranking periods. Thus, the evidence confirms the big size effect in the China stock market and concludes that the difference in size between loser and winner portfolios offers a significant explanation of momentum profits in China. The big size effect further explains the previous finding that the momentum effect on the SHSE is stronger than that on the SZSE, since the average size of firms listed on the SHSE is much larger than that on the SZSE (see Table 3.1).

5.4.3 B/M and momentum profits

Another factor generally found to be significant in explaining equity returns is B/M measured as the ratio of a firm's book value of common equity to its market value. Stattman (1980) reports the central role played by B/M in explaining the cross-section of average returns in the US stock market. In a multivariate approach, Fama and French (1992) that higher B/M ratios are associated with higher returns and argue that B/M is able to explain the average returns for the US stocks when regressed alone or together with other variables. Capaul et al. (1993) report that shares with high B/M generate excess returns than shares with low B/M by 0.53 per cent per month employing data from the French stock market, 0.13 per cent per month employing data from the German stock market, 0.50 per cent per month employing data from the Japanese stock market, and 0.23 per cent per month employing data from the UK stock market.

Table 5.9: Weekly momentum profits divided by B/M

Stocks are sorted into High, Middle, and Low B/M groups by the highest 30 per cent, middle 40 per cent, and lowest 30 per cent B/M of stocks on quoted the SHSE and SZSE. In each group I form the 24-24 and 36-36 momentum strategies. In this case I form five quintile portfolios instead of ten decile portfolios. Finally, I build a B/M-neutral winner (loser) portfolio picking stocks contained in the winner (loser) quintile from each B/M group. The average weekly returns of these portfolios are presented in percentage. The *t*-statistics are reported in parentheses.

		High	Middle	Low	B/M-neutral	*t*-stat
24-24 strategy	Mean	0. 100	0. 146	0.135	0. 117	(1.11)
	t-stat	(1.76)	(2.44)[a]	(2.12)[a]	(1.98)[a]	
36-36 strategy	Mean	0. 181	0. 195	0. 180	0. 181	(0.04)
	t-stat	(3.99)[a]	(4.11)[a]	(3.56)[a]	(3.84)[b]	

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

Following the similar methodology previously described for the size factor, I first sort all stocks initially on the basis of their B/M at each week *t*. The value of the B/M is subsequently used to classify firms as high B/M, middle B/M, or low B/M, according to whether their B/M is included in the highest 30 per cent, middle 40 per cent, or lowest 30 per cent range. Within each B/M group, stocks are then sorted according to the 24-24 and 36-36 strategies, producing five quintile portfolios in each group. Finally, B/M-neutral portfolios are constructed by selecting stocks from the winner and loser quintiles in the high and low B/M groups. Therefore, both winner and loser portfolios will contain the same number of stocks and in that sense approximately B/M-neutral.

Table 5.9 shows that the B/M-neutral zero-cost portfolio yields abnormal profits in both the 24-24 and 36-36 strategies. The returns of B/M-neutral portfolio for the two strategies are significant at 0.117 per cent per week (*t*-stat = 1.98) and 0.181 per cent (*t*-stat = 3.84), respectively. As for the 24-24 strategy, the average of the returns from the middle B/M group at 0.146 per cent per week (*t*-stat = 2.44), appears to be slightly higher and more significant than its counterparts in the high and low B/M groups, 0.100 per cent per week (*t*-stat = 1.76) and 0.135 per cent per week (*t*-stat = 2.12). The difference between the high and low B/M groups is statistically insignificant (t-stat = 1.11). Results from the two groups are more alike in the 36-36 strategy. Winner minus loser portfolios in the high and low B/M groups generate significant profits of 0.181 per cent per week (t-stat = 3.99) and 0.180 per cent per week (t-stat = 3.84), respectively. There is no significant difference (t-stat = 0.04) of momentum profits between the high and low B/M groups. In conclusion, the B/M factor seems to have no strong explanatory power on momentum profits in the China stock market.

5.4.4 Momentum profits in a two-factor risk-adjusted framework

The persistence of the momentum effect in a risk-adjusted framework is examined using a time-series multivariate approach. A two-factor model including the market premium ($R_{mt} - R_{ft}$) and SMB is run:[34]

$$R_{decile,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{m,t} - R_{f,t}\right) + s_i SMB_t + \varepsilon_{i,t}\,, \qquad (5.4)$$

where $R_{f,t}$ represents the weekly three-month household deposit interest rate, $R_{decile,t} - R_{f,t}$ represents the excess return of decile portfolios, $R_{m,t} - R_{f,t}$ represents the market premium, which is computed as the difference between the equally weighted return of the SHSE and SZSE A-share Indices and risk free rate. In this case, I use the three-month household deposit interest rate as the risk free rate; α_i is the intercept term; β_i and s_i are the slopes, SMB_t is the mimicking portfolio for the size factor, and e_i is the zero mean disturbance term (see Appendix 5.1).

[34] I exclude the B/M factor from the Fama and French (1993) three-factor model since previous analysis shows no strong explanatory power of B/M in momentum profits in China.

Table 5.10: Risk-adjusted momentum profits with the two-factor model

As for the 24-24 strategy, I run the two-factor model as: $R_{decile t} - R_{ft} = a_i + \beta_i (R_{mt} - R_{ft}) + s_i SMB_t + e_{it}$, where R_{ft} is the weekly three-month household deposit interest rate; $R_{decile t} - R_{ft}$ is the excess return of decile portfolios; $R_{mt} - R_{ft}$ is the market premium; a_i is the intercept term; β_i and s_i are the slopes in the time series regression; SMB_t is the mimicking portfolio for the size factor; and e_{it} is the zero mean disturbance term. Raw returns of each decile portfolio are reported along the second column. The top decile (D1) represents the loser portfolio and the bottom decile (D10) represents the winner portfolio. All weekly returns of these portfolios are presented as per centages. The t-statistics are reported in parentheses.

	Raw	a_i	t-stat	β_i	t-stat	s_i	t-stat	Adj. R^2
Panel A: The period of 2001 to 2006								
D1 Loser	−0.247	−0.132	(−13.92)[b]	0.906	(67.21)[b]	1.415	(28.99)[b]	0.963
D2	−0.235	−0.129	(−15.45)[b]	0.905	(76.01)[b]	1.246	(28.91)[b]	0.969
D3	−0.227	−0.128	(−18.05)[b]	0.927	(91.47)[b]	1.092	(29.76)[b]	0.977
D4	−0.238	−0.141	(−17.83)[b]	0.885	(78.20)[b]	1.026	(25.04)[b]	0.969
D5	−0.234	−0.15	(−20.24)[b]	0.876	(82.91)[b]	0.889	(23.26)[b]	0.971
D6	−0.236	−0.156	(−20.17)[b]	0.867	(78.57)[b]	0.831	(20.80)[b]	0.968
D7	−0.240	−0.169	(−19.14)[b]	0.827	(65.47)[b]	0.723	(15.81)[b]	0.954
D8	−0.230	−0.172	(−16.25)[b]	0.830	(55.02)[b]	0.478	(8.75)[b]	0.931
D9	−0.189	−0.147	(−13.82)[b]	0.821	(54.12)[b]	0.210	(3.83)[b]	0.925
D10 Winner	−0.105	−0.075	(−5.53)[b]	0.835	(43.25)[b]	−0.008	(−0.11)	0.883
Winner − Loser	**0.142**	**0.023**	**(1.37)**	**−0.071**	**(−2.96)[b]**	**−1.426**	**(−16.42)[b]**	**0.550**
Panel B: The Period of 1995 to 2006								
D1 Loser	0.021	0.011	(7.44)[b]	0.956	(35.92)[b]	1.515	(15.49)[b]	0.913
D2	0.087	0.048	(8.48)[b]	0.955	(41.72)[b]	1.346	(15.87)[b]	0.919
D3	0.115	0.065	(10.18)[b]	0.977	(51.58)[b]	1.192	(16.78)[b]	0.927
D4	0.127	0.075	(10.56)[b]	0.935	(46.33)[b]	1.126	(14.83)[b]	0.919
D5	0.149	0.099	(13.49)[b]	0.926	(55.27)[b]	0.989	(15.51)[b]	0.921
D6	0.143	0.095	(13.33)[b]	0.917	(51.94)[b]	0.931	(13.75)[b]	0.918
D7	0.139	0.098	(13.48)[b]	0.877	(46.10)[b]	0.823	(11.13)[b]	0.904
D8	0.133	0.100	(12.15)[b]	0.880	(41.15)[b]	0.578	(6.54)[b]	0.881
D9	0.121	0.094	(10.75)[b]	0.871	(42.09)[b]	0.310	(2.98)[b]	0.875
D10 Winner	0.115	0.082	(3.95)[b]	0.885	(30.89)[b]	0.092	(0.08)	0.833
Winner − Loser	**0.094**	**0.015**	**(1.22)**	**-0.121**	**(−2.47)[a]**	**−1.326**	**(−2.66)[b]**	**0.500**

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

To detect the risk-adjusted momentum effect, I focus on the intercept parameters obtained by this regression. Results are presented in Panel A of Table 5.10 for the 24-24 strategy. Estimates of the intercept terms can be read along the third column. In the two-factor model, the alpha value of the winner minus loser portfolio is much lower and statistically insignificant, 0.023 per cent (t-stat = 1.37). Compared with previous raw profit of 0.142 per cent (t-stat = 2.36), more than 80 per cent profit disappears after controlling for beta and size risks. The result is robust when I examine the risk-adjusted framework over the whole time period 1995 to 2006. Results presented in Panel B show that the alpha value of the winner minus loser portfolio is much lower and statistically insignificant, 0.015 per cent (*t*-stat = 1.22). Compared with previous raw profit of 0.094 per cent (*t*-stat = 1.98), more than 80 per cent profit disappears after controlling for beta and size risks. Therefore, I conclude that the two-factor model with beta and size factors capture a significant proportion of momentum profits.

5.5 Summary of findings

This chapter focuses on the examination of the role of short sales constraints in explaining the medium-term momentum strategies for stocks traded on the SHSE and SZSE exchanges over the period 2001 to 2006, during which momentum strategies show strong profits. I note that observed momentum is likely to be a result of exogenously set short sales constraints in China in which context it is not possible to access risk free profits through conventional arbitrage processes. I report a significantly positive relation between momentum and short sales constraints by using the determinants suggested by D'Avolio (2002). Moreover, the prediction that the longer momentum duration in China than reported elsewhere is due to the more severe short sales constraints is confirmed.

In further detailing this work, I employ beta, size, and B/M factors to explain abnormal momentum profits in the China stock market and find that the results are not consistent with those found in other markets: loser portfolios have higher beta values than winner portfolios; big size firms always outperform small size firms; and there is no significant difference in momentum profits between high and low B/M firms. What I do find is that, after adjusting returns of winner minus loser portfolios using the two-factor model including beta and size factors, most of abnormal returns disappear.

Appendix 5.1 Construction of the Fama and French (1993) three factors in the China stock market

Following the methodology developed by Fama and French (1993), I construct mimicking portfolios for size and B/M factors in the China stock market. First, on 30th June of each year from 1995 to 2006, all stocks on the SHSE and SZSE are ranked by their market values. The median market value of all stocks on the both exchanges is then used to divide all stocks into two groups: small size (*S*) and big size (*B*). Stocks are also divided into three B/M groups: high B/M (*H*), middle B/M (*M*), and low B/M (*L*), according to whether the value of their B/M is included in the top 30, middle 40, or bottom 30 percentile, respectively. I then calculate monthly value-weighted returns of six portfolios, *SL*, *SM*, *SH*, *BL*, *BM*, and *BH*, which are constructed from the intersections of two size groups and three B/M groups. For example, the *SL* portfolio contains stocks in both the small size group and the low B/M group, and the *BH* portfolio contains stocks in both the big size group and the high B/M group.

Second, I mimic the size risk factor *SMB* (small minus big) and the value factor *HML* (high minus low). *SMB* is calculated as the difference, at each week t, between the simple average returns of the stocks contained in the three small size portfolios (*SL*, *SM*, and *SH*) and the simple average returns of the stocks contained in the three big size portfolios (*BL*, *BM*, and *BH*), while *HML* is calculated as the difference between the simple average returns of the stocks contained in the two high B/M portfolios (*SH* and

BH) and the simple average returns of the stocks contained in the two low B/M portfolios (*SL* and *BL*). Thus, *SMB* is the difference between returns on small and big size portfolios with about the same equally weighted B/M, while *HML* is the difference between returns on high and low B/M portfolios with about the same equally weighted market value.

SMB represents the return on a zero investment portfolio formed by subtracting the return on a big size firm portfolio from the return on a small size firm portfolio. *SMB* is calculated as:

$$SMB = \frac{(SL + SM + SH)}{3} - \frac{(BL + BM + BH)}{3}.$$

HML represents the return on a zero investment portfolio formed by subtracting the return on a low B/M firm portfolio from the return on a high B/M firm portfolio. *HML* is calculated as:

$$HML = \frac{(SH + BH)}{2} - \frac{(SL + BL)}{2}.$$

If I reorganise the SMB and HML formulas, it is possible to get a clearer picture as follows:

$$SMB = \frac{(SL - BL) - (SM - BM) - (SH - BH)}{3};$$

$$HML = \frac{(SH - SL) - (BH - BL)}{2},$$

both of which show that *SMB* (*HML*) should be largely free of the influence of B/M (size), focusing instead on the different return behaviours of small and big size (high and low B/M) firms. A positive SMB in a particular week indicates that a small-size portfolio outperformed a large-cap portfolio in that respective week, whereas a negative SMB in a given week indicates the large-cap outperformed the small-size portfolio. Similarly, a positive HML in a week indicates that high book-to-market portfolio outperformed low B/M portfolio in that given week, whereas a negative HML in a particular week indicates the low B/M portfolio outperformed the high B/M portfolio.

CHAPTER 6

STYLE MOMENTUM

6.1 Introduction

In the financial markets, when investors make portfolio allocation decisions, they generally first categorise assets into broad classes across style dimensions, such as size measured by market capitalisation of equity, value/growth measured by B/M, and industry sector, and then decide how to allocate their funds across the various asset classes. These asset classes utilised in this process are sometimes called *styles*, and the process where investors allocate their funds among styles is known as *style investing* (Bernstein (1995)). Sharpe (1992) shows that investment style, rather than specific stock selection, determines more than 90 per cent of superior performance of mutual funds. Barberis and Shleifer (2003) document that style investing helps both individual and institutional investors to construct and simplify diversified portfolios, to effectively identify and manage sources of risk on the investment, as well as to easily measure and evaluate the performance relative to specified style benchmarks, such as the growth or value index.

It has been well known that size and B/M, which represent two major components of risk and returns in the stock market, play vital roles in predicting stock returns. Banz (1981) first shows that the small size firms outperform the large size firms, while Stattman (1980) appreciates the central role played by B/M in explaining the cross-section of average returns. Fama and French (1992) demonstrate the small size effect and the value effect in the US equity returns. Chen (2003) summarises that *"firm* *characteristics represent the underlying pervasive forces affecting asset returns, and the style portfolios formed by such characteristics can thus be used to identify the current in-favour and out-of-favour equity styles"* (p. 141). In practice, fund managers generally tend to break mutual funds down based on the size and value/growth and claim to follow a particular investment style, such as small-size or value.

Several recent studies confirm that styles perform differently over time and provide theoretical models in attempts to capture any predictability in style returns. Lucas, Dijk, and Kloek (2002) summarise some early developments in the style rotation literature and suggest that style performance is time-varying and partially a function of the economic environment. Barberis and Shleifer (2003) suggest that some investors consider recent style return differentials to be an important factor for predicting future style returns. They argue that prices can deviate substantially from fundamental values as styles' popularity changes over time and conclude that the return patterns are complex and extremely noisy and consequently hard to predict.

A recent study of Chen and De Bondt (2004) proposes that a simple trading rule based on past returns and firm characteristics can generate significant returns in the future. During the period 1976 to 2000, they first classify the constituents of the S&P 500 Index into three classes along firm characteristics: size, value/growth, and dividend yield, and then rank the obtained style portfolios by their past three- to twelve-month returns. They find that style momentum strategies that buy stocks with characteristics that are currently in-favour and sell stocks with characteristics that are currently out-of-favour generate significant returns in the following three to twelve months. For example, the 9-9 style momentum strategy generates a profit of 0.30 per cent per month (*t*-stat =

2.07), while the 12-12 style momentum strategy generates a profit of 0.43 per cent per month (t-stat = 2.49).

Motivated by Chen and De Bondt (2004), this study extends the regular price momentum strategies to portfolio-based momentum strategies in style context. I examine whether active style momentum strategies, the combination of momentum strategy based on past medium-term returns and style investing based on size and B/M, make profits in the China stock market. Such scrutiny is designed to test whether a past winner (loser) style portfolio continues performing well (poor) during the portfolio holding period. To conveniently compare with the profitability of regular price momentum strategies, I focus on the same sample and time period when analysing price momentum strategies in Chapter 4. This study of style momentum in the China stock market contributes to the literature in three main aspects as follows:

First, empirical evidence shows that compared with regular price momentum strategies, style momentum strategies generally generate much stronger profits over the period 1995 to 2006 and the style portfolios are robust in two sub-periods. I also find that style momentum is distinct from industry momentum. The results, on the one hand, have strong implication for investment management that it is possible to explore zero-cost momentum profits even after controlling for direct transaction costs. On the other hand, the out-of-sample evidence from an emerging market helps to rule out the possibility that the result of Chen and De Bondt (2004) is due to a data mining bias.

Second, several aspects of the momentum effect other than the mean returns are particularly intriguing. For example, Chordia and Shivakumar (2002) and Cooper et al.

(2004) document that momentum profits are strong in economic expansions but nonexistent in recessions. In this study, I further examine style momentum strategies in two opposite market states, while I find that style momentum strategies shows significantly profitable in both states. In addition, it is winner (loser) portfolios drive the style momentum profits during the booming (depressed) periods.

Finally, a number of previous studies fail to document direct evidence of risk on momentum portfolios (see, e.g., Jegadeesh and Titman (1993), Fama and French (1996), Grundy and Martin (2001), and Griffin et al. (2003)). A recent study of Liu and Zhang (2008), however, focus on the growth rate of industry production (MP) and conclude that the MP factor explains more than half of momentum profits. However, in this study, I examine whether microeconomic risk is an important indicator of momentum in the China stock market, but find no evidence showing that macroeconomic risk like MP can explain style momentum profits.

6.2 Methodology

To extend the regular momentum strategies to portfolio-based momentum strategies in style context, at the end of each year from 1995 to 2006, I create nine style portfolios. Each of them comprises stocks with similar characteristics: the year-end annual market capitalisation (size) and B/M. For the breaking points between small-cap and mid-cap stocks as well as between mid-cap and large-cap stocks, I use the respective 30th percentile and 70th percentile of the size rankings, respectively. For the B/M, I set the breaking points between growth and blend stocks as well as between blend and value stocks as the 30th and 70th percentile, respectively. All stocks are first ranked independently by their year-end market capitalisation and B/M and then allocated to three size groups: small, middle, or big group, as well as three B/M groups: value, blend, or growth group. I check the portfolio at the intersection of size and B/M a firm belongs to once a year on 31st December. Thus, after portfolio formation, the changes in size or B/M due to the deletions and additions of firms in the two exchanges will not affect the investment strategies until the next 31st December when portfolios are re-built. The nine portfolios are big-value (BH), middle-value (MH), Small-value (SH), big-blend (BM), middle-blend (MM), small-blend (SM), big-growth (BL), middle-growth (ML), and small-blend (SL).

To test the profitability of style momentum strategies, I calculate the equally weighted returns for each style portfolio in previous F weeks (F equals 12, 24, 36, or 48). This method closely follows Jegadeesh and Titman (1993) and allows meaningful comparison with price momentum strategies examined in Chapter 4. On the basis of past returns, I construct arbitrage portfolios that go long in the past winner style portfolio and short sell the past loser style portfolio based on a zero-cost strategy. Two arbitrage portfolios are constructed: one holding two extreme portfolios (Top 1 and Bottom 1) and the other holding four extreme portfolios (Top 1, 2 and Bottom 1, 2). The arbitrage portfolios are held for the period of H weeks (H equals 12, 24, 36, or 48) as well as two and three years. A four-week gap between the performance ranking and portfolio holding periods is set to control for the market microstructure bias.

6.3 Summary statistics

Table 6.1 summarises the descriptive statistics of the nine style portfolios. Panels A and B present the average market capitalisation and B/M, respectively, in each portfolio at the end of each year from 1995 to 2006. For example, at the end of 2000, the BL firms have an average market capitalisation of RMB8,070.0 million; the SH firms have an average market value of RMB2,199.4 million. At the end of 2000, the BL firms have an average B/M of 0.089; the SH firms have an average B/M of 0.287. Panel C also shows the average market capitalisation of each style portfolio as a fraction of the total value of all stocks in the sample from 1995 to 2006. On average, the BL portfolio represents 24.12 per cent of the market value of all firms. Two portfolios that show extreme variation are SL and SH portfolios, which represent 3.29 per cent and 2.77 per cent, respectively, of the market value of all sample firms.[35]

Table 6.2 describes the performance of passive style portfolios. I report value-weighted average weekly returns between 1996 and 2006 and find significant return differentials among the nine portfolios. In general, returns are higher for large size firms and for growth firms, while returns are lower for small size firms and for value firms. For example, the average value-weighted weekly return of the large size portfolios (BH, BM, and BL) is 0.383 per cent per week, smaller than that of small-size portfolios (SH, SM, and SL) of 0.211 per cent per week; the average value-weighted weekly return of value portfolios (BL, ML, and SL) is 0.208 per cent per week, smaller than that of growth portfolios (BH, MH, and SH) of 0.403 per cent per week.

[35] The data vary drastically over time from 1995 to 2006. For instance, at its peak in 1997, the BL portfolio counts for 41.2 per cent of the market value of all sample firms.

Table 6.1: The characteristics of style portfolios

Nine style portfolios are formed at the end of each year between 1995 and 2005. All available stocks listed on the SHSE and SZSE are independently ranked according to market capitalisation and B/M. Nine size-B/M portfolios are defined as the intersections of the three size and three B/M groups. All stocks are first ranked independently by their year-end market capitalisation and B/M and then allocated to three size groups: small (Bottom 30 per cent), middle, or big (Top 30 per cent) group, as well as three B/M groups: value (Top 30 per cent), blend, or growth (Bottom 30 per cent) group. I report average market values (in millions of RMB) and B/M of each portfolio at the end of each year. I also list the cross-sectional average percentile rank of the stocks in each portfolio for all stocks in the sample. The ranks represent the per cent of all publicly traded firms with lower market values or lower book-to-market ratios. In the last row, I list the time-series average market value of each portfolio as a percentage of the cumulated value of all stocks in sample. The nine portfolios are big-value (BH), middle-value (MH), Small-value (SH), big-blend (BM), middle-blend (MM), small-blend (SM), big-growth (BL), middle-growth (ML), and small-blend (SL).

	SH	SM	SL	MH	MM	ML	BH	BM	BL
Panel A: Market capitalisation									
End 1995	449.3	513.2	484.7	925.6	910.5	1141.6	6997.3	3370.0	2646.5
End 1996	724.4	827.7	812.8	1525.5	1496.2	1615.1	9563.0	7587.6	4560.9
End 1997	880.5	876.8	1091.8	1802.3	1788.6	1658.7	10261.8	6491.7	8148.4
End 1998	1149.6	986.4	1256.6	1960.7	2069.6	1826.1	11354.5	6411.4	4868.6
End 1999	1183.4	1135.6	1134.6	2025.3	2022.6	2100.0	6180.6	4672.9	5494.8
End 2000	2199.4	2159.2	1958.3	3515.8	3521.6	3406.7	8686.9	8000.7	8070.0
End 2001	1757.8	1693.7	1577.0	2768.0	2601.7	2761.3	6533.7	6677.3	5714.5
End 2002	1275.2	1327.3	1238.7	2207.7	2084.4	2169.5	5470.0	5588.2	4844.8
End 2003	962.5	996.6	917.5	1855.5	1842.1	1864.3	4790.6	6432.8	6207.8
End 2004	770.7	764.8	730.2	1540.5	1506.8	1521.7	5546.1	6080.4	5292.8
End 2005	599.1	582.0	561.3	1148.9	1187.7	1185.8	3983.3	5111.3	5260.0
End 2006	748.9	785.2	738.8	1650.4	1714.9	1783.6	7839.2	8451.3	8809.5
Panel B: B/M									
End 1995	0.811	0.436	0.320	0.827	0.491	0.283	0.738	0.421	0.285
End 1996	0.506	0.313	0.211	0.496	0.346	0.174	0.470	0.316	0.217
End 1997	0.555	0.327	0.236	0.521	0.352	0.189	0.474	0.295	0.206
End 1998	0.510	0.291	0.193	0.478	0.292	0.181	0.628	0.299	0.188
End 1999	0.412	0.253	0.146	0.443	0.254	0.140	0.466	0.258	0.142
End 2000	0.287	0.176	0.089	0.300	0.181	0.091	0.324	0.179	0.089
End 2001	0.438	0.250	0.128	0.412	0.256	0.120	0.435	0.245	0.128
End 2002	0.499	0.327	0.155	0.535	0.340	0.166	0.588	0.337	0.171
End 2003	0.625	0.411	0.212	0.642	0.415	0.224	0.665	0.404	0.228
End 2004	0.805	0.497	0.261	0.823	0.508	0.283	0.788	0.497	0.295
End 2005	1.023	0.645	0.314	1.066	0.647	0.359	1.094	0.629	0.347
End 2006	0.782	0.457	0.222	0.815	0.456	0.234	0.777	0.457	0.208
Panel C: Percentage of market value of all stocks									
	2.77	4.41	3.29	9.21	10.23	6.43	15.42	24.78	24.12

Table 6.2 The returns of passive style portfolios

Nine style portfolios are formed at the end of each year between 1995 and 2005. I study the returns earned by these portfolios between January 1996 and December 2006. For each portfolio, I list time-series averages of 1) portfolio returns for each month (expressed in per cent per week); 2) value-weighted average portfolio returns (expressed in per cent per week); and 3) the time-series average number of stocks in each portfolio. The nine portfolios are big-value (BH), middle-value (MH), Small-value (SH), big-blend (BM), middle-blend (MM), small-blend (SM), big-growth (BL), middle-growth (ML), and small-blend (SL).

	BL	BM	BH	ML	MM	MH	SL	SM	SH
January	0.491	0.279	0.173	0.231	0.139	0.188	0.479	−0.000	0.213
February	1.528	1.529	1.795	1.731	0.699	0.740	1.054	0.554	0.331
March	1.126	1.221	1.369	0.980	0.703	0.773	0.468	0.812	0.612
April	1.301	0.531	0.285	0.639	0.586	0.348	0.546	1.082	0.459
May	0.807	1.412	0.938	0.973	0.161	0.737	1.082	0.172	0.606
June	1.273	0.867	1.176	1.519	0.890	1.172	1.572	1.502	0.979
July	−0.001	−0.009	−0.008	0.000	−0.005	−0.007	−0.007	−0.002	−0.008
August	−0.275	0.255	0.665	−0.167	−0.049	−0.064	−0.295	−0.446	−0.743
September	−0.003	0.448	0.343	0.135	0.109	−0.158	−0.056	−0.367	−0.604
October	0.441	−0.240	0.142	0.042	0.691	0.257	0.547	0.067	0.245
November	0.229	−0.116	−0.104	0.207	0.017	−0.166	−0.219	0.119	0.078
December	−0.945	−0.791	−0.948	−0.735	−0.347	−0.573	−0.224	−0.402	−0.459
V.W. return	0.449	0.333	0.368	0.425	0.244	0.190	0.334	0.232	0.066
Ave. stocks	36.7	58.8	47.0	67.5	75.1	47.3	39.1	54.5	49.0

Furthermore, I report value weighted weekly returns from month to month. Empirical evidence shows relatively high return in May and June, but relatively low return in December. With an average return of 0.066 per cent per week, the SH portfolio performs worst in all style portfolios. The BL portfolio performs best and earns an average 0.449 per cent per week. The average differences in returns between high and low B/M stocks with similar size range 0.117 and 0.269 per cent per week. Along the size dimension, differences in average annualised returns between small and large size firms with similar B/M are between 0.115 and 0.303 per cent per week. Table 6.2 also reports the time-series average cross-sectional standard deviation of returns for the stocks in each style portfolio. The statistics may be used to measure the risk on stock selection. It tells that, on average, the range of returns offered by individual stocks in small size portfolios is much wider than those in the large size portfolios.

Table 6.3: Average weekly returns of style momentum portfolios

Nine style portfolios are ranked every week by their return performance for the past F weeks (F equals 12, 24, 36, or 48 weeks). I buy the top (or the top two) winner style portfolio(s) and sell the corresponding loser portfolio(s). The arbitrage portfolios are held for the subsequent H test periods (H equals 12, 24, 36, or 48 weeks, or two or three years), with a four-week skip between performance ranking and portfolio holding periods to avoid market microstructure biases.

F		H = 12	24	36	48	2 years	3 years
Panel A: Arbitrage portfolio holds two extreme style portfolios							
12	Winner	0.4339	0.4085	0.3862	0.3677	0.2310	0.1793
	Loser	0.0262	0.0546	0.1168	0.1713	0.1663	0.1814
	Winner – Loser	0.4077	0.3539	0.2694	0.1964	0.0648	−0.0020
	t-stat	(2.61)[b]	(3.25)[b]	(2.94)[b]	(2.39)[a]	(1.04)	(−0.08)
24	Winner	0.5165	0.4834	0.4424	0.3962	0.1961	0.1362
	Loser	−0.0521	0.0537	0.1280	0.1583	0.1599	0.1934
	Winner – Loser	0.5686	0.4297	0.3144	0.2378	0.0362	−0.0572
	t-stat	(3.62)[b]	(3.88)[b]	(3.37)[b]	(2.82)[b]	(1.15)	(−1.12)
36	Winner	0.5663	0.5101	0.4379	0.3717	0.1659	0.1181
	Loser	−0.0228	0.0763	0.1237	0.1521	0.1508	0.1759
	Winner – Loser	0.5891	0.4337	0.3143	0.2196	0.0151	−0.0578
	t-stat	(3.68)[b]	(3.89)[b]	(3.34)[b]	(2.57)[b]	(0.49)	(−1.15)
48	Winner	0.5646	0.4756	0.3861	0.3223	0.1308	0.0930
	Loser	−0.0261	0.0420	0.0928	0.1240	0.1240	0.1446
	Winner – Loser	0.5907	0.4337	0.2933	0.1983	0.0068	−0.0516
	t-stat	(3.66)[b]	(3.85)[b]	(3.11)[b]	(2.41)[a]	(0.23)	(−0.97)
Panel B: Arbitrage portfolio holds four extreme style portfolios							
12	Winner	0.3349	0.3431	0.3372	0.3245	0.2242	0.1928
	Loser	0.0865	0.1001	0.1427	0.1877	0.1766	0.1882
	Winner – Loser	0.2483	0.2430	0.1946	0.1369	0.0477	0.0046
	t-stat	(1.68)	(2.36)[a]	(2.24)[a]	(1.78)	(0.58)	(0.17)
24	Winner	0.4323	0.4204	0.3964	0.3595	0.2072	0.1631
	Loser	−0.0077	0.0663	0.1410	0.1700	0.1552	0.1842
	Winner – Loser	0.4400	0.3541	0.2554	0.1895	0.0520	−0.0211
	t-stat	(2.96)[b]	(3.36)[b]	(2.89)[b]	(2.39)[a]	(0.74)	(−0.79)
36	Winner	0.4880	0.4462	0.3910	0.3467	0.1818	0.1379
	Loser	−0.0172	0.0553	0.1036	0.1315	0.1304	0.1670
	Winner – Loser	0.5051	0.3909	0.2874	0.2152	0.0515	−0.0292
	t-stat	(3.27)[b]	(3.70)[b]	(3.22)[b]	(2.69)[b]	(0.75)	(−1.10)
48	Winner	0.5147	0.4285	0.3734	0.3195	0.1555	0.1117
	Loser	−0.0146	0.0356	0.0823	0.1143	0.1203	0.1537
	Winner – Loser	0.5293	0.3929	0.2912	0.2052	0.0351	−0.0421
	t-stat	(3.44)[b]	(3.65)[b]	(3.25)[b]	(2.60)[b]	(1.20)	(−1.60)

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

6.4 Empirical results of style momentum strategies

Table 6.3 reports the average weekly return of the different winner, loser, and winner minus loser portfolios. It is noteworthy that the returns of the winner minus loser portfolios are all positive and statistically significant when the holding periods are no more than 48 weeks. The most successful style momentum strategies are those selecting stocks based on past 12-, 24-, 36-, or 48-week returns and hold them for the subsequent 48 weeks. Panel A of Table 6.3 shows that the 12-48 style momentum strategy yields a profit of 0.591 per cent per week (t-stat = 3.66). The results remind us of the findings on regular price momentum reported in Table 4.1. The 24-24 regular price momentum strategy generates a profit of 0.112 per cent per week (t-stat = 2.36), while in this study I find a profit of 0.430 per cent per week (t-stat = 3.88) generated from the 24-24 style momentum strategy. Compared with regular momentum strategies, style momentum strategies generally make much higher profits. The style momentum profits are strong over the portfolio holding periods up to 48 weeks, whereas they become statistically insignificant once the arbitrage portfolios are held for more than one year. When the holding periods are two or three years, all strategies generate small, even negative profits and none of them are significant. I perform various robustness checks. For instance, I also study arbitrage portfolios that hold four extreme style portfolios. Not surprisingly, the profits presented in Panel B of Table 6.3 are a little smaller, compared with those shown in Panel A, but still significant. In addition, I also calculate the momentum profits without skipping four weeks, the unreported results are qualitatively unchanged.

Table 6.4: Style momentum portfolios by quarter and year, 1996 to 2005

At the beginning of each quarter (year) I rank nine style portfolios by their cumulated returns over the previous quarter (year). I denote the most extreme winner portfolio and the most extreme loser portfolio. The quarterly (annual) rank period return, in percent, of the winner portfolio and the loser portfolio are presented. The nine portfolios are big-value (BH), middle-value (MH), Small-value (SH), big-blend (BM), middle-blend (MM), small-blend (SM), big-growth (BL), middle-growth (ML), and small-blend (SL).

	Winner		Loser			Winner		Loser	
1996Q1	BL	−2.93	BM	−18.30	2001Q1	SL	14.07	BH	3.80
1996Q2	ML	−3.84	SH	−14.72	2001Q2	BH	4.68	SL	−4.58
1996Q3	BL	71.26	SH	9.81	2001Q3	SL	14.21	BH	−0.83
1996Q4	ML	27.43	SH	−10.67	2001Q4	BL	−13.78	SH	−23.78
1996	BL	12.33	SM	−16.73	2001	BL	115.97	BH	47.56
1997Q1	ML	21.31	MH	1.66	2002Q1	BH	−4.20	SM	−10.42
1997Q2	SH	42.54	BH	5.13	2002Q2	BL	4.77	SH	−4.80
1997Q3	BM	32.06	BH	−14.88	2002Q3	ML	7.07	MM	3.72
1997Q4	BH	−4.12	BM	−25.50	2002Q4	BL	−1.25	MH	−10.00
1997	BL	128.48	MH	5.11	2002	BL	−9.76	SM	−26.55
1998Q1	BM	15.33	BH	−15.32	2003Q1	BL	−7.88	SH	−17.04
1998Q2	ML	24.05	BH	−3.82	2003Q2	BL	4.81	MH	−1.30
1998Q3	ML	48.28	BH	−0.15	2003Q3	BL	9.02	SH	−9.74
1998Q4	SM	18.53	BL	−11.05	2003Q4	ML	−3.82	SH	−11.24
1998	BL	38.35	BH	−14.05	2003	BL	2.30	SH	−22.95
1999Q1	BL	−2.45	BH	−10.82	2004Q1	BH	10.83	SL	−17.57
1999Q2	ML	5.04	BM	−4.75	2004Q2	BL	26.44	BH	14.74
1999Q3	BL	79.45	SH	23.31	2004Q3	BL	−16.03	SL	−26.49
1999Q4	ML	2.12	MH	−8.22	2004Q4	BL	9.98	SL	−6.35
1999	BL	31.04	BH	−12.05	2004	BH	13.04	SM	−33.50
2000Q1	BL	−6.92	BH	−17.34	2005Q1	BL	−4.86	SH	−14.39
2000Q2	BL	60.61	BH	24.96	2005Q2	BL	−1.48	SM	−16.73
2000Q3	BL	20.39	MH	7.27	2005Q3	BL	1.45	SL	−10.78
2000Q4	BL	8.73	SH	−4.92	2005Q4	BL	10.78	MH	−1.70
2000	BL	61.42	SH	8.42	2005	BL	10.08	SH	−23.81

I further explore the investment styles that the imaginary investors would in fact have followed when they construct the style momentum strategies. Table 6.4 lists the best and worst performing investment styles and the corresponding cumulative ranking period returns (over 12 or 48 months) at the end of each quarter and at the end of each year since 1996. It is interesting to note that at the end of each year from 1996 to 2005 the big growth (BL) portfolio is a frequent winner (nine out of ten years) and loser is dominated by value portfolios (BH and SH), consistent with evidence presented in Table 6.2.

Table 6.5: The composition of style momentum portfolios

Every week between 1996 and 2005, nine portfolios are ranked by their returns for the prior 12, 24, 36, or 48 weeks. I create a style momentum portfolio that buys winners, i.e., the one or two style portfolios with the best past returns, and that sells losers, i.e., the style portfolios with the worst past returns. I report the percentage of strategy replications that features a given style portfolio, either on the winner (buy) or on the loser (sell) side.

	SH	SM	SL	MH	MM	ML	BH	BM	BL	Value	Growth	Big	Small
Panel A: Past 12-week ranking period													
Buy one	2.35	2.94	9.78	1.76	0.39	20.35	4.5.0	7.05	50.88	8.61	81.01	62.43	15.07
Sell one	28.38	7.24	17.81	6.46	1.57	1.57	29.94	5.87	1.17	64.78	20.55	36.98	53.43
Buy two	3.91	7.83	23.87	2.74	2.74	46.58	14.87	31.51	65.95	21.52	136.4	112.33	35.61
Sell two	47.95	28.38	24.46	30.92	9.00	4.31	37.96	14.87	2.15	116.83	30.92	54.98	100.79
Panel B: Past 24-week ranking period													
Buy one	2.54	2.74	3.13	0.00	0.20	10.76	0.59	6.46	73.58	3.13	87.47	80.63	8.41
Sell one	34.05	12.72	10.57	12.52	0.78	0.59	26.81	1.96	0.00	73.38	11.16	28.77	57.34
Buy two	3.52	4.31	15.07	0.59	3.91	49.32	3.52	35.81	83.95	7.63	148.34	123.28	22.9
Sell two	55.38	29.55	18.98	45.4	2.15	1.37	40.51	6.26	0.39	141.29	20.74	47.16	103.91
Panel C: Past 36-week ranking period													
Buy one	1.17	0.20	2.54	0.00	1.17	9.39	0.39	5.68	79.45	1.56	91.38	85.52	3.91
Sell one	38.16	9.39	8.41	20.94	0.00	0.39	22.70	0.00	0.00	81.80	8.80	22.70	55.96
Buy two	3.91	1.37	9.2	0.00	2.94	52.05	1.76	42.47	86.30	5.67	147.55	130.53	14.48
Sell two	54.21	31.31	20.74	48.92	0.59	1.17	40.31	2.74	0.00	143.44	21.91	43.05	106.26
Panel D: Past 48-week ranking period													
Buy one	0.59	0.00	1.76	0.00	0.39	8.41	1.37	4.11	83.37	1.96	93.54	88.85	2.35
Sell one	37.57	10.37	7.83	19.77	0.00	0.00	24.46	0.00	0.00	81.80	7.83	24.46	55.77
Buy two	3.91	1.57	7.44	0.00	1.57	52.64	2.94	42.27	87.67	6.85	147.75	132.88	12.92
Sell two	55.97	35.42	18.2	49.71	0.00	0.00	39.92	0.78	0.00	145.60	18.20	40.70	109.59

In Table 6.5, I compute the fraction of all weekly strategy replications that a particular style portfolio is held long or sold short. I report separate statistics for style momentum portfolios that have one or two portfolios on the buy and sell side, based on prior 12-, 24-, 36-, and 48-week ranking periods. The results clearly show that style momentum strategies focus on buying the large size or growth portfolios and selling the small size or value portfolios. For example, Panel A shows that based on past 12-month performance ranking period, 81.01 per cent of stocks the style momentum strategies sell is growth portfolios and 62.43 per cent of stocks they buy is large size portfolios, while 64.78 per cent of stocks the style momentum strategies buy is value portfolios and 53.43 per cent of stock they sell is small size portfolios. The empirical evidence in Panels B, C, and D of Table 6.5 shows the consistent results when the ranking periods are based on prior 24-, 36-, or 48-week returns.

6.5 Industry momentum and style momentum

Moskowitz and Grinblatt (1999) find a similar pattern in industry portfolios: the best-performing industries continue to beat the worst performers. They divide stocks into twenty industry portfolios over the period 1963 to 1995, and then sort the industry portfolios based on their past six-month returns. The top-three industry portfolios with the highest past returns are called the winner portfolios and the bottom-three industry portfolios with lowest past returns are called the loser portfolios. They present evidence of strong momentum effect across industries: when stocks from past winner industries are bought and stocks from loser industries are sold, the industry-based winner minus loser strategy appears to be highly profitable, even after controlling for cross-sectional dispersion in mean returns and likely microstructure differences. For example, investing in a winner minus loser portfolio shows a historical average return of 9.5 per cent per year during a twelve-month holding period after formation.

In this section, I first examine the industry momentum effect in the China stock market and then investigate whether style momentum is a phenomenon that can be distinguished by industry momentum. Two alternative approaches, the industry-adjusted excess style momentum profits and an independent two-way classification scheme, are employed to disentangle the two phenomena.

6.5.1 Industry-adjusted style momentum profits

Nine style portfolios are ranked based on their previous 12- to 48-week returns and repeat this procedure for every week between 1996 and 2005. I create an arbitrage portfolio that buys the greatest past winner style portfolio and that sells the greatest past loser style portfolio. I calculate the value-weighted average weekly raw returns for the style momentum strategies. I further assign every stock to 1 of 25 industry sectors as defined by S&P and FTSE (see Appendix 6.1) and then adjust the raw returns of style momentum strategies by deducting the contemporaneous value-weighted returns of their matching industry portfolios. Panels A, B, C, and D of Table 6.6 report the value-weighted weekly return on style momentum, industry momentum, and industry-adjusted style momentum, based on past 12-, 24-, 36-, or 48-week ranking period.

Table 6.6: Average raw weekly returns and industry-adjusted weekly returns of style momentum portfolios

This table presents the value-weighted weekly raw return of style and industry momentum strategies as well as the industry-adjusted return of style momentum strategies (Top 1 winner minus Bottom 1 loser). Every week, starting in January 1996, I rank all stocks into nine portfolios based on the past 12-, 24-, 36-, or 48-week returns of the style portfolios to which they belong or the past 12-, 24-, 36-, or 48-week returns of the industry portfolios to which they belong. I employ return data through the end of the year 1996. I create arbitrage portfolios that buy the greatest past winners and that sell the greatest past losers. The style momentum strategy assigns all stocks to portfolios as explained in Table 6.1. The industry momentum strategy only buys (sells) all stocks that belong to the four industries that perform the best (the worst) during the ranking period.

I report value-weighted average raw returns of style and industry momentum, as well as industry-adjusted style returns during the portfolio holding period, all expressed in percent per week. (The value weights use the market capitalisation figures for the last trading day of the previous week.)

	H = 12	24	36	48	2 years	3 years
Panel A: Past 12-week ranking period						
Raw returns of style momentum	0.3876	0.3581	0.2818	0.2008	0.0554	−0.0162
t-stat	(4.80)[b]	(6.49)[b]	(6.22)[b]	(4.89)[b]	(0.75)	(−0.61)
Industry-adj. returns of style momentum	0.2649	0.2745	0.2246	0.154	0.0392	−0.0112
t-stat	(3.73)[b]	(3.59)[b]	(3.24)[b]	(2.33)[a]	(0.88)	(−0.50)
Raw returns of industry momentum	−0.0258	0.0139	−0.0056	0.0134	−0.0123	−0.0357
t-stat	(−0.34)	(0.25)	(−0.13)	(0.35)	(−0.42)	(−1.39)
Panel B: Past 24-week ranking period						
Raw returns of style momentum	0.6204	0.4882	0.3468	0.2536	0.0387	−0.0593
t-stat	(7.88)[b]	(8.78)[b]	(7.48)[b]	(6.00)[b]	(1.23)	(−1.46)
Industry-adj. returns of style momentum	0.4922	0.3996	0.2839	0.1965	0.0367	−0.0457
t-stat	(4.05)[b]	(3.53)[b]	(2.83)[b]	(2.79)[b]	(1.02)	(−0.37)
Raw returns of industry momentum	0.0556	0.0572	0.0649	0.0606	−0.0113	−0.0511
t-stat	(0.73)	(1.06)	(1.46)	(1.55)	(−0.40)	(−1.05)
Panel C: Past 36-week ranking period						
Raw returns of style momentum	0.6246	0.4833	0.3394	0.2368	0.02	−0.0685
t-stat	(7.70)[b]	(8.44)[b]	(7.09)[b]	(5.48)[b]	(0.64)	(−1.55)
Industry-adj. returns of style momentum	0.477	0.3676	0.2542	0.1758	0.0134	−0.0559
t-stat	(4.20)[b]	(3.31)[b]	(3.92)[b]	(2.93)[b]	(0.62)	(−0.34)
Raw returns of industry momentum	0.0217	0.0512	0.0421	0.0337	−0.0732	−0.0919
t-stat	(0.28)	(0.93)	(0.93)	(0.85)	(−0.48)	(−1.58)
Panel D: Past 48-week ranking period						
Raw returns of style momentum	0.6458	0.4707	0.3096	0.2088	0.014	−0.0576
t-stat	(8.08)[b]	(8.21)[b]	(6.42)[b]	(4.95)[b]	(0.46)	(−1.16)
Industry-adj. returns of style momentum	0.4671	0.3394	0.2256	0.1523	0.0007	−0.0541
t-stat	(4.35)[b]	(3.23)[b]	(2.13)[a]	(2.02)[a]	(0.09)	(−0.82)
Raw returns of industry momentum	0.0511	0.0361	0.0058	−0.0178	−0.0206	−0.1198
t-stat	(0.67)	(0.68)	(0.13)	(−0.47)	(−0.36)	(−1.83)

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

The results in Table 6.6 imply that it is difficult to disregard style momentum for ranking periods based on the past 12 to 48 weeks, because the industry-adjusted style momentum profits all remain statistically significant and the magnitude is similar to that of the raw results. For example, the raw return of the 24-24 style strategy is 0.488 per cent per week (*t*-stat = 8.78), while the industry-adjusted return is 0.400 (*t*-stat = 3.53) per cent per week. As before, these profits do not persist during the second and third year after portfolio formation. The arbitrage profits are slightly different from that presented in Table 6.3 is due to the fact that the returns listed in Table 6.3 are equal-weighted while the returns in Table 6.6 are value-weighted.

The result implies that the industry factor has little influence on the style momentum. One possible interpretation of the findings is that the industry momentum phenomenon may not exist in the China stock market. Empirical evidence presented in Table 6.6 supports this argument. I examine industry momentum strategies that buy stocks that belong to the four of 25 industries that perform the best and meanwhile sell stocks that belong to the four of 25 industries that perform the worst during the ranking periods. I estimate raw returns of the industry strategies in a comparable way to what I do for style momentum strategies. For 12- to 48-week ranking periods, industry momentum strategies are not statistically significant in arbitrage portfolios over the subsequent 12 to 48 weeks and two to three years.

Table 6.7: Average weekly returns of industry momentum portfolios that vary in style momentum

Every week, starting in 1996, I form groups of stocks based on rank indicators for style (S) and industry (I) momentum. In the case of S, nine style portfolios are ranked by their returns by their prior 12, 24, 36, or 48 weeks. The top three style portfolios are labelled as S1 (winner style portfolio), the bottom three are labelled S3 (loser style portfolio). Portfolios in the middle are labelled S2. In the case of I, 25 industry portfolios are ranked by their prior 12-, 24-, 36-, or 48-week returns. The top eight industry portfolios are labelled I1 (winner industry portfolio) and the bottom eight are labelled I3 (loser industry portfolio). Portfolios in the middle are labelled I2. In pair-wise firms between I and S, every stock is assigned to one of nine portfolios defined as the intersections of S and I. (By construction, the nine portfolio do not hold the same number of stocks.) In panels A, B, C, and D, I report equally weighted average returns during the holding period for the I-S portfolios when the ranking periods are based on past 12-, 24-, 36-, or 48-week returns and hold in the subsequent 12, 24, 36, or 48 weeks, respectively.

	H = 12	24	36	48	2 years	3 years
Panel A: Past 12-week ranking period						
I1S1	0.2979	0.3138	0.2985	0.2996	0.2116	0.1954
I1S2	0.1839	0.2011	0.2265	0.2638	0.2214	0.2099
I1S3	0.1241	0.1884	0.2268	0.2607	0.2226	0.2124
I1S1 – I1S3	0.1738	0.1253	0.0718	0.0389	–0.0110	–0.0170
	(2.49)[a]	(2.26)[a]	(1.57)	(0.94)	(–0.35)	(–0.62)
I2S1	0.3681	0.3842	0.3702	0.3529	0.2584	0.2155
I2S2	0.1574	0.1919	0.2337	0.2532	0.2082	0.1988
I2S3	0.1087	0.1189	0.1471	0.1847	0.1946	0.1955
I2S1 – I2S3	0.2594	0.2653	0.223	0.1682	0.0638	0.02
	(3.37)[b]	(4.79)[b]	(4.88)[b]	(4.24)[b]	(1.04)	(0.73)
I3S1	0.3424	0.3411	0.346	0.3277	0.2221	0.2012
I3S2	0.1652	0.1828	0.2127	0.2336	0.2198	0.2265
I3S3	0.096	0.0834	0.1179	0.1609	0.1767	0.1993
I3S1 – I3S3	0.2463	0.2577	0.2281	0.1668	0.0454	0.0019
	(3.23)[b]	(4.62)[b]	(4.82)[b]	(4.08)[b]	(1.43)	(0.07)
Panel B: Past 24-week ranking period						
I1-S1	0.3619	0.355	0.3374	0.3181	0.1868	0.1617
I1-S2	0.1476	0.201	0.2428	0.2706	0.2042	0.199
I1-S3	0.113	0.1296	0.1958	0.23	0.1848	0.2076
I1-S1 – I1-S3	0.2489	0.2254	0.1415	0.0881	0.002	–0.046
	(3.12)[b]	(4.05)[b]	(3.10)[b]	(2.12)[a]	(0.06)	(–1.65)
I2-S1	0.4083	0.442	0.4129	0.3739	0.2486	0.2051
I2-S2	0.184	0.2179	0.2623	0.2569	0.1996	0.192
I2-S3	0.0501	0.0984	0.1636	0.1972	0.1924	0.1966
I2-S1 – I2-S3	0.3581	0.3436	0.2493	0.1766	0.0562	0.0085
	(4.56)[b]	(5.95)[b]	(5.23)[b]	(4.26)[b]	(1.72)	(0.29)
I3-S1	0.344	0.3623	0.3773	0.3467	0.2333	0.2026
I3-S2	0.1194	0.1589	0.1987	0.2045	0.1806	0.2033
I3-S3	0.0227	0.0517	0.1232	0.1609	0.165	0.1967
I3-S1 – I3-S3	0.3213	0.3106	0.2541	0.1858	0.0683	0.0059
	(4.14)[b]	(5.57)[b]	(5.24)[b]	(4.42)[b]	(1.14)	(0.21)

continued

Table 6.7 (continued)

Panel C: Past 36-week ranking period						
I1-S1	0.3796	0.3751	0.3381	0.3113	0.1528	0.1286
I1-S2	0.1641	0.2314	0.2788	0.2847	0.1969	0.1899
I1-S3	−0.0158	0.0979	0.1648	0.2063	0.1678	0.2093
I1-S1 − I1-S3	0.3954	0.2771	0.1733	0.105	−0.015	−0.0807
	(5.23)[b]	(5.19)[b]	(3.87)[b]	(2.55)[a]	(−0.50)	(−2.90)
I2-S1	0.4615	0.4808	0.4044	0.3587	0.214	0.1664
I2-S2	0.1746	0.2387	0.2511	0.2377	0.1844	0.1785
I2-S3	0.0241	0.0906	0.1401	0.1607	0.1497	0.1678
I2-S1 − I2-S3	0.4374	0.3903	0.2643	0.198	0.0643	−0.0015
	(5.42)[b]	(6.73)[b]	(5.50)[b]	(4.62)[b]	(1.03)	(−0.05)
I3-S1	0.392	0.4452	0.4012	0.3657	0.2225	0.1864
I3-S2	0.2126	0.21	0.2355	0.226	0.1909	0.1976
I3-S3	0.0039	0.0755	0.132	0.1539	0.1587	0.1899
I3-S1 − I3S3	0.3881	0.3697	0.2692	0.2118	0.0638	−0.0036
	(4.93)[b]	(6.50)[b]	(5.57)[b]	(5.10)[b]	(1.05)	(−0.13)
Panel D: Past 48-week ranking period						
I1-S1	0.4444	0.3948	0.3523	0.2983	0.1324	0.1097
I1-S2	0.2204	0.252	0.2718	0.251	0.1801	0.1783
I1-S3	−0.0287	0.0654	0.1268	0.1643	0.1481	0.1836
I1-S1 − I1-S3	0.4732	0.3293	0.2255	0.134	−0.0157	−0.0739
	(6.45)[b]	(6.26)[b]	(5.02)[b]	(3.32)[b]	(−0.51)	(−0.61)
I2-S1	0.5082	0.4665	0.3884	0.3321	0.1713	0.1267
I2-S2	0.2428	0.2546	0.244	0.2303	0.1754	0.1688
I2-S3	0.023	0.0516	0.1008	0.1317	0.1312	0.1582
I2-S1 − I2-S3	0.4852	0.4149	0.2876	0.2004	0.0401	−0.0315
	(6.45)[b]	(7.56)[b]	(6.29)[b]	(5.02)[b]	(1.35)	(−1.17)
I3-S1	0.5412	0.5011	0.4333	0.3775	0.231	0.1754
I3-S2	0.1695	0.1682	0.1648	0.1642	0.1569	0.1674
I3-S3	0.0313	0.0647	0.1007	0.1213	0.1321	0.1666
I3-S1 − I3-S3	0.5099	0.4364	0.3326	0.2562	0.0989	0.0088
	(6.17)[b]	(7.19)[b]	(6.66)[b]	(6.01)[b]	(1.10)	(0.32)

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

6.5.2 Two way classification scheme

Table 6.7 further examines the interaction of style and industry momentum on the basis of an independent two-way classification scheme. Every week, nine style portfolios are formed based on past 12- to 48-week ranking period returns. Style portfolios in the top three are labelled S1 (winner style portfolio), while stocks in the bottom three are labelled S3 (loser style portfolio). Portfolios in the middle are labelled as S2. Next, 25 industry portfolios are also ranked by prior 12- to 48-week performance. Industry portfolio in the top 8 are labelled as I1 (winner industry portfolio), while portfolios in the bottom eight are labelled as I3 (losers industry portfolio). Portfolios in between are labelled I2. Every stock on the SHSE and SZSE is assigned to one of the nine industry and style momentum portfolios (I-S-portfolios). In Panel A of Table 6.7, I report equal-weighted average weekly returns for I,S-portfolios during the holding period when the ranking periods are based on past 12-week returns. Sorted by winner, medium, and loser industries, the best past investment styles continue to beat the worst past styles by profits of 0.174 per cent per week (t-stat = 2.49), 0.260 per cent per week (t-stat = 3.37), and 0.246 per cent per week (t-stat = 3.23). Panels B, C, and D of Table 6.7 show consistent and even larger returns for portfolios ranked by past 24-, 36-, and 48-week returns.

In sum, the results based on the independent two-way classification scheme confirm that profits generated by style momentum are not affected by industry momentum phenomenon because of the non-existence of industry momentum effect in the China stock market and because of the significant style momentum effect after controlling for industry factor.

Table 6.8: The average weekly returns of style momentum portfolios in two sub-periods

Every week, starting in 1996, nine style portfolios are ranked by their prior 12-, 24-, 36-, or 48-week returns. I buy the style portfolio with the best returns over the ranking period and sell the portfolio with the worst returns. The arbitrage portfolio is held for H = 12, 24, 36, or 48 weeks. I report equally weighted average test period returns, expressed in per cent per week. In Panels A, B, C, and D, I study the style strategies in two sub-periods: the booming period 1995 to 2000 and the depressed period 2001 to 2006.

		H = 12	24	36	48
Panel A: Past 12-week performance ranking period					
	Winner	0.8180	0.7899	0.7319	0.6986
The period 1995 to 2000	Loser	0.3019	0.3508	0.4390	0.4747
	Winner – Loser	0.5162	0.4391	0.2929	0.2238
	t-stat	(4.28)b[b]	(5.50)b[b]	(4.50)b[b]	(4.08)b[b]
	Winner	–0.0143	–0.0365	–0.0170	–0.0183
The period 2001 to 2006	Loser	–0.2954	–0.2910	–0.2590	–0.1827
	Winner – Loser	0.2811	0.2545	0.2420	0.1644
	t-stat	(3.43)b[b]	(4.71)b[b]	(5.54)b[b]	(3.85)[b]
Panel B: Past 24-week performance ranking period					
	Winner	0.8819	0.8521	0.7975	0.7263
The period 1995 to 2000	Loser	0.2705	0.4281	0.4982	0.4961
	Winner – Loser	0.6114	0.4240	0.2992	0.2302
	t-stat	(4.90)[b]	(5.13)[b]	(4.55)[b]	(4.03)[b]
	Winner	0.1091	0.0724	0.0465	0.0280
The period 2001 to 2006	Loser	–0.4118	–0.3637	–0.2848	–0.2183
	Winner – Loser	0.5209	0.4361	0.3313	0.2463
	t-stat	(6.70)[b]	(8.41)[b]	(7.59)[b]	(5.77)[b]
Panel C: Past 36-week performance ranking period					
	Winner	0.9759	0.9100	0.7966	0.6890
The period 1995 to 2000	Loser	0.3442	0.4752	0.5057	0.5008
	Winner – Loser	0.6317	0.4348	0.2909	0.1882
	t-stat	(4.91)[b]	(5.25)[b]	(4.32)[b]	(3.16)[b]
	Winner	0.1307	0.0847	0.0566	0.0343
The period 2001 to 2006	Loser	–0.4130	–0.3479	–0.2826	–0.2188
	Winner – Loser	0.5437	0.4326	0.3392	0.2530
	t-stat	(7.03)[b]	(8.26)[b]	(7.72)[b]	(5.91)[b]
Panel D: Past 48-week performance ranking period					
	Winner	1.0059	0.8725	0.7252	0.6158
The period 1995 to 2000	Loser	0.3455	0.4370	0.4666	0.4624
	Winner – Loser	0.6604	0.4355	0.2586	0.1535
	t-stat	(5.02)[b]	(5.10)[b]	(3.70)[b]	(2.67)[b]
	Winner	0.1218	0.0791	0.0397	0.0204
The period 2001 to 2006	Loser	–0.3945	–0.3515	–0.2912	–0.2259
	Winner – Loser	0.5163	0.4306	0.3308	0.2463
	t-stat	(6.72)[b]	(8.17)[b]	(7.49)[b]	(5.73)[b]

[b] indicates statistical significance at the 1 percent level.

6.6 Robustness test of style momentum

6.6.1 Style momentum in two sub-periods

To investigate the robustness of the style momentum strategy, I assess the performance of the style momentum strategy in two sub-periods: a relatively booming period 1995 to 2000 and a relatively depressed period 2001 to 2006. The robustness tests are carried out in four group strategies, based on the performance over the previous 12, 24, 36, or 48 weeks.

The results of the robustness test are reported in Table 6.8. First, style momentum is general through time in the China market. Unlike the regular momentum strategies that show distinct results in the two sub-periods, style momentum strategies are profitable in both sub-periods, but the profits are relatively higher during the depressed period 2001 to 2006, compared with those generated from the booming period 1995 to 2000. For example, the 24-24 style momentum strategy generates 0.424 (t-stat = 5.13) and 0.436 (t-stat = 8.41), respectively, over the period 1995 to 2000 and 2001 to 2006. In addition, consistent with regular price momentum, it is the loser portfolios that drive the style momentum profits over the depressed period 2001 to 2006 because the loser portfolios lose much more that do the winner portfolios. However, over the booming period 1995 to 2000, it is the winner portfolios that drive the style momentum profits, because the winner portfolios gain much higher profits than do the loser portfolios.

6.6.2 Style momentum profits and market states

Previous studies document the key relationship between the state of the market and the predictability of stock returns. For example, Pesaran and Timmermann (1995), focusing on some economic factors, such as the T-bill rate, inflation, and industry output, etc, reveal that the predictability is strong when the market is *turbulent* and the predictability is weak when market is *calm*. Since momentum strategies make profits based on past returns, it is logical to test the relationship between the market state and the profitability of momentum strategies.

Chen and De Bondt (2004) observe that style momentum strategies perform better following a turbulent market compared with following a peaceful market, suggesting that momentum might be predictable at some time horizons. Motivated by the work of Chen and De Bondt (2004) and Cooper et al. (2004), I test the impact of market states on the profitability of style momentum strategies. The state of the market is set as Up and Down, with the use of the definition of Cooper et al. (2004). Cooper et al. (2004) document significant momentum profits following an Up market, where previous 36-month market returns are positive, and record negative momentum profits following a Down market, where the previous 36-month market returns are negative. Cooper et al. (2004) argue that the longer horizons should capture greater differences in market states, but longer horizons also yield fewer observations of Down states. Since the relative short sample period in this study, I use lagged two-year market returns to define the state of the market. Therefore, an Up (Down) market is defined when past two-year value-weighted market return on the SHSE and SZSE A-share Indices is non-negative (negative).

Table 6.9 shows some interesting results. First, different from the findings of Cooper et al. (2004) and Chen and De Bondt (2004), all style momentum strategies generate strong profits following both Up and Down markets. Second, profits generated by style momentum strategies following the Down market are relatively higher and more significant than those generated following the Up market. For example, the 24-24 style momentum strategy generates a profit of 0.598 per cent per week (t-stat = 7.89) following the Down market, while a relative low profit of 0.339 per cent per week (t-stat = 4.19) following the Up market. The reason why style momentum strategies perform better following the Down market than following the Up market can be attributed to the performance of the loser portfolios. For the 24-24 style momentum strategy, the loser portfolio generates a positive profit of 0.140 per cent per week following the Up market, while a negative profit of –0.072 per cent per week following the Down markets. Third, the style momentum profits decrease with the increase of the holding period, while the speed is faster following the Up markets. For example, the style momentum strategies with 24-week ranking periods generates a profit of 0.649 per cent per week (t-stat = 6.26) after holding for 12 weeks and a profit of 0.560 per cent per week (t-stat = 6.27) after holding for 48 weeks following the Down markets. The same style momentum strategy following the Up markets generate a profit of 0.534 per cent per week (t-stat = 4.65) after holding for 12 weeks and a profit of 0.116 per cent per week (t-stat = 2.12) after holding for 48 weeks. The result is robust to other style momentum strategies based on different ranking and holding periods.

Table 6.9: The average weekly returns of style momentum portfolios following different market states defined by Cooper et al. (2004)

Every week, starting in 1996, nine style portfolios are ranked by their prior 12-, 24-, 36-, or 48-week returns. I buy the style portfolio with the best returns over the ranking period and sell the portfolio with the worst returns. The arbitrage portfolio is held for H = 12, 24, 36, or 48 weeks. I report equally weighted average test period returns, expressed in per cent per week. In panels A, B, C, and D, I study the style strategies following two opposite market states: the Up markets and the Down market. An Up (Down) market is defined when past two-year value-weighted market return on the SHSE and SZSE A-share Indices is non-negative (negative).

		H = 12	24	36	48
Panel A: Past 12-week performance ranking period					
Following the Down markets	Winner	0.3192	0.4117	0.4206	0.4244
	Loser	−0.0926	−0.0259	−0.0195	0.0822
	Winner – Loser	0.4118	0.4377	0.4401	0.3421
	t-stat	(4.23)[b]	(6.17)[b]	(7.11)[b]	(5.61)[b]
Following the Up markets	Winner	0.4960	0.4137	0.3554	0.3283
	Loser	0.1966	0.1491	0.2370	0.2388
	Winner – Loser	0.2994	0.2646	0.1184	0.0895
	t-stat	(2.49)[a]	(3.24)[b]	(1.81)	(1.64)
Panel B: Past 24-week performance ranking period					
Following the Down markets	Winner	0.4778	0.5260	0.5049	0.4827
	Loser	−0.1709	−0.0721	−0.0084	−0.0776
	Winner – Loser	0.6487	0.5982	0.5133	0.5603
	t-stat	(6.26)[b]	(7.89)[b]	(7.75)[b]	(6.27)[b]
Following the Up markets	Winner	0.5932	0.4791	0.4132	0.3563
	Loser	0.0590	0.1404	0.2409	0.2409
	Winner – Loser	0.5342	0.3387	0.1722	0.1155
	t-stat	(4.65)[b]	(4.19)[b]	(2.63)[b]	(2.12)[a]
Panel C: Past 36-week performance ranking period					
Following the Down markets	Winner	0.5162	0.5601	0.4910	0.4581
	Loser	−0.1498	−0.0077	−0.0248	−0.0996
	Winner – Loser	0.6660	0.5677	0.5158	0.5577
	t-stat	(6.27)[b]	(7.34)[b]	(6.74)[b]	(5.33)[b]
Following the Up markets	Winner	0.5666	0.4729	0.4149	0.3257
	Loser	0.0639	0.1341	0.2255	0.2172
	Winner – Loser	0.5027	0.3388	0.1894	0.1085
	t-stat	(4.24)[b]	(4.11)[b]	(2.85)[b]	(2.02)[a]
Panel D: Past 48-week performance ranking period					
Following the Down markets	Winner	0.5538	0.5192	0.4189	0.3718
	Loser	−0.1248	−0.0385	−0.0245	−0.0384
	Winner – Loser	0.6786	0.5578	0.4434	0.4102
	t-stat	(6.36)[b]	(7.22)[b]	(6.51)[b]	(5.24)[b]
Following the Up markets	Winner	0.5557	0.4636	0.3738	0.2899
	Loser	0.0277	0.1093	0.2104	0.2083
	Winner – Loser	0.5281	0.3543	0.1634	0.0817
	t-stat	(4.61)[b]	(4.31)[b]	(2.46)[a]	(1.53)

[a] and [b] indicate statistical significance at the 5 percent and 1 percent levels, respectively.

6.6.3 Style momentum based on macroeconomic factors (MP)

It is well known that macroeconomic factors play an important role in explaining stock returns (see, e.g., Roll and Ross (1980), Chen et al. (1986), and Poon and Taylor (1991)). Several APT models containing macroeconomic factors have been developed in an attempt to explain the momentum strategy returns, but without reaching a consensus. For example, Chelley-Steeley and Siganos (2004) conclude that their APT model which contains seven factors cannot capture the momentum returns. Liu, Zhang and Fan (2005), however, find that momentum strategies no longer offer abnormal returns after adjusting for the macroeconomic risk, and conclude that macroeconomic factors play important roles in the explanation of the documented momentum profits. A recent study of Liu and Zhang (2008) argue that *"the growth rate of industrial production is a price risk factor in standard asset pricing tests. In many specifications, this macroeconomic risk factor explains more than half of momentum profits"* (p. 2417).

In this section, I examine whether the style momentum profits can be explained by the growth rate of industrial production (MP) in the China stock market. I concentrate on the 6-6 style momentum strategy with past six-month performance ranking period and six-month portfolio holding period.[36] I skip one-month gap between the end of the ranking and the beginning of the holding periods to avoid the potential microstructure biases. First, I present empirical evidence on systematic variation in MP risk exposure across momentum portfolios, and then report MP loadings using the calendar-time regressions. If the MP plays an important role in explaining the style momentum profits,

[36] When analysing the relationship between style momentum and MP, I re-construct the style momentum strategies with the use of monthly return data.

I expect the MP loadings show significant variation for the winner and loser style portfolios. Second, I examine how the MP loadings evolve during the twelve-month holding periods after the portfolio formation. Finally, a robustness test is conducted using other style momentum strategies with different ranking and holding periods.

Table 6.10 presents the MP loadings for each of the nine style momentum portfolios. Following Chen, et al. (1986), I lead MP by one month to align the timing of macroeconomic and financial factors. Panel A of Table 6.10 use MP as the single factor. Winner and loser portfolios have an MP loading of –0.052 and –0.046, respectively. It also can be inferred from Panel A that the MP loadings for the nine style momentum portfolios are all insignificant. Especially, *t*-statistic shows that the difference in MP loadings between the winner and loser portfolios is statistically insignificant (*t*-stat = 0.08). Therefore, the hypothesis that the winner portfolio has an MP loading higher or lower than the loser portfolio can be rejected.

Fama and French (1996) and other studies (see, e.g., Gaunt (2004), Lam (2002), and Connor and Sehgal (2001)) have demonstrated the superiority of the Fama and French (1993) three-factor model in explaining the cross-sectional variation of stock returns. I further investigate whether the behaviour of momentum returns could be explained by an augmented Fama and French (1993) model with an additional macroeconomic factor, MP. The Fama and French (1993) three-factor model augmented with MP is presented as follows:

$$R_{it+1} - R_f = \alpha + \beta_1(R_m - R_f) + \beta_2 SMB + \beta_3 HML + \beta_4 MP + \varepsilon\,, \qquad (4.1)$$

where R_p represent the return on the winner minus loser portfolio based on past returns and firm-specific styles; R_m represents the monthly return on the value-weighted SHSE and SESE A-share Indices; R_f represents the risk free rate, measured by the monthly return on the three-month household deposit interest rate; *SMB* represents the monthly return on small size firms minus the monthly return on big size firms; *HML* represents the monthly return on high B/M firms minus the monthly return on low B/M firms; and *MP* represents the business cycle risk, which is measured by the growth rate of industrial production.

From Panel B of Table 6.10, after controlling for the Fama and French (1993) three factors in the regressions, the earlier results in Panel A are not materially affected. MP loadings of the winner and loser portfolios slightly change to –0.030 and –0.031, respectively, but the spread between the two loadings is decreased relative to that in Panel A. In addition, the MP loadings for the nine portfolios remain insignificant. The hypothesis that the MP loadings of the style momentum portfolios are not jointly zero is again strongly rejected.

Table 6.10 Factor loadings of style momentum returns on the growth rate of industrial production (MP), January 1995 to December 2006

This table reports the results from monthly regressions on the growth rate of industrial production (MP) using returns of nine style momentum portfolios, where L denotes the loser portfolio and W denotes the winner portfolio. The sample is monthly from January 1995 to December 2006. Panels A and B present the loadings of MP based on one factor MP model and the Fama and French (1993) model augmented with MP, respectively. For each portfolio formation month t from 1995 to 2006, I calculate the equal-weighted returns for the nine momentum portfolio for t + m, where m = 1, 2, 3, ..., 12. Panel C reports the loadings of MP for every month during the twelve-month holding period after portfolio formation, bas on the one-factor MP model.

	D1 (Winner)	D2	D3	D4	D5	D6	D7	D8	D9 (Loser)	t-stat (D9 – D1)
Panel A: One factor MP										
Coefficient	−0.0518	−0.0458	−0.0478	−0.0269	−0.0124	−0.0243	−0.0264	0.0025	−0.0456	−0.0062
t-stat	(−0.45)	(−0.44)	(−0.5)1	(−0.29)	(−0.14)	(−0.29)	(−0.28)	(0.03)	(−0.56)	(−0.08)
Panel B: Fama and French (1993) three factors + MP										
Coefficient	−0.0296	0.0754	−0.0204	−0.0033	0.0110	−0.0027	−0.0031	0.0268	−0.0308	0.0002
t-stat	(−0.30)	−0.30)	−0.26)	−0.04)	0.14)	−0.04)	−0.04)	0.36)	−0.41)	(0.02)
Panel C: MP time-series from month 1 to month 12 (based on one-factor model)										
1	0.1002	0.1382	0.0660	0.3682	0.1868	0.1968	0.3049	0.3720	0.3371	(−1.39)
2	−0.0335	−0.0808	−0.0439	−0.1816	−0.0833	−0.1292	−0.0965	−0.1030	−0.0744	(0.25)
3	0.0981	0.1011	0.1543	0.0335	0.0814	0.1623	0.0125	0.0601	−0.0314	(0.70)
4	−0.0600	−0.1114	−0.1091	−0.1498	−0.0759	−0.0608	−0.0910	−0.1631	−0.1587	(0.54)
5	0.2397	0.2654	0.2483	0.2610	0.3825	0.2792	0.3471	0.3503	0.2612	(−0.13)
6	−0.6556	−0.5875	−0.6023	−0.4928	−0.5659	−0.5938	−0.6353	−0.5015	−0.6073	(−0.24)
7	0.2711	0.2416	0.4319	0.3307	0.2249	0.3798	0.4154	0.4030	0.3367	(−0.36)
8	−0.0898	−0.1784	−0.2575	−0.2698	−0.0960	−0.1722	−0.1828	−0.2671	−0.2031	(0.72)
9	0.2112	0.1797	0.3136	0.1953	0.1880	0.2462	0.1501	0.2310	0.2121	(−0.01)
10	−0.2163	−0.1452	−0.2501	−0.2269	−0.1974	−0.1685	−0.1638	−0.2717	−0.2679	(0.33)
11	0.2226	0.0922	0.1055	0.1947	0.2464	0.2072	0.3391	0.1879	0.2532	(−0.20)
12	0.0044	−0.0265	0.0182	0.0209	−0.0644	−0.0285	0.1329	−0.0575	0.0768	(−0.48)

Since the style momentum portfolios used in the Panel A have a six-month holding period, the reported loadings are effectively averaged over the six months. I further examine whether the loading spread evolves over time. I perform an event-time factor regression for each of twelve months after the portfolio formation. For each month t from January 1995 to December 2006, I calculate the equal-weighted returns for all the nine style momentum portfolios for t + m, where m = 1, 2, ..., 12. Panel C of Table 6.10 reports the MP loadings of the style momentum portfolios for every month during the 12-month holding periods after the portfolio formation. The underlying model is the one-factor MP model.[37] In each row, the fluctuation of the MP loadings for each style momentum portfolios is small. Further, the last column shows that in each holding month, the differences in returns between the winner and loser portfolios are insignificant.

I have shown so far that the winner and loser portfolios have no significantly different MP loadings with the use of the 6-6 style momentum strategy that sorts stocks based on their prior six-month returns and firm-specific characteristics, skips one month, and holds the arbitrage portfolios for the subsequent six months. I find that the MP has no influence on the style momentum returns. I, finally, examine whether the result is robust to the general *F-H* style momentum strategies that sorts stocks based on their prior *F*-month return, skips one month, and holds the resulting portfolios for the subsequent *H* months.

[37] The results are robust to the use of the augmented Fama and French (1993) three-factor model.

Table 6.11: Robustness test of factor loadings of style momentum returns on the growth rate of industrial production (MP), based on *F-H* style momentum

This table reports the factor loadings on MP of the style momentum strategies. Panels A and B use the one-factor MP model and the Fama-French (1993) three-factor model augmented with MP, respectively. In constructing momentum portfolios, I vary the sorting period F and the holding period H. The F-H strategies generate nine style portfolios by sorting on the prior F-month compounded returns, skipping one month, and then holding the resulting portfolios in the subsequent H months.

F	H = 3	6	9	12	H = 3	6	9	12
	Panel A: One-factor MP model				Panel B: Three-factor + MP			
3	0.0670	0.0219	−0.0019	0.0058	0.0660	0.0216	−0.0001	0.0059
	(0.60)	(0.27)	(−0.03)	(0.11)	(0.63)	(0.27)	(0.00)	(0.11)
6	−0.0222	−0.0062	0.0010	−0.0035	−0.0140	0.0012	0.0080	0.0001
	(−0.20)	(−0.08)	(0.02)	(−0.07)	(−0.15)	(0.02)	(0.12)	(0.00)
9	−0.0431	−0.0310	−0.0293	−0.0094	−0.0480	−0.0309	−0.0287	−0.0092
	(−0.42)	(−0.42)	(−0.48)	(−0.19)	(−0.59)	(−0.43)	(−0.49)	(−0.18)
12	−0.0494	−0.0501	−0.0398	−0.0352	−0.0594	−0.0535	−0.0427	−0.0374
	(−0.48)	(−0.76)	(−0.73)	(−0.78)	(−0.72)	(−0.87)	(−0.83)	(−0.85)

For brevity, Table 6.11 displays only the MP loadings for the winner minus loser portfolio that buys the equal-weighted portfolio of the top one winner style portfolio and sells the bottom one loser style portfolio and reports t-statistics of the MP loadings. I find that all the MP loadings are statistically insignificant. Further, Panel B shows that adding the Fama and French (1993) three factors in to the regressions yields largely similar results. In sum, I conclude that the macroeconomic factor (MP), the growth rate of industrial production, has no influence on the profitability of the style momentum strategies in the China stock market.

Munira and Muradoglu (2010) control for the Fama and French (1993) three factors, while they cannot explain momentum returns in either speculative-grade or investment-grade stocks. However, after controlling for Up and Down market states, momentum returns can be explained in investment-grade stocks, but not in speculative-grade stocks. They also control for macroeconomic risk factors developed by Chordia and Shivakumar (2002), including the default premium, dividend yield, term premium, and the yield on short-term T-bill. They find that macroeconomic factors explain momentum returns for both speculative-grade and investment-grade stocks.

6.7 Summary of findings

In this chapter, I extend the regular momentum strategies based on individual stocks to the portfolio-based momentum strategies in style context. The style momentum strategies are based on both past medium-term returns and firm-specific characteristics, such as size and B/M. In order to conveniently compare with the earlier results, I examine the same data in to construct nine style portfolios during the same time period as analysing the regular momentum strategies. I find style momentum strategies generate significantly positive returns during the whole sample periods and the profitability is robust to two sub-periods, suggesting that investment strategies based on past returns and styles are likely to be profitable even controlling for direct transaction costs. In addition, I rule out the concern that style momentum profits might arise from industry momentum. Furthermore, I examine the style momentum strategies in two opposite market states and find significant profitability following both market states.

Finally, I examine whether the macroeconomic factor, the growth rate of industrial production have an impact on the style momentum returns. Empirical evidence shows no significant variations in the MP loading across style momentum strategies. In particular, the difference of profits between the winner and loser portfolios is also statistically insignificant.

Appendix 6.1 FTSE / DJ Industry Classification Benchmark (ICB)

FTSE / DJ Industry Classification Benchmark (ICB)

Industry	Super Sector	Sector
0001 Oil & Gas	0500 Oil & Gas	0530 Oil & Gas Producers
		0570 Oil Equipment, Services & Distribution
1000 Basic Materials	1300 Chemicals	1350 Chemicals
	1700 Basic Resources	1730 Forestry & Paper
		1750 Industrial Metals
		1770 Mining
2000 Industrials	2300 Construction & Materials	2350 Construction & Materials
	2700 Industrial Goods & Services	2710 Aerospace & Defense
		2720 General Industrials
		2730 Electronic & Electrical Equipment
		2750 Industrial Engineering
		2770 Industrial Transportation
		2790 Support Services
3000 Consumer Goods	3300 Automobiles & Parts	3350 Automobiles & Parts
	3500 Food & Beverage	3530 Beverages
		3570 Food Producers
	3700 Personal & Household Goods	3720 Household Goods
		3740 Leisure Goods
		3760 Personal Goods
		3780 Tobacco
4000 Health Care	4500 Health Care	4530 Health Care Equipment & Services
		4570 Pharmaceuticals & Biotechnology
5000 Consumer Services	5300 Retail	5330 Food & Drug Retailers
		5370 General Retailers
	5500 Media	5550 Media
	5700 Travel & Leisure	5750 Travel & Leisure
6000 Telecommunications	6500 Telecommunications	6530 Fixed Line Telecommunications
		6570 Mobile Telecommunications
7000 Utilities	7500 Utilities	7530 Electricity
		7570 Gas, Water & Multiutilities
8000 Financials	8300 Banks	8350 Banks
	8500 Insurance	8530 Nonlife Insurance
		8570 Life Insurance
	8700 Financial Services	8730 Real Estate
		8770 General Financial
		8980 Equity Investment Instruments
		8990 Nonequity Investment Instruments
9000 Technology	9500 Technology	9530 Software & Computer Services
		9570 Technology Hardware & Equipment

CHAPTER 7

CONCLUSIONS

7.1 Conclusions

This thesis examines medium-term momentum strategies in the China stock market. The primary findings confirm the presence of a degree of the momentum effect over the period 1995 to 2006, but these momentum profits are generated mainly in the depressed market conditions over the period 2001 to 2006. This finding is robust using the definitions of market states developed by Cooper et al. (2004) and alone challenges behavioural explanations of the momentum phenomenon developed by Daniel et al. (1998) and Hong and Stein (1999). I note that observed momentum is likely to be a result of short sales constraints in China in which context it is not possible to access risk free profits through conventional arbitrage processes. I report a significantly positive relation between momentum and short sales constraints with the use of a modified model developed by D'Avolio (2002) to measure the magnitude of short sales constraints in the China stock market. More evidence shows that it is loser portfolios that drive momentum profits, since momentum strategies make profits because loser portfolios lose much more during the depressed period. Moreover, empirical evidence that the momentum duration is longer in China than reported elsewhere is consistent with more severe short sales constraints. In conclusion, momentum profits are a feature of the China stock market, are of longer duration than in other exchanges, and manifest in ways not previously reported. However, I would argue that momentum in China is explicable in terms of trading restrictions. Specially, the existence of momentum in depressed market conditions rejects behavioural explanations and is fully consistent with trading restrictions I observe.

In further detailing this work, I find that momentum is associated with firms that have relatively large market capitalisations, a finding which challenges the results and conclusions reported in Hong et al. (2000) in which large size supports information diffusion. This finding is supported by a separate analysis of momentum profits between firms listed on the two exchanges examined which demonstrated that stocks on the SHSE exhibits a significantly stronger momentum effect than do stocks on the SZSE and that this is associated with different mean market capitalisations between the two exchanges (SHSE being larger). The lack of a small size effect rejects hypotheses that relate momentum to stock illiquidity. I also employ beta, size, and B/M factors to explain abnormal momentum profits in the China stock market and find that the results are not consistent with those found in other markets: loser portfolios have higher beta values than winner portfolios; big size firms always outperform small size firms; and there is no significant difference in momentum profits between high and low B/M firms. What I do find is that, after adjusting returns of winner minus loser portfolios using the two-factor model including beta and size factors, most of abnormal returns disappear.

I further extend the regular momentum strategies to the portfolio-based momentum strategies in style context, according to both past medium-term returns and two important firm-specific characteristics, size and B/M. With the use of the same sample and time period, I find that style momentum strategies generate significantly positive returns during the whole sample periods and that the profitability is robust to two sub-periods and in opposite market states, suggesting that investment strategies based on past returns and styles are likely to be profitable even controlling for direct transaction costs. In addition, I rule out the concern that style momentum profits might arise from industry momentum. Finally, empirical evidence shows that macroeconomic factor, such as the growth rate of industrial production (MP), has no impact on the style momentum returns.

7.2 Limitations and suggestions for future research

Nevertheless, this thesis is subject to some limitations relative to data availability. Based on the limitations of this thesis, this study also poses interesting questions that require further examinations.

First, although empirical evidence shows that momentum strategies are significantly profitable over the period 2001 to 2006, it is difficult for investors to make abnormal profits following the momentum strategy in the China stock market. One the one hand, since the winner and loser portfolios contain ten per cent of all stocks in the market, in practice, small investors are not in the financial position to undertake these strategies buying and selling short some hundreds of stocks. On the other hand, the momentum strategy assumes that investors can sell short shares without any limitations, while it is very difficulty to short sell in China during the sample period.[38]

Second, when studying the role of short sales constraints in explaining the momentum effect in Chapter 5, I drop six variables included in the model developed by D'Avolio (2002), such as *IO* (institutional ownership), *Disperz* (dispersion in analyst forecasts),

[38] China started the trading of stock index futures from 16th April, 2010. Sources are from the China Financial Futures Exchange: http://www.cffex.com.cn/zjs_en.

Authors (the number of contributions to the stock's Yahoo! Finance message board), *CF* (cash flow), *Internet* (a type dummy variable), and *Loser* (a momentum dummy variable). Although empirical results support the explanatory power of the remaining five determinants of short sales constraints, the dropped six variables are expected to be examined in the future when the data are available.

Third, the findings of Chapters 4 and 6 show that momentum profits are related to some kinds of risk factors with business cycle pattern (market states suggested by Cooper et al. (2004) for the regular price momentum and MP suggested by Liu and Zhang (2008) for style momentum). Future work could examine the effects of some new macroeconomic variables, such as the recently proposed distress risk by Agarwal and Taffler (2008) and credit risk with uncertainty by Avramov and Hore (2008) on the firm-level momentum and momentum in different contexts in the China stock market.

Finally, this study examines the regular price momentum and momentum in style and industry contexts. Further research could focus on momentum in different contexts, such as analyst coverage, dispersion in analyst forecasts, and credit ratings, etc.

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