Three Essays on Momentum Returns

A thesis

submitted in partial fulfilment

of the requirements for the Degree of

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by

Muhammad Ahmad Cheema

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I dedicate this work to my parents, my sisters, and my brother for all their love, support and encouragement.

Abstract of a thesis submitted in partial fulfilment of the

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This dissertation consists of three essays on momentum returns. The first essay is entitled 'Momentum Returns, Market States and the Global Financial Crisis'. This essay investigates the profitability of the momentum trading strategy in the stock exchanges of Shanghai, Shenzhen and Hong Kong over the period 1994 to 2010. My results show that there are significantly large momentum returns for Shanghai and Hong Kong but small and insignificant momentum returns for Shenzhen. Momentum returns remain almost the same for all datasets even after adjusting for the Fama-French risk factors. However, the momentum trading strategy generates negative returns for all markets during the Global financial crisis; it appears that the momentum trading strategy fails during a financial or stock market crisis and especially in the months when the market conditions improve. I find no significant relationship between momentum returns and market states, which contradicts the results of an earlier study conducted in the U.S. market. Instead of market state it appears that it is economic activity that explains momentum returns.

In the second essay, entitled 'Momentum Returns and Information Uncertainty', I study the impact of information uncertainty on the profitability of the momentum trading strategy. Prior literature attributes returns of the momentum trading strategy to investor behavioural biases, such as under reaction to new information, and provides evidence that firms with higher information uncertainty earn lower future returns and higher momentum returns. This study investigates the relationship between information uncertainty, future returns and the momentum trading strategy in China over 1994 to 2010. Using age, volatility, volume and firm size as information uncertainty proxies, I find that firms with higher information uncertainty earn higher average returns over the succeeding 6-month period when information uncertainty is defined in terms of firm size and volume, consistent with the traditional risk based theories. However, firms with high information uncertainty earn lower returns if information uncertainty is defined in terms of firm age; however, firm age might not be an important factor in explaining future returns as the age difference among young and old firms is quite small and it might be the other firm-specific characteristics that drive lower future returns for the younger firms instead of their age. Therefore, my study rejects the findings of Jiang, Lee and Zhang (2005) that stocks with higher information uncertainty earn lower returns over the succeeding 6-month period. Using portfolio-level analysis and firm-level Fama and Macbeth regressions, I find that no robust significant relationship exists between information uncertainty and momentum returns. My findings suggest that it might be the activities of retail investors that drive momentum returns since China's market is dominated by retail investors, whereas the momentum effect is weak among the U.S. stocks with higher institutional holdings.

In the third and final essay, entitled 'Momentum Returns, Long-Term Reversal and Idiosyncratic Volatility', I study the impact of idiosyncratic volatility (IV) on the profitability of momentum and long-term reversal trading strategies in China over the period 1994 to 2010. The literature suggests that IV deters arbitrage, which results in higher momentum and reversal returns for stocks with high idiosyncratic volatility. However, my results indicate that the choice of the proxy used for IV, sorting method and number of portfolios (tercile versus quintile) play critical roles in determining the existence and significance of a relationship between IV and the profitability of momentum or reversal trading strategies. Both portfolio-level analysis and firm-level Fama and Macbeth regressions indicate that no robust relation exists between IV and momentum or reversal, which contradicts the results of earlier studies in the U.S. market. However, my findings suggest that reversal returns might be related to transaction costs since I find greater reversal returns among the stocks with high transaction costs. My findings also do not support the suggestion that momentum and reversal are part of same phenomenon.

Keywords: Momentum returns, market states, Global financial crisis, information uncertainty, retail investors, long-term reversal, idiosyncratic volatility

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While this thesis was being written, my grandma, Rahmat Bibi, passed away. She used to pray for my success. I can imagine how happy she would be if she were able to see me graduate.

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Chapter 1
Introduction

1.1 Introduction

This thesis consists of three essays on stock market anomalies. Stock market anomalies describe a situation that cannot be explained by the widely accepted financial models. It is important to study stock market anomalies because understanding these anomalies can greatly enhance our understanding of stock markets. Two of the most important recent stock market anomalies are momentum and long-term reversal. Jegadeesh and Titman (1993) show momentum or return continuation for U.S. stocks for the medium-term horizon, i.e., buying (selling) past three to 12 months winners (losers) stocks generate an abnormal return of 1% per month (12% per year) whereas DeBondt and Thaler (1985, 1987) and Chopra, Lakonishok and Ritter (1992) find long-term return reversals for U.S. stocks, i.e., buying (selling) stocks with low (high) returns over past two to five years generate significant positive returns in the next two to five years.

There is a consensus among researchers about the profitability of momentum and reversal trading strategies across international stock markets and time periods, but what causes these effects is still a matter of debate. The sources of momentum and reversal profitability are mostly anchored on behavioural and risk-based theories. However, the risk-based theories are considered less reliable because the Fama-French three-factor model fails to explain momentum profits (Fama and French, 1996, 2008, 2012). In contrast, some studies find that the profitability of the long-term reversal strategy disappears once risk factors are accounted for (see Chan, 1988; Fama, 1998; McLean, 2010). The failure of risk-based models has led to the development of several behavioural theories to jointly explain the profitability of momentum- and reversal-based trading strategies (see Barberis, Shleifer and Vishny, 1998; Daniel, Hirshleifer and Subrahmanyam, 1998; Hong and Stein, 1999). The behavioural model of Barberis et al. (1998) and Hong and Stein (1999) attributes momentum returns to investor under reaction to new information, whereas Daniel et al. (1998) attribute momentum returns to investor over-reaction, which results from investor overconfidence in their private information. Though these three theories differ in their explanation of momentum returns, they all agree that reversal returns arise from mispricing, which results from investor over-reaction that is eventually corrected.

Cooper, Gutierrez and Hameed (2004) extend Daniel et al.'s (1998) investor overconfidence argument in investigating the differences in momentum returns across UP and DOWN market states. Cooper et al. (2004) argue that there would be more over-reaction after UP market states as investor overconfidence is high following UP market states. Using NYSE and AMEX listed stocks, they find significant positive momentum returns in the UP market state and weak insignificant momentum returns in the DOWN market state. Based on Daniel et al.'s (1998) overconfidence bias, Jiang et al. (2005) and Zhang (2006) argue that investors would overestimate the precision of their private information and therefore would under react even more to the firms with greater information uncertainty. These authors find higher momentum returns for stocks with higher information uncertainty and lower momentum returns for stocks with lower information uncertainty. Based on the under reaction theories of Barberis et al. (1998) and Hong and Stein (1999), Arena, Haggard and Yan (2008) argue that investors under react more to firms with higher idiosyncratic volatility (IV). Using U.S. data, they find greater momentum returns for stocks with higher IV and lower momentum returns for stocks with lower IV. In contrast, McLean (2010) finds that momentum is not related to IV; he finds that reversals are stronger in high IV stocks.

The main objective of this thesis is to examine momentum returns in China and Hong Kong, and reversal returns in China. Previous studies about the relationship of momentum returns to market states and information uncertainty, and the relation of IV to momentum and reversal focused mainly on developed markets, such as the U.S., and have not been tested for China and Hong Kong, which differ from the U.S. and other developed markets in many ways. First, both China and Hong Kong have a large number of small-cap stocks and institutional investors have a weaker role than in developed markets. Second, China is the fastest growing economy in the world, and largest equity market amongst the emerging markets. These distinct features of China and Hong Kong, along with the lack of academic studies on the sources of momentum and reversal profitability, ignited my motivation to embark upon this research.

The first essay is titled "Momentum Returns, Market States and the Global Financial Crisis". In the first part of this essay, I examine and compare the profitability of the momentum trading strategy on the two mainland Chinese stock markets, the Shanghai Stock Exchange (hereafter **SSE**) and the Shenzhen Stock Exchange (hereafter **SZSE**) as well as the Hong Kong Stock Exchange (hereafter **HKSE**). I find large momentum returns for SSE and HKSE but weak and insignificant momentum returns for SZSE.[1] I find greater momentum returns for larger stocks, therefore, the weak momentum returns for SZSE appear to be related to firm size since SZSE is dominated by small companies. For all the markets, momentum returns were larger before the Global financial crisis. However, momentum returns for all datasets are negative during the Global financial crisis (2007-2010). The losses from the momentum trading strategy during the Global financial crisis appear to be related to investors' fears since they avoid loser stocks during the crisis resulting in a price decrease of loser stocks beyond their fundamental levels. Any improvement in market conditions after a severe downturn returns the prices of loser stocks back to their fundamental levels; hence losers generate higher returns than winners, which results in losses for the momentum trading strategy. Consistent with this argument, I find the worst momentum returns during economic downturns and stock market crises, especially in the month when the market starts to improve. In the second part of this essay, I investigate the relationship between momentum returns and market state and find that momentum returns are not related to market state, which contradicts the results of Cooper et al. (2004) for U.S. market. Therefore, I suggest that it might be economic activity that explains momentum returns because there were greater momentum returns before the Global financial crisis.

The second essay is titled "Momentum Returns and Information Uncertainty". In this essay, I study the relationship between information uncertainty (IU) and future returns and momentum returns on the SSE, China. Using volume, volatility, firm age and firm size as proxies to measure (IU), I find that firms with higher IU earn higher returns over the succeeding 6 months when IU is defined in terms of volume and firm size. This positive relationship between IU and future returns contradicts the results of Jiang et al. (2005) for U.S. stocks, but it is consistent with traditional risk based theories. In contrast, firms with high IU earn lower returns when IU is defined in terms of firm age. However, firm age might not be an important factor in explaining future returns because the age difference between young and old firms is small. Therefore, it might be other firm-specific characteristics that drive lower future returns for younger firms instead of their age. I also examine the relationship between IU and momentum returns. Using portfolio-level analysis and firm-level Fama and Macbeth (1973) cross-sectional regressions, I find no robust significant relationship between the level of IU and momentum returns. My findings suggest that it might be the activities of retail investors that result in momentum returns since China is dominated by retail investors. This explanation

[1] Value-weighted momentum returns for SZSE are smaller than SSE and HKSE but statistically significant for 6- and 9-month holding periods. However, equal-weighted momentum returns for SZSE are insignificant for all the holding periods.

is consistent with the findings of Zhang (2006) who reports a weak momentum effect in stocks that the literature describes as those with high institutional holdings, i.e., stocks with large firm size, lower analyst forecast dispersion and higher analyst coverage.

The third essay is titled “Momentum Returns, Long-term Reversal and Idiosyncratic Volatility”. In this essay, I study the impact of idiosyncratic volatility (IV) on the profitability of momentum and reversal in SSE, China. Consistent with McLean (2010), I find that momentum is not related to IV, but this contradicts the results of Arena et al. (2008). Inconsistent with McLean’s (2010) study, I find large, statistically significant reversal returns for all IV quintiles. Therefore, reversal is also not related to IV. My results that IV is not related to momentum and reversal are robust to controls for exclusion of low and small size stocks. However, my results indicate that the existence and significance of a relationship between IV and momentum or reversal depends on the choice of the proxy used for IV, the sorting method and the number of portfolios (tercile versus quintile). My findings appear to be consistent with Bali and Cakici (2008) who find an insignificant relation between IV and expected returns when they account for the data frequency (daily versus monthly) used to estimate IV, the weighting-scheme used to calculate portfolio returns (equal- or value-weighted), breakpoints used to sort stocks into portfolios and use of low and small price filters. In sum, my results do not find significant evidence that IV is limiting arbitrage among momentum and reversal stocks. However, I find that the profitability of reversal may be the result of mispricing caused by high transaction costs since I find greater reversal returns among stocks with the highest transaction costs when I use the Fama and MacBeth (1973) cross-sectional approach. This argument is consistent with the findings of Jordan (2009), who shows that there is a cross-sectional relation between transaction costs reversal profits.

1.2 My Contributions

This study has several research contributions to the literature. The research contributions of Chapter 2 are as follows:

1. It is the first study that finds a strong relationship between momentum returns and economic activity for Chinese and Hong Kong stocks.

2. This study also explains the contradictory evidence of momentum effect in China by finding that there is large momentum returns in China but it is limited to SSE stocks.

3. This is also the first study that finds higher value-weighted momentum returns in China and Hong Kong compared with equally-weighted momentum returns. In addition, it finds that momentum returns are limited to medium and large size stocks.

4. This study also brings new knowledge about the relationship of momentum returns with market states by finding that UP and DOWN market states cannot explain momentum returns in China and Hong Kong.

The research contributions of Chapter 3 are as follows:

5. This study reveals new knowledge by finding that the negative relationship between IU and future returns suggested by Jiang et al. (2005) does not hold in the largest emerging market, China. Instead, this study finds that high IU firms earn higher future returns when IU is defined in terms of volume and size, consistent with risk-based theories.

6. This study contributes to the literature by finding that there is no robust relationship between IU and momentum returns in China, unlike Zhang (2006) and Jiang et al. (2005) for U.S. stocks. Therefore, the findings of developed markets like U.S. cannot be fully generalized to other markets, especially emerging markets.

7. This is the first study that discusses that IU can explain momentum returns in a market dominated by institutional investors (U.S. market) but it cannot explain momentum returns in a market dominated by retail investors (China). Therefore, it suggests future research to find a relationship between momentum returns and retail investors.

The research contributions of Chapter 4 are as follows:

8. This study contributes to the existing finance literature by highlighting the fact that the findings of McLean (2010) and Arena et al. (2008) for U.S. stocks cannot be fully generalized to the other markets, especially emerging markets, since I find that IV is not related to either momentum or reversal in the world's largest emerging market, China.

9. My results further contribute to the literature by highlighting the fact that the significance of a relationship between IV and momentum or reversal depends on the

choice of IV measures, sorting method and number of portfolios. Therefore, no robust relationship exists between IV and momentum or reversal.

10. This study also finds that momentum profits in China are robust to transaction costs unlike McLean (2010).

11. This study contributes to the literature by finding that reversal returns in China can be explained by transaction costs, which is consistent with McLean (2010).

12. This study also contributes to the literature by finding large and significant reversal returns in the largest emerging market, China. In addition, this study finds that reversal returns are not limited to small size stocks unlike McLean (2010).

13. Another contribution of this study is to find that momentum and reversal in China are not part of the same phenomenon and suggests that each effect is strongest in different kind of stocks.

In sum, the major contributions of this study are to explain the contradictory evidence of momentum returns in China, IU is not related to momentum returns and IV is not related to either momentum or reversal when accounted for different IV measures, sorting method and number of portfolios.

Chapter 2

Momentum Returns, Market States and the Global Financial Crisis

2.1 Introduction

Momentum refers to the tendency for past winners to continue winning while past losers continue losing. The momentum effect has been a popular issue in recent finance literature and is considered most prominent among all the stock market anomalies (Fama and French, 2008). Jegadeesh and Titman (1993) report that the momentum trading strategy of buying recent winners and selling recent losers generates an abnormal return spread of 1% per month (12% per year) in the U.S. market over the period 1965 to 1989. However, Jegadeesh and Titman (1993) find negative momentum return spreads for the period 1975 to 1979. A recent study by Novy-Marx (2012) reports a stronger momentum effect for U.S. stocks when an intermediate horizon past performance instead of recent performance is used to select stocks for the momentum trading strategy. Novy-Marx (2012) defines "intermediate" as the firm performance over the past 12 to 7 months before the portfolio formation date.

The presence of the momentum effect in U.S. stock markets has led to a number of studies in international stock markets. Rouwenhorst (2002) examines 12 European countries and finds evidence consistent with that of Jegadeesh and Titman (1993). Bekaert, Erb, Harvey and Viskanta (1997) previously find inconsistent momentum returns for emerging markets but Rouwenhorst (1999) documents significant momentum returns in emerging markets. Chan, Hameed and Tong (2000) examined the stock market indexes of 23 countries and report strong momentum returns especially for short holding periods of less than four weeks. Chui, Wei and Titman (2000) examined the stocks of eight Asian countries and report significant momentum returns in Asia except Japan. However, the magnitude and quality of these returns are comparatively weaker than the U.S. and European stock markets. Bhojraj and Swaminathan (2001) show strong momentum returns for up to a year after the portfolio formation date both in developed and emerging equity markets. Similar results have been found by researchers in other stock markets, e.g., Schiereck and Weber (1995) for the German market, Bacmann and Dubois (2000) for the Swiss market, Bacmann, Dubois and Isakov (2001) for the G-7 countries, Hameed and Kusnadi (2002) for six Asian markets and Alsubaie and Najand (2008) for the Saudi Arabian market. This breadth of evidence from all over the world indicates statistically significant and economically large momentum returns in international stock markets.

The robustness of the momentum effect across international markets and time periods motivated researchers to develop several explanations. These explanations are mostly anchored on behavioural and risk-based theories. The risk-based explanations argue that momentum returns are just compensation for bearing some common risk associated with all stocks and it disappears once priced for these common risk factors. For example, Chordia and Shivakumar (2002) suggest that the profitability of the momentum trading strategy is related to the business cycle and show that the profitability of the momentum strategy disappears once stock returns are adjusted for their predictability based on the macroeconomic variables. However, subsequent studies, including Cooper et al. (2004), reject the hypothesis put forth by Chordia and Shivakumar (2002) and show that momentum returns remain unexplained after adjustment for their predictability based on macroeconomic variables. Several other risk factors and transaction costs are also considered related to momentum returns (see Fama and French, 1993, 1996; Grundy and Martin, 2001; Jegadeesh and Titman, 2001; Korajczyk and Sadka, 2005). However Fama and French (2008, 2012) suggest that the Fama-French three factors cannot explain momentum returns.

Behavioural explanations of the momentum anomaly are considered more reliable because the Fama-French and other risk factors fail to explain momentum returns. Behavioural theories assume that investor irrationality and psychological biases are responsible for momentum returns. The behavioural factors that the extant literature relate to the momentum effect are investor conservatism, representative heuristic, biased self-attribution, overconfidence and bounded rationality (for example, see among others, Barberis et al., 1998; Daniel et al., 1998; Daniel, Hirshleifer and Subrahmanyam, 2002; Hong and Stein, 1999, 2007). The behavioural model of Barberis et al. (1998) explains momentum returns as the result of investor under reaction to new public information and over-reaction to their own beliefs. They argue that this tendency for investors to over-react to their own beliefs causes prices to continue in the same direction; under reaction to new public information takes time to stop the continuity of prices. They show that under reaction to new information and over-reaction to their prior beliefs results from investors’ cognitive biases including representativeness and conservatism. In the representativeness bias, investors assume that the extraordinary growth (reduction) of the firm will continue in the future and, as a result, take prices away from their fundamental values. The conservatism bias, on the other hand, leads to under reaction to new information.

Daniel et al. (1998) argue that investor overconfidence is responsible for over-reaction in stock prices, which results in momentum returns. Cooper et al. (2004) extended Daniel et al.'s (1998) over-reaction theory to predict differences in momentum returns across UP and DOWN market states. They argue that, since in aggregate investors hold long positions, investor overconfidence must be higher after an UP market because the UP market brings in gains. They further explain that investors will attribute the rise in stock prices to their skills leading to a further boost in their overconfidence. The large increase in investor overconfidence then turns into over-reaction that generates momentum returns. So, they argue that the large rise in investor overconfidence is a result of the UP market state and hence it is the market state that explains momentum returns. Using NYSE and AMEX listed stocks, they find significant positive momentum returns in the UP market state. Daniel (2011) extends Cooper et al.'s (2004) study and reports losses to the momentum trading strategy when the market is under stress. Daniel (2011) finds that major losses to the momentum trading strategy occur after a severe market downturn and in the months when the market starts to rise. Daniel (2011) argues that his results are loosely consistent with behavioural findings (see Loewenstein, 2000; Loewenstein, Weber, Hsee and Welch, 2001; Sunstein and Zeckhauser, 2008). These behavioural findings suggest that investors are more fearful in extreme situations and ignore probabilities. Daniel (2011) argues that individuals will ignore the probability of gains for loser stocks in extreme situations because they are fearful and focus only on losses. Their fear drives the loser stocks below fundamental levels; consequently, when the market improves, loser stocks over perform. Given that market state can explain momentum returns in the U.S., it is worth testing the market state explanation in markets outside the U.S. to show that this relationship is not due to data snooping.

In this chapter, I examine and compare the profitability of the momentum trading strategy in the two mainland Chinese stock markets - Shanghai Stock Exchange (hereafter **SSE**), and Shenzhen Stock Exchange (hereafter **SZSE**) - as well as in the Hong Kong Stock Exchange (hereafter **HKSE**). SSE is the world's sixth largest stock market by market capitalization (*List of stock exchanges*, 2012) and, together, the SSE and SZSE comprise the world's largest emerging market. The mainland Chinese stock markets are unique and are considered less rational (Drew, Naughton and Veeraraghavan, 2004), are dominated by individual investors (Kang, Liu and Ni, 2002), and differ in regulations, the behaviour of investors and trading practices from the rest of the world (Hu, 1999). The HKSE is the world's fifth largest and Asia's second largest stock market by market capitalization (*List of stock exchanges*, 2012). The HKSE is different from SSE and SZSE because the latter are not entirely open to foreign investors. However, from 2004, foreign investors were allowed to trade in all shares of the

SSE and SZSE with some restrictions (Jun Lin and Chen, 2005). The HKSE is also different from the U.S. stock markets because institutional investors have a weaker role in the HKSE, accounting for only 60% of total turnover in volume compared with 96% for the U.S. markets (Jones and Lipson, 2004; *Overview of the HKEx Markets*, 2013). SSE and SZSE are also different from each other since the SSE is dominated by large-cap companies, whereas the SZSE is dominated by small, joint ventures and export oriented companies. The differences among these markets could result in different momentum returns.

This study is motivated by the following issues: first, there are very few studies on the profitability of momentum trading strategies in the Hong Kong and Chinese stock markets and the empirical evidence provided in those studies about the profitability of momentum trading strategy is mixed. The main reason for the lack of studies on the Chinese and Hong Kong markets is the short history of stock trading and limited access for foreign investors to the Chinese stock markets (Kang et al., 2002). The mixed evidence about the profitability of momentum in China and Hong Kong is due to the use of different holding and formation periods (from 1 week to 2 years), size of sample data sets, and the differential use of the Shanghai and Shenzhen stocks. For example, Naughton, Truong and Veeraraghavan (2008), Wang (2008), Kang et al. (2002) and Wang and Chin (2004) report that momentum strategies are profitable , but Pan, Tang and Xu (2013), Wang (2004), Chen, Kim, Yao and Yu (2010), Wu (2011) and Cakici, Chan and Topyan (2011) report insignificant momentum returns. Hameed and Kusnadi (2002) find insignificant momentum returns for the HKSE in their study of six Asian markets; however, Cheng and Wu (2010) find significant momentum returns for the HKSE and they argue that Hameed and Kusnadi's (2002) findings might be the result of including small and illiquid stocks in their sample. Secondly, there are no studies about the profitability of the momentum trading strategy in China and Hong Kong during the Global financial crisis.[2] Therefore, I want to test the impact of the Global financial crisis on the profitability of momentum returns because the literature provides evidence that crises can affect the profitability of this trading strategy.

Thirdly, according to the best of my knowledge, this is the first study that relates momentum returns to market states in Chinese and Hong Kong markets. Cooper et al. (2004) consider only U.S. firms and their findings have not been tested for other markets, especially emerging markets, which are different from U.S. markets in many ways. First, emerging markets have a large number of small-cap stocks and institutional investors have a weaker role than in

[2] The Global financial crisis is also known as 2007-2009 financial crisis and great recession. However, I find the term "Global financial crisis" more appealing.

developed markets. Second, some anomalies discovered in developed markets do not apply to emerging markets (see Nartea, Ward and Yao, 2011). Third, emerging markets are growing much faster than developed markets and it is expected that emerging markets will lead economic growth in the next 10 years, so it is important for the financial world to gain a deeper understanding of the major emerging financial markets. Among the emerging markets, I chose China and Hong Kong because they are considered among the world's fastest growing emerging markets and China is expected to be the largest economy in the world by 2041 (see Wilson and Purushothaman, 2006).[3]

This chapter contributes to the literature since it is the first to examine, compare and explain momentum returns (both equally-weighted and value-weighted) in each stock market (SSE, SZSE and HKSE) and also at the All China level (stocks traded on SSE and SZSE). Secondly, the data used for this study are more recent than previous studies of the Chinese and Hong Kong markets. I include all A and B shares traded on the SSE and SZSE and shares listed in HKSE. The data span the period from November 1994 to November 2010 and hence cover the period during the Global financial crisis. I expect different results for the momentum strategy from 2007 because of the worldwide recession as Chordia and Shivakumar (2002) find insignificant momentum returns for U.S. stocks during recessionary periods and Daniel (2011) reports worst momentum returns during economic downturns and stock market crises.[4] The results from this study could be used by investors to make decisions in the construction of investment strategies following different market conditions.

Using SSE, SZSE and HKSE data, I find that equally-weighted momentum returns are positive and significant for all markets except SZSE for the full sample, when I use a 6-month formation period and 6-month holding period (skipping a month between the formation and holding period).[5] I also calculate value-weighted momentum returns to ensure that momentum returns are not the result of small size stocks since some studies find a decline in momentum returns in value-weighted portfolios (see Chan et al., 2000). In this study, the value-weighted momentum returns for all datasets with 6-month formation and 6-month holding period are positive and statistically significant for the full sample period. As a robustness test, I also use 3-, 9- and 12- month holding periods. However, I find that the monthly average return for a 6-

[3] Hong Kong is also included in the list of emerging markets by "The Economist" (*Emerging markets*, 2013http://en.wikipedia.org/wiki/Emerging_markets).

[4] Chordia and Shivakumar (2002) find six of nine post-war recessionary periods had positive momentum returns, but only one was statistically significant.

[5] The convention of skipping a month is widely used in recent literature to avoid bid-ask spread, price pressure, and any lagged reaction effect. However, the skipping time period varies in different studies, e.g., Jegadeesh and Titman (1993) skip a week whereas Cooper et al. (2004) skip a month.

month holding period is larger than those with 3-, 9- and 12-month holding periods except for the HKSE. I also compute momentum returns for strategies based on intermediate horizon past performance as in Novy-Marx (2012) but I find the returns to be smaller than for strategies based on Jegadeesh and Titman's (1993) recent past performance.

Interestingly, both equally- and value-weighted momentum returns for all markets are larger before the Global financial crisis (until December 2006). However, both equally- and value-weighted momentum returns for all datasets are negative from 2007 until November 2010. In addition, I find that the worst returns with the momentum trading strategy occur in months when the market conditions improved. The results show that the momentum trading strategy was successful in China and Hong Kong only until 2007. This is consistent with the findings of Chordia and Shivakumar (2002) that the profitability of momentum is related to the business cycle. This is also consistent with the results reported in Jegadeesh and Titman (1993) where momentum returns turned negative in the U.S. over the period 1975 to 1979, immediately after the 1973-1975 recession.[6] Negative momentum returns during financial crises are broadly consistent with Daniel (2011) who reports worst momentum returns during recessions and financial crises, especially in months when market conditions improved. I also examine whether momentum returns remain once I controlled for the Fama-French risk factors. By using both contemporaneous and lagged variables, I find that momentum returns remain almost the same after controlling for the Fama-French three factors.

I also examine whether market states can explain momentum returns. I define two market states - the "UP" market state when the lagged 36-month market return is positive and the "DOWN" market state when the lagged 36-month market return is negative. I find no robust relationship between momentum returns and market states in the All China, SSE, SZSE and HKSE data. However, there is a difference in the magnitude of momentum returns following UP and DOWN market states when market states are defined using 36-, 24- and 12-month lagged market returns, i.e., larger momentum returns for All China, SSE and SZSE following the 36-month DOWN market state than following the 36-month UP market state but larger momentum returns for All China, SSE and SZSE following the 12-month UP market state than following the 12-month DOWN market state.

In summary, I do not find any evidence that market state can explain momentum returns for China and Hong Kong. However, I find positive and large momentum returns in a normal

[6] Jegadeesh and Titman (1993) do not provide any explanation for negative momentum returns in their paper. The recession in U.S. lasted from November 1973 to March 1975. Although the recession officially ended in March 1975, its effects were felt on the U.S. economy until 1982 (*1973–75 recession*).

market environment (before 2007) since it appears that investors underreact to public information, whereas I find negative momentum returns from 2007 to 2010 with past losers earning more than past winners. The rest of the chapter is organized as follows: section 2 discusses the data and methodology, section 3 presents the momentum returns for all datasets and section 4 presents the momentum returns in the UP and DOWN market states using 36-, 24- and 12-month lagged market returns and section 5 concludes the study.

2.2 Data and Model

2.2.1 Sample and Descriptive Statistics

I use all stocks listed on the SSE, SZSE and HKSE from the China Securities Market (CSMAR) and DataStream from November 1994 to November 2010. I exclude the period before 1994 since only a limited number of stocks were traded during that period. I also exclude all financial institutions, closed-end funds and real estate stocks. In addition, I also exclude stocks with monthly returns greater than 100% to avoid any possible data recording errors and to ensure that my results are not driven by stocks with extreme returns.[7] At the beginning of the sample period, there were 155, 95, and 455 stocks from the SSE, SZSE and HKSE, respectively. At the end of the sample period, the number of stocks in the sample increased to 745, 690, and 815, for SSE, SZSE and HKSE, respectively.

Table 2.1 reports the summary statistics for the monthly value-weighted market returns for All China, HKSE, SSE and SZSE and monthly risk-free rates for All China and HKSE.[8] Panel A reports that the average monthly (mean) value-weighted market return for the full sample (1994-2010) for All China, HKSE, SSE and SZSE is 1.58% , 0.75%, 1.50% and 1.83%, respectively. In Panel A, Table 2.1, the average monthly risk-free rates for All China and HKSE are 0.32% and 0.40%, respectively. The summary statistics in Panel A show that, in the long-run, market returns are larger for stock markets than for risk-free rates, consistent with risk-based theories. Panels B and C report the summary statistics before the Global financial crisis and during the Global financial crisis, respectively. The average monthly (mean) value-weighted market returns before the Global financial crisis (November 1994 - September 2007) are 1.98% for All China, 0.91% for HKSE, 1.94% for SSE and 2.12% for SZSE. However, the average monthly (mean) value-weighted market returns during the Global financial crisis (October 1997-November 2010) are very small and even negative for

[7] The number of deleted stocks is less than 0.3% of total number of observations and it does not affect my results since my results remain similar with or without extreme returns.

[8] The risk-free rate for All China (SSE and SZSE) is the monthly rate charged by People's Bank of China to financial institutions. The risk-free rate for Hong Kong refers to the monthly interbank rate.

All China and SSE. The summary statistics results provide the evidence that the Global financial crisis affected the Chinese and Hong Kong markets. Therefore, I expect to find different results before the Global financial crisis and during the Global financial crisis.

2.2.2 Methodology

First, I calculate momentum returns for each market based on the methodology proposed by Jegadeesh and Titman (1993). I use arithmetic returns for the momentum trading strategy.[9] I use the conventional 6-month formation period for the momentum trading strategy. A month is skipped between the formation and holding period to mitigate the bid-ask bounce effect. I exclude all those stocks in a portfolio with any missing values either during the formation or holding period. At the end of each month t, all stocks are ranked in ascending order on the basis of their past 6-month returns (t-6 to t-1). These rankings are used to form equally-weighted decile portfolios, where the top decile portfolio (P1) is called the losers decile and the bottom (P10) is the winners decile. I buy (sell) the winners (losers) decile and define the return of the momentum trading strategy as P10-P1. The portfolios are held for K months (K= 3, 6, 9 and 12). Following Jegadeesh and Titman (1993), the portfolio monthly return for a K-month holding period is based on an equal-weighted average of portfolio returns from strategies implemented in the current month and the previous K-1 months. To illustrate, the monthly return for a 6-month holding period is based on an equal-weighted average of portfolio returns from the strategy in the current month, and the strategies from one, two, three, four and five months ago. This is equivalent to revising the weights of approximately one-sixth of the portfolio each month and carrying over the rest from the previous month. P10-P1 represents the return of the momentum trading strategy of buying the winners and selling losers. As a robustness test, I also form portfolios based on intermediate horizon past performance where portfolios are formed based on their past t-12 to t-7 month returns and held for one month (t+1).

After calculating equally-weighted momentum returns, I find the value-weighted momentum returns to ensure that these returns are not the result of small size stocks. To calculate value-weighted momentum returns, I follow the same procedure as for equally-weighted momentum returns except that I invest money in stocks according to their market capitalization instead of equal money in all stocks.

[9] I find the similar results with log returns. However, I find that log returns are negatively biased consistent with (Barber and Lyon, 1997).

In the next stage, I divide the data into sub-samples according to firm size and firm beta to test if the profitability of the momentum trading strategy depends on these variables. Stocks are divided into terciles on the basis of firm size and firm beta; momentum return spreads are calculated for each group separately.

Finally, I investigate if market states affect momentum returns by following Cooper et al. (2004) who employ UP and DOWN market states. I employ value-weighted market returns for All China, SSE composite index, the SZSE composite index, and the Hang Seng index as proxies for the market for All China, SSE, SZSE, and HKSE over 36 months before the portfolio formation date to define the market state. If the lagged 36-month value-weighted market return is positive (negative), then the market state is defined as UP (DOWN). A longer horizon is expected to capture major changes in market states but, on the other hand, it reduces the number of observations for UP and DOWN market states (see Cooper et al., 2004). As a robustness test, I apply 24-month and 12-month market states against these momentum returns. Following Cooper et al. (2004), I use buy-and-hold momentum returns to investigate the relationship between momentum returns and market. Buy-and-hold momentum returns are calculated at the end of 6-month holding periods instead of revising portfolio weight every month. Since the buy-and-hold returns are overlapping, I use robust Newey-West t-statistics.

Following Cooper et al. (2004), the momentum returns followed by UP and DOWN market states are adjusted for CAPM and Fama-French risk factors to ensure that the momentum returns remain significant and cannot be explained by the risk factors.[10]

$$MR_{t,6\times 6} = \alpha + \sum_{m=1}^{n} \beta_m f_{i,t} + e_t \tag{2.1}$$

$MR_{t,6X6}$ is the raw momentum return spread following UP and DOWN market states generated at time t with a 6-month formation and 6-month holding period. The notation $f_{i,t}$ (i=*1,2)* are risk factors (1= CAPM, 2= Fama-French) used in this study at time t, β_m **(**m= 1,2,….,n) is the loading for risk factors, α is the coefficient estimate for constant and e_t is the residual, with $(e_t) = 0$, $Cov(e_t, f_t) = 0$ *and* $e_t \approx (0, \sigma^2)$. I use the excess returns of the value-weighted market returns over risk-free return as the sole factor for the CAPM risk adjustment. I use the excess returns of value-weighted market returns; the small-minus-big return factor and the high-book-to-market-minus-low-book-to-market return factors for the Fama-French risk adjustment.

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[10] Momentum returns with 6-month formation and holding periods are adjusted for risk factors.

2.3 Empirical Findings

2.3.1 Momentum Returns for Different Markets

Table 2.2 presents the average monthly returns of the winners (P10), losers (P1) and winners minus losers (P10-P1) over the period November 1995 to November 2010.[11]

Panel A of Table 2.2 presents equally-weighted momentum returns for all markets. The average monthly equally-weighted momentum return spreads for All China (SSE and SZSE) are positive for different holding periods of 3 (0.56% per month), 6 (0.58% per month), 9 (0.41% per month) and 12 months (0.22% per month) and statistically significant for all the holding periods. The average monthly equally-weighted return spreads for HKSE are positive and significant for 3 (0.76% per month), 6 (0.60% per month) and 9 month (0.43% per month) holding periods, but small and insignificant for 12 months (0.20% per month) holding period. The return spreads for SSE are positive and statistically significant for the different holding periods of 3 (0.80% per month), 6 (0.83% per month), 9 (0.73% per month) and 12 months (0.53% per month). In contrast, there is no evidence of a momentum effect for equally-weighted portfolios in the SZSE since average monthly return spreads for different holding periods are not statistically different from zero.

Panel B of Table 2.2 reports the value-weighted returns for all markets. I find large momentum returns for the Chinese and Hong Kong markets. The value-weighted momentum return spreads for All China are larger than equally-weighted return spreads and statistically significant for all holding periods. This indicates that momentum returns are not driven by small size stocks. For HKSE, the value-weighted return spreads are larger and significant for the 3- 6- and 9-month holding periods than for the corresponding equally-weighted returns, but small and insignificant for the 12-month holding period. Momentum returns for the SSE are somewhat larger and statistically significant when I use value-weighted returns. Interestingly, the return spreads for the SZSE increase when I use value-weighted returns and becomes statistically significant for 6- and 9-month holding periods.

Panel C of Table 2.2 reports the average monthly return spreads for all markets based on intermediate horizon past performance for the period November 1995 to November 2010. I find that when I use intermediate horizon past performance (t-12 to t-7) over the period 1995 to 2010, the return spreads for all markets are smaller (insignificant) than the spreads generated when I use immediate past performance (t-6 to t-1).

[11] The estimation period for momentum trading strategy with 3-month holding period starts from August 1995 and ends on November 2010.

The equal-weighted and value-weighted results in Table 2.2 show that the momentum trading strategy is profitable both in the SSE and HKSE markets. However, return spreads for SZSE are small and insignificant (equally-weighted). The value-weighted return spreads for the momentum trading strategy are higher than equal-weighted momentum returns for all markets in the sample. These higher value-weighted return spreads are consistent with those shown in McLean (2010) and Korajczyk and Sadka (2005). This study also finds evidence consistent with McLean (2010) and Korajczyk and Sadka (2005) that the momentum winner effect for Chinese stocks is stronger in the equal-weighted portfolio, but the momentum loser effect is stronger in the value-weighted portfolios. The results reported in Table 2.2 are consistent with studies documenting a momentum effect in China (see for example Kang et al., 2002; Naughton et al., 2008; Wang, 2008). There are, however, studies that report insignificant momentum returns in China. For example Pan et al. (2013), Wang (2004), Chen et al. (2010), Wu (2011) and Cakici et al. (2011) all report insignificant equally-weighted momentum returns using A shares for both the SSE and SZSE. If I include only A-shares of both SSE and SZSE, then I get the similar results. In sum, I find that there is no evidence of a momentum effect in A- and B-shares of SZSE using equally-weighted returns but the effect is stronger and significant for both A- and B-shares in SSE.

Table 2.3 reports the average monthly returns of the winners (P10), losers (P1) and winners minus losers (P10-P1) before (November 1995- December 2006) and during (January 2007-November 2010) the Global financial crisis.[12] Panels A and B report equally-weighted and value-weighted returns before 2007, respectively. Panels C and D show equally-weighted and value-weighted returns for the period January 2007 to November 2010. Columns one and two report loser and winner portfolios, respectively; column three presents the return spread, which is the difference in the returns of the winner and loser portfolios. The next column titled "%> 0" is the percentage of return spreads that are positive over the sample period. The last column reports the number of months used to calculate the return spreads.

Panel A of Table 2.3 presents equally-weighted momentum returns for all markets before the Global financial crisis. The equally-weighted return spreads for All China before the Global financial crisis (SSE and SZSE) are almost twice larger (1.07% per month) than the entire sample period and are statistically significant with 69.70% of the months greater than zero. The equally-weighted returns for HKSE are also large, positive and significant (1.11% per

Although the Global financial crisis officially started in late 2007, for convenience I define the 2007-2010 period as "the Global financial crisis". However, my results are robust if I define "the Global financial crisis period" from 2008 to 2010.

month) before the Global financial crisis. The SSE returns are also high (1.41% per month) before the Global financial crisis. Interestingly, the SZSE returns are also large (0.31% per month) before the Global financial crisis and statistically significant. Panel B of Table 2.3 reports the value-weighted returns for all markets before the Global financial crisis. I find large, significant value-weighted return spreads for both the Chinese and Hong Kong markets.

Panel C of Table 2.3 reports the equally-weighted returns for all markets during the Global financial crisis (2007-2010). I find negative and significant momentum return spreads for all markets. Panel D of Table 2.3 reports the value-weighted returns for all markets during the Global financial crisis; there are negative return spreads for all markets but they are statistically insignificant. The negative momentum returns during the Global financial crisis are consistent with the findings of Chordia and Shivakumar (2002) that the profitability of momentum is related to the business cycle. This is also consistent with the results reported in Jegadeesh and Titman (1993) that momentum returns turned negative in the U.S. over the period 1975 to 1979, immediately after the 1973-1975 recession. Negative momentum returns during a financial crisis are broadly consistent with Daniel (2011) who reports worst momentum returns during recessions and financial crises, especially in the months when market conditions improved. These results are also consistent with the small and negative value-weighted market returns shown in Table 2.1 for All China and SSE during the Global financial crisis.

Panels C and D of Table 2.3 show that, from 2007, the momentum trading strategy underperformed and experienced large losses because loser stocks outperformed winner stocks. Figure 2.1 also shows losers outperforming winners, especially during the Global financial crisis years and, to a lesser degree, during and after the 1997 Asian financial crisis. It is evident from Figure 2.1 that, before 2007, past winners generally outperform past losers but, after 2007, there were many months when losers outperform winners especially in the months when the market started rising.

The sub-period analysis in Table 2.3 shows higher and significant momentum returns in all markets before the Global financial crisis. However, the momentum trading strategy fails to earn profits following the Global financial crisis. The results in Table 2.3 are consistent with Daniel’s (2011) study, which argues that the momentum trading strategy is large and significant during normal environments and turns into losses during market downturns or crises.

Table 2.4 reports the 10 worst monthly momentum returns with 6-month formation and 6-month holding period for All China, SSE, SZSE and HKSE over the period November 1995 to November 2010. The results show that most of the worst momentum returns are clustered. For HKSE, four of the 10 worst momentum returns happened from May 2009 till August 2009 and, for All China (SSE and SZSE), four of the 10 worst returns happened in consecutive months during 2009. Interestingly, most of the worst momentum returns happened during the time of stock and financial disasters, particularly in the months when the market improved. For HKSE, four of the worst momentum returns were in 2009 during the Global financial crisis; the other six occurred during the 2000 Dot Com bubble crisis (*Stock disasters in Hong Kong*, 2012). For the Chinese stock markets (SSE and SZSE), most of the worst momentum returns also happened during the Global financial crisis and the 2000 Dot Com bubble crisis (*List of stock market crashes and bear markets*, 2012). My results are consistent with those in Daniel (2011) to the extent that he reports the worst momentum returns during recessions and financial crises especially in the months when the market improved, i.e., seven of 11 worst momentum returns in his study occurred during a great depression, one in the 2000 dot com bubble and the remaining three during the Global financial crisis. However, unlike Daniel (2011), who finds that 10 of the 11 worst momentum returns occur when the lag 24-month market returns were negative, I find that only half of the worst momentum returns in China and Hong Kong happened following the DOWN market state (lag 12-month market return). I find that the worst momentum returns occur when the market improves during times of crisis or recession and the worst momentum returns have no relationship with either lagged 12-month or 24-month market returns. The difference between my results and those of Daniel (2011) might be due to the difference in sample periods since his sample includes data from the great depression of 1929 to 1939 when the overall market performance was very poor, therefore the probability of 24-month lag market returns being negative was much larger (seven of the 11 worst momentum returns in his study occurred during the great depression). In addition, Daniel (2011) does not use 12-month lagged or 36-month lagged market returns as robustness tests, whereas I also use lag-24 and lag-36 month market returns and find that there is no relationship between the worst momentum returns and lagged market returns. Figure 2.1 also shows that the underperformance of the momentum trading strategy over the period 2007 to 2010 can be attributed to the loser side as previous losers outperformed previous winners. For example over January to June 2009 (Panel A, Table 2.4), the HKSE market index rose by 5% but the loser portfolio rose from negative 18% per month (formation period) to 16% per month (holding period). However, for the same period the winner portfolio rose only from negative 2.5% per month (formation period) to almost 6% per month (holding period) (part of the result not reported in Table 2.4).

To summarize, my results provide evidence of large momentum returns in mainland Chinese markets but they basically come from SSE stocks since I find insignificant momentum returns from SZSE stocks.[13] The difference in momentum returns across SSE and SZSE appears to be related to firm size since I find (see Table 2.2) that value-weighted returns for SSE and SZSE are higher. Higher value-weighted returns indicate that large-cap companies generate higher momentum returns, consistent with McLean (2010) and Korajczyk and Sadka (2005). Note that SSE is dominated by large-cap companies, whereas SZSE is dominated by small companies. Momentum returns for HKSE stocks are also positive and statistically significant except for 12-month holding period. The sub-period analysis shows higher and significant momentum returns in all markets before the Global financial crisis. However, I find negative momentum returns following the Global financial crisis and it is evident that the momentum trading strategy fails to earn profits during the Global financial crisis. My results suggest that consistent momentum returns happen in normal environments where the market supposedly underreacts to public information. The presence of consistent momentum returns in a normal environment is in line with Daniel's (2011) findings, because it takes time for information to be adjusted into prices. On the other hand, after 2007, I find negative momentum returns and it appears that the worst returns for the momentum trading strategy occur in the months when the market conditions improve (see Figure 2.1). Figure 2.1 shows that the winner portfolio generally performs well in a normal environment and the loser portfolio performs well when the market emerges from severe crises. I also find that during a market crisis, loser stocks decline more than winners during the holding periods when the market is declining. For example, for SSE, the loser portfolio (P1) performs worse than the winner portfolio (P10) during market downturns (1998:09, 1999:05, 2001:09, 2002:06, 2002:10, 2003:04, 2003:09, 2003:12, 2004:07, 2004:11, 2005:03 and 2005:08).[14] This trend is somewhat consistent with some other behavioural findings (see Loewenstein, 2000; Loewenstein et al., 2001; Sunstein and Zeckhauser, 2008). During market downturns, investors are fearful and appear to focus more on losses especially if they already hold a loser stock. So there is a greater tendency for loser stocks to decline more than winner stocks during market downturns. When the market conditions improve, these loser stocks experience large gains because their losses were the

[13] Value-weighted momentum returns for SZSE are smaller than SSE and HKSE but statistically significant for 6- and 9-month holding periods. However, equal-weighted momentum returns for SZSE are insignificant for all the holding periods.

[14] I find the same trend for HKSE and SZSE stocks.

result of fear instead of bad performance. The strong gains of loser stocks then result in losses for the momentum trading strategy.

2.3.2 Do Momentum Returns Remain after Adjusting for the Fama-French Three-Factors?

In this section, following Munira, Muradoglu and Hwang (2008), I test if momentum returns (6-month holding period) remain after adjusting for the Fama-French three factors at the portfolio-level.

I regress the momentum return spreads (P10 – P1) of the entire dataset of each market on the Fama-French three factors to test if alpha is different from zero.[15] If the Fama-French three factors can fully explain momentum returns, then I expect alpha to be insignificant. Panel A, Table 2.5, reports the coefficients of the regressions when contemporaneous Fama-French three factors are used to explain the momentum returns. Columns two through five of Table 2.5 report the intercept (alpha), MKT_RF factor, small-minus-big size factor (SMB) and high-minus-low BTM factor (HML); the last column reports the adjusted R-square of the regression. I provide evidence of positive and significant alphas for All China, HKSE and SSE; however, the alpha for SZSE is weak and insignificant. The coefficients of the three Fama-French factors, MKT_RF, SMB and HML, are weak and insignificant except for the coefficient of SMB and HML for HKSE. The presence of positive significant alphas suggests that momentum returns for All China, HKSE and SSE cannot be explained by the Fama-French three factors.

Previous literature suggests that momentum returns can be explained by the lagged variables of the predictable components of stock returns (see Chordia and Shivakumar, 2002). It might be possible that the results would differ if the predicted Fama-French three factors are measured using the lag of these variables (see Munira et al., 2008). I consider this by re-estimating the results in Panel B, Table 2.5, using lagged Fama-French three factors to explain the momentum returns. I still find positive and significant alphas for the All China, HKSE and SSE markets with the alpha for SZSE still weak and insignificant. The coefficients of the three Fama-French factors, MKT_RF, SMB and HML, are likewise weak and insignificant except for the coefficient of SMB for HKSE and SZSE and the coefficient of HML for All China. Although the use of lagged variables does not change the alphas, it changes the signs of the some of the coefficients, which shows systematic differences across the momentum returns when exposed to the Fama-French three factors as contemporaneous

[15] See Appendix for the construction of the Fama-French three factors.

and lagged variables. For example, the negative signs of HML for All China turn positive when I use the Fama-French three factors as lagged variables.

In summary, I find that the Fama-French three factors cannot explain the momentum returns for the combined dataset of Chinese markets especially for SSE and HKSE, whether these variables are contemporaneous or lagged. The momentum returns for SZSE, however, remain insignificant after adjustment for the Fama-French three factors. This is consistent with earlier studies that the Fama-French three factors model cannot explain momentum returns.[16]

2.3.3 Profitability of the Momentum Strategy within Size- and Beta-based Subsamples

In this section, following Jegadeesh and Titman (1993), I test the profitability of the momentum-trading strategy within subsamples sorted on the basis of firm size and beta to examine whether momentum returns are limited to any particular subsample of stocks. The literature provides evidence that small size and high beta stocks have higher returns.[17] I implement the momentum trading strategy on stocks with three size-based subsamples (small, medium and big) and three beta-based subsamples (low-beta, medium-beta and high-beta stocks). I define size as the market capitalization of each stock at the portfolio formation date. I estimate beta from the monthly returns in the calendar year before the portfolio formation date.[18]

Table 2.6 presents the average monthly returns for each size- and beta-based subsample of the momentum trading strategy with 6-month formation and 6-month holding periods. The momentum return spreads for All China are not related to firm size since the difference in return spreads between the small and big size stocks (S1-S3) is small and insignificant. However, small (0.89% per month) and big stocks (0.80% per month) earn higher momentum returns than medium sized stocks (0.14% per month). The momentum return spreads for All China are also not related to beta as the difference in momentum returns between the high and low beta stocks ($\beta3$-$\beta1$) is also small (0.32% per month) and insignificant. However the return spreads for All China stocks with high (0.91% per month) and medium beta (0.93% per month) are larger than the return spreads of the low beta (0.59% per month) stocks. The return spreads for subsamples by size and beta for All China are approximately the same as the

[16] Jegadeesh and Titman (2001) report that the Fama-French (1996, 2008, 2012) three factors cannot explain momentum returns for U.S. stocks.

[17] See Fama and French (1993).

[18] See Appendix for the estimation of beta.

return spreads for the entire subsample of All China except for the return spreads for medium size subsample.

The momentum return spreads for HKSE are related to firm size and beta since return spreads of medium and big size and medium and high beta subsamples are large and significant; however, the return spreads of small size and low beta subsamples are small and insignificant. These results indicate that momentum returns for HKSE are limited to medium and high risk stocks since the results of medium and high beta-based subsamples are positive and significant. The difference in momentum returns between small and big size (-0.94% per month) and high and low beta (1.26% per month) stocks is statistically significant, which implies that momentum returns depend on size and beta. These results are consistent with the higher momentum returns for value-weighted portfolios than for equal-weighted portfolios reported in Table 2.2.

The momentum return spreads for SSE indicate that the returns for subsamples of size and beta are large and statistically significant for all size and beta categories. However, the return spreads of high beta stocks (1.31% per month) are larger than those of the low beta stocks (0.70% per month) and the difference in return spreads between high and low beta stocks ($\beta 3$-$\beta 1$) is statistically significant. The return spread for SSE is not related to size since the difference in return spreads between big and small size firms (S1-S3) is small (-0.17% per month) and insignificant. However, big stocks (0.95 % per month) have higher return spreads than small (0.78% per month) and medium stocks (0.51% per month). This is consistent with the results reported in Table 2.2 where momentum return spreads are higher for value-weighted than for equal weighted portfolios. These results indicate that momentum returns for SSE are not primarily due to the differences in systematic risk and they also indicate that the profitability of the momentum trading strategy for SSE is not confined to any particular subsample of stocks. In contrast, the size- and beta-based momentum returns for SZSE are insignificant and statistically not different from zero. These results are consistent with insignificant equally-weighted results for the full SZSE sample (see Table 2.2).

In summary, when I sort data on size and beta, the results for SSE are almost consistent with the full sample results and show that the cross-sectional differences are not entirely responsible for momentum returns since all size- and beta-based results are positive and statistically significant. However, the results for HKSE imply that momentum returns are related to firm size and beta though this is not so for SZSE. Therefore the All China result seems to be driven by the SSE since there is no evidence of momentum returns in SZSE. I can conclude that only the momentum returns of SSE are positive and statistically significant for all subsamples of size and beta, whereas momentum returns of HKSE are limited to medium and big size and medium and high beta subsamples.

2.4 Market State Effects on Momentum Returns

In this section, following Cooper et al. (2004), I examine the effect of the market state on momentum returns. The monthly average raw returns of the momentum trading strategy as well as the CAPM and Fama-French adjusted returns (i.e., alphas) following UP and DOWN market states are shown in Table 2.7. Panel A reports the results when market state is defined based on the past 36 months, whereas Panels B and C report the results when market state is defined based on the past 24 and 12 months, respectively. Panel A shows that during the period November 1995 to November 2010, using 36 months to define UP and DOWN markets, the UP market raw momentum returns, CAPM, and Fama-French alphas for All China are 0.34%, 0.37% and 0.35% per month, respectively, but statistically insignificant. Following DOWN market states, the raw momentum returns, CAPM and Fama-French alphas are 1.57%, 1.55% and 1.85%, respectively. When I define market state based on the past 24 months (Panel B), the returns for All China in the DOWN market state are larger (significant) than for UP market state (insignificant). However, when market state is defined based on the past 12 months (Panel C), I find that the raw momentum returns as well as the CAPM and Fama-French alphas following UP markets are large and statistically significant whereas those following DOWN markets are small and insignificant. In sum, I find positive momentum returns following both UP and DOWN markets but the magnitude of momentum returns is larger and significant only for the 36- and 24-month DOWN market states and the 12-month UP market state. I conclude that there is no relationship between market state and momentum returns for China and that the magnitude of momentum returns depends on the definition of market state.

The raw, CAPM and Fama-French adjusted momentum returns for HKSE in Panels A and B following 36- and 24-month (both UP and DOWN) market states are similar but statistically insignificant except the Fama-French alpha. However, the raw, CAPM and Fama-French adjusted momentum returns for the HKSE reported in Panel C following the 12-month DOWN market states are larger than the corresponding values for UP market states but they are insignificant except for the Fama-French alpha. I do not find any relationship between market states and momentum returns for HKSE stocks since the raw and CAPM adjusted momentum returns following UP and DOWN market states are insignificant.

All the raw, CAPM and Fama-French adjusted momentum returns for SSE following the 36-, 24- and 12-month UP and DOWN market states are positive but statistically significant only for the 36- and 24-month DOWN market states and the 12-month UP market state. The momentum returns following the 36- and 24-month DOWN market states are larger than those following the 36- and 24-month of UP market states (see Panels A and B, Table 2.7). The raw, CAPM and Fama-French adjusted momentum returns for SSE in Panel C following the 12-month UP and DOWN market states are positive but momentum returns following the 12-month UP market states are larger and statistically significant than returns following 12-month DOWN market state (insignificant). These results show that the DOWN market state explains momentum returns better for SSE if 36- and 24-month lagged market returns are used to define the DOWN market state. However, I find larger momentum returns following the UP market state when I use 12-month lagged market returns to define the market state. I conclude that there is no reliable relationship between market state and momentum returns for SSE; the magnitude of the momentum returns depends on the definition of market state. The momentum returns for the entire sample of SZSE stocks are statistically not different from zero except the Fama-French alpha following the 36-month DOWN market state. I conclude that market state cannot explain momentum returns for SZSE since there is no evidence of a relationship between momentum returns and 36-, 24- and 12-month market states.

I also conduct a sub-period analysis and report the results in the rest of the Panels in Table 2.7. Panels D, E and F, Table 2.7, report momentum returns for the sub-period November 1995 until December 2006 following the 36-, 24- and 12-month UP and DOWN market states, respectively. The raw, CAPM and Fama-French adjusted momentum returns following the 36-, 24- and 12-month UP and DOWN market states are positive and significant for All China, SSE and HKSE but insignificant though positive for HKSE for the 12-month UP market state and positive but insignificant for SSE for the 12-month DOWN market state except the Fama-French alpha. However, the raw, CAPM and Fama-French adjusted momentum returns for SZSE are positive but statistically insignificant except for the Fama-French adjusted momentum returns following the 36-, and 24-month DOWN market states. Momentum returns for SZSE following UP markets states are small and statistically insignificant. I conclude that there is no relationship between momentum returns and market state before the Global financial crisis because momentum returns for All China, HKSE and SSE are significant following the 36-, 24- and 12-month UP and DOWN market states except for HKSE (SSE), which has positive but insignificant momentum returns following the 12-month UP (DOWN) market state.

Panels G, H and I of Table 2.7 show the momentum returns for the sub-period January 2007 to November 2010 following the 36-, 24- and 12-month UP and DOWN market states, respectively. The raw, CAPM and Fama-French adjusted returns following the 36-, 24- and 12-month UP and DOWN market states are negative for all markets except for the small insignificant returns for HKSE (0.24% per month) and SZSE (0.03% per month) following the 12-month UP market state. I conclude that there is no reliable relationship between momentum returns and market state after the Global financial crisis since momentum returns for all markets are negative following UP and DOWN market states. Hence, it might be economic activity that explains momentum returns because it seems that investors act differently during a financial crisis than in normal market conditions. The failure of the momentum trading strategy during a crisis is consistent with the results reported in Daniel (2011) with all 11 worst momentum returns occurring during stock market crises.[19]

In summary, it appears that momentum returns do not depend on market state since I report significant momentum returns for All China and SSE stocks regardless of the market state before the Global financial crisis except following the 12-month DOWN market state where returns for SSE stocks are lower and insignificant than the corresponding UP market state. Before the Global financial crisis, I also find significant momentum returns for HKSE following all UP and DOWN market states except following the 12-month UP market state where returns are lower and insignificant than the corresponding DOWN market state. However, the momentum returns for SZSE are insignificant following all market states before the Global financial crisis. Interestingly, the momentum returns disappear or become negative for all markets following UP and DOWN market states from 2007 until 2010. Therefore momentum returns seem to follow worldwide business cycle expansions and recessions since momentum returns are totally different before and after 2007.[20]

2.4.1 The Market State as a Continuous Variable

In the previous section, I test momentum returns following UP and DOWN market states. In this section, following Cooper et al. (2004), I examine the relationship between lagged market returns and momentum returns by treating the market return as a continuous variable. The purpose of this test is to determine if momentum returns increase or decrease monotonically with lagged market return. In particular, I test if momentum returns are negatively related to lagged market returns given that I find comparatively high momentum returns for Chinese

[19] Seven of 11 worst momentum returns in Daniel's (2011) study occurred during the great depression, one in the 2000 dotcom bubble and remaining three during the Global financial crisis.

[20] The word "recession" here refers to a "period of reduced economic activity".

stocks following the 36- and 24-month DOWN market states rather than following the corresponding UP market states.

To determine this, I regress momentum returns in turn against the lagged 36-, 24-, and 12-month market returns and the corresponding square of the lagged market returns. I include the square of lagged market returns to test whether momentum returns decrease linearly with lagged market returns. Panel A, Table 2.8, shows that momentum return spreads for All China, HKSE, SSE and SZSE stocks are negatively related to the 36-month lagged market returns but the coefficient is statistically insignificant. This is consistent with the earlier finding that momentum return spreads for All China, SSE and SZSE are low following 36-month UP market states compared with the corresponding DOWN market state.[21] In Panel A, though the coefficient of the square of lagged market returns is negative for all markets, it is not statistically significant. These results show that there is no systematic relationship between momentum returns and market states for All China, HKSE, SSE and SZSE. These results support the results reported earlier since I find significant momentum returns following both the 36-month UP and DOWN market states before the Global financial crisis.

Panel B, Table 2.8, shows that momentum returns for All China and SSE (HKSE and SZSE) are positively (negatively) related to the lagged market returns and negatively (positively) related to the square of lagged market returns when regressed against the 24-month lagged market returns and the square of lagged market returns; all are statistically insignificant. I conclude that there is no systematic relationship between momentum returns and market states for All China, HKSE, SSE and SZSE when regressed against the 24-month lagged market returns and the square of lagged market returns. These results are consistent with those reported earlier of the significant momentum returns irrespective of the market state (based on the 24-months UP and DOWN market states) before the Global financial crisis.

Panel C, Table 2.8, shows that momentum returns for All China, SSE, HKSE and SZSE are positively related to the lagged market returns and negatively related to the square of lagged market returns when regressed against the 12-month lagged market returns and the square of lagged market returns; all are statistically significant except for the lagged market returns for HKSE. These results confirm, to some extent, the earlier findings that momentum return spreads are high (low) when 12-month lagged market returns are high (low). However, momentum return spreads are negatively related to the square of lagged market returns, which means that return spreads do not increase linearly with the 12-month lagged market returns. I

[21] Momentum returns for HKSE are almost the same following 36-month UP and DOWN market states.

conclude that there is a weak relationship between momentum returns and market state for All China, SSE and SZSE when regressed against the 12-month lagged market returns and the square of lagged market returns. However, the relationship between momentum returns and market state is different when regressed against the 36-month lagged market returns compared with the 12-month lagged market returns i.e., momentum returns are negatively related to the lagged market returns when regressed against the 36-month lagged market returns but positively related to lagged market returns when regressed against the 12-month lagged market returns. These results also support those reported earlier that there is no systematic relationship between momentum returns and market state as the magnitude of momentum returns following UP and DOWN market states is not consistent across different definitions of market state. I therefore suggest that it might be economic activity that explains momentum returns not the market state.

Finally, I divide the full sample of monthly momentum returns into quintiles based on 36-, 24- and 12-month lagged market returns to test if momentum returns increase or decrease from the lowest to the highest level of lagged market returns. The results are reported in Panels D, E, and F of Table 2.8. Quintile 1 shows the momentum return spreads for the lowest lagged market return quintile; quintile 5 shows the return spread for the highest lagged market return quintile. In Panel D, momentum return spreads for All China decrease as the market moves from quintile 1 to quintile 5 except for the return spreads for quintile 3, which are higher than quintile 2. However, the momentum return spreads for All China are significant only for quintile 1. The momentum return spreads for HKSE are insignificant for all quintiles. The momentum return spreads for SSE decrease from the quintile 1 to quintile 2. However, the return spreads dramatically increase from quintile 2 to quintile 3 but then decrease in quintiles 4 and 5. The return spreads for SSE are significant only for quintiles 1 and 3. The return spreads for SZSE increase from quintile 1 to quintile 2 and then decrease from quintile 2 to quintile 5 but the return spread is statistically significant only for quintile 2. These results are consistent with earlier results that there is no systematic relationship between momentum returns and market state.

In Panel E, where I sort the momentum returns according to the 24-month lagged market returns, the momentum return spreads for All China are statistically significant only for quintiles 1 and 2. Though the return spread for quintile 4 is higher than other quintiles it is still statistically insignificant. The return spreads for HKSE are the highest and are statistically significant for quintile 4 but they are small and insignificant for all other quintiles. The momentum return spreads for SSE are high and significant for quintiles 1, 2 and 4 but are low and insignificant for quintiles 3 and 5. The return spreads for SZSE are statistically insignificant from quintiles 1 to 5 of the 24-month lagged market returns. The absence of any consistent increase or decrease in return spreads as the market moves from one state to another confirms earlier results that there is no systematic relationship among momentum returns and market state.

In Panel F, I define market state according to the 12-month lagged market returns. I find that momentum return spreads for All China are positive and statistically significant for quintiles 2 and 3, but negative and insignificant for quintiles 1 and 5. The return spreads for HKSE are positive for quintiles 1 to 4 but statistically insignificant. The return spreads for SSE are high and significant for quintiles 2, 3 and 4 but are low and insignificant for quintiles 1 and 5. The spreads for SZSE are significant only for quintile 3 of the lagged market returns. These results also show that there is no consistent relationship between momentum returns and market state when market states are defined according to 12-month lagged market returns.

In summary, consistent with results reported in earlier sections, I find that momentum returns are not related to market state since there is no monotonic relationship between momentum return spreads and lagged market returns (36, 24 and 12 months) in all markets.

2.5 Conclusions

The momentum trading strategy, first found profitable by Jegadeesh and Titman (1993), still remains most prominent among all the anomalies found in the finance literature. The momentum effect is robust across international markets and time periods and though a few empirical studies link momentum returns with market state none has done so for the markets of China and Hong Kong. Given that China and Hong Kong are the world’s fastest growing emerging markets with China expected to be the largest economy of the world by 2041, it is imperative for the global investment community to gain a deeper understanding of its financial markets. In addition, the impact of the Global financial crisis on momentum returns has not been tested. The literature suggests a relationship between momentum returns and economic activity; therefore, it is important to test the relationship between momentum returns and the Global financial crisis.

In this chapter, I investigate the impact on momentum returns of market state and the Global financial crisis in the Chinese and Hong Kong markets. I report positive and significant momentum returns for All China, HKSE and SSE and small insignificant momentum returns for SZSE.[22] The difference in momentum returns between SSE and SZSE appears to be related to firm size since SZSE is dominated by small companies. However, I find large momentum returns before the Global financial crisis and negative momentum returns from 2007 until 2010 for all markets. There is a dramatic impact of the Global financial crisis on momentum returns since the loser portfolio generates higher returns than the winner portfolio from 2007 until 2010 and hence negative momentum returns. Before the Global financial crisis, all markets seem to under react to public information resulting in consistent momentum returns. However, during the Global financial crisis, it appears that investors were fearful and avoided loser stocks resulting in a decrease in the price of loser stocks beyond their fundamental level. Any improvement in market conditions after a severe downturn returns the prices of loser stocks back to their fundamental level; hence losers generate higher returns than winners. My results indicating the worst momentum returns during the Global financial crisis are in line with Daniel (2011), who also finds the worst momentum returns during recessions and stock market crises. My results also appear to be consistent with some behavioural findings.[23] These behavioural findings imply that individuals are fearful in extreme situations and appear to focus more on losses and, therefore, probabilities are largely ignored. Research is needed to examine whether the empirical results documented for China and Hong Kong are fully consistent with these behavioural findings.

In the finance literature, there are largely two possible explanations for the momentum anomaly, one is risk-based and the other is behaviour-based. I find that momentum returns cannot be explained by risk factors because momentum returns remain almost the same after controlling for the Fama-French risk factors. I also confirm that momentum returns cannot be explained even when I use the Fama-French three factors as predictor variables. Among the behavioural explanations, Daniel et al.'s (1998) overreaction theory is well known, where investor overconfidence results in over-reaction that generates momentum returns. Cooper et al. (2004) extend Daniel et al.'s (1998) theory to predict differences in momentum returns across market states suggesting that if investor overconfidence is responsible for momentum returns, then overconfidence would be greater following UP market states. Cooper et al. (2004) find positive significant momentum returns following UP market states (36, 24 and 12 months) in the U.S. market.

[22] Value-weighted momentum returns for SZSE are smaller than SSE and HKSE but statistically significant for 6- and 9-month holding periods. However, equal-weighted momentum returns for SZSE are insignificant for all the holding periods.

[23] See Loewenstein (2000), Loewenstein et al. (2001) and Sunstein and Zeckhauser (2008).

However, unlike Cooper et al. (2004), I find no systematic relationship between market state and momentum returns in China and Hong Kong, which highlights the fact that we cannot simply generalize the findings in mature markets to new and emerging markets. Nonetheless, I find a strong relationship between momentum returns and economic activity because there are large momentum returns before the Global financial crisis.

This study contributes to the literature because it is the first study that finds a strong relationship between momentum returns and economic activity for Chinese and Hong Kong stocks. The results of this study have important implications because they provide supplementary evidence that investors could have increased their returns by using the momentum strategy because it was profitable before the Global financial crisis. In addition, the results suggest that from 2007-2010 investors could have earned greater returns over next 3 to 12 months by buying previous loser stocks because the profitability of this strategy turns into losses because loser stocks outperform winners during economic downturns.

In future work, I hope to further explore the effect of economic activity on momentum returns and develop a model that can predict momentum returns based on the level of economic activity. The literature provides mixed evidence about the effect of macroeconomic variables on the profitability of momentum strategy; however; I could not test the relationship since the data for macroeconomic variables for Greater China were unavailable over the sample period.

Table 2.1
Summary Statistics (Market Return, Risk-Free Retun)

This table reports the summary statistics for the value-weighted market return (RET) of All China, HKSE, SSE and SZSE. It also reports summary statistics for the risk-free rate (RF) for All China and HKSE. Panel A reports the summary statistics for the full sample (November 1994- November 2010), Panel B reports the summary statistics before the Global financial crisis (November 1994-Septmber 2007) and Panel C reports the summary statistics during the financial crisis (October 2007-November 2010). The average monthly mean, median, 25%, 75% and 90% of the values are given in per cent.

Panel A: Summary Statistics for the full sample (1994-2010)

Variable	N	Mean	StdDev	Median	25%	75%	90%
All China-RET	193	1.58	9.67	1.34	-4.86	6.45	13.31
HKSE-RET	193	0.75	7.72	1.28	-3.61	4.55	9.53
SSE-RET	193	1.50	9.43	1.38	-4.87	5.94	12.58
SZSE-RET	193	1.83	10.56	1.16	-4.93	7.17	13.59
All CHINA-RF	193	0.32	0.22	0.19	0.19	0.39	0.73
HKSE-RF	193	0.40	0.19	0.50	0.25	0.54	0.58

Panel B: Summary Statistics before the Global financial crisis (1994-2007)

Variable	N	Mean	StdDev	Median	25%	75%	90%
All China-RET	155	1.98	9.16	0.90	-4.80	6.45	14.18
HKSE-RET	155	0.91	7.55	1.33	-3.44	4.85	9.53
SSE-RET	155	1.94	8.84	1.21	-4.60	5.94	13.11
SZSE-RET	155	2.12	10.22	0.84	-4.81	6.27	13.59
All CHINA-RF	155	0.34	0.24	0.19	0.19	0.46	0.87
HKSE-RF	155	0.46	0.14	0.52	0.32	0.56	0.58

Panel A: Summary Statistics during the Global financial crisis (2007-2010)

Variable	N	Mean	StdDev	Median	25%	75%	90%
All China-RET	38	-0.25	11.71	2.69	-7.68	8.50	13.42
HKSE-RET	38	0.17	8.68	0.38	-5.24	3.85	12.92
SSE-RET	38	-0.47	11.63	2.48	-7.98	7.38	13.90
SZSE-RET	38	0.43	12.18	2.45	-7.49	9.27	16.57
All CHINA-RF	38	0.24	0.07	0.19	0.19	0.32	0.34
HKSE-RF	38	0.15	0.16	0.04	0.04	0.29	0.38

Table 2.2
Equal-Weighted and Value-Weighted Momentum Returns

At the beginning of each month t, All China, SSE, SZSE and HKSE stocks are allocated into deciles based on their lagged 6-month (t-6 to t-1 for Panels A and B and t-12 to t-7 for Panel C) returns and portfolios are formed one month after the lagged returns used for forming these portfolios are measured (Panels A and B). All stocks are ranked in ascending order on the basis of 6-month lagged returns. I then form an equal-weighted and value-weighted (Panels A and B only) zero-cost portfolio selling (buying) the decile of stocks with the lowest (highest) 6-month lagged returns. For Panels A and B, portfolios are held for K months (K=3, 6, 9 and 12 months). For Panel C, portfolios are held for one month. The average monthly returns of portfolio P1 (Losers), P10 (Winners) and momentum returns (P10-P1) are reported in per cent and *t*-statistics provided in parentheses. The sample period is November 1994 to November 2010.

Panel A: Equal-weighted Momentum Returns					
	#Months	184	181	178	175
Market	K=	3	6	9	12
All China	P1 (Losers)	1.36	1.37	1.50	1.62
		(3.64)	(4.03)	(4.80)	(5.59)
	P10 (Winners)	1.92	1.95	1.91	1.84
		(5.59)	(6.16)	(6.54)	(6.93)
	P10-P1	0.56	0.58	0.41	0.22
		(3.04)	(3.80)	(3.29)	(2.12)
HKSE	P1 (Losers)	0.39	0.13	0.25	0.41
		(0.92)	(0.34)	(0.78)	(1.50)
	P10 (Winners)	1.15	0.73	0.67	0.61
		(3.28)	(2.45)	(2.50)	(2.51)
	P10-P1	0.76	0.60	0.43	0.20
		(4.12)	(3.58)	(3.36)	(1.67)
SSE	P1 (Losers)	1.27	1.32	1.39	1.48
		(3.42)	(3.80)	(4.52)	(5.17)
	P10 (Winners)	2.06	2.15	2.12	2.02
		(6.09)	(6.88)	(7.51)	(7.94)
	P10-P1	0.80	0.83	0.73	0.53
		(3.88)	(4.78)	(4.74)	(4.08)
SZSE	P1 (Losers)	1.68	1.68	1.76	1.81
		(4.11)	(4.49)	(5.10)	(5.75)
	P10 (Winners)	1.71	1.71	1.82	1.80
		(4.74)	(5.14)	(5.61)	(6.00)
	P10-P1	0.02	0.04	0.06	-0.01
		(0.13)	(0.27)	(0.53)	(-0.06)

Table 2.2: Continued

Panel B: Value-weighted Momentum Returns					
	#Months	184	181	178	175
Market	K=	3	6	9	12
All China	P1 (Losers)	0.97	0.90	0.99	1.15
		(2.78)	(2.85)	(3.42)	(4.32)
	P10 (Winners)	1.66	1.67	1.63	1.58
		(4.90)	(5.25)	(5.47)	(5.77)
	P10-P1	0.69	0.77	0.64	0.43
		(3.68)	(4.93)	(4.99)	(3.93)
HKSE	P1 (Losers)	-0.84	-0.25	0.33	0.66
		(-2.20)	(-0.68)	(1.08)	(2.43)
	P10 (Winners)	0.98	0.79	0.80	0.78
		(3.06)	(2.84)	(3.14)	(3.16)
	P10-P1	1.82	1.04	0.48	0.12
		(7.18)	(4.27)	(2.52)	(0.72)
SSE	P1 (Losers)	0.85	0.80	0.84	0.93
		(2.57)	(2.60)	(3.00)	(3.66)
	P10 (Winners)	1.72	1.72	1.69	1.62
		(5.20)	(5.60)	(5.96)	(6.17)
	P10-P1	0.87	0.92	0.85	0.69
		(4.34)	(5.43)	(5.88)	(5.42)
SZSE	P1 (Losers)	1.36	1.33	1.48	1.57
		(3.29)	(3.70)	(4.45)	(5.24)
	P10 (Winners)	1.72	1.70	1.74	1.70
		(4.80)	(5.13)	(5.38)	(5.62)
	P10-P1	0.36	0.37	0.26	0.13
		(1.63)	(2.38)	(2.08)	(1.26)

Panel C: Momentum Returns Based on Intermediate Horizon Past Performance					
Country	P1 (Losers)	P10 (Winners)	P10-P1	%>0	#Months
All China	1.81	1.96	0.15	52.94%	181
	(2.27)	(2.69)	(0.34)		
HKSE	-0.31	0.27	0.58	61.18%	181
	(-0.41)	(0.42)	(1.23)		
SSE	1.59	2.27	0.68	64.42%	181
	(2.03)	(1.88)	(1.38)		
SZSE	2.00	1.70	-0.30	43.72%	181
	(2.26)	(2.24)	(-0.65)		

Table 2.3
Momentum Returns and Financial Crisis

At the beginning of each month t, All China, SSE, SZSE and HKSE stocks are allocated into deciles based on their lagged 6-month (t-6 to t-1) returns and portfolios are formed one month after the lagged returns used for forming these portfolios are measured. All stocks are ranked in ascending order on the basis of 6-month lagged returns. I then form an equal-weighted and value-weighted zero-cost portfolio selling (buying) the decile of stocks with the lowest (highest) 6-month lagged returns. These portfolios are held for 6 months. The average monthly returns of portfolio P1 (Losers), P10 (Winners) and momentum returns (P10-P1) are reported in per cent and *t*-statistics provided in parentheses. The sample period is November 1994 to November 2010.

Panel A: Equal-weighted Momentum Returns before the Global Financial Crisis

Market	P1 (Losers)	P10 (Winners)	P10-P1	%>0	#Months
All China	0.50	1.56	1.07	69.70	134
	(1.73)	(5.97)	(6.10)		
HKSE	-0.38	0.73	1.11	80.30	134
	(-1.05)	(2.45)	(6.60)		
SSE	0.44	1.85	1.41	76.52	134
	(1.62)	(6.89)	(6.06)		
SZSE	0.92	1.23	0.31	58.33	134
	(2.49)	(4.41)	(2.11)		

Panel B: Value-weighted Momentum Returns before the Global Financial Crisis

Market	P1 (Losers)	P10 (Winners)	P10-P1	%>0	#Months
All China	0.27	1.46	1.19	80.60	134
	(1.10)	(5.30)	(7.62)		
HKSE	-0.80	0.86	1.67	79.85	134
	(-2.26)	(2.29)	(6.98)		
SSE	0.14	1.59	1.45	80.60	134
	(0.65)	(6.24)	(8.43)		
SZSE	0.62	1.33	0.72	70.90	134
	(1.82)	(4.94)	(4.67)		

Table 2.3: Continued

Panel C: Equal-weighted Momentum Returns from 2007 to 2010					
Country	P1 (Losers)	P10 (Winners)	P10-P1	%>0	#Months
All China	3.81	3.03	-0.78	31.91	47
	(4.11)	(3.21)	(-3.69)		
HKSE	1.50	0.68	-0.82	61.97	47
	(1.53)	(0.90)	(-2.25)		
SSE	3.83	2.99	-0.84	25.31	47
	(4.11)	(3.25)	(-4.52)		
SZSE	3.81	3.07	-0.74	34.30	47
	(4.17)	(3.13)	(-2.76)		

Panel D: Value-Weighted Momentum Returns from 2007 to 2010					
Country	P1 (Losers)	P10 (Winners)	P10-P1	%>0	#Months
All China	2.72	2.29	-0.43	42.55	47
	(2.81)	(2.39)	(-1.24)		
HKSE	1.32	0.59	-0.73	44.68	47
	(1.38)	(0.89)	(-1.26)		
SSE	2.69	2.08	-0.61	53.19	47
	(2.77)	(2.23)	(-1.79)		
SZSE	3.35	2.76	-0.59	42.55	47
	(3.60)	(2.72)	(-1.46)		

Table 2.4
Worst Monthly Momentum Returns

This table presents the 10 worst monthly momentum returns for All China, SSE, SZSE and HKSE stocks over the 1995-2010 period. The worst monthly momentum returns (P10-P1) with 6-month formation and 6-month holding period are shown as MOMR in the table along with their ranking and market return (MKT) over the same holding period; 12-month lagged market returns (MKT-12M) before the portfolio formation dates are also shown.

Panel A: Worst Momentum Returns for HKSE					Panel B: Worst Momentum Returns for All China				
RANK	DATE	MKT	MOMR	MKT-12M	RANK	DATE	MKT	MOMR	MKT-12M
1	200905	5.27%	-12.03%	-70.00%	1	200904	7.71%	-5.97%	-82.51%
2	200008	-0.08%	-10.40%	58.56%	2	200905	6.68%	-5.603%	-107.68%
3	200906	4.92%	-9.97%	-61.45%	3	200009	1.22%	-4.96%	51.93%
4	200009	-1.79%	-9.94%	65.90%	4	200907	9.56%	-4.60%	-92.95%
5	199909	2.88%	-7.97%	-5.12%	5	200906	8.19%	-4.53%	-79.44%
6	200908	8.13%	-7.30%	-46.97%	6	199906	6.86%	-4.51%	8.30%
7	200007	1.36%	-7.16%	61.66%	7	199610	9.04%	-4.09%	-4.12%
8	200002	4.24%	-6.94%	62.47%	8	200010	1.34%	-4.08%	51.90%
9	200003	5.46%	-6.26%	72.84%	9	199708	1.46%	-3.83%	84.64%
10	200907	8.20%	-6.20%	-54.92%	10	199711	-2.12%	-3.50%	88.28%

Table 2.4: Continued

Panel C: Worst Momentum Returns for SSE					Panel D: Worst Momentum Returns for SZSE				
RANK	DATE	MKT	MOMR	MKT-12M	RANK	DATE	MKT	MOMR	MKT-12M
1	200009	2.54%	-5.91%	51.16%	1	199610	14.01%	-8.10%	-13.91%
2	200905	6.44%	-5.87%	-109.96%	2	200904	10.22%	-6.24%	-78.74%
3	200904	1.50%	-5.58%	-82.37%	3	200008	2.99%	-6.13%	36.63%
4	200906	5.85%	-4.93%	-82.44%	4	199906	6.85%	-5.62%	5.52%
5	199712	-3.30%	-4.80%	78.18%	5	200905	8.29%	-5.07%	-97.60%
6	200907	7.64%	-4.69%	-95.69%	6	200906	8.78%	-4.90%	-66.28%
7	200010	0.84%	-4.11%	51.01%	7	199707	1.39%	-4.62%	113.46%
8	199906	0.70%	-3.57%	10.68%	8	200907	9.97%	-4.60%	-82.53%
9	200804	-9.27%	-3.35%	143.38%	9	199612	9.68%	-4.24%	21.91%
10	199711	-3.99%	-3.30%	81.44%	10	199704	3.38%	-4.17%	76.46%

Table 2.5
Momentum Returns Regressed on Fama-French Factor Variables

This table presents the coefficients and the *t*-statistics obtained by regressing momentum return spreads against the Fama French three factor variables, i.e., MKT_RF, SMB and HML. The sample period is November 1994 to November 2010. MKT_RF is the value-weighted monthly market return in excess of one month risk-free return; SMB and HML are the Small-Minus-Big size factor and the High-Minus-Low book-to-market ratio factor, respectively. The regressions are $MR_{t,6\times6} = \alpha + \sum_{j=1}^{n} \beta_j X_t + e_t$ and $MR_{t,6\times6} = \alpha + \sum_{j=1}^{n} \beta_j X_{t-1} + e_t$ where X is the vector of the Fama-French factors both as contemporaneous and lagged variables. Panel A reports the output for the Fama-French three factor variables when used as contemporaneous variables, whereas Panel B shows the regression output when lagged Fama-French variables are used. The *t*-statistics are reported in parentheses and adjusted R-squared is provided in the last column.

Panel A: Fama French Three Factors as Contemporaneous Variables

Country	Alpha	MKT_RF	SMB	HML	Adj R-squared
All China	0.007	-0.017	0.027	-0.093	-0.002
	(3.30)	(-0.76)	(0.51)	(-1.32)	
HKSE	0.007	0.009	-0.112	-0.095	0.096
	(2.93)	(-0.30)	(-3.83)	(-2.15)	
SSE	0.011	-0.016	-0.039	-0.111	0.001
	(4.31)	(-0.63)	(-0.58)	(-1.30)	
SZSE	0.001	-0.016	0.027	-0.092	0.001
	(0.58)	(-0.88)	(0.68)	(-1.58)	

Panel B: Fama French Three Factors as Lagged Variables

Country	Alpha	MKT_RF	SMB	HML	Adj R-squared
All China	0.006	-0.026	-0.035	0.140	0.011
	(3.02)	(-1.19)	(-0.66)	(1.98)	
HKSE	0.006	0.025	-0.085	-0.022	0.048
	(2.53)	(0.79)	(-2.84)	(-0.47)	
SSE	0.010	0.013	-0.084	0.068	-0.007
	(4.08)	(0.49)	(1.24)	(0.79)	
SZSE	0.001	-0.016	-0.083	0.048	0.001
	(0.77)	(-0.88)	(-2.12)	(0.82)	

Table 2.6
Momentum Returns for Size and Beta Based Portfolios

At the beginning of each month t, All China, SSE, SZSE and HKSE stocks are allocated into deciles based on their 6-month lagged returns and portfolios are formed one month after the lagged returns used for forming these portfolios are measured. All stocks are ranked in ascending order on the basis of 6-month lagged returns and an equally-weighted portfolio of the stocks in the lowest 6-month lagged return decile is the portfolio P1(Losers), the equally-weighted portfolio of stocks in the top decile is portfolio P10(Winners). The average monthly returns of momentum trading strategy or momentum return spread (P10-P1) for size and beta subsamples are reported in per cent and *t*-statistics provided in parentheses. The subsample S1 contains the smallest firms, subsample S2 contains the medium-sized firms and S3 contains the big firms. Subsamples β1, β2 and β3 contain the firms with low, medium, and the high Scholes-Williams betas estimated from the returns data in the calendar year before the portfolio formation date. The sample period is November 1994 to November 2010.

		Average Monthly Returns							
Country		S1	S2	S3	S1-S3	β1	β 2	β3	β3-β1
All China	P1 (Losers)	1.80	1.52	0.92		1.41	1.38	1.20	
	P10 (Winners)	2.69	1.66	1.72		2.00	2.31	2.11	
	P10-P1	0.89	0.14	0.80	0.09	0.59	0.93	0.91	0.32
		(2.90)	(0.93)	(4.12)	(0.24)	(2.35)	(3.76)	(3.22)	(1.23)
HKSE	P1 (Losers)	1.14	-0.17	-0.47		1.34	0.94	0.09	
	P10 (Winners)	1.72	0.88	1.05		1.52	2.09	1.53	
	P10-P1	0.58	1.05	1.52	-0.94	0.18	1.15	1.44	1.26
		(1.55)	(3.75)	(3.29)	(-1.96)	(0.31)	(3.33)	(3.99)	(1.97)
SSE	P1 (Losers)	1.48	1.22	0.68		1.33	1.02	1.05	
	P10 (Winners)	2.31	2.02	1.68		2.03	2.40	2.36	
	P10-P1	0.78	0.51	0.95	-0.17	0.70	1.38	1.31	0.61
		(2.17)	(3.40)	(4.46)	(-0.44)	(2.20)	(4.94)	(4.42)	(2.18)
SZSE	P1 (Losers)	1.73	1.04	0.97		2.11	1.81	1.50	
	P10 (Winners)	1.68	1.19	1.34		1.87	1.75	1.61	
	P10-P1	-0.05	0.15	0.37	-0.42	0.00	0.14	0.21	0.21
		(-0.18)	(0.79)	(1.57)	(-1.40)	(0.00)	(0.54)	(0.83)	(0.59)

Table 2.7
Momentum Returns and Market States

At the beginning of each month t, All China, SSE, SZSE and HKSE stocks are allocated into deciles based on their 6-month lagged returns and portfolios are formed one month after the lagged returns used for forming these portfolios were measured. These portfolios are held for another six months. Holding period returns are then calculated. Positive (negative) returns of the Value-Weighted Market Returns for All China, VW SSE index, VW SZSE Index and Hang Seng Index over months t-m (m=36, 24 and 12 months) are used to define UP (DOWN) market states for each market. Monthly average returns of "winner minus loser" portfolio (momentum return spreads), CAPM alphas, and Fama-French alphas over the sample period are reported below. CAPM (Fama-French) alpha refers to the CAPM (Fama-French three factor model) alpha using the average monthly returns for momentum portfolio. Panels A, B, and C report momentum returns following 36-, 24- and 12- month UP and DOWN markets over the period from 1995 to 2010, respectively. Panels D, E, and F report momentum returns following 36-, 24- and 12- month UP and DOWN markets over the period from 1995 to 2006, respectively. Panels G, H, and I report momentum returns following 36-, 24- and 12- month UP and DOWN markets over the period from 2007 to 2010, respectively. All the returns are reported in per cent and the numbers in the parentheses represent t- statistics, where standard errors are adjusted for overlap with the method of Newey and West (1987).

Panel A: Momentum Returns Following 36-month UP and DOWN Markets

	All China		HKSE		SSE		SZSE	
	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market
N	136	45	151	30	137	44	127	54
Momentum return spread	0.34	1.57	0.54	0.51	0.65	1.97	-0.18	0.67
(t-statistic)	(1.04)	(3.71)	(1.03)	(1.06)	(1.07)	(4.56)	(-0.43)	(1.66)
%>0	56.60	72.27	61.25	65.00	52.55	83.70	56.56	67.90
CAPM alpha	0.37	1.55	0.51	0.50	0.66	1.59	-0.17	0.75
(t-statistic)	(1.01)	(3.58)	(1.08)	(1.06)	(1.08)	(4.46)	(-0.57)	(1.74)
Fama-French alpha	0.35	1.85	0.83	0.52	0.72	1.61	-0.14	1.01
(t-statistic)	(1.03)	(3.70)	(2.01)	(1.21)	(1.26)	(4.69)	(-0.56)	(2.01)

Table 2.7: Continued

Panel B: Momentum Returns Following 24-month UP and DOWN Markets

	All China		HKSE		SSE		SZSE	
	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market
N	117	64	134	47	118	63	113	68
Momentum return spread	0.48	0.93	054	0.53	0.77	1.31	-0.15	0.42
(t-statistic)	(1.18)	(2.92)	(1.32)	(0.86)	(1.73)	(2.98)	(-0.38)	(1.26)
%>0	56.00	71.88	61.66	61.70	50.40	77.80	55.36	67.60
CAPM alpha	0.55	0.90	0.53	1.01	0.79	1.65	-0.14	0.48
(t-statistic)	(1.10)	(2.88)	(1.60)	(1.64)	(1.86)	(3.02)	(-0.36)	(1.31)
Fama-French alpha	0.51	0.89	0.82	0.78	0.90	1.58	-0.13	0.55
(t-statistic)	(1.14)	(2.99)	(2.06)	(1.67)	(1.92)	(3.13)	(-0.39)	(1.56)

Panel C: Monthly Momentum Returns Following 12-month UP and DOWN Markets

	All China		HKSE		SSE		SZSE	
	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market
N	111	70	126	55	115	66	103	78
Momentum return spread	0.84	0.33	0.38	0.88	1.20	0.55	0.15	-0.03
(t-statistic)	(2.06)	(1.08)	(0.99)	(1.20)	(2.50)	(1.59)	(0.57)	(-0.13)
%>0	59.00	65.70	57.60	65.70	57.10	65.15	60.78	59.00
CAPM alpha	0.85	0.42	0.37	1.10	1.20	0.69	0.13	0.13
(t-statistic)	(2.05)	(1.19)	(1.12)	(1.67)	(2.48)	(1.60)	(0.51)	(0.47)
Fama-French alpha	0.82	0.54	0.66	1.23	1.25	0.79	0.17	0.22
(t-statistic)	(2.03)	(1.27)	(1.71)	(1.97)	(2.55)	(1.86)	(0.62)	(0.79)

Table 2.7: Continued

Panel D: Momentum Returns Following 36-month UP and DOWN Markets before 2007

	All China		HKSE		SSE		SZSE	
	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market
N	89	45	114	20	90	44	80	54
Momentum return spread	0.90	1.57	0.99	1.02	1.41	1.97	0.08	0.67
(t-statistic)	(2.19)	(3.71)	(2.04)	(2.01)	(2.50)	(5.03)	(0.30)	(1.67)
%>0	66.30	72.27	65.80	68.40	64.44	83.70	65.00	67.90
CAPM alpha	0.97	1.55	0.97	1.06	1.44	1.97	0.11	0.75
(t-statistic)	(2.12)	(3.58)	(2.32)	(2.14)	(2.57)	(4.63)	(0.40)	(1.71)
Fama-French alpha	0.90	1.85	1.23	1.07	1.42	1.96	0.12	1.01
(t-statistic)	(2.03)	(3.70)	(2.39)	(1.96)	(2.68)	(4.96)	(0.45)	(2.24)

Panel E: Momentum Returns Following 24-month UP and DOWN Markets before 2007

	All China		HKSE		SSE		SZSE	
	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market
N	80	54	98	36	83	51	69	65
Momentum return spread	1.08	1.19	0.89	1.26	1.55	1.66	0.09	0.56
(t-statistic)	(2.16)	(4.16)	(2.13)	(2.02)	(2.47)	(4.97)	(0.27)	(1.79)
%>0	63.75	79.25	65.31	68.57	60.24	88.00	66.32	70.31
CAPM alpha	1.20	1.16	0.87	1.48	1.59	1.65	0.12	0.65
(t-statistic)	(2.29)	(4.01)	(2.13)	(2.07)	(2.59)	(5.32)	(0.36)	(1.81)
Fama-French alpha	1.06	1.19	1.00	2.06	1.56	1.58	0.01	0.71
(t-statistic)	(2.16)	(4.10)	(2.19)	(2.32)	(2.51)	(5.11)	(0.27)	(2.03)

Table 2.7: Continued

Panel F: Momentum Returns Following 12-month UP and DOWN Markets before 2007

	All China		HKSE		SSE		SZSE	
	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market
N	77	57	90	44	68	66	68	66
Momentum return spread	1.27	0.91	0.44	2.10	1.20	0.55	0.20	0.43
(t-statistic)	(2.47)	(3.01)	(1.27)	(3.75)	(2.42)	(1.69)	(0.60)	(1.64)
%>0	64.47	77.20	58.43	81.81	57.10	65.15	64.20	68.20
CAPM alpha	1.35	0.92	0.63	2.11	1.20	0.69	0.23	0.51
(t-statistic)	(2.87)	(3.09)	(1.60)	(3.86)	(2.48)	(1.79)	(0.69)	(1.65)
Fama-French alpha	1.33	1.04	0.41	2.47	1.25	0.79	0.23	0.59
(t-statistic)	(2.69)	(3.52)	(1.19)	(3.21)	(2.67)	(1.98)	(0.67)	(1.68)

Panel G: Momentum Returns Following 36-month UP and DOWN Markets from 2007

	All China		HKSE		SSE		SZSE	
	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market
N	47	No	44	3	47	NO	47	No
Momentum return spread	-0.70		-0.68	-7.60	-0.81		-0.64	
(t-statistic)	(-1.45)		(-1.29)	(-4.53)	(-2.13)		(-1.29)	
%>0	50.00		45.65	0.00	29.80		42.55	
CAPM alpha	-0.61		-0.99	-7.14	-0.82		-0.73	
(t-statistic)	(-1.32)		(-1.63)	(-4.14)	(-2.12)		(-1.73)	
Fama-French alpha	-0.35		-0.67	-4.95	-0.71		-0.65	
(t-statistic)	(-0.59)		(-1.10)	(-4.42)	(-1.97)		(-1.37)	

Table 2.7: Continued

Panel H: Momentum Returns Following 24-month UP and DOWN Markets from 2007

	All China		HKSE		SSE		SZSE	
	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market
N	36	11	35	12	34	13	43	4
Momentum return spread	-0.83	-0.32	-0.14	-2.53	-1.11	-0.04	-0.53	-1.80
(t-statistic)	(-2.01)	(-0.61)	(-0.39)	(-1.69)	(-2.08)	(-0.11)	(-1.40)	(-2.05)
%>0	38.90	36.36	51.43	41.66	26.47	38.46	44.20	25.00
CAPM alpha	-0.84	-0.36	-0.14	-3.57	-1.12	-0.09	-0.62	-1.31
(t-statistic)	(-2.02)	(-0.82)	(-0.40)	(-1.60)	(-2.04)	(0.24)	(-1.59)	(-1.71)
Fama-French alpha	-0.69	-0.53	0.05	-3.61	-1.10	-0.26	-0.42	-1.21
(t-statistic)	(-1.61)	(-0.59)	(0.10)	(-1.25)	(-2.14)	(-0.32)	(-0.97)	(-1.31)

Panel I: Momentum Returns Following 12-month UP and DOWN Markets from 2007

	All China		HKSE		SSE		SZSE	
	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market	UP Market	DOWN Market
N	34	13	36	11	34	13	35	12
Momentum return spread	-0.13	-2.23	0.24	-4.00	-0.36	-2.01	0.03	-2.60
(t-statistic)	(-0.44)	(-2.58)	(0.78)	(-2.83)	(-1.35)	(-2.39)	(0.09)	(-2.89)
%>0	47.00	15.40	55.55	27.27	35.30	15.38	54.30	8.33
CAPM alpha	-0.15	-1.98	0.25	-2.60	-0.31	-1.67	-0.05	-2.30
(t-statistic)	(-0.51)	(-2.13)	(0.77)	(-1.78)	(-1.23)	(-2.22)	(-0.14)	(-2.12)
Fama-French alpha	-0.04	-1.07	0.51	-2.67	-0.26	-1.30	0.11	-3.10
(t-statistic)	(-0.13)	(-0.87)	(1.27)	(-1.14)	(-0.87)	(-1.22)	(0.27)	(-2.04)

Table 2.8
The Lagged Market Returns as a Continuous Measure of the State of the Market

At the beginning of each month t, All China, SSE, SZSE and HKSE stocks are allocated into deciles based on their 6-month lagged returns. Momentum return spreads (returns of winner minus loser portfolio) are calculated over the months t+1 to t+6. These return spreads are regressed against an intercept, lagged market return (LAGMKT), and lagged market return squared ($LAGMKT^2$). Panels A, B and C provide the monthly regression coefficients and robust t-statistics (Newey-West) following 36-, 24- and 12-month lagged market returns. In Panels D, E and F, momentum portfolios (winner minus loser deciles) are sorted into quintiles (5-portfolios) based on the full sample of lagged 36-, 24- and 12-month market returns. Average monthly momentum return spreads are reported in per cent along with their robust *t*-statistics (Newey-West) in parentheses. Quintile 1 shows return spreads for the lowest lagged market return quintile and quintile 5 for the highest lagged market return quintile.

Panel A: 36-month Lagged Market

	All China	HKSE	SSE	SZSE
Intercept	1.28	0.59	1.40	0.44
	(3.01)	(1.46)	(3.35)	(1.60)
LAGMKT	-0.96	-0.15	-0.69	-0.39
	(-1.49)	(-0.11)	(-0.83)	(-0.77)
$LAGMKT^2$	-0.20	-0.03	-0.53	-0.21
	(-0.42)	(-0.02)	(-0.88)	(-0.51)
Adj-R^2	-0.061	-0.01	0.050	0.022

Panel B: 24-month Lagged Market

	All China	HKSE	SSE	SZSE
Intercept	0.73	0.82	1.22	0.13
	(2.22)	(0.78)	(3.37)	(0.60)
LAGMKT	0.65	-1.92	1.02	-0.54
	(0.87)	(-1.66)	(1.15)	(-0.84)
$LAGMKT^2$	-0.72	4.60	-1.12	0.25
	(-1.35)	(1.76)	(-1.77)	(0.54)
Adj-R^2	0.001	0.015	0.010	-0.006

Table 2.8: Continued

Panel C: 12-month Lagged Market				
	All China	HKSE	SSE	SZSE
Intercept	1.10	1.66	1.56	0.52
	(3.57)	(3.23)	(4.69)	(1.96)
LAGMKT	2.15	0.51	2.22	2.26
	(2.82)	(0.61)	(2.76)	(2.81)
$LAGMKT^2$	-3.71	-12.57	-3.87	-3.28
	(-4.56)	(-4.13)	(-3.98)	(-3.65)
Adj-R^2	0.167	0.154	0.130	0.150

Panel D: Momentum Returns by Quintiles of Lagged 36-month Market States					
Country	1	2	3	4	5
All China	1.79	0.56	1.09	0.20	-0.44
(t-statistic)	(2.89)	(1.64)	(1.78)	(0.39)	(-0.98)
HKSE	0.33	0.65	1.19	0.00	0.50
(t-statistic)	(0.62)	(0.93)	(1.82)	(0.01)	(1.62)
SSE	2.10	0.61	2.09	0.50	-0.48
(t-statistic)	(4.03)	(1.73)	(2.05)	(1.02)	(-1.09)
SZSE	0.52	0.88	-0.13	-0.57	-0.36
(t-statistic)	(1.30)	(2.12)	(-0.40)	(-1.19)	(-0.78)

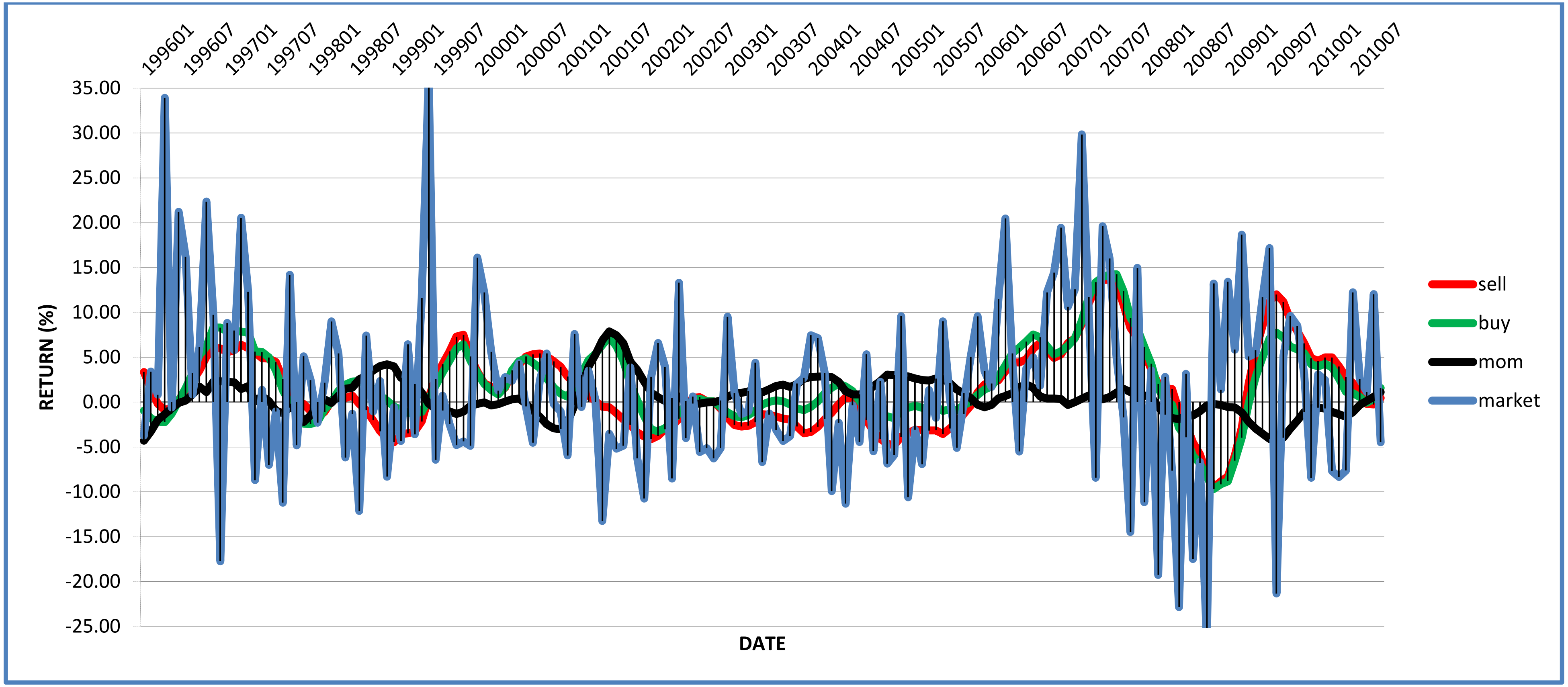
Table 2.8: Continued

Panel E: Momentum Returns by Quintiles of Lagged 24-month Market States					
Country	1	2	3	4	5
All China	0.85	0.89	-0.29	1.20	0.57
(t-statistic)	(2.16)	(2.43)	(-0.70)	(1.79)	(1.24)
HKSE	0.64	0.04	0.77	0.94	0.28
(t-statistic)	(0.88)	(0.09)	(1.61)	(2.12)	(0.43)
SSE	1.28	1.00	-0.12	2.18	0.48
(t-statistic)	(2.99)	(2.46)	(-0.30)	(2.01)	(1.06)
SZSE	0.34	0.40	-0.20	-0.55	0.35
(t-statistic)	(0.99)	(1.01)	(-0.48)	(-1.22)	(0.73)

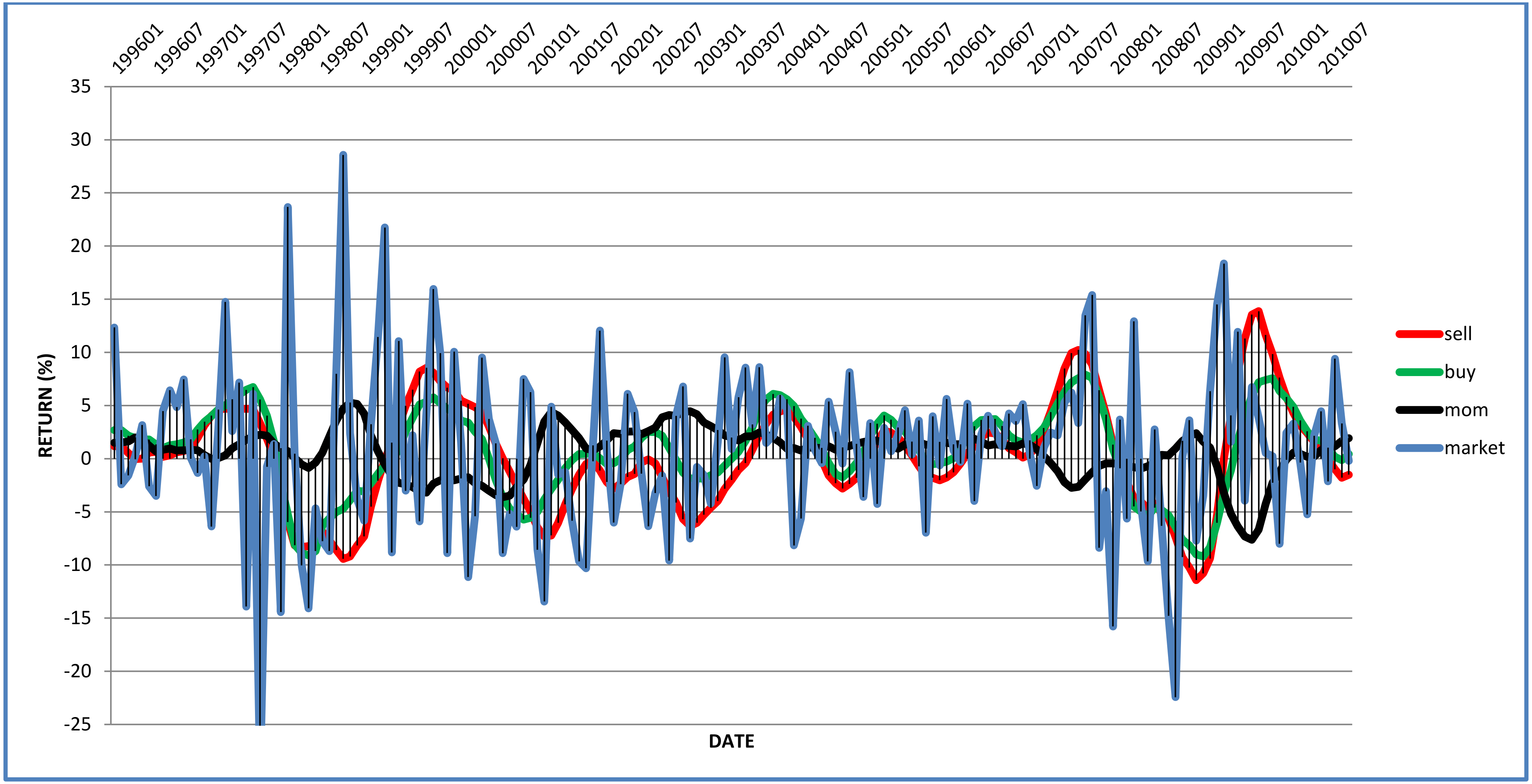
Panel F: Momentum Returns by Quintiles of Lagged 12-month Market States					
Country	1	2	3	4	5
All China	-0.27	0.93	1.54	1.32	-0.32
(t-statistic)	(-0.68)	(2.28)	(2.67)	(1.91)	(-0.86)
HKSE	0.94	0.78	0.59	1.14	-0.78
(t-statistic)	(1.23)	(1.86)	(1.54)	(1.85)	(-1.32)
SSE	0.08	1.32	1.33	2.50	-0.41
(t-statistic)	(0.20)	(2.95)	(2.41)	(2.96)	(-0.93)
SZSE	-0.72	0.43	0.99	0.11	-0.46
(t-statistic)	(-1.82)	(1.09)	(2.03)	(0.26)	(-1.14)

Figure 2.1 Momentum Returns Performance for All China, HKSE, SSE and SZSE

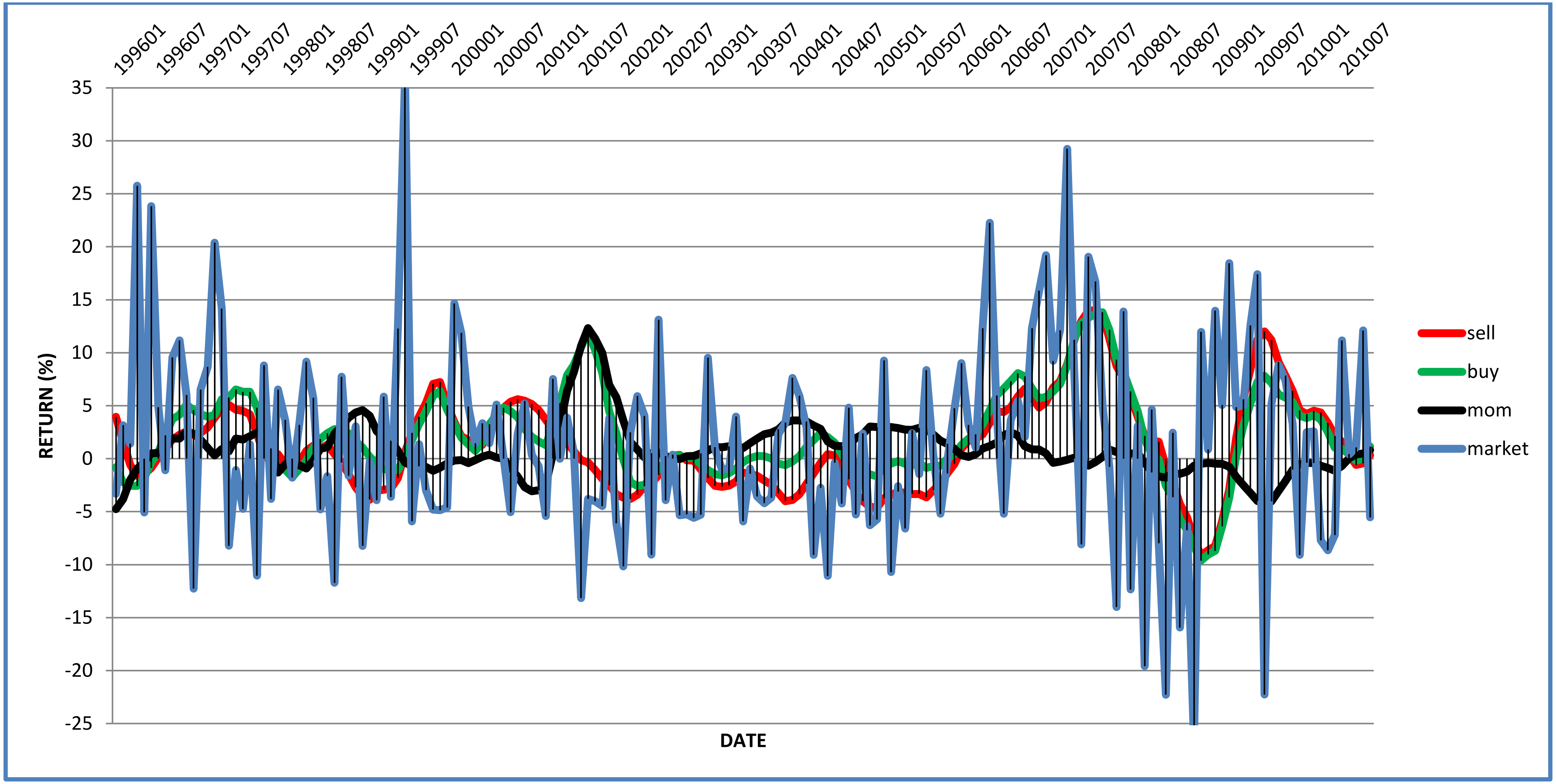
This figure provides the average monthly returns of losers (P1), winners (P10), momentum returns (P10-P1) and contemporaneous market returns of a momentum trading strategy with 6-month formation and 6-month holding period over the entire sample period.



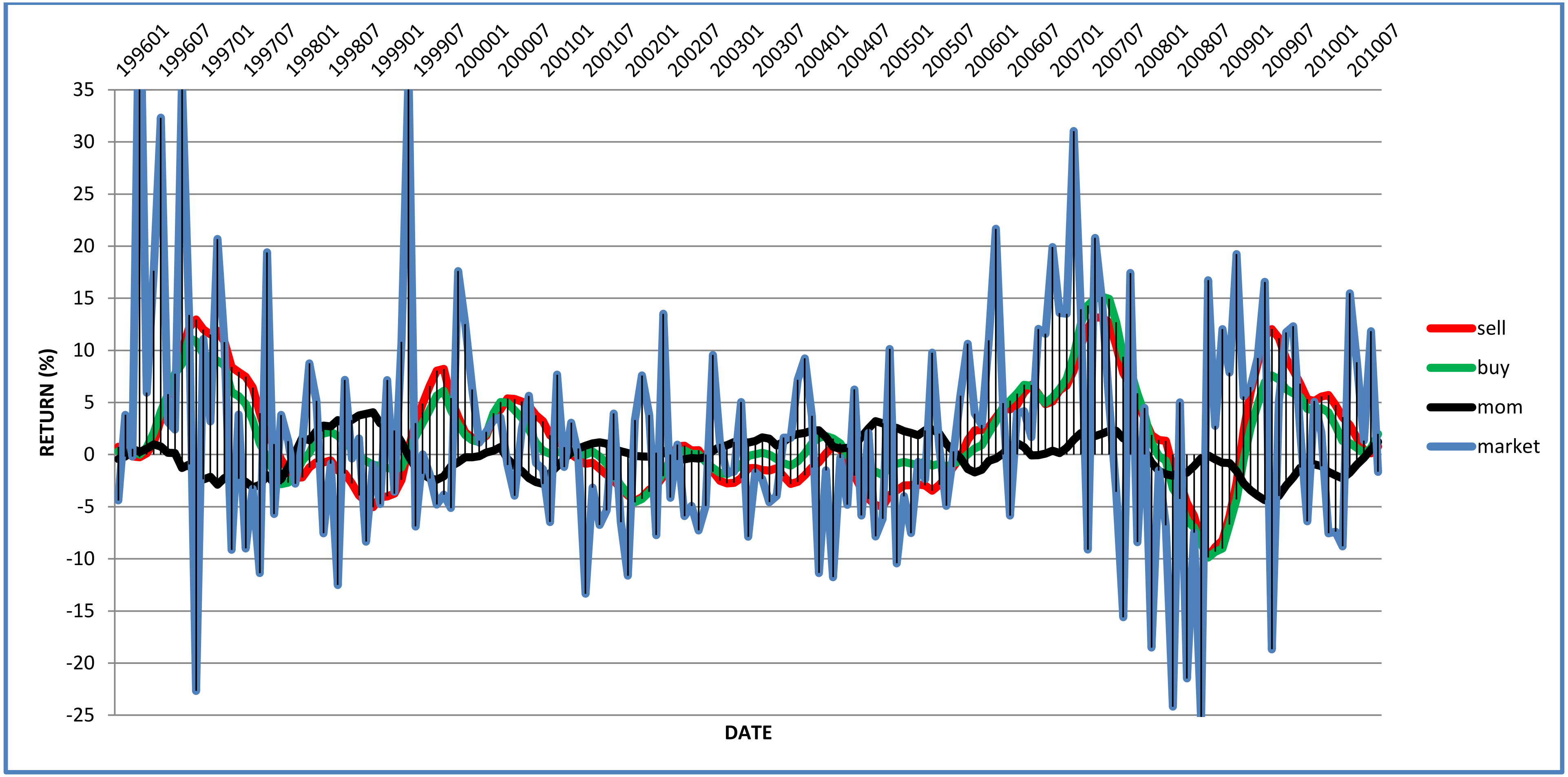
(a) Momentum Returns Performance for All China



(b) Momentum Returns Performance for HKSE



(c) Momentum Returns Performance for SSE



(d) Momentum Returns Performance for SZSE

Chapter 3

Momentum Returns and Information Uncertainty

3.1 Introduction

This study examines the relationship between information uncertainty (hereafter IU) and momentum returns. IU refers to the ambiguity of new information as it relates to firm valuation. There will be more ambiguity related to new information if new information of some firms is less known than for other firms because of the nature of business or less interest of investors in those firms. Momentum returns refer to the returns earned by buying past winners and selling past losers. The profitability of the momentum trading strategy has been a popular issue in recent finance literature and is considered the most prominent among all the stock market anomalies (Fama and French, 2008). Prior literature attributes investors' under reaction to new public information as explaining momentum returns because information might take more time to adjust into prices. Studies about under-reaction to new public information rely on behavioural theories that assume that investors suffer from some form of irrationality (see Thaler, 1993). Some behavioural biases, such as conservatism or overconfidence, have been incorporated into formal models that confirm under-reaction patterns (see Barberis et al., 1998; Daniel et al., 1998, 2002; Hong and Stein, 1999). The theories of Hong and Stein (1999) and Daniel et al. (1998, 2002) imply that these psychological biases become stronger when there is more uncertainty about the value of a firm, i.e., IU.

Some recent papers have tried to test the argument in behavioural theories that psychological biases increase with the level of IU. Zhang (2006) argues that if investors' under reaction to new public information is due to psychological biases, such as overconfidence, then investors would under react even more to the firms with greater IU. Zhang (2006) tests his claim by dividing U.S. stocks into five groups based on IU proxies and finds higher momentum returns for firms with higher IU and lower (but insignificant) momentum returns for the firms with lower IU. Jiang et al. (2005) also find higher significant momentum returns for firms with higher IU and lower (but insignificant) momentum returns for those with lower IU. Jiang et al.'s (2005) hypothesis is based on behavioural finance literature and attributes IU to investor psychological biases such as overconfidence.

In this study, I examine and compare the relationship between IU and the momentum trading strategy of buying past winners and selling past losers in the Shanghai Stock Exchange China (hereafter **SSE)**. SSE was established in December 1990 and is considered the largest emerging stock market by market capitalization (*List of stock exchanges*, 2012). SSE is considered an emerging stock market because it has a short history of stock trading, a large number of small-size stocks, a large number of share classes, a dominance of retail investors and strict regulation of IPOs by the government (see Gao, 2002). SSE is the world's sixth largest stock market by market capitalization (*List of stock exchanges*, 2012). SSE is different from the U.S. and other developed stock markets because it is not entirely open to foreign investors. However, from 2004, foreign investors were allowed to trade in all shares of SSE, with some restrictions (see Jun Lin and Chen, 2005).

My study is motivated by the following issues: first, there is a limited number of studies available about the relationship between the momentum trading strategy and the level of IU. This limited number of studies is only of U.S. firms (see Jiang et al., 2005; Zhang, 2006). My motive in this study is to test if IU can explain momentum returns in other markets, especially China, since it is the largest emerging market and China is different from the U.S. and other developed markets in many ways including the dominance of retail investors compared with the dominance of institutional investors in U.S. and other developed markets. Institutional investors are different from retail investors because institutional investors invest in large stocks and stocks with higher institutional holdings are more efficient (see Boehmer and Kelley, 2009). In addition, analyst following is also related to institutional holdings (see Brennan and Subrahmanyam, 1995). Based on the findings of Boehmer and Kelley (2009) and Brennan and Subrahmanyam (1995), it appears that stocks with higher institutional holdings have higher information available than stocks with retail dominance. Therefore, it will be interesting to test if IU plays a role in explaining momentum returns in a market dominated by retail investors since retail investors have less information available than institutional investors.

Secondly, the data used for this study span the period 1994 to 2010 and hence are the most recent compared with the data used for the U.S. studies.[24] Results from this study could be used by investors to make decisions in the construction of momentum trading strategies based on IU variables because Zhang (2006) and Jiang et al. (2005) report large momentum returns in a high-IU setting.

Thirdly, this study examines if momentum returns are robust to both an "independent and dependent sorting technique". Zhang (2006) and Jiang et al. (2005) use only an "independent

[24] 1983-2001 sample period for Zhang (2006) and 1965-2001 for Jiang et al. (2005).

sorting technique" to calculate momentum returns. There are some benefits of independent sorting because it includes a firm in a portfolio irrespective of its ranking on the other variable. However, using this technique might leave a small number of stocks in one portfolio and a large number of stocks in another portfolio. In the contrast, the "dependent sorting technique" makes sure that the results are not driven by a portfolio with a small number of stocks since each portfolio has an equal number of stocks over the same holding period.

Using the succeeding 6-month returns as a proxy for expected returns, I find that firms with higher level of IU earn higher expected returns when IU is defined in terms of firm size, volatility and volume. However, only the firm size and volume results are economically large and statistically significant. In contrast, when IU is defined in terms of firm age, firms with higher level of IU earn lower returns. However, firm age might not be an important factor in explaining future returns in China since the age difference between young and old firms is small; it might be other firm-specific characteristics that drive lower future returns for younger firms rather than their age. The higher future returns for high volume and small size firms is consistent with the traditional risk based theories since investors require higher returns for holding stocks with high risk.

Using portfolio-level analysis based on four IU proxies, I find that the level of IU cannot explain momentum returns except when IU is defined in terms of size or age. However, momentum returns do not increase linearly with the level of IU even when it is defined in terms of size or age and the difference of momentum returns across high and low IU (size or age) firms is insignificant except 6-month holding period (3-month holding period) when defined in terms of size (age). Therefore, it might be the risk premium for holding small size and younger firms that result in momentum returns. This argument is consistent with traditional risk-based theories because investors require a risk premium for holding stocks with higher risk. However, low IU firms provide larger momentum returns when IU is defined in terms of volume, contrary to the suggestion of Jiang et al. (2005). Using a combination of two proxies to measure the level of IU and the Fama and MacBeth (1973) cross-sectional regressions, I do not find a robust significant relationship between the level of IU and momentum returns.

In sum, this chapter contributes to the existing literature in many ways. First, according to the best of my knowledge, this is the first study that tests the relationship between the level of IU and momentum returns in a Chinese stock market. Secondly, this study provides evidence that the level of IU cannot explain the momentum effect in a market dominated by retail investors. Thirdly, the results of this study suggest that it might be the trading of retail investors that drives momentum returns since the momentum effect is weak among U.S. firms with higher institutional holdings, i.e., large stocks, stocks with higher analyst following and stocks with lower analyst forecast dispersion.

The rest of the study is organized as follows: section 2 reviews the related literature and presents the hypotheses, section 3 reports sample and descriptive statistics, section 4 presents portfolio returns by IU proxies, section 5 reports portfolio returns by momentum and IU proxies, section 6 conducts risk adjustments and discusses the robustness checks and the last section concludes the chapter.

3.2 Literature Review and Hypothesis Development

In the finance literature, the term "momentum trading strategy" refers to the trading strategy of buying winners and selling losers. With this trading strategy, investors buy the stocks with the highest returns and sell the stocks with the lowest returns based on the past 3 to 12 months' returns and hold them for another 3 to 12 months. Jegadeesh and Titman (1993) find that the momentum trading strategy generated abnormal returns of 1% per month (12% per year) in the U.S. market from 1965 to 1989.

There is enormous evidence of the success of the momentum trading strategy across international stock markets and time periods (Rouwenhorst, 1999, 2002). The success of this strategy has motivated researchers to develop several explanations for the momentum effect. Most explanations of the momentum effect include behavioural- and risk-based theories. However, the risk-based explanation of the momentum effect is considered less reliable since Fama and French (1996, 2008, 2012) admit that the Fama-French three-factor model cannot explain the profits of the momentum trading strategy. In contrast, some researchers attribute the profitability of the momentum trading strategy to investors' irrationality and psychological biases such as investors under reaction and over-reaction.

Barberis et al. (1998) argue that returns from the momentum trading strategy are due to investor under reaction to new public information. As a consequence, this new public information takes a longer time to adjust into prices that generate momentum returns. Their model is based on two investor cognitive biases - representative heuristic and the conservatism.[25] In the representative heuristic bias, investors assume that firms with abnormal returns will continue to earn extraordinary returns in the future. In the conservatism bias, investors under react to new information because they are slow to update prior beliefs. In the

[25] Edwards (1968) established the conservatism bias and Tversky and Kahneman (1974) studied the behavioural heuristic.

conservatism bias, investors underweight new public information compared with their prior information or beliefs. They adjust their beliefs slowly, so it takes time for new information to adjust into stock prices. The reason behind the conservatism bias might be investors are more overconfident about their prior information or beliefs. Barberis et al. (1998) argue that the representative bias causes prices to overshoot fundamental values whereas the conservatism bias leads to under-reaction to new public information.

Hong and Stein (1999) argue that the initial under reaction to new information causes momentum returns that are reversed in the long run by subsequent over-reaction. In their study, they use two types of investors, news watchers and momentum traders. News watchers make forecasts based on private information for their trade whereas momentum traders consider the information in past prices. Hong and Stein (1999) assume that trading by news watchers pushes prices to some extent, which results in initial under reaction to news. The movement of prices caused by trading by news watchers attracts the attention of momentum traders and hence their trading activity ultimately results in over-reaction to the news, which reverses in the long run.

Daniel et al.(1998) present a theory based on investors' overconfidence in their private information and over-react to it, but they underreact to public signals. They argue that investors' overconfidence increases if subsequent public information confirms their private information. The increase in overconfidence further triggers an over-reaction to their private information and causes momentum returns. Daniel et al. (1998) further suggest that future returns are predictable and the return predictability should be stronger in firms with a high level of IU since investors tend to be over confident if it is difficult to value a firm's business. Chan, Jegadeesh and Lakonishok (1996) argue that momentum returns are a result of investors' under reaction to public information. Hirshleifer (2002) argues that psychological biases increase with the high level of IU hence the larger uncertainty results in larger biases.

Combining the ideas of Chan et al. (1996), Hirshleifer (2002) and Daniel et al. (1998, 2002), Zhang (2006) argues that if under reaction to information is due to psychological biases such as overconfidence, then these psychological biases will be larger and the price response will be slower when there is a higher level of IU. Zhang (2006) documents that investors tend to underreact to new public information and their under reaction further increases with the level of IU because it is hard to estimate the value of a firm when the information is more uncertain. Jiang et al. (2005) introduce a behaviour-based framework to explain how the level of IU might affect momentum returns.[26] They show that the level of IU is positively correlated with decision bias (investors' overconfidence) and arbitrage costs (see Jiang et al., 2005). They also show that these two effects (investors' overconfidence and arbitrage costs) produce lower mean returns and greater momentum returns. Zhang (2006) and Jiang et al. (2005) observe high momentum returns in high IU firms, i.e., small and young firms, as well as firms with high trading volume turnover, high return volatility, high cash flow volatility, low duration, high analysts' earnings forecast dispersion and low analyst coverage.

Zhang (2006) and Jiang et al. (2005) agree that investors' behavioural biases or overconfidence will be higher in a high information setting providing results are consistent with their hypothesis for U.S. firms. It would be interesting to test if high IU firms also provide high momentum returns in emerging markets because emerging markets are different from developed markets in many ways including the dominance of retail investors compared with the dominance of institutional investors in U.S. and other developed markets.

Institutional investors are banks, financial institutions, mutual funds, pension funds and all other companies that trade securities in large quantities in stock markets. On the other hand, retail investors are individuals and small groups who invest in stock markets only on their personal account and not for another company or organization. There are many differences among institutional and retail investors including the type of companies in which they choose to invest. Boehmer and Kelley (2009) document that institutional investors invest in large stocks and they also find that stocks with higher institutional holdings are more efficient. Boehmer and Kelley (2009) report that analyst following is high in stocks with higher institutional holdings. Scherbina (2004) document that institutional investors reduce their holdings in stocks with large analyst forecast dispersion. Based on their findings, it appears that institutional investors invest in stocks with higher information. Zhang (2006) defines stocks with high information or low IU as stocks with large firm size, lower analyst forecast dispersion and higher analyst coverage and finds that these stocks have lower momentum returns than high IU stocks. Therefore, my argument is that stocks with higher institutional holdings are more efficient because institutional investors have access to more information and analyst following is high among these stocks, so information adjusts into prices more quickly than stocks with retail dominance. On the other hand, stocks with higher retail holdings have less or ambiguous information available because retail investors do not have access to lots of information compared with institutional investors and analyst following is

[26] Jiang et al. (2005) also show how IU affects earnings momentum.

also lower among these stocks; therefore, information would take more time to adjust into prices. This agrees with Zhang (2006) who argues that investors would underreact more to firms with less information, i.e., small firms, firms with low analyst coverage, firms with higher analyst forecast dispersion. Since China has a large number of small-cap stocks and is dominated by retail investors, information availability for Chinese stocks might be lower than in the U.S. market. Therefore, it would be interesting to test if the IU proxies used by Zhang (2006) and Jiang et al. (2005) can explain the momentum effect in the world's largest emerging market.

Zhang (2006) uses six proxies to define IU and Jiang et al. (2005) use four proxies. Zhang (2006) uses firm size, analyst coverage, the dispersion in analyst forecast revision, firm age, stock return volatility, and cash flow volatility as proxies of IU. Jiang et al. (2005) use only two (firm age, stock return volatility) of the six proxies used by Zhang (2006) and use two different proxies, trading volume and implied equity duration. According to Jiang et al. (2005, p. 191) "some of Zhang's IU measures are arguably more closely aligned with the underlying economic construct. However, a potential disadvantage of these measures is that they are only available for firms that have analyst coverage."

In this study, I use four proxies to measure the level of IU since it is not directly observable. These proxies are firm age, stock return volatility, volume and firm size. Firm age and stock return volatility are used by both Zhang (2006) and Jiang et al. (2005) as IU proxies, trading volume was used only by Jiang et al. (2005) and firm size only by Zhang (2006). I am not using other proxies like analyst coverage and analyst's earnings forecast dispersion because these measures are not available for China.[27] The four proxies might capture some other effects but the common factor among them is their ability to quantify the level of IU.

Following Zhang (2006) and Jiang et al. (2005), I use firm age as one proxy but I measure it as the number of months since the firm was established. Barry and Brown (1985) suggest that older firms have more information available to the market than younger firms and they find that there is a firm age effect in CRSP monthly returns data.[28] They report significant positive abnormal returns for CRSP firms with the shortest listing periods (age). Zhang (2006) and Jiang et al. (2005) measure firm age from the time that the stock appears in CRSP and show that younger firms have higher momentum returns than older firms. However, data for Chinese firms are not available before 1990, so the establishment date is more suitable to

[27] Analyst coverage is available for few Chinese firms but only for a recent period.

[28] CRSP (Centre for Research in Security Prices) provides historical data on securities with primary listing on NYSE, AMEX, ARCA and NASDAQ.

measure firm age for China since the establishment date defines their incorporation date. Schultz (2005) suggests that the incorporation date is a better measure of firm age.

My second proxy is stock volatility, measured by the standard deviation (at the portfolio formation date) of daily stock returns over the past 25 trading days. The literature has mixed evidence about the relationship between volatility and the level of IU. Both Zhang (2006) and Jiang et al. (2005) use stock volatility as a proxy to measure IU. They argue that stock volatility is a naturally good predictor of IU because less volatile firms are more stable and have more information available than more volatile firms. However, Baker and Haugen (2012) report that high volatility stocks get more news and analyst coverage hence have more information available than stocks with low volatility. Both Zhang (2006) and Jiang et al. (2005) show higher momentum returns for the stocks with higher volatility.

My third proxy is trading volume, "defined as the average daily turnover in percentage over the past six months, where daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day" (Jiang et al., 2005, p. 192). The literature suggests that firms with high trading volume posit high IU in expected returns (see Jiang et al., 2005). Both Jiang et al. (2005) and Lee and Swaminathan (2000) report higher momentum returns for stocks with higher trading volume.

My fourth and final proxy is firm size measured by the market capitalization (in millions of CNY) at portfolio formation date. The literature documents that information availability increases with firm size (see Bernard and Thomas, 1989; Foster, Olsen, and Shevlin, 1984; Freeman and Tse, 1989). Zhang (2006) argues that there is less information available about smaller firms than larger firms because smaller firms have fewer clients, suppliers and employees and therefore the accessibility of information can be more difficult. Using firm size as an IU proxy, Zhang (2006) finds that smaller firms (high IU) have larger momentum returns than larger firms. However, the evidence about the relationship of firm size to momentum is mixed since Hong, Lim, and Stein (2000) and Lesmond, Schill, and Zhou (2004) report weak momentum returns in small stocks.

3.3 Sample and Descriptive Statistics

I use all firms listed on the SSE and source the data from the China Securities Market and Accounting Research (CSMAR) from November 1994 to November 2010. I exclude the period before 1994 because of the limited number of firms listed during that period. I deleted stocks with monthly returns greater than 100% to avoid the influence of extreme returns and any possible data recording errors. I exclude all financial institutions, closed-end funds and real estate firms. At the beginning of the sample period there are 155 firms, which increased to 745 at the end of the period.

At the beginning of each month t, I compute four IU proxies as follows. *Firm Age* is measured as the difference in months between the establishment date of firm and the current month t. *Stock volatility* (hereafter volatility) is defined as the standard deviation of daily returns for the past 25 trading days. *Trading Volume* (hereafter volume) is measured as the average daily turnover (as a percentage) over the past 6 months. *Firm size* (hereafter size) is the market capitalization (in millions of CNY) at the end of month t.

Table 3.1 reports the summary statistics for the four IU variables. Panel A, Table 3.1, reports the summary statistics for the IU variables and Panels B and C show the Pearson and Spearman correlations between the IU variables, respectively. Panel A shows that the mean (median) age of the firms is 109 (105) months, the mean (median) size is CNY6411 million (2132), the mean (median) volatility is 0.030 (0.027) and the mean (median) volume is 1.076% (0.581%). The number of firm-month observations ranges between 109,437 and 141,710 for the different IU variables.

Panels B and C, Table 3.1, show the correlation matrix. The Pearson correlation between firm age and size is -0.001, which shows that young firms tend to have higher size, lower volatility and volume. However, the Spearman correlation shows that younger firms tend to have lower size (0.118), volatility and volume. The correlations between size and volatility and size and volume are low, i.e., range between -0.026 (volatility and size) and 0.062 (size and volume). However, firm age and volume are more highly correlated (0.318 and 0.353) than the correlation between firm age and other variables. Volume and volatility are more highly correlated (0.359 and 0.553) than the correlation between other variables. The correlation among IU proxies is statistically significant at the 1% level except for the Spearman correlations between firm age and size and firm age and volatility.

3.4 Portfolio Returns by Information Uncertainty Proxy

Table 3.2 presents the average monthly returns to the single sorted portfolios formed on the basis of the four IU proxies and past 6-month returns. In Panel A, Table 3.2, each month I rank firms into quintiles using the past 6-month (t-6 to t-1) returns, skipping month t. These rankings are used to form five equally weighted portfolios, where the top portfolio (P1) is called the losers portfolio and the bottom one (P5) is the winners portfolio. I buy the winners and sell the losers in a momentum trading strategy. These portfolios are held for K months (K = 3, 6, 9, 12 months). Following Jegadeesh and Titman (1993) the portfolio monthly return for a K-month holding period is based on an equal-weighted average of portfolio returns from strategies implemented in the current month and the previous K-1 months. To illustrate, the monthly return for a six-month holding period is based on an equal-weighted average of portfolio returns from the strategy in the current month, and the strategies from one, two, three, four, and five months ago. This is equivalent to revising the weights of approximately one-sixth of the portfolio each month and carrying over the rest from the previous month. P5-P1 represents the return of the momentum trading strategy of buying winners and selling losers. The last column in Panel A, Table 3.2, shows the existence of significant momentum returns for next 3-, 6-, 9- and 12-month holding periods. The existence of momentum returns shows that past winners outperform past losers on a monthly basis by 0.57% (3 months holding period), 0.62% (6-month holding period), 0.51% (9-month holding period) and 0.36% (12-month holding period). I find larger momentum returns for all holding periods when I use decile portfolios (see Table 2.2). However, this chapter uses quintiles to make sure that enough stocks are available, especially when double sorting portfolios on momentum and IU proxies.

In Panels B, C, D and E, Table 3.2, each month I sort firms into quintiles using firm age, volatility, volume and size as proxies for IU. I find that high IU firms tend to have higher returns over the succeeding 6-month period, when sorted on volume and size and the returns are monotonic across the five portfolios for size. Firms with higher IU tend to have higher returns when defined in terms of volatility; however, average returns across the volatility quintiles are not monotonic and the difference between high IU (high volatile) and low IU (low volatile) is not significant. In contrast, high IU firms earn lower returns over the succeeding 6-month period when sorted on firm age. The higher future returns for stocks with higher volume (high IU) agree with Gervais, Kaniel and Mingelgrin (2002) who find that stocks with higher volume over a day or a week tend to have higher returns over next 100 days. However, my volume results are inconsistent with Jiang et al. (2005) who show lower returns for stocks with high volume (high IU). The higher future returns for small size firms (high IU) are consistent with Fama and French (1992). The returns of high and low volatile stocks are almost similar, that is, consistent with Scherer (2011), who documents that there is no difference in the expected returns of high and low volatile stocks. The lower future returns for younger firms are consistent with Jiang et al. (2005). However, firm age might not be an important factor in explaining the future returns in China because the age difference between young and old firms is quite small compared with U.S. firms; therefore, it might be other firm-specific characteristics that drive lower future returns for the younger firms instead of their age.[29] In summary, my results are inconsistent with Jiang et al.'s (2005) findings that higher IU firms earn lower future returns. In contrast, I find that higher IU firms earn higher returns when IU is defined in terms of volume and size, consistent with traditional risk-based theories.

3.5 Momentum Returns Sorted on Information Uncertainty

Table 3.3 presents the average monthly returns to the portfolios formed by first sorting firms on the IU proxy and then each IU portfolio is sorted further into five portfolios based on the past 6-month returns.[30] At the beginning of each month t, all stocks are sorted on each IU variable and then divided into five equal-weighted portfolios. The portfolio with low IU stocks is IU1 (old firms, low volatility, low volume and large size) and the portfolio with high IU stocks is IU5 (young firms, high volatility, high volume and small size). Each IU portfolio is further sorted into five groups based on the past 6-month returns (t-6 to t-1).[31] A month is skipped between the formation and holding period to mitigate the bid-ask bounce effect. These portfolios are held for 3-, 6-, 9- and 12-month periods (for example the 6-month holding period, t+1 to t+6). P1 represents the losers portfolio and P5 represents the winners portfolio. P5-P1 represents the average monthly momentum returns (winners- losers) for each IU portfolio with 3-, 6-, 9- and 12-month holding periods. IU1 (IU5) represents the returns of low-IU (high-IU) portfolio. IU5-IU1 represents the return difference between high-IU portfolio (IU5) and low-IU portfolio (IU1). P5-P1 represents the return difference (momentum returns) for each IU portfolio. The t-statistics in parentheses are simple time-series t-statistics for average monthly returns. The last column on the bottom right of each trading strategy reports the difference between P5-P1 of IU5 (IU5-IU1 of P5) and P5-P1 of IU1 (IU5-IU1 of P1).

Panel A, Table 3.3, reports the average monthly returns of stocks sorted on firm age and past 6-month returns. Using a 3-month holding period, momentum returns for the youngest firms (high IU) are larger (1.06% per month) than those of older firms (low IU) (0.21% per month). The difference in momentum returns (P5-P1) between young and old firms (IU5-IU1) is statistically significant at 0.86% per month. However, the momentum returns for 6-, 9- and

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[29] The difference between younger (lower quartile) and older (higher quartile) firms is almost 7 years for the Chinese firms compared with 21 years for the U.S. firms (Jiang et al., 2005, p. 194)

[30] I perform dependent sorts to make sure sufficient number of firms in the extreme IU portfolios. However, following Jiang et al. (2005) and Zhang (2006), I also sort firms independently and find that momentum returns increase somewhat but the number of firms in a few IU portfolios drops.

[31] The total number of portfolios will be 25 as first I divided stocks into five IU portfolios based on information uncertainty and then each IU portfolio is further divided into five groups based on their past 6 month returns.

12-month holding periods are similar for young and old firms. These results suggest that firm age might not be an important factor in explaining the momentum returns in China because the age difference between young and old firms is quite small compared with U.S. firms. Therefore, the smaller difference in age might not be able to capture the effect of IU shown in Zhang (2006) and Jiang et al. (2005).

Panel B, Table 3.3, shows the average monthly returns of stocks sorted on volume and past 6-month returns. Consistent with results reported in Table 2, high-IU stocks have higher returns when IU is proxied by volume for both loser (P1) and winner (P5) portfolios though the relationship is not monotonic. The only exception is the winner portfolio (P5) with 3-month holding period, whose returns are unrelated to IU. More importantly, the momentum returns (P5-P1) appear to be higher for low-IU than for high-IU firms for 9- and 12-month holding periods. For the 3- and 6-month holding periods there is no significant difference in the momentum returns (P5-P1) of high- and low-IU stocks. These results are inconsistent with both Jiang et al. (2005) and Lee and Swaminathan (2000) who find higher momentum returns for firms with higher trading volume using decile momentum and tercile volume portfolios for the U.S. stocks over the period of 1965 to 2001 (Jiang et al., 2005) and 1965 to 1995 (Lee and Swaminathan, 2000). However, my results are consistent with Sam's (2006) results for the UK where he finds higher momentum returns for low volume stocks using decile momentum and tercile volume portfolios over the period of 1988 to 2005. My results are also consistent with those with Li, Brooks and Miffre (2010) who find higher momentum returns for low volume stocks using decile momentum and tercile volume portfolios over the period 1985 to 2005.

Panel C, Table 3.3, shows that momentum returns are similar between high (high IU) and low volatility (low IU) firms. Momentum returns are prevalent in almost all volatility quintiles with 3-, 6- and 9-month holding periods, but statistically insignificant for the third volatility quintile. These results are inconsistent with Jiang et al.'s (2005) and Arena et al.'s (2008) studies that report higher momentum returns for stocks with higher volatility using tercile portfolios for volatility and decile portfolios for momentum.[32]

Panel D, Table 3.3, shows the average monthly returns sorted on size and past 6-month returns. Momentum returns for the small (IU5) and the two largest (IU1 and IU2) size firms are large and statistically significant for all holding periods. However, momentum returns for IU4 are negative and statistically significant for all the holding periods. Momentum returns

[32] Jiang et al. (2005) and Arena et al. (2008) find significant momentum returns for low and medium volatility portfolios but smaller than high volatility portfolios.

for IU3 are positive but statistically significant for 3- and 6-month holding periods. Although the momentum returns for high IU firms (small size) are larger than low IU firms (large firms), the difference is small and statistically insignificant except for the 6-month holding period. My results are not consistent with Zhang (2006) who shows that there is a large and statistically significant difference between high IU (small size) and low IU (large size) firms. However, my results are consistent with Hameed and Kusnadi (2002) who report smaller returns for medium-size firms.

I find similar momentum returns for low- and high-IU firms when IU is defined in terms of volatility, size and firm age except that younger firms earn greater momentum returns than older firms when considered over a 3-month holding period and small size firms (IU5) earn larger momentum returns than large size firms (IU1) over a 6-month holding period. However, I find higher momentum returns for low volume firms but the difference between high (IU) and low volume (IU) firms is insignificant except for 9- and 12-month holding periods. In summary, there appears to be no significant relationship between momentum returns and IU and it appears that the small differences in momentum returns among stocks sorted on volume, volatility, size and firm age might be driven by firm-specific characteristics related to these variables.

Table 3.4 presents average monthly returns to portfolios formed using two proxies to measure IU instead of one because one proxy might not fully capture the effect of IU. To construct this table, stocks are independently sorted at the beginning of each month based on two IU proxies that results in four IU portfolios. Those four IU portfolios are low-low IU, low-high IU, high-low IU and high-high IU. However I am reporting momentum returns for only high (High IU based on two IU proxies) and low IU portfolios (Low IU based on two IU proxies) since my motive in this chapter is to test if momentum returns are limited to high IU stocks. For example, in the first row, I report results when IU is defined in terms of age and volume. In other words, a firm is defined as high-IU (low-IU) if it is in the upper- (lower-) half by both age and volume.[33] All stocks are then divided into portfolios where high-IU (low-IU) portfolio includes the firms with upper- (lower-) half by both age and volume. The second row repeats the procedure with other IU proxies defined by age and volatility, and so on. Each high- and low-IU portfolio is further sorted into five portfolios based on past 6-month returns (t-6 to t-1). A month is skipped between the formation and holding period to mitigate the bid-ask bounce effect. These portfolios are held for the conventional 6-month holding period.

[33] I am using two IU portfolios to ensure that enough stocks are available in each IU portfolio. However, my results are consistent with those when I sort stocks into IU terciles though the average number of stocks drops.

Table values represent the average monthly returns for the momentum trading strategies (P5-P1) of high- and low-IU portfolios. The t- statistics in parentheses are simple time-series t-statistics for average monthly returns.

The results from Table 4 show that when IU is defined in terms of age and volume, momentum returns are higher for high-IU firms than for low-IU firms, consistent with the prediction of Jiang et al. (2005) and Zhang (2006). The same applies when IU is defined in terms of age and volatility. These results are likely driven by the age proxy consistent with the results reported in Table 3.3 showing higher momentum returns for high-IU firms if IU is proxied by firm age with 3-month holding period. However, if IU is defined in terms of age and size or volume and volatility, I find no significant difference in the momentum returns of high- and low-IU firms. Finally, if I define IU in terms of size and volume or size and volatility, high-IU firms have lower momentum returns than low-IU firms contrary to the prediction of Jiang et al. (2005) and Zhang (2006). In summary, the results in Tables 4.3 and 4.4 show, at best, weak evidence that momentum returns are related to the level of IU.

3.6 Risk Adjustments and Robustness Checks

The literature is divided into risk-based and behavioural explanations of momentum returns. Risk-based theories argue that momentum returns are compensation for bearing market-wide common risk associated with stock returns. A few previous studies link momentum returns with risk factors but Fama and French (1996, 2008, 2012) admit that their risk-based model cannot explain momentum returns. However, as a robustness check, I ensure that my results are not driven by differences in risk factors.[34]

Table 3.5 reports the results of the Fama and French (1993) time-series regression of excess monthly returns of the momentum trading strategy and high and low IU portfolios over the period November 1994 to November 2010. For these regressions, I sort firms independently on two IU proxies (volume and volatility) and then divide them into two groups. I further sort firms of each IU portfolio on past 6-month returns into five portfolios (after imposing a one-month lag) and hold these portfolios for another 6 months. At the end of the 6-month holding period, I calculate momentum returns as the difference between the average monthly returns for the 6-month holding period of winners and losers. The high-IU (low-IU) portfolio represents the firms with upper- (lower-) half by both volume and volatility. P1 represents the losers portfolio, P5 represents the winners portfolio and P5-P1 represents the average monthly momentum returns of high-IU, low-IU and high-low IU portfolios.

[34] Jiang et al. (2005) also test their results for risk adjustments.

I estimate the following three-factor (Fama and French, 1993) time series regression for each portfolio.

$$r_{p,t} - r_{f,t} = \alpha_{p,t} + \beta_{1,t}(r_{m,t} - r_{f,t}) + \beta_{2,t}SMB_t + \beta_{3,t}HML_t + e_{p,t} \quad (3.1)$$

where $r_{p,t}$ is the return for each portfolio *p* at time *t*; r_m is the return on the value-weighted SSE index at time *t*; SMB is the small-minus-big size factor at time *t*; and HML is the high-minus-low BTM factor at time *t*.[35] The numbers in parentheses represent simple time-series t-statistics.

The results in Table 3.5 show no significant difference in the market beta ($\beta1$) of high- and low-IU portfolios. There is also no significant difference in the factor loadings on SMB ($\beta2$) and HML ($\beta3$) for high- and low-IU portfolios. The results show that the Fama and French three factors cannot explain momentum returns of IU portfolios since the estimated intercepts (α) for P5-P1 are significant for both high- and low-IU portfolios. More importantly, the difference in the intercept values between the high-IU and low-IU portfolios (-0.05) is not statistically significant (*t*-stat of -0.29), which suggests no significant difference in momentum returns between high- and low-IU portfolios.

As a further robustness test, following Jiang et al. (2005), I also conduct Fama and MacBeth (1973) cross-sectional regressions of stock returns against various firm characteristics. For the cross-sectional regressions, size is defined as the natural logarithm of the market value of the firm at the beginning of the month; book-to-market ratio (BTM) is defined as the natural logarithm of the book-to-market ratio of the firm, where book value of equity of the previous fiscal year is divided by the beginning of the month market value, and formation period return (*J*6) is the average monthly return in the past 6 months (skipping month t).

In these cross-sectional regressions, IU is a dummy variable that is defined differently for each set of regressions. High- and low-IU firms are defined in terms of age and volume, age and volatility, and volatility and volume.

For Table 3.6, I estimate the following Fama-MacBeth cross-sectional regression each month:

$$r_i = \alpha_i + b\,Size_i + c\,BTM_i + d\,IU\,(L)_i + e\,IU\,(H)_i + f\,J6_i \quad (3.2)$$

$$+ g\,J6_i * IU\,(L)_i + h\,J6_i * IU\,(H)_i + e_i$$

where r_i defines the average monthly returns over next 6 months. The independent variables are Size, BTM, and past 6-month returns (*J6*). IU (H) is a dummy variable that has only two

[35] See Appendix for the construction of the Fama-French three factors.

values “zero and one”; one if firm belongs to the high IU group (upper-half by both IU proxies) otherwise zero.[36] IU (L) is also a dummy variable that also has only two values “zero and one”; one if firm belongs to the low IU group (lower-half by both IU proxies) otherwise zero. Reported values in Table 3.6 are the estimated coefficients from the monthly regressions, with Newey-West t-statistics in parenthesis.

Table 3.6 shows a significantly negative size and positive BTM effect, which is consistent with previous studies. However, the significant intercepts (α) mean that the dependent variables cannot fully explain returns over the next 6 months. The coefficients of IU(L) and IU(H) for all regressions are insignificant except for the coefficient of IU(L) when I use age and volatility to define IU. This confirms my earlier results that there is no relationship between IU and future returns. The significantly positive coefficient of J6 in all regressions confirms the existence of price momentum in the Chinese stock market. However, except for the coefficient of J6*IU(H), when IU is defined in terms of volatility and volume (IU = volatility + volume), the coefficients of J6*IU (H) are all statistically insignificant, which suggests that high IU is unrelated to momentum returns, contrary to the evidence in Jiang et al. (2005) and Zhang (2006) that momentum returns are higher in high IU-firms. The coefficient of J6*IU (H) is negative and statistically significant when IU is defined in terms of volatility and volume but this indicates that momentum returns are lower (not higher) for high-IU firms, which is also contrary to the evidence in Jiang et al. (2005) and Zhang (2006). I find that low IU is also unrelated to momentum returns except for the coefficient of J6*IU(L), when IU is defined in terms of age and volatility, which is positive indicating that momentum returns are higher (not lower) for low-IU firms that is also contrary to the evidence in Jiang et al. (2005) and Zhang (2006). In summary, the results of the portfolio analysis, Fama-French regressions and Fama-MacBeth cross-sectional regressions all indicate very little empirical support for the theory of information uncertainty proposed by Jiang et al. (2005) as an explanation of the momentum effect.

3.7 Conclusions

This chapter examines the role of information uncertainty (IU) in explaining future returns and the profitability of momentum returns in China. This study is motivated by the findings of Jiang et al. (2005) that document that IU plays a critical role in the prediction of cross-sectional stock returns and the explanation of the momentum effect in U.S. stocks. Given the fact that emerging markets are different from U.S. and other developed markets in many

[36] My results are consistent with tercile sorting to include stocks in low and high IU dummy variables.

ways, including the dominance of retail investors and a large number of small-cap stocks, it is worth testing if IU can explain future returns and momentum profitability in emerging markets. Among emerging markets, I chose China because it is the largest and is considered one of the most important members of the global economy. China's economy is the world's fastest growing economy and is expected to be the largest economy by 2041.

I find that stocks with higher IU earn higher future returns when IU is defined in terms of volume and firm size. These results are inconsistent with Jiang et al. (2005) who show that IU is negatively correlated with future returns. However, I also find that higher IU earns lower returns if it is defined in terms of firm age. My results are consistent with traditional risk based theories since small size and high volume firms require a risk premium. The negative correlation of firm age with future returns appears to be consistent with Jiang et al. (2005); however, firm age might not be an important factor in explaining future returns because the age difference between young and old firms is quite small. Therefore it might be that other firm-specific characteristics actually drive lower future returns for younger firms instead of their age.

This chapter finds no robust relationship between momentum returns and the level of IU, which is contrary to the empirical findings of Jiang et al. (2005) and Zhang (2006) for U.S. markets. Instead, I find higher momentum returns for low IU firms when IU is defined in terms of volume, but momentum returns for other proxies are similar among high- and low-IU firms.[37] The momentum returns difference between high- and low-IU firms is statistically insignificant for most of the holding periods, which provides further evidence that momentum returns are not related to the level of IU. The relationship between momentum returns and IU remains contrary to the findings of Jiang et al. (2005) and Zhang (2006) even when IU is defined in terms of two IU proxies, except when IU is defined in terms of age and volume or age and volatility. These results are likely driven by the age proxy since I find higher momentum returns for younger firms. However, if IU is defined in terms of size and volume or size and volatility, high-IU firms have lower momentum returns than low-IU firms contrary to the prediction of Jiang et al. (2005) and Zhang (2006). Therefore, momentum returns of high- and low-IU firms do not appear to be related to IU since they might be driven by firm-specific characteristics like volume and size. As a further robustness test, I also conduct Fama-MacBeth cross sectional regressions of monthly stock returns on various firm

[37] Momentum returns of younger firms with 3-month holding period are larger than older firms. Momentum returns of small size firms with 6-month holding period are larger than large size firms.

characteristics and IU proxies. My cross-sectional results also show that momentum returns are not related to the level of IU.

Overall, my results show that no robust relationship exists in China between the level of IU and the momentum effect. The difference in the results between my study and those of Zhang (2006) and Jiang et al. (2005) appears to be related to different characteristics between emerging markets and the U.S. market. Emerging markets, especially China, are dominated by retail investors whereas the U.S. market is dominated by institutional investors. The literature strongly documents that prices of stocks held by institutional investors are more efficient and that these stocks also enjoy high analyst following. Therefore, low IU stocks in the U.S. market might be the stocks with higher institutional holdings as most of the IU proxies used by Zhang (2006) are related to institutional investors, i.e., number of analysts, analyst forecast dispersion and firm size. Therefore, it appears that the stocks with higher institutional holdings have weak momentum returns because new information adjusts into prices quickly. In contrast, China is dominated by retail investors; therefore information might take more time to adjust into prices as retail investors have less information available. This could be the reason why IU is not relevant in determining momentum returns in China.

This study contributes to the existing literature in four ways. First, this study uses Chinese market data and provides evidence that the findings of Zhang (2006) and Jiang et al. (2005) for U.S stocks cannot be fully generalized to other markets, especially emerging markets. Unlike Zhang (2006) and Jiang et al. (2005), I find no robust relationship between momentum returns and IU in China. Secondly, this study links IU with the type of investors, i.e., IU could explain momentum returns in a market dominated by institutional investors (U.S. market) but it cannot explain momentum returns in a market dominated by retail investors (China). Thirdly, the results of this study suggest that investors could have earned higher returns in the succeeding 6-month period by investing in small size and high volume stocks. Fourthly, the results of this study also suggest that momentum traders could have earned higher profits by investing in either small or large size firms.

Table 3.1
Summary Statistics

This table reports summary statistics for the information uncertainty variables used in this study. My sample consists of all firms listed in Shanghai Stock Exchange China excluding financial institutions, closed-end funds and real estate firms. At the beginning of each month t, I compute the information uncertainty variables for each stock. *Firm age* is defined as the difference in months between the establishment date of firm and current month t. *Volatility* is defined as the standard deviation of daily returns for the past 25 trading days; and *Volume* turnover is defined as the average daily turnover in percentage over the past 6 months, where daily turnover is the ratio of the number of shares traded each day to the number of shares outstanding at the end of the day. *Firm Size* is defined as the market capitalization (in millions of CNY) for each stock in month t. Panel B reports the Pearson correlation coefficients and Panel C reports Spearman correlation coefficients.

Panel A: Summary Statistics for Information Uncertainty (IU) Variables

	N	Mean	10%	25%	Median	75%	90%	StdDev
Firm Age	109437	109	41	68	105	145	184	53.078
Size	110467	6411	635	1146	2132	4177	9017	51982
Volatility	137789	0.030	0.015	0.020	0.027	0.037	0.047	0.014
Volume	141710	1.076	0.113	0.235	0.581	1.415	2.765	1.290

Panel B: Pearson Correlation Coefficients between Information Uncertainty (IU) Variables

	Firm Age	Size	Volatility	Volume
Firm Age	1.00	-0.001	0.119	0.318
Size		1.00	-0.004	-0.029
Volatility			1.00	0.359
Volume turnover				1.00

Panel C: Pearson Correlation Coefficients between Information Uncertainty (IU) Variables

	Firm Age	Size	Volatility	Volume
Firm Age	1.00	0.118	0.184	0.353
Size		1.00	-0.026	0.062
Volatility			1.00	0.553
Volume turnover				1.00

Table 3.2
Returns to Momentum Trading Strategy and Information Uncertainty Portfolios

This table presents the average monthly returns of single sorted portfolios formed on the momentum based trading strategy of buying winners and selling losers and four information uncertainty proxies. Starting in November 1994, I sort firms into five portfolios based on their past 6-month returns, skipping month t and holding them for another *K* months, where *K* is equal to 3, 6, 9 and 12 months. At the end of the holding period, I calculate average monthly returns. The average monthly returns of portfolio P1 (Losers), P5 (Winners) and P5-P1 (momentum returns) are reported in per cent terms and *t*-statistics provided in parentheses. In each month t, I also sort firms into five portfolios based on each IU proxy (volume, firm age, volatility and firm size) and report average monthly returns for the next *K* (k=6) months. The average monthly returns of portfolio IU1 (Low IU), IU5 (High IU) and IU difference (IU5-IU1) are reported in per cent and *t*-statistics provided in parentheses.

Panel A: Average Monthly Returns of Momentum-based Trading Strategy

	P1	P2	P3	P4	P5	P5-P1
K=3	1.46	1.84	1.93	1.84	2.02	0.57
	(4.03)	(5.25)	(5.54)	(5.46)	(6.14)	(3.61)
K=6	1.42	1.82	1.88	1.90	2.04	0.62
	(4.35)	(5.67)	(5.88)	(6.00)	(6.66)	(4.46)
K=9	1.52	1.82	1.93	1.90	2.03	0.51
	(5.09)	(6.24)	(6.63)	(6.65)	(7.28)	(4.35)
K=12	1.61	1.84	1.93	1.90	1.97	0.36
	(5.78)	(6.83)	(7.28)	(7.24)	(7.75)	(3.66)

Panel B: Average Monthly Returns to Firm Age Portfolios

	IU1	IU2	IU3	IU4	IU5	IU5-IU1
K=6	2.00	1.62	2.08	1.74	1.71	-0.29
	(6.28)	(5.18)	(6.82)	(5.65)	(5.86)	(-3.51)

Panel C: Average Monthly Returns to Volatility Portfolios

	IU1	IU2	IU3	IU4	IU5	IU5-IU1
K=6	1.78	1.99	1.88	1.91	1.86	0.08
	(5.53)	(6.32)	(6.04)	(6.15)	(6.00)	(0.98)

Panel D: Average Monthly Returns to Volume Turnover Portfolios

	IU1	IU2	IU3	IU4	IU5	IU5-IU1
K=6	1.38	1.68	1.97	2.08	1.99	0.61
	(4.58)	(5.42)	(6.36)	(6.85)	(6.42)	(5.81)

Panel E: Average Monthly Returns to Size Portfolios

	IU1	IU2	IU3	IU4	IU5	IU5-IU1
K=6	1.21	1.47	1.59	1.69	1.82	0.61
	(4.14)	(4.89)	(5.31)	(5.59)	(6.03)	(5.96)

Table 3.3
Returns to Portfolios Based on Momentum and One Information Uncertainty Proxy

This table presents average monthly returns to portfolios formed by first sorting firms on one information uncertainty proxy and then past 6-month returns. At the beginning of each month, firms are sorted into five portfolios based on each IU proxy and then each IU portfolio is sorted into five portfolios based on past 6-month returns. To avoid potential microstructure biases, I compute past returns after imposing a one-month lag. For Panels A to D, IU5 represents the highest IU portfolio (young, high volatile, high volume and small size) and IU1 represents the lowest IU portfolio (old, low volatility, low volume and large size). For Panels A to D, P1 represents the losers portfolio, P5 represents the winners portfolio and P5-P1 represents the momentum returns. For Panels A to D, table values are the average monthly returns for next *K* holding months, where *K* is equal to 3, 6, 9 and 12 months. The average monthly returns are reported in per cent terms and *t*-statistics provided in parentheses.

Panel A: Portfolios Based on Firm Age and Past Price Momentum						
(*K*=3)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.84	1.49	1.83	1.35	1.10	-0.74
	(4.94)	(3.74)	(5.05)	(3.68)	(3.06)	(-5.02)
P5 (Winners)	2.04	1.34	2.21	2.27	2.16	0.12
	(5.74)	(4.11)	(6.35)	(6.50)	(6.83)	(0.89)
P5-P1	0.21	-0.15	0.38	0.92	1.06	0.86
	(0.97)	(-0.76)	(1.79)	(5.63)	(6.62)	(4.75)
(*K*=6)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.70	1.29	1.71	1.42	1.24	-0.47
	(5.08)	(3.75)	(5.27)	(4.32)	(3.86)	(-3.77)
P5 (Winners)	2.14	1.54	2.28	2.16	1.92	-0.22
	(6.43)	(5.03)	(7.07)	(6.89)	(6.66)	(-1.82)
P5-P1	0.44	0.25	0.57	0.74	0.68	0.24
	(2.30)	(1.75)	(3.06)	(5.38)	(5.30)	(1.76)
(*K*=9)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.74	1.44	1.73	1.51	1.42	-0.32
	(5.72)	(4.62)	(5.83)	(4.98)	(4.87)	(-3.32)
P5 (Winners)	2.12	1.60	2.28	2.06	1.80	-0.33
	(7.10)	(5.64)	(7.82)	(7.33)	(6.84)	(-2.94)
P5-P1	0.38	0.16	0.54	0.55	0.37	-0.01
	(2.54)	(1.41)	(3.49)	(4.77)	(3.32)	(-0.08)
(*K*=12)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.78	1.50	1.90	1.54	1.53	-0.25
	(6.33)	(5.24)	(6.67)	(5.42)	(5.69)	(-2.77)
P5 (Winners)	2.01	1.65	2.13	2.06	1.76	-0.26
	(7.62)	(6.23)	(8.24)	(8.05)	(7.17)	(-2.65)
P5-P1	0.23	0.14	0.24	0.52	0.22	-0.01
	(1.86)	(1.37)	(1.86)	(5.11)	(2.29)	(-0.09)

Table 3.3: Continued

Panel B: Portfolios Based on Volume and Past Price Momentum						
(*K*=3)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.32	1.39	1.90	1.57	1.88	0.55
	(3.53)	(3.61)	(5.19)	(4.50)	(5.24)	(2.81)
P5 (Winners)	1.64	1.50	2.19	2.40	1.96	0.32
	(5.04)	(4.54)	(6.57)	(6.97)	(5.48)	(1.70)
P5-P1	0.31	0.11	0.29	0.83	0.08	-0.23
	(1.80)	(0.59)	(1.92)	(5.18)	(0.37)	(-1.11)
(*K*=6)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.15	1.38	1.75	1.68	1.85	0.69
	(3.43)	(4.17)	(5.30)	(5.28)	(5.53)	(4.32)
P5 (Winners)	1.53	1.63	2.00	2.39	1.98	0.44
	(5.02)	(5.33)	(6.25)	(7.72)	(6.01)	(2.65)
P5-P1	0.38	0.26	0.25	0.71	0.13	-0.25
	(2.57)	(1.80)	(1.70)	(4.66)	(0.71)	(-1.51)
(*K*=9)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.24	1.45	1.73	1.76	1.99	0.75
	(4.09)	(4.82)	(5.61)	(6.01)	(6.53)	(5.04)
P5 (Winners)	1.52	1.65	1.95	2.40	1.88	0.36
	(5.26)	(5.92)	(6.77)	(8.55)	(6.32)	(2.28)
P5-P1	0.28	0.20	0.21	0.65	-0.11	-0.39
	(2.21)	(1.65)	(1.75)	(4.79)	(-0.72)	(-2.73)
(*K*=12)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.39	1.54	1.72	1.88	2.02	0.63
	(4.86)	(5.44)	(5.97)	(6.78)	(7.23)	(4.17)
P5 (Winners)	1.52	1.69	1.86	2.32	1.82	0.30
	(5.69)	(6.74)	(7.19)	(9.00)	(6.65)	(1.96)
P5-P1	0.14	0.16	0.14	0.44	-0.19	-0.33
	(1.25)	(1.49)	(1.37)	(3.92)	(-1.53)	(-2.62)

Table 3.3: Continued

Panel C: Portfolios Based on Volatility and Past Price Momentum						
(*K*=3)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.35	1.53	1.47	1.17	1.14	-0.21
	(3.50)	(4.19)	(3.95)	(3.22)	(2.89)	(-1.37)
P5 (Winners)	1.97	2.02	1.64	1.83	1.92	-0.05
	(5.65)	(5.73)	(4.77)	(5.17)	(5.04)	(-0.18)
P5-P1	0.62	0.49	0.17	0.66	0.79	0.17
	(4.81)	(3.74)	(1.29)	(4.56)	(2.99)	(0.68)
(*K*=6)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.29	1.46	1.47	1.36	1.19	-0.10
	(3.69)	(4.40)	(4.41)	(3.97)	(3.27)	(-0.68)
P5 (Winners)	1.88	1.83	1.70	1.78	1.91	0.03
	(5.65)	(5.49)	(5.23)	(5.50)	(5.18)	(0.12)
P5-P1	0.59	0.37	0.23	0.42	0.72	0.13
	(4.55)	(3.04)	(1.81)	(3.19)	(2.93)	(0.51)
(*K*=9)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.52	1.59	1.63	1.54	1.47	-0.05
	(4.63)	(5.02)	(5.09)	(4.78)	(4.21)	(-0.37)
P5 (Winners)	1.89	1.99	1.89	1.88	2.09	0.20
	(6.20)	(6.25)	(6.04)	(6.05)	(5.91)	(0.86)
P5-P1	0.37	0.40	0.26	0.34	0.62	0.25
	(2.44)	(2.95)	(1.89)	(2.07)	(2.67)	(1.02)
(*K*=12)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.17	1.35	1.32	1.31	1.16	-0.01
	(4.04)	(4.73)	(4.57)	(4.52)	(3.68)	(-0.04)
P5 (Winners)	1.50	1.51	1.48	1.49	1.61	0.10
	(5.27)	(5.28)	(5.27)	(5.49)	(5.47)	(0.64)
P5-P1	0.34	0.16	0.16	0.18	0.44	0.11
	(3.75)	(1.53)	(1.49)	(1.93)	(2.52)	(0.63)

Table 3.3: Continued

Panel D: Portfolios Based on Size and Past Price Momentum						
(*K*=3)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.15	1.04	1.58	1.95	1.87	0.72
	(3.21)	(3.10)	(4.54)	(5.18)	(4.51)	(3.45)
P5 (Winners)	1.86	1.84	1.85	1.61	2.86	1.00
	(5.39)	(5.45)	(5.31)	(4.83)	(6.60)	(2.87)
P5-P1	0.71	0.79	0.27	-0.34	0.99	0.28
	(4.32)	(5.78)	(2.17)	(-3.30)	(3.54)	(0.88)
(*K*=6)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.14	1.17	1.57	1.94	1.73	0.59
	(3.49)	(3.81)	(5.02)	(5.85)	(4.70)	(3.39)
P5 (Winners)	1.77	1.80	1.80	1.64	2.93	1.17
	(5.54)	(5.77)	(5.75)	(5.45)	(7.15)	(3.55)
P5-P1	0.63	0.63	0.23	-0.30	1.21	0.58
	(4.22)	(5.17)	(2.39)	(-3.04)	(4.80)	(2.09)
(*K*=9)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.13	1.30	1.75	1.96	1.83	0.71
	(3.81)	(4.64)	(6.05)	(6.50)	(5.44)	(4.64)
P5 (Winners)	1.74	1.74	1.80	1.70	2.89	1.15
	(5.96)	(6.19)	(6.26)	(6.20)	(7.84)	(3.96)
P5-P1	0.61	0.44	0.05	-0.26	1.06	0.45
	(4.57)	(4.22)	(0.54)	(-3.03)	(4.93)	(1.87)
(*K*=12)	IU1	IU2	IU3	IU4	IU5	IU5-IU1
P1 (Losers)	1.16	1.44	1.78	1.96	2.01	0.85
	(4.38)	(5.53)	(6.56)	(6.93)	(6.24)	(5.10)
P5 (Winners)	1.68	1.74	1.79	1.68	2.75	1.07
	(6.22)	(6.65)	(6.73)	(6.71)	(8.44)	(4.28)
P5-P1	0.52	0.30	0.01	-0.28	0.74	0.22
	(4.29)	(3.54)	(0.14)	(-3.90)	(4.21)	(1.07)

Table 3.4
Momentum Returns Based on Two Information Uncertainty Proxies

This table presents average monthly returns (P5-P1) to portfolios formed by first sorting firms on two information uncertainty proxies and then past 6-month returns. At the beginning of each month, firms are independently sorted into two portfolios based on two IU proxies. All the stocks are then divided into portfolios where high-IU (low-IU) portfolio includes the firms with upper- (lower-) half by two IU proxies. Each IU portfolio is sorted into five portfolios based on past 6-month returns. To avoid potential microstructure biases, I compute past returns after imposing a one- month lag. Low IU (High IU) represents the average monthly momentum returns (P5-P1) for lowest (highest) information uncertainty portfolio over the period of next 6-months and High-Low represents the difference in average monthly momentum returns (P5-P1) between highest and lowest IU portfolios. The average monthly returns (P5-P1) are reported in per cent terms and *t*-statistics provided in parentheses.

IU Pairs	Low IU	High IU	High-Low
Age and Volume	0.03	0.55	0.52
	(0.20)	(3.55)	(2.85)
Age and volatility	0.29	0.63	0.34
	(2.22)	(3.56)	(2.23)
Age and Size	0.45	0.60	0.15
	(3.36)	(3.08)	(0.69)
Volume and Volatility	0.40	0.46	0.06
	(3.33)	(2.32)	(0.33)
Size and Volume	0.02	-0.56	-0.58
	(0.13)	(-2.68)	(-3.11)
Size and Volatility	0.36	-0.01	-0.36
	(2.62)	(-0.02)	(-1.99)

Table 3.5
Momentum-Information Uncertainty Portfolios Regressed on Fama-French Three Factors

This table reports the three-factor regression results for average monthly returns on momentum and information uncertainty (IU) portfolios using a formation period of the past 6-months' returns (*t-6 to t-1*) and holding period of subsequent 6-months' returns (*t+1 to t+6*) from 1994 to 2010. At the beginning of each month, firms are independently sorted into two portfolios based on two IU measures (low volume and low volatility) and then each IU portfolio is sorted into five portfolios based on past 6-month returns. The low IU portfolio includes the lower-half of the firms by two IU measures and high IU portfolio includes the upper-half of the firms by two IU measures. P1 represents the losers portfolio, P5 represents the winners portfolio and P5-P1 represents the momentum returns. The regression model is: $r_{p,t} - r_{f,t} = \alpha_{p,t} + \beta_{1,t}(r_{m,t} - r_{f,t)} + \beta_{2,t}SMB_t + \beta_{3,t}HML_t + e_{p,t}$. Where r_p is the return for portfolio p, r_m is the return on the SSE value- weighted market index; SMB is the small-minus-big size factor, and HML is the high-minus-low BTM factor. The numbers in the parentheses represent simple time-series t- statistics.

	a			β1(market)			β2(SMB)			β3 (HML)			Adj. $\mathbf{R}^2$(%)		
	Low IU	High IU	High-Low	Low IU	High IU	High-Low	Low IU	High IU	High-Low	Low IU	High IU	High-Low	Low IU	High IU	High-Low
P1	0.81	1.15	0.34	24.44	23.72	-0.72	18.16	20.00	1.84	-2.94	-4.37	-1.43	24.69	23.34	-0.94
	(2.62)	(3.68)	(3.76)	(7.36)	(7.06)	(-0.74)	(2.16)	(2.35)	(0.74)	(-0.39)	(-0.58)	(-0.65)			
P2	1.19	1.35	0.16	25.00	23.70	-1.30	18.18	17.57	-0.61	-3.31	-2.28	1.03	25.75	24.36	-0.35
	(3.87)	(4.48)	(2.03)	(7.58)	(7.30)	(-1.50)	(2.17)	(2.13)	(-0.27)	(-0.44)	(-0.31)	(0.52)			
P3	1.29	1.56	0.27	24.99	24.65	-0.34	17.84	19.28	1.44	-4.34	-5.08	-0.74	26.36	24.61	-1.49
	(4.27)	(5.02)	(3.14)	(7.71)	(7.34)	(-0.37)	(2.17)	(2.26)	(0.59)	(-0.59)	(-0.67)	(-0.32)			
P4	1.34	1.54	0.20	25.13	24.17	-1.00	14.94	20.45	5.51	-6.29	-5.21	1.08	26.54	24.80	0.46
	(4.48)	(5.05)	(1.61)	(7.82)	(7.33)	(-0.72)	(1.83)	(2.45)	(1.58)	(-0.87)	(-0.70)	(0.35)			
P5	1.27	1.56	0.29	23.68	22.66	-4.46	14.02	23.64	5.91	-6.10	0.97	7.39	26.14	22.72	0.48
	(4.47)	(4.95)	(1.41)	(7.74)	(6.70)	(-1.36)	(1.81)	(2.76)	(0.70)	(-0.88)	(0.13)	(0.99)			
P5-P1	0.46	0.41	-0.05	-0.76	-1.06	-0.30	-4.14	3.64	7.79	-3.16	5.35	8.51	0.51	-0.44	2.83
	(3.70)	(1.96)	(-0.29)	(-0.57)	(-0.48)	(-0.15)	(-1.23)	(0.65)	(1.51)	(-1.05)	(1.07)	(1.86)			

Table 3.6
Fama-MacBeth Regressions of Returns on Size, Book-to-market, Momentum and Information Uncertainty Proxies

This table reports Fama-MacBeth cross-sectional regression results for average monthly returns (*K*6) on size, book-to-market ratio (BTM), momentum (*J*6) and information uncertainty (IU) proxies for China over the period 1994 to 2010. The descriptions of Firm Age, Volume and Volatility are same as described in Table 3.1. Size is the natural logarithm of the average market value of equity at the beginning of the month. BTM is the natural logarithm of book-to-market ratio, where book value of equity in the previous fiscal year is divided by the beginning of month market capitalization. *J*=6 shows the average monthly formation period returns (*t-6 to t-1)* of momentum trading strategy, computed with one-month lag, while *K*=6 shows the average monthly returns on subsequent six months (*t+6 to t+1*). IU is a dummy variable and high-IU and low-IU firms are defined in terms of Volume, Firm Age and Volatility. I sort stocks into two portfolios by IU proxies at the beginning of each month. The independent variables used in this regression are Size, BTM, *J*6, and dummy variables for high and low IU. The numbers in the parentheses represent t- statistics, where standard errors are adjusted for overlap with the method of Newey and West (1987).

IU=	Intercept	Size	BTM	IU (L)	IU (H)	J6	J6*IU(L)	J6*IU(H)
Age+ Volume	0.092	-0.005	0.008	0.001	0.001	0.059	0.000	0.007
	(4.18)	(-3.54)	(3.60)	(0.60)	(1.11)	(2.28)	(0.01)	(0.31)
Age+ Volatility	0.093	-0.005	0.009	0.002	-0.001	0.055	0.053	0.005
	(4.36)	(-3.73)	(3.89)	(2.11)	(-0.60)	(2.59)	(2.09)	(0.34)
Volatility+ Volume	0.098	-0.005	0.008	0.001	-0.001	0.085	0.014	-0.048
	(4.57)	(-3.89)	(3.64)	(0.48)	(-0.99)	(3.01)	(0.72)	(-2.15)

Chapter 4

Momentum Returns, Long-Term Reversal and Idiosyncratic Volatility

4.1 Introduction

An extensive body of finance literature has uncovered various price anomalies suggesting that investors can predict future stock returns based on historical returns. The two pricing anomalies that have gained most attention recently are momentum and long-term reversal. Momentum refers to the tendency for past winners to continue winning while past losers continue losing over a horizon of three to 12 months, whereas long-term reversal is the tendency of past losers to outperform past winners over a longer horizon of two to five years. Jegadeesh and Titman (1993, 2001) report that the momentum trading strategy of buying recent winners and selling recent losers generates an abnormal return of 1% per month (12% per year) in U.S. markets and DeBondt and Thaler (1985, 1987) and Chopra, Lakonishok and Ritter (1992) document that the long-term reversal trading strategy of buying losers and selling winners generates economically large statistically significant returns over two to five year horizons for U.S stocks. Although the magnitude and significance of momentum and reversal returns for both U.S. and non-U.S. stocks are well accepted among researchers, no such consensus exists about the cause of excess returns, especially about momentum returns. Some studies argue that the profitability of momentum- and reversal-based trading strategies is just compensation for bearing some systematic risk (see Conrad and Kaul, 1998). However, Fama and French (1996, 2008) suggest that the profitability of reversal strategies disappears once they account for risk-factors though this was not so for the momentum strategy. Some other studies link the profitability of both momentum and reversal strategies with investor behavioural biases (see Barberis et al., 1998; Daniel et al., 1998; Hong and Stein, 1999).

Some recent papers have tried to test the relationship between “idiosyncratic volatility” (IV hereafter) and the profitability of both the “momentum trading strategy” (momentum hereafter) and the long-term reversal trading strategy (reversal hereafter). Based on the findings presented in risk-based and behavioural theories, Arena et al. (2008) argue that momentum profit might be the result of under reaction to firm-specific information and limits to arbitrage. Using IV as a proxy for firm-specific information and limits to arbitrage, Arena et al. (2008) show higher momentum returns for stocks with high IV and lower momentum returns for stocks with low IV. Based on the findings presented in several papers that both the momentum and reversal profits result from mispricing, McLean (2010) uses IV as a proxy for holding costs arguing that the largest mispricing would be found among stocks with high IV since high IV stocks are more costly to trade and, therefore, have higher arbitrage costs. In contrast to Arena et al. (2008), McLean (2010) finds that momentum returns are not related to IV and it's the transaction costs instead of IV that limit arbitrage opportunities for momentum. However, he finds that IV limits arbitrage opportunities for reversal stocks because stocks with high IV display greater reversal returns.

In this study, I examine and compare the relationship between IV, on one hand, and momentum and reversal returns on the other, on the Shanghai Stock Exchange, China (hereafter **SSE)**. The SSE was established in December 1990 and is considered the largest emerging stock market by market capitalization (*List of stock exchanges*, 2012). SSE is considered an emerging stock market because it has a short history of stock trading, a large number of small-cap stocks, a large number of share classes, a dominance of retail investors, and strict regulation of IPOs by the government (see Gao, 2002). SSE is the world's sixth largest stock market by market capitalization (*List of stock exchanges*, 2012). SSE is different from the U.S. and other developed stock markets because it is not entirely open to foreign investors. However, from 2004, foreign investors were allowed to trade in all shares of SSE, with some restrictions (see Jun Lin and Chen, 2005).

My study is motivated by the following issues: first, there is a limited number of studies available about the relationship of IV to momentum and reversal and the empirical evidence about the relationship of IV, especially with momentum, is mixed (see Arena et al., 2008; McLean, 2010). This limited number of studies is available only for U.S. firms and the findings have not been tested for the other markets, especially emerging markets, which are different from the U.S. and other developed markets in many ways. First, emerging markets, especially the largest emerging market, China, is different from developed markets because it has a large number of small-cap stocks and trading is dominated by retail investors compared with developed markets, which have larger cap stocks and are dominated by institutional investors. Second, some stock market anomalies in emerging markets, especially the "relationship between IV and one-month ahead stock returns" do not conform to findings in the U.S. and other developed markets (see Nartea et al., 2011). Third, emerging markets are growing much faster than developed markets and it is expected that emerging markets will lead economic growth over the next 10 years, so it is important for the global investment community to gain a deeper understanding of the major financial markets of the emerging world. Among the emerging markets, I chose China because it is the world's largest emerging market and is expected to be the world's largest economy by 2041 (see Wilson and Purushothaman, 2006).

Secondly, the data span the period 1994 to 2010 and hence is the most recent compared with the data used for U.S. studies and it also covers the period of the Global financial crisis.[38] The results from this study have important implications for the investment community because investors, especially institutional ones, include stocks in their portfolios based on past returns (momentum and reversal) and stock volatility.

Thirdly, this study employs the methodology of both Arena et al. (2008) and McLean (2010) to test the robustness of the relationship between IV and momentum returns with different methods of estimating IV and number of portfolios (tercile versus quintile). As the empirical evidence about the relationship between IV and momentum returns is mixed, it is important to determine if IV can explain momentum returns (see Arena et al., 2008; McLean, 2010).

Fourthly, this study examines if momentum and reversal returns are robust to the type of portfolio sorting technique. Arena et al. (2008) and McLean (2010) use only the "independent" sorting technique to sort stocks into portfolios. There are some benefits of independent sorting because it includes a firm in a portfolio irrespective of its ranking on other variables. However, using this technique sometimes leaves a small number of stocks in one portfolio and a large number of stocks in another portfolio. In contrast, the "dependent" sorting technique makes sure that each portfolio has an equal number of stocks over the same holding period; the results are thus not biased by portfolios with a small number of stocks.

Consistent with McLean (2010), I find that momentum returns are not related to IV, and are strong among low and 2nd IV quintiles. The difference in raw and Fama-French adjusted momentum returns between high and low IV quintiles is small and statistically insignificant for all holding periods. However, contrary to McLean (2010), I find large, statistically significant reversal returns for all IV quintiles. Therefore, reversal is not related to IV. My findings that IV is not related to momentum and reversal are robust to controls for exclusion of low and small size stocks. However, my results indicate that the proxy used for IV; sorting method and number of portfolios (tercile versus quintile) play critical roles in determining the existence and significance of a relationship between IV and the momentum or reversal effects. My findings appear to be consistent with those of Bali and Cakici (2008) who find an insignificant relationship between IV and expected returns when they account for the data frequency used to estimate IV, the weighting-scheme used to calculate portfolio returns

[38] 1965-2002 is the sample period for Arena et al. (2008) and 1965-2004 for McLean (2010).

(equal- or value-weighted), the breakpoints used to sort stocks into portfolios and the use of low and small price filters. My findings do not support the suggestion that IV limits arbitrage among momentum and reversal stocks. However, I find that the profitability of reversal may be the result of mispricing that persists due to limits to arbitrage caused by high transaction costs because I find greater reversal returns among stocks with the highest transaction costs when I use the Fama and MacBeth (1973) cross-sectional approach. This argument is consistent with findings in the literature that suggest a cross-sectional relationship between transaction costs and reversal returns (see Jordan, 2009).

In summary, this chapter contributes to the existing literature in two ways. First, according to the best of my knowledge, this is the first study that examines the relationship of IV with momentum and reversal outside U.S. markets. Secondly, this study enriches the existing literature on the relationship of IV with momentum and reversal by using different IV estimation methods, number of portfolios and different sorting methods for the robustness tests.

The rest of the study is organized as follows: section 2 discusses the literature, section 3 reports the sample and descriptive statistics, section 4 presents the main results, section 5 conducts risk adjustments and robustness checks and last section concludes the study.

4.2 Literature Review

I examine two trading strategies in this chapter: long-term reversal, which relies on return reversals, and momentum, based on return continuation. Jegadeesh and Titman (1993) show return continuation for U.S. stocks for the medium-term horizon, i.e., buying (selling) past three to 12 months winner (loser) stocks, generates an abnormal return of 1% per month (12% per year); DeBondt and Thaler (1985, 1987) and Chopra, Lakonishok and Ritter (1992) find long-term return reversals for U.S. stocks, i.e., buying (selling) stocks with low (high) returns over the past two to five years, generates significant positive returns in the next two to five years.

There is an enormous amount of evidence of the success of momentum and long-term reversal trading strategies across international stock markets and time periods (see Alsubaie and Najand, 2008; Bacmann and Dubois, 2000; Bacmann et al., 2001; Bhojraj and Swaminathan, 2001; Chan et al., 2000; Chui et al., 2000; Conrad and Kaul, 1993, 1998; Fama and French, 2012; Hameed and Kusnadi, 2002; Jegadeesh and Titman, 2001; Rouwenhorst, 1999; Rouwenhorst, 2002). The robustness of momentum returns and long-term reversal returns across international markets and time periods has motivated researchers to propose several explanations for the momentum and reversal effects. These explanations are mostly anchored in behavioural and risk-based theories. The risk-based explanation of the momentum effect is considered less reliable since Fama and French (1996, 2008, 2012) admit that the Fama-French three-factor model cannot explain the profits of the momentum trading strategy. In contrast, some studies find that the profitability of the long-term reversal strategy disappears once risk factors are accounted for (see Chan, 1988; Fama, 1998; McLean, 2010).

A number of behavioural models try to explain the returns of both the momentum and long-term reversal strategies. Barberis et al. (1998) explain the returns of the momentum and long-term reversal strategies with their model based on two investor cognitive biases, representative and the conservatism heuristic.[39] In the representative heuristic bias, investors assume that firms with abnormal returns will continue to earn extraordinary returns. As a result of their beliefs, they bid the stock prices up too much, which causes the prices to overshoot the fundamental levels and eventually results in long-term reversal. In the conservatism bias, investors underreact to new information because they are slow in updating their prior beliefs; in the conservatism bias, investors underweight new public information so they stick to their prior beliefs. They adjust their prior beliefs slowly, so it takes time for new information to adjust into stock prices, which then results in momentum returns.

Hong and Stein (1999) explain momentum returns with two types of investor, news watchers and momentum traders. In their model, the news watchers rely on private information for their trades whereas momentum traders consider the information in past prices. Hong and Stein (1999) assume that private information diffuses slowly in the market, which, in turn, generates initial under reaction to news. The news watchers trade based on their private information; therefore information is transmitted with delay and hence is partially incorporated in the prices. This leads to under reaction and results in momentum returns. This under reaction and subsequent return continuation attracts momentum traders whose trading activities result in over-reaction to the news, which eventually turns into long-term reversal.

Daniel et al. (1998) present a model in which investors are overconfident about their private information and over-react to it, but they underreact to public signals. They argue that investor overconfidence increases if subsequent public information confirms their private information. The increase in overconfidence further triggers over-reaction to their private

[39] Edwards (1968) established the conservatism bias and Tversky and Kahneman (1974) studied the behavioural heuristic.

information and causes stock prices to overshoot the justified price. This unjustified price later reverses and results in long-term reversal.

Arena et al. (2008) add a new area of momentum study by reporting that momentum and reversal returns can be explained by IV. Based on the behavioural models of Barberis et al. (1998), Hong and Stein (1999) and Daniel et al. (1998), Arena et al. (2008) argue that momentum profits are attributable to under reaction to firm-specific information as stocks with more firm-specific information have higher IV and experience greater under reaction that results in greater momentum returns. Arena et al. (2008) further argue that firms with higher IV also have higher arbitrage costs, which is another reason for their higher momentum returns. Using U.S. data over 1965-2002, they find that high IV stock have higher momentum returns than low IV stocks and that the relationship is driven by losers. They also find that high IV stocks experience large reversals. As a robustness test, they further show that the momentum returns of high IV stocks cannot be explained by size, trading volume, share price, market beta and price delay.

McLean (2010) attempts to explore the relationship of IV not only with momentum but also with long-term reversal. He reports that there is still a debate about the sources of the profitability of trading strategies based on momentum and long-term reversal. However, there appears to be a consensus in the literature that both momentum and long-term reversal are the result of mispricing (see Barberis et al., 1998; Cooper et al., 2004; Daniel et al., 1998; DeBondt and Thaler, 1985, 1987; Hong and Stein, 1999; Hong et al., 2000; Lee and Swaminathan, 2000). McLean (2010) further argues that, in order for mispricing to be persistent, it must be that the costs that limit arbitrageurs to keep markets efficient are high. The costs that limit arbitrageurs in their efforts at keeping markets efficient are transaction costs and holding costs. Several authors have argued that the primary source of arbitrage costs comes from the holding costs (Ackert and Tian, 2000; Ben-David and Roulstone, 2005; Pontiff, 1996; Pontiff and Schill, 2002). McLean (2010) chooses to focus on IV as Shleifer and Vishny (1997) and Pontiff (2006) identify IV as the primary arbitrage holding cost. Shleifer and Vishny (1997) argue that IV is the largest cost for risk-averse arbitrageurs who cannot hedge the IV risk of individual stocks. Pontiff (2006) argues that IV imposes a significant holding cost for arbitrageurs even if arbitrageurs have access to a diversified portfolio and large number of arbitrage resources. Therefore, mispricing would be largest among stocks with high IV as a result of limited arbitrage. Using IV as proxy for arbitrage costs, McLean (2010) finds that stocks with higher IV display greater reversal returns than do stocks with lower IV. However, in contrast to Arena et al. (2008), he finds that the profitability of the momentum strategy is not related to IV because momentum returns are weakest in stocks with higher IV. He further argues that the profitability of the momentum strategy might be related to transaction costs since momentum is a shorter-term mispricing than reversal and, therefore, transaction costs might be enough to limit arbitrage. In reversal, transaction costs cannot be the binding cost because reversal is long-term mispricing and, therefore, has a better chance of recovering transaction costs.

Empirical evidence on the cross-sectional relationship between IV and expected stock returns is also mixed. Ang, Hodrick, Xing and Zhang (2006, 2009) report a negative relationship between IV and expected returns at the firm level in developed markets. In contrast, Nartea et al. (2011) find a positive relationship between IV and expected stock returns for emerging Southeast Asian stock markets. Bali and Cakici (2008) replicated Ang et al.'s (2006) study and report that the existence and significance of the cross-sectional relationship between IV and expected returns depends on the data frequency used to calculate IV, the portfolio-weighting scheme to compute average portfolio returns, the breakpoints used to sort stocks into portfolios and the inclusion or exclusion of size, price and other liquidity measures. Based on their findings, they conclude that there is an insignificant relationship between IV and expected returns.

4.3 Sample and Method

4.3.1 Sample

The sample includes all common listed firms on the SSE; data were sourced from the China Securities Market and Accounting Research (CSMAR) from November 1994 to November 2010. I exclude the period before 1994 because of the limited number of firms listed during that period. In order to be included in the sample, a firm must have at least three years of returns, size and book-to-market data. I deleted stocks with monthly returns greater than 100% to avoid the influence of extreme returns and any possible data recording errors. I exclude all financial institutions, closed-end funds and real estate firms; at the beginning of the sample period there are 155 firms which increased to 745 at the end of the sample period.

4.3.2 Momentum Trading Strategy

In this study, momentum returns are calculated using the methodology proposed by Jegadeesh and Titman (1993). I use the conventional 6-month formation period for the momentum trading strategy. A month is skipped between the formation and holding period to mitigate the bid-ask bounce effect. I exclude all those stocks in a portfolio with any missing values either during the formation or holding period. At the end of each month, t, all stocks are ranked in ascending order on the basis of their past 6-months' returns (t-6 to t-1). These rankings are used to form equal-weighted quintile portfolios where the top quintile portfolio (P1) is called the losers quintile and the bottom one (P5), the winners quintile. With the momentum trading strategy, I buy (sell) the winners (losers) quintile. The portfolios are held for K months (K= 3, 6, 9 and 12). Following Jegadeesh and Titman (1993), the portfolio monthly return for a K-month holding period is based on an equal-weighted average of portfolio returns from the strategies implemented in the current month and the previous K-1 months. To illustrate, the monthly return for a 6-month holding period is based on an equal-weighted average of portfolio returns from the strategy in the current month, and the strategies from 1, 2, 3, 4, and 5 months ago. This is equivalent to revising the weights of approximately one-sixth of the portfolio each month and carrying over the rest from the previous month. P5-P1 represents the return of the momentum trading strategy of buying the winners and selling losers.

4.3.3 Long-Term Reversal Strategy

Following McLean (2010), at the end of each month I rank all stocks in the sample based on their returns from month t-36 through t-7 and group them into equally weighted quintile portfolios based on their rank.[40] The rankings are used to form five equal-weighted quintile portfolios, where the top quintile portfolio (P1) is the losers quintile and the bottom one (P5) is the winners quintile. In the momentum trading strategy, I buy past winners and sell past losers but in the long-term reversal strategy, I buy past losers and sell past winners. The portfolios are held for 6 months (t+1 to t+6). Following McLean (2010), the portfolio monthly return for a 6-month holding period reversal strategy is based on an equal-weighted average of portfolio returns from strategies implemented in the current month and the previous 5 months. P1-P5 represents the return of the reversal trading strategy of buying the losers and selling winners.

4.3.4 IV Measurements

This section provides the different measures of IV estimation using three different models: volatility of residuals from the market model, volatility of residuals from the Fama-French three-factor model, and volatility of residuals from a market model with an additional lagged market factor. The first two models use monthly returns; the third model uses daily returns. Obviously, the daily calculation will produce a standard deviation roughly $1/\sqrt{12}$ the size of the monthly calculation. I also use total volatility of monthly returns for comparison.

[40] The measurement ends at month t-7 to avoid any overlap with the measure of the momentum trading strategy.

Market Model Monthly IV (IV-M)

Following McLean (2010) and Bali and Cakici (2008), I calculate IV using the market model residuals estimated from the regression:

$$r_{i,t} = \alpha_i + \beta_{i,t} r_{m,t} + e_{i,t} \tag{4.1}$$

where $r_{i,t}$ is the monthly return on stock *i*; $r_{m,t}$ is the monthly return on the SSE index; and $e_{i,t}$ is the regression residual. I estimate equation (4.1) for each stock on formation date using monthly data over the past 36 months. I calculate the IV for stock i as the time series standard deviation of e(i,t).[41]

Fama-French IV (IV-FF)

Following Arena et al. (2008), I calculate the Fama-French IV (IV-FF hereafter) using the standard deviation of the monthly residuals of the Fama-French three-factor regression of monthly returns over the 36 months before the portfolio formation date as an alternative measure of IV. I produce the residuals using the regression:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{i,1}(r_{m,t} - r_{f,t}) + \beta_{i,2} SMB_t + \beta_{i,3} HML_t + e_{i,t} \tag{4.2}$$

where $r_{i,t}$ is the monthly return on stock *i*; $r_{m,t}$ is the monthly return on SSE index; and $e_{i,t}$ is the regression residual. SMB is the small-minus-big size factor and, HML is the high-minus-low BTM factor.[42] I estimate the above regression given in equation (4.2) for each stock on the formation date using monthly data over the past 36 months. I calculate IV for stock i as the time series standard deviation of e(i,t).

Market Model Daily IV (IV-M)

Following Arena et al. (2008), Ali et al. (2003) and Wurgler and Zhuravskaya (2002), I calculate IV using the daily market model residuals (with additional market lag) estimated from the regression:

$$r_{i,t} = \alpha_i + \beta_{i,1} r_{m,t} + \beta_{i,2} r_{m,t-1} + e_{i,t,} \tag{4.3}$$

where $r_{i,t}$ is the daily return on stock *i*; $r_{m,t}$ is the daily return on the SSE index; $r_{m,t-1}$ is the lagged value of $r_{m,t}$; and $e_{i,t}$ is the regression residual. I estimate equation (4.3) for each stock on the formation date using daily data over the previous 12 months. I calculate IV for stock i as the time series standard deviation of e(i,t).

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[41] The market model monthly IV (IV-M) is the main IV measure in this chapter unless otherwise stated.

[42] See Appendix for the construction of Fama-French three factors.

Total Volatility (TOTV)

Following Arena et al. (2008), I calculate total volatility as the standard deviation of monthly returns over the 36-month period up to the portfolio formation date.

4.3.5 Descriptive Statistics

Panel A of Table 4.1 reports the summary statistics for the variables used in this study. The mean (median) IV-M of the firms in my sample is 10.82 (10.11), the mean (median) size is 7.72 (7.80), the mean (median) price is CNY10.28 (CNY8.20), the mean (median) TOTV is 14.95 (14.04) and the mean (median) CNY Volume is 19.68 (19.72). The number of firm-month observations for all the variables is 107,344.

Panel B of Table 4.1 reports the correlations between the variables in this study. The correlation between IV-M and IV-FF is 0.98, the correlation between IV-M and TOTV is 0.85 and the correlation between IV-M and IV-MM (IV-FF) is 0.68 (0.64). The smaller correlation between IV-M and IV-MM or IV-FF is consistent with Fink, Fink and He (2012) who show that IV measures are not highly correlated when using different measures (estimating using daily and monthly data) to estimate IV. The smaller correlation (0.68) between IV-M and IV-MM or IV-FF provides an indication that the relationship between IV and momentum or reversal might depend on the use of the IV measure. By contrast, the correlation between the different IV measures, except the correlation between IV-M and IV-MM or IV-FF, is consistent with McLean (2010) who reports that the different measures of IV are highly correlated using monthly data to estimate IV. All the IV measures are positively correlated with price, size and CNY volume. All correlations are significant at the 1% level.

Panels C, D and E of Table 4.1 report the time series means of all variables in this study within the momentum, reversal and IV quintiles. The quintiles are constructed each month and the monthly averages of the each quintile are averaged over the entire sample period. The difference between the high (winners, i.e., P5) and low (losers, i.e., P1) quintiles is reported as H-L (P5-P1) with respective t-statistics provided in parentheses.

For the momentum quintiles, Panel C shows that both winners (high past returns) and losers (low past returns) have relatively higher IV-M than other quintiles, consistent with McLean (2010). The other IV (IV-FF, IV-MM) and TOTV measures also show that the winners (P5) and losers (P1) have relatively high IV and total volatility. Inconsistent with Arena et al. (2008), I find that winners (losers) have higher (lower) market capitalization than the rest of the quintiles. The higher (lower) market capitalization for the winners (losers) suggests that momentum returns might be greater for small and big size stocks than for medium size stocks.

Consistent with Arena et al. (2008), share prices increase from the lowest quintile (losers) to the highest quintile (winners). This phenomenon of increasing prices is understandable because losers (P1) have lower returns than winners (P5) during the portfolio formation period. CNY volume increases from the lowest quintile (losers) to the highest quintile (winners). As CNY volume is one of the proxies for transaction costs, this implies that transaction costs of losers are higher than winners. The IV difference between the winners and losers (P5-P1) is statistically insignificant for IV-M and IV-FF but not for TOTV and IV-MM. However, price, size and CNY volume differences between winners and losers (P5-P1) are large and statistically significant. This phenomenon of small price, size and CNY volume for losers is understandable since stocks included in this quintile are considered more risky.

Panel D shows that for the reversal quintiles sorted on the past t-36 to t-7 month returns, winners (P5) have relatively higher IV-M than the other quintiles, contrary to McLean (2010) who reports high IV for the losers in the U.S. stock markets. The IV-FF and TOTV are also highest in the winners quintile (P5). However, IV-MM is highest in the losers (P1) consistent with McLean (2010). IV-M, IV-FF and TOTV show high IV for winners (P5) but the IV difference between winners and losers (P5-P1) is small though statistically significant.[43] Therefore, all IV measures and TOTV except IV-MM show that winners (P5) are more volatile than the other quintiles. Losers (P1) have the lowest size and price of all the quintiles. This is consistent with McLean (2010), Chopra et al. (1992) and Ball, Kothari, and Shanken (1995), who show that the profitability of reversal is limited to small and low-priced stocks. CNY volume increases from the losers (P1) quintile to the winners (P5) quintile. Since CNY volume is one proxy for transaction costs, this implies that transaction costs of the losers (P1) might be higher than for other quintiles. The price, size and CNY volume differences between winners and losers (P5-P1) are large and statistically significant.

Panel E of Table 4.1 shows that there is variation in IV across the firms in the sample. The average IV-M (IV-FF) in the low IV quintile is 7.10 (6.90) whereas the average IV-M (IV-FF) in the high IV quintile 16.70 (16.50). The variation in IV values between high and low (H-L) quintiles is large and statistically significant. Firm size monotonically decreases in the IV quintiles, inconsistent with Panel B results where I find size is positively correlated with IV. However, Panel B reports the correlation between size and IV for the full sample whereas Panel E reports the time series means of size for every month sorted on IV. Therefore, the different methodologies used in Panels B and E of Table 4.1 provides different results. IV and transaction costs are correlated if only firm size is used as a proxy for transaction costs since

[43] The second highest IV-MM is winners stocks.

smaller firms have higher IV and transaction costs than other firms. However, IV and transaction costs are not correlated when price and CNY volume are used as proxies for transaction costs since I find higher transaction costs among low IV quintiles (low price and CNY volume).

4.4 Main Results

4.4.1 Momentum and Reversal Measured via Different Weighting Schemes

This section uses different weighting schemes to test if arbitrage costs can affect the returns of the momentum trading strategy since the literature suggests that arbitrage costs can affect the profits of the momentum and long term-reversal trading strategies (see Arena et al., 2008; McLean, 2010). McLean (2010) argues that if limits to arbitrage are responsible for the persistence of momentum and reversal, then there would be larger momentum and reversal returns in firms with small size and high IV because they are more costly to transact and hold. Hence if the condition of limited arbitrage is valid, equal-weighted and IV-weighted portfolios should yield higher momentum and reversal returns than value-weighted portfolios.

Panels A, B and C, Table 4.2, report average monthly returns of equal-weighted, value-weighted and IV-weighted momentum portfolios for 3-, 6-, 9- and 12-month holding periods. The average monthly equal-weighted momentum returns (P5–P1) reported in Panel A range from 0.36% per month (12-month holding period) to 0.62% per month (6-month holding period) and are significant for all holding periods. I find larger momentum returns for all holding periods when I use decile portfolios (see Table 2.2). However, this chapter uses quintiles to make sure that enough stocks are available, especially when double sorting portfolios on momentum and IV and reversal and IV.

Panel B, Table 4.2, displays value-weighted momentum returns. To calculate the value-weighted momentum returns, I follow the same procedure as for the equal-weighted momentum returns in section 4.3.2 except that I invest money in stocks according to their market capitalization instead of equal money in all stocks. The average monthly value-weighted momentum returns range from 0.48% per month (12-month holding period) to 0.71% per month (9-month holding period) and are statistically significant for all holding periods. The value-weighted momentum returns shown in Panel B are somewhat larger than those of the equal-weighted momentum returns and are consistent with those reported in McLean (2010) for U.S. stocks. Consistent with McLean (2010) and Korajczyk and Sadka (2005), this study finds that the momentum winners effect is stronger in the equal-weighted portfolios, but the momentum losers effect is stronger in value-weighted portfolios. This means that the momentum returns in equal-weighted portfolios come from the winners' side (high winners' returns) whereas the momentum returns in value-weighted portfolios come mainly from the losers' side (low losers' returns).

Panel C, Table 4.2, shows the IV-weighted momentum returns. To calculate the IV-weighted momentum returns, I follow the same procedure as for equal-weighted momentum returns in section 4.3.2 except that I invest money in stocks according to their IV weights instead of equal money in all stocks i.e., a stock with higher IV gets more weight than a stock with smaller IV. The average monthly IV-weighted momentum returns range from 0.18% per month (3-month holding period) to 0.47% per month (9-month holding period) and, except for the 3-month holding period, are statistically significant for all holding periods. Consistent with McLean (2010), I find that IV-weighted momentum returns are smaller than equal- and value-weighted momentum returns, which suggests that IV does not limit arbitrage opportunities. The returns of equal-weighted, value-weighted and IV-weighted momentum portfolios remain unchanged after adjusting for the Fama-French three factors.

The results in Panels A, B and C, Table 4.2, are inconsistent with IV explaining the persistence of momentum returns since the returns of value-weighted portfolios are greater than equal- and IV-weighted portfolios. However, this does not mean that the profitability of the momentum trading strategy cannot be explained by limits to arbitrage because it could be the transaction costs that limit arbitrageurs from correcting the mispricing of the momentum trading strategy.

Panel D, Table 4.2, displays the equal-weighted, value-weighted and IV-weighted returns for the long-term reversal portfolios. The returns of the reversal portfolios are positive and significant for all weighting schemes. However, the reversal returns (P1- P5) of the value-weighted (0.35% per month) portfolios are small compared with equal- (0.72% per month) and IV-weighted (0.79% per month) reversal portfolios. These results are consistent with the condition of limited arbitrage since larger weights for high cost stocks (small size stocks) results in higher returns.

The equal- and value-weighted returns of the reversal portfolios are consistent with McLean's (2010) results for U.S. stocks. However, the results for IV-weighted reversal portfolios differ from McLean (2010) since he finds much higher returns for IV-weighted reversal portfolios; I find similar results for both equal- and IV-weighted reversal portfolios. My results are consistent with the condition of limited arbitrage but it could be that transaction costs prevent arbitrageurs from correcting reversal mispricing since the result of equal- and IV-weighted portfolios are similar. I return to this issue in section 4.5.4. All returns of the equal-weighted, value-weighted and IV-weighted reversal portfolios remain unchanged after adjusting for the Fama-French three factors.

Panels E and F, Table 4.2, report the profitability of momentum and reversal within the subsamples sorted on the basis of firm size, respectively. The literature is mixed about the existence of momentum and reversal returns in size-sorted portfolios. Lesmond et al. (2004) find that momentum returns are weak in small stocks but Fama and French (2012) report higher momentum returns for small stocks. Clare and Thomas (1995) report that reversal returns are limited to small firms, but Arnold and Baker (2007) report reversal returns both in small and large stocks. So I implemented momentum and reversal strategies on stocks with five size-based subsamples (S1, S2, S3, S4 and S5). I define size as the market capitalization of each stock at portfolio formation date. At the beginning of each month, I sort stocks into size quintiles, S1 to S5. Within each size quintile, I further sort into quintiles based on returns from t-6 to t-1 (for momentum) and t-36 to t-7 (for reversal) and determine momentum and reversal returns in the usual way.

I find large, statistically significant momentum returns in S1 (small), S4 and S5 (large). However, the momentum returns of S3 are significant but small and the momentum returns of S2 are -0.30% per month, which is statistically significant.[44] My size-based momentum returns are consistent with Hameed and Kusnadi (2002), who report comparatively smaller insignificant momentum returns for medium-size portfolios than for small- and large-size portfolios of Asian stocks. Except for S5, the reversal returns in Panel F, Table 4.2, are statistically significant for all size-based quintiles. However, reversal returns are strongest (0.83% per month) in S1 (small), which implies a small-firm effect in reversal returns. This also suggests that reversal returns might be the result of limited arbitrage due to transaction costs because the transaction costs of small size stocks are likely higher than for other stocks.

Consistent with McLean (2010), the results in Table 4.2 show that the profitability of momentum and reversal strategies is not part of the same phenomenon since the momentum effect is somewhat stronger in the smallest and two largest size quintiles whereas the reversal effect is strongest in the smallest size quintile and generates negative though insignificant returns for the largest size quintile. Hence, my findings do not support the findings of

[44] The results reported here are with 6-month holding period. I find a similar trend with 3-, 9- and 12-month holding periods.

Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999) who argue that the profitability of momentum and reversal strategies is part of the same phenomenon.[45]

4.4.2 Cross-Sorted Momentum and Reversal Portfolios based on IV

Table 4.3 presents momentum and reversal returns for IV-sorted portfolios. The purpose of cross-sorting momentum and reversal portfolios on IV is to test if IV can explain momentum and reversal returns since the literature links IV with limited arbitrage. At the beginning of each month, I sort stocks independently into quintiles based on the returns from t-6 to t-1 (for momentum), t-36 to t-7 (for reversal) and IV. The quintile with lowest past returns and lowest IV values (highest past returns and lowest IV values) is described as "low IV loser portfolio" ("low IV winner portfolio"). The quintile with lowest past returns and highest IV values (highest past returns and highest IV values) is described as "high IV loser portfolio" ("high IV winner portfolio"). Momentum (long-term reversal) returns for each IV portfolio are referred to as "P5-P1" ("P1-P5"). The last column (High-Low) reports the difference in momentum (reversal) returns between high and low IV quintiles.

The results in Panel A, Table 4.3, are consistent with those reported in Table 4.2 and provide further evidence that the returns of the momentum trading strategy do not strengthen with IV (see Figure 4.1). The difference in momentum returns between high and low IV portfolios ranges from -0.01% per month (3-month holding period) to -0.18% per month (9-month holding period) but is statistically insignificant for all holding periods. The returns of the momentum trading strategy for different holding periods are positive in all IV-based quintiles. However, the returns are significant for the low IV quintile (all holding periods), 2nd IV quintile (all holding period), 3rd IV quintile (6-month holding periods), 4th IV quintile (3-, 6- and 9-month holding periods) and high IV quintile (3-, 6- and 9-month holding periods). The returns of the momentum trading strategy based on IV remain almost unchanged after adjusting for the Fama-French three factors, except for small changes in statistical significance.

The results in Panel A, Table 4.3, show that the momentum effect is somewhat weak in the third, fourth and high IV quintiles compared with the first and second IV quintiles. McLean (2010) shows that if arbitrageurs are deterred by IV, then the momentum returns of low IV stocks should be weak because low IV stocks should get far greater arbitrage resources. My results are inconsistent with the suggestion that IV limits arbitrage because the momentum

[45] I used size of each stock at time t (portfolio formation date) to calculate the momentum and reversal returns based on size. In addition, I hold both momentum and reversal portfolios for 6 months.

returns are weak for medium and high IV portfolios. My results are consistent with McLean (2010) who shows that IV is not related to momentum returns.

Panel B, Table 4.3, shows that the average monthly returns for the long-term reversal strategy are positive and statistically significant for all IV-based quintiles (see Figure 4.1), which is inconsistent with McLean's (2010) study that shows that reversal returns exist only in high IV stocks. I find that the average monthly reversal returns for all IV quintiles range from 0.59% (low IV quintile) to 0.94% (4th and high IV quintiles). The small differences in reversal returns across IV quintiles are consistent with the small value-weighted reversal returns reported in Panel D, Table 4.2. Reversal returns seem to be related to firm size since 47.50% of firms in low IV quintile are from largest 40% of size-based firms and the proportion of small and medium size stocks is low (results not reported).[46] Fama-French adjusted returns for all the IV quintiles are similar to the raw returns and are statistically significant. The difference in monthly reversal returns between high and low IV quintiles is 0.35% but statistically insignificant.

I find that the difference of reversal returns among high IV-losers (1.79% per month) and low IV-losers (1.60%) is small compared with McLean's (2010) study that shows that high IV losers earn much larger returns than low IV losers. Similarly, I find that the difference of reversal returns among high IV winners (0.85% per month) and low IV winners (1.01% per month) is also smaller than in McLean's (2010) study that shows that high IV winners earn much lower returns than low IV winners. Therefore, it is evident that the IV effect is not prevalent both in the long and short positions of the reversal portfolio.

The effect of IV on long and short positions is inconsistent with the findings of Duan, Hu, and McLean (2009, 2010). Duan et al. (2010) show that the highly shorted stocks earn low subsequent returns only for stocks with high IV, whereas I find that the lower returns of IV-reversal winners (short side) are not limited to the high IV quintile. Duan et al. (2009) find that only those stocks bought by mutual funds earn high future returns that belong to the high IV group, whereas I find that the higher returns of IV-reversal losers (buy side) are not limited to the high IV quintile.

The results in Table 4.3 do not support the argument that IV prevents arbitrage in momentum and long-term reversal portfolios. However, the profitability of momentum and reversal strategies might persist due to limited arbitrage caused by transaction costs.

[46] Small stocks generate larger reversal returns. Therefore, excluding the number of small size stocks in a portfolio would result in smaller reversal returns.

4.5 Robustness Tests

This section examines the robustness of the results reported in Table 4.3 after excluding small and low-priced stocks, using alternative proxies to estimate IV and using alternative sorting and number of portfolios (tercile versus quintile). At the beginning of each month, the momentum and reversal portfolios are cross-sorted into IV. For all the robustness tests, I use only the conventional 6-month holding period for the momentum trading strategy.

4.5.1 The Exclusion of Small and Low-Priced stocks

In this section, I exclude small and low-priced stocks to ensure that the results are not driven by small and illiquid stocks or by the bid-ask bounce and report the results in Table 4.4.[47] Following McLean (2010), I consider two sample adjustments at the beginning of the holding period: (i) stocks priced below CNY1, and (ii) stocks either priced below CNY1 or with a market capitalization that places them in the lowest size decile.[48]

Table 4.1 shows that the total sample contains 107,344 firm-month observations. If I exclude stocks priced below CNY1, I lose 1.5% of the sample; most of these firms belong to the medium and high IV quintiles. If I exclude stocks that are either priced below CNY1 or in the smallest size decile, I lose 10.50% of the sample. Exclusion (ii) eliminates 12% of the firms in the high IV quintile and 10% of the firms in the low IV quintile. Exclusion (ii) affects each IV quintile but exclusion (i) mostly affects medium and high IV quintiles. It appears that the exclusion of low-priced and small size stocks does not affect any specific quintile, which is inconsistent with McLean's (2010) study that shows that excluding low-priced and small stocks eliminates 80% of the firms in the high IV quintile of U.S. firms.

4.5.1.1 Momentum Returns

The P5-P1 row in Panel A, Table 4.3, shows that the momentum returns (6-month holding period) are positive and significant for all IV quintiles, suggesting that the momentum effect cannot be explained by IV. Panels A and B, Table 4.4, show momentum returns based on IV with exclusions (i) and (ii), respectively. Panel A shows that even with the exclusion of stocks priced below CNY1, momentum returns are still positive for all IV quintiles, and statistically significant except the third IV quintile. With exclusion (ii), the momentum effect shown in Panel B is still significant in the two lowest and high IV quintiles. This shows that momentum returns decrease with exclusions (i) and (ii), which is inconsistent with Hong et al.'s (2000)

[47] Conrad and Kaul (1993)find that much evidence of long horizon means reversions in DeBondt and Thaler (1985) disappears when low-prices stocks are excluded .

[48] Stock prices in SSE, China, are small and the mean stock price is CNY10.50. Hence it is reasonable to exclude only stocks priced below CNY1. Chen et al. (2010) exclude stocks below CNY1.

study that shows negative momentum returns for small size and low-priced stocks. However, these results are consistent with the size-based momentum returns reported earlier in Table 4.2. The robustness test in Table 4.4 confirms the results in Panel A, Table 4.3, that IV does not limit arbitrage opportunities to eliminate momentum returns. The Fama-French adjusted returns for all the momentum portfolios based on IV are similar to the raw returns even with exclusions (i) and (ii) except the alpha of low IV with exclusion (ii) that is insignificant.

4.5.1.2 Reversal

The full sample results in Panel B, Table 4.3, show that the reversal effect is prevalent in all IV quintiles. Panels C and D, Table 4.4, show reversal returns based on IV with exclusions (i) and (ii). The results reported in Table 4.3 survive with exclusions (i) and (ii). However, reversal returns of all IV quintiles become somewhat stronger with exclusion (ii), which appears to be inconsistent with the low value-weighted reversal returns reported in Panel D, Table 4.2. However, I find that reversal returns are larger among small size stocks except the lowest size decile (results not reported).

In summary, the exclusion of low-priced and small size stocks does not appear to affect any specific quintile. However, the momentum returns of almost all IV quintiles become weaker than the results (6-month holding period) reported in Panel A, Table 4.3. In contrast, reversal returns appear to be somewhat stronger with exclusions (i) and (ii), which agrees with the weak reversal returns among very small stocks (results not reported).

4.5.2 Alternative Specification of IV

In the previous tests, following McLean (2010), I estimate IV (V-M) as the standard deviation of the monthly residuals from a regression of monthly stock returns on the monthly returns of the SSE index over the past 36 months. However, in this section, I will estimate IV using three alternative specifications seen in the literature. The purpose of using alternative specifications to estimate IV is to test whether my results are robust to the other measures of IV because Bali and Cakici's (2008) results indicate that there is no robust relationship between IV and expected returns. Table 4.5 reports the results using different specifications for IV and TOTV.

4.5.2.1 Fama-French IV (IV-FF)

In this section, I repeat my analysis using the standard deviation of the residuals of the Fama-French three-factor regression of monthly returns over the 36 months before the portfolio formation date as an alternative measure of IV (see section *4.3.4* for a detailed description).

Panels A and B, Table 4.5, present the average monthly momentum and reversal returns based on the Fama-French IV. The returns of both the momentum and reversal trading strategies are quite close to those reported in Table 4.3. The difference in momentum and reversal returns across IV quintiles is insignificant and these results confirm the earlier findings that IV is not related to momentum and reversal.

4.5.2.2 Market model Daily IV (IV-MM)

Following Arena et al. (2008), Ali et al. (2003) and Wurgler and Zhuravskaya (2002), I calculate IV using the standard deviation of market model (with additional market lag) daily residuals over the previous 12 months (see section *4.3.4* for a detailed description).[49]

Arena et al. (2008), using IV-MM, find that stocks with high IV display greater momentum returns than stocks with low IV. However, my results (Panel C, Table 4.5) are similar to the results in Panel A, Table 4.3, and show that IV is not related to momentum returns.

Surprisingly, when I use IV-MM, reversal returns (Panel D, Table 4.5) of the highest IV quintile increases to 1.34% per month compared with the returns reported in Panel B, Table 4.3 (0.94% per month). The difference in reversal returns (Panel F, Table 4.5) between the high and low IV quintiles becomes 0.94% and is statistically significant (*t*-statistic = 3.83). This suggests that the reversal returns based on IV-M reported in Panel B, Table 4.3, are not robust to changes in IV estimation. This argument is consistent with the findings of Bali and Cakici (2008) who show that the existence and significance of the relationship between IV and expected returns is not robust to the different data frequencies used to estimate IV (monthly versus daily). However, the IV measure obtained from monthly data is more reliable than the IV measure obtained from daily data.

4.5.2.3 Total volatility (TOTV)

I also use total volatility (TOTV) of monthly returns as a comparison with IV. I calculate TOTV as the standard deviation of monthly returns over the 36-month period before portfolio formation. Arena et al. (2008) also use total volatility as a robustness test, but they use daily returns over the past year to estimate it.

Panels E and F, Table 4.5, report the average monthly momentum and reversal returns based on total volatility. Recall that Panel A, Table 4.3 (6-month holding period), showed that momentum returns are greatest for the second and low IV quintiles. However, when I use TOTV, the momentum returns of the high TOTV quintile (1.17% per month) become

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[49] Daily data are considered noisy. Bali and Cakici (2008) document that the IV measure obtained from monthly data is more reliable than the IV measure obtained from daily data.

stronger. The difference in momentum returns between the high and low TOTV quintiles also becomes positive (0.33% per month) but statistically insignificant. Reversal returns become stronger for low and high TOTV quintiles when I use TOTV, but the differences in reversal returns between high and low TOTV quintiles are still small and insignificant. The use of TOTV as a robustness test also shows that both IV and total risk are not related to momentum and reversal. However, momentum returns are largest in the high TOTV quintile, rather than the second IV quintile (Panel A, Table 4.3).

4.5.3 Alternative Sorting and Portfolio Schemes

In all previous tests, I use independent sorting for IV, momentum and reversal. There are some benefits of independent sorting since it includes a firm in a portfolio irrespective of its ranking on the other variable. However, using independent sorting sometimes leaves a small number of stocks in one portfolio and large number of stocks in another portfolio. In contrast, dependent sorting ensures that the results are not driven by a portfolio with a small number of stocks because all portfolios have an equal number of stocks over the same holding period. Therefore, in this section (Panels A and B, Table 4.6), I use dependent sorting as a robustness test.[50]

Arena et al. (2008) report greater momentum returns for high IV stocks using tercile portfolios for IV and decile portfolios for momentum. The advantage of tercile portfolios is the availability of a sufficiently large number of stocks in each portfolio but the disadvantage is that it cannot provide a clear picture about the tail values compared with quintile or decile portfolios. However, in this section (Panels C and D, Table 4.6), I sort stocks into tercile portfolios based on IV and decile portfolios based on past returns t-6 to t-1, for momentum and t-36 to t-7 for reversal, to test whether my results are robust to the portfolio scheme used by Arena et al. (2008).

In Panels E and F of Table 4.6, I report the results with stocks sorted into IV terciles and momentum and reversal quintiles. The advantage of this is to ensure that there are enough stocks in each portfolio; this scheme results in only 15 portfolios compared with 25 portfolios (30 portfolios) for the IV and momentum or reversal quintiles (IV terciles and momentum or reversal deciles), respectively.

Panel A, Table 4.6, shows that momentum returns of each IV quintile are quite close to those reported in Panel A, Table 4.3, when I double sort stocks, first on IV and then each IV

[50] I use dependent sorts only in Panels A and B, Table 4.6.

quintile on past 6-month returns. The difference in momentum returns between the high and low IV quintiles is very similar to those shown in Panel A, Table 4.3.

Panel B, Table 4.6, reports the reversal returns for quintiles sorted on IV with dependent sorts. The results in Panel B are inconsistent with the results shown in Panel B, Table 4.3. The reversal return of the lowest IV quintile becomes insignificant in dependent sorts but the returns in other quintiles remain significant. More importantly, the difference in reversal returns between high- and low-IV quintiles is positive and significant, which is inconsistent with the results reported in Table 4.3. This highlights a shortcoming of the portfolio-sorting technique especially in emerging markets which typically have relatively small numbers of stocks. In such markets, the choice of the sorting procedure could play a critical role in determining the relationship between IV (and possibly other firm characteristics) and cross-sectional stock returns.

In the next four Panels, I test the effect of changing the number of portfolios used in the analysis. Panels C and D, Table 4.6, report the average monthly momentum and reversal returns for IV terciles and the momentum and reversal deciles. At the beginning of each month, stocks were sorted into IV terciles and past return deciles. The past returns and IV were sorted independently. In Panels E and F, I use IV terciles and momentum or reversal quintiles.

Panel C, Table 4.6, shows that momentum returns for the low IV tercile double (1.63% per month) compared with the 6-month holding period returns of the low IV quintile reported in Panel A, Table 4.3 (0.79% per month). The momentum returns of the second (0.69% per month) and high IV (0.93% per month) terciles are also large and statistically significant. The large increase in momentum returns with IV terciles and momentum deciles appears to be related to the decile sort of momentum since I find that momentum returns are large in the decile sort compared with the quintile sort (see Table 2.2). Interestingly, the difference in momentum returns between the high and low IV terciles decreases to -0.70 % per month (*t*-statistic = -3.54) compared with the insignificant -0.07% per month (*t*-statistic = -0.34) between the high and low IV quintiles (6-month holding period) reported in Panel A, Table 4.3. Therefore, these results indicate that momentum returns become larger and statistically more significant with decile sorts on past 6-month returns. The larger momentum returns of the low IV tercile might be related to the size effect instead of low IV since I find that the average market capitalization for low IV stocks is CNY6078 million compared with CNY5665 million for medium IV and CNY4363 for high IV stocks. This argument is consistent with the momentum returns of size-based terciles where the momentum returns of big size terciles are larger than small and medium size terciles (see Table 2.6). These results also suggest that the existence and significance of a relationship between IV and momentum depends on the breakpoints used to sort stocks into portfolios since I find an insignificant difference between high and low IV quintiles (Panel A, Table 4.3) when I sort stocks into IV and momentum quintiles but a significant difference between high and low IV terciles when I sort stocks into IV terciles and momentum deciles.

Panel D, Table 4.6, shows that reversal returns of the high IV tercile increases to1.34% per month when I sort stocks into IV terciles and reversal deciles compared with the reversal returns of the high IV quintile (0.94% per month) reported in Panel B, Table 4.3. Reversal returns of the second (0.44% per month) and low IV (0.51% per month) terciles are insignificant compared with the significant results for all quintiles shown in Panel B, Table 4.3 Surprisingly, the difference in reversal returns between the high and low IV terciles increases to 0.83 % per month (*t*-statistic = 2.48) compared with the insignificant 0.35% per month (*t*-statistic = 1.57) between the high and low IV quintiles reported in Panel B, Table 4.3. These results indicate that the reversal returns of the high IV tercile becomes larger and statistically significant than the reversal returns of high IV portfolio reported in Panel B, Table 4.3. However, there is a small decrease in reversal returns in the low and second IV terciles. These results also indicate that the significance of a relationship between IV and reversal depends on the breakpoints used to sort stocks since I find an insignificant difference between high and low IV quintiles (Panel B of Table 4.3) but a significant difference between high and low IV terciles when I sort stocks into IV terciles and reversal deciles. The results in Panels C and D, Table 4.6 are consistent with the findings of Bali and Cakici (2008) who find that the relationship between IV and expected returns is not robust to different breakpoints used to sort stocks into portfolios.

Panels E and F, Table 4.6, report average monthly momentum and reversal returns based on IV terciles and momentum and reversal quintiles instead of momentum and the reversal deciles used in Panels C and D. At the beginning of each month, stocks are independently sorted into terciles based on their IV ranking and into quintiles based on the past returns of momentum (t-6 to t-1) and reversal (t-36 to t-7).

Panel E, Table 4.6, shows that momentum returns for the low IV tercile (0.98% per month) are somewhat higher than the momentum returns of the low IV quintile (0.79% per month) reported in Panel A, Table 4.3 (6-month holding period). However, the momentum returns of the high IV tercile falls to 0.55% per month, when I sort stocks into IV terciles, from 0.72% per month reported in Panel A, Table 4.3. Interestingly, the difference in momentum returns between the high and low IV terciles decreased to -0.44 % per month (*t*-statistic = -3.81) from the insignificant -0.07% per month (*t*-statistic = -0.34) for the 6-month holding period reported in Panel A, Table 4.3. These results also indicate that the existence and significance of a relationship between IV and momentum depends on the different breakpoints used to sort stocks into portfolios since I find an insignificant difference between high and low IV quintiles (Panel A, Table 4.3) but a significant difference between the high and low IV terciles. This argument is also consistent with the findings of Bali and Cakici (2008), who find that the relationship between IV and expected returns is not robust to different breakpoints used to sort stocks into portfolios.

The reversal returns of the IV terciles in Panel F, Table 4.6, become larger than the returns of the IV quintiles reported in Panel B, Table 4.3. The increases in reversal returns suggest that a change in the number of IV portfolios affects the reversal returns.

The results reported in Table 4.3 show that IV is not related to momentum and reversal. In the robustness tests, I find that the existence and significance of a cross-sectional relationship between IV and momentum or reversal changes with the different IV measures, sorting methods and different number of IV portfolios (tercile versus quintile). On balance, these results suggest that IV is not related to momentum and reversal. These results are consistent with the findings of Bali and Cakici (2008), who find that the relationship between IV and expected returns is not robust to different portfolio-weighting schemes, different data frequency to estimate IV and breakpoints used to sort stocks into portfolios.

4.5.4 Regression Analysis

The results in the previous sections show that momentum and reversal profits persist not because of the holding costs (proxied by IV) limiting arbitrage opportunities. However, it is possible that transaction costs could be the limiting factor since the literature suggests that mispricing should be greatest in firms with high transaction costs (see Pontiff, 1996; Shleifer and Vishny, 1997). Lesmond et al. (2004) find that stocks included in a momentum trading strategy are usually stocks with the highest transaction costs and momentum returns disappear once transaction costs are included. Jordan (2009) also find that the profits of long-term reversal strategies disappear once transaction costs are included.

Therefore, in this section I conduct Fama-MacBeth cross-sectional regressions (Fama and MacBeth, 1973) to test the relationship of momentum and reversal with IV, transaction costs and other explanatory variables.[51] I use firm size, price and CNY volume as transaction cost proxies.[52] These three proxies might capture some other effects but the common factor among them is their ability to quantify transaction costs. McLean (2010), Duan et al. (2010), Ali et al. (2003) and Pontiff (1996) use firm size as a transaction cost proxy. Pontiff (1996) reports that smaller stocks are more illiquid, have higher bid-ask spread and larger price impacts. Firm size is measured as the natural logarithm of market value at the end of the previous month. Price is used as a transaction cost proxy by Duan et al. (2010), Ali et al. (2003) and Pontiff (1996). Pontiff (1996) argues that low-priced stocks are more expensive to trade than high-priced stocks. Following Pontiff (1996), I use the inverse of the share price at the end of the previous month as a proxy for transaction cost. Duan et al. (2010) and Spiegel and Wang (2006) use dollar volume as another proxy to measure transaction cost.[53] Spiegel and Wang (2006) report that dollar volume is the only significant liquidity measure based on their multivariate test for illiquidity measures that also includes IV among other measures of liquidity. I use CNY volume as another transaction cost proxy. CNY volume is measured as the average volume over the previous month multiplied by the closing share price. Following Spiegel and Wang (2006), CNY volume is measured as the natural logarithm of CNY volume over the previous month.

The regression variables also include MOM, REV, IV and BTM along with proxies for transaction costs. MOM is the past return over t-6 to t-1months and REV is the past return over t-36 to t-7 months. BTM is measured as the natural logarithm of the book value of equity of the previous fiscal year divided by the end of previous month's market capitalization. I also include some interaction terms to find the effect of high IV and high transaction costs on the profitability of the momentum and reversal trading strategies. For interaction terms, I create dummy variables for IV, price, size and volume. IV is equal to one if a firm is in the highest IV quintile, otherwise zero. As a robustness test, I interact momentum and reversal with the high IV dummy variable. For transaction costs, I create dummy variables for low price, small size and low CNY volume. Price, size, and CNY volume are equal to one if a firm is in the lowest price, smallest size and lowest CNY volume quintiles, respectively, otherwise zero.

[51] I run the Fama-MacBeth cross-sectional regressions for the full sample (1994-2010) and before the Global financial crisis (1994-2007). The results of Fama-MacBeth cross-sectional regressions before the Global financial crisis are qualitatively similar with the full sample results and show that IV cannot explain momentum and reversal. For the brevity's sake, I do not produce the results before Global financial crisis.

[52] CNY volume is measured as the average volume traded in the previous month multiplied by the closing share price expressed in Chinese Yuan (CNY).

[53] Dollar volume as the prices are in U.S. dollars.

The dependent variable in each regression is the average monthly return over the subsequent six-months (t+1 to t+6), skipping month t. Table 4.7 presents the cross-sectional regression results. The first regression in Panels A and B establishes the base results. The coefficient for size (BTM) is negative (positive) and both are significant, which is consistent with Fama and French (1992). The coefficients for momentum (reversal) is positive (negative) and both are significant, which is consistent with the results reported earlier in Table 4.2.[54]

4.5.4.1 Momentum Regression Results

Panel A, Table 4.7, confirms the findings in Tables 4.2 and 4.3 that there is a statistically significant momentum effect in all regression equations. However, the momentum effect is weaker in high IV firms than in low IV firms, consistent with the results reported in Panel A of Table 4.3. For example, in regression 2, the high IV momentum interaction coefficient (MOM*HIGH IV) is -0.055 (*t*-statistic = -3.12), but the momentum coefficient in regression 2 is 0.064 (*t*-statistic = 2.44). The MOM*HIGH IV coefficient values and t-statistics are similar in the other regressions. The weak momentum returns in high IV firms is consistent with McLean's (2010) findings that shows weak momentum returns for high IV firms compared with other firms for the U.S. sample. I also find a negative but insignificant relationship between IV and the subsequent 6-month returns, consistent with Ang et al. (2006, 2009) and McLean (2010).

Regression 3 shows that the profitability of the momentum trading strategy is strong among small stocks but statistically insignificant. Regressions 4 and 5 show a linear relationship between transaction costs and subsequent 6-month returns. The coefficient of the inverse price is 0.028 (*t*-statistic = 1.67) and it shows that subsequent 6-month returns increase with decreasing prices, consistent with the findings of Pontiff's (1996) study that shows stronger mispricing among the low-priced assets because they are costly to trade. Regression 4 shows that momentum returns are stronger in low-priced firms but statistically insignificant. Regression 5 shows that the coefficient of CNY volume is -0.002 (*t*-statistic = -3.10) and is statistically significant, which is consistent with Spiegel and Wang (2006) who show that low dollar volume firms have higher future returns. The interaction effect coefficients for all three transaction cost proxies, though positive, are insignificant which indicates that the momentum effect does not strengthen with transaction cost, contrary to the view that transaction cost limits arbitrage. These results are inconsistent with the findings of Hong et al. (2000), Lesmond et al. (2004) and McLean (2010) for the U.S. markets, which highlights the importance of verifying in emerging markets results taken from mature markets.

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[54] Momentum in regression 1 is significant at the 10% level.

4.5.4.2 Reversal Regression Results

Panel B of Table 4.7 confirms the findings shown in Tables 4.2 and 4.3 that there is a strong reversal effect but it is not related to IV. The coefficient for high IV reversal (REV*HIGH IV) is statistically not different from zero in all the regressions, which is inconsistent with McLean's (2010) findings that show that reversal is stronger in high IV firms. The difference in the results between my study and McLean's (2010) one appears to be related to the difference in reversal portfolio characteristics between the two studies. McLean's (2010) results (Panel B, Table 1 in his study) indicate the possibility of higher reversal returns for smaller stocks and previous studies document a negative relationship between IV and firm size. However, my results in Panel D, Table 4.1, do not indicate a major size difference across reversal quintiles.

Regressions 3, 4 and 5 show that reversal is related to transaction costs especially when I use CNY volume as a proxy for transaction costs. Regressions 3 and 4 show that reversal is stronger in small size and low-priced stocks but statistically insignificant. Regression 5 shows that reversal is limited to low CNY volume firms (firms with high transaction costs). In regression 5, the reversal coefficient is insignificant, but the low CNY volume reversal coefficient (REV*LOW CNY VOLUME) is -0.155 (*t*-statistic = -3.78). This shows that reversal is stronger in low CNY volume firms because low CNY volume firms have higher transaction costs. This argument is consistent with the findings reported in Jordan (2009), which show that transaction costs limit arbitrage opportunities and reversal profits disappear once transaction costs are included.

In summary, the results in Table 4.7 show that neither IV nor transaction costs are related to the profitability of the momentum trading strategy. However, the profitability of reversal might persist because of transaction costs since they serve to limit arbitrage of its profits. This argument is consistent with the findings in Jordan (2009) that show that there are cross-sectional relationships between transaction costs and reversal profits.

4.6 Conclusions

This chapter examines the relationship between IV and returns of momentum and reversal based trading strategies. To my knowledge, this is the first study that examines the relationship of IV with momentum and reversal in the largest emerging market, China. Given that China is the world's fastest growing major economy and is expected to be the largest economy in the world by 2041, it is imperative for the global investment community to gain a deeper understanding of its financial markets.

I find that the returns of a momentum trading strategy are not related to IV. This is consistent with McLean's (2010) study that shows that momentum returns are not the result of limited arbitrage due to IV. Using size, price and CNY volume as proxies for transaction costs, I find that momentum returns are also unrelated to transaction costs. Therefore my findings do not support the view that momentum returns persist because of limits to arbitrage due to IV and transaction costs. In addition, I find that medium size stocks (second and third size quintiles) have small momentum returns, consistent with Hameed and Kusnadi (2002) who find the lowest momentum returns for medium size stocks. I suggest that momentum in the largest emerging market is not pervasive and may be driven by firm specific characteristics like size.

In contrast to the findings of McLean (2010), I do not find any relationship between reversal returns and IV since the reversal returns of all IV quintiles are large and statistically significant. The difference in the results between my study and that by McLean (2010) appears to be related to the firm size effect since McLean's (2010) results indicate the possibility of higher reversal returns for smaller stocks and the literature documents a negative relationship between IV and firm size. Therefore, my findings contradict the claim that IV is limiting arbitrage among reversal stocks. However, transaction costs might be limiting arbitrage for reversal stocks. I find that reversal is stronger in stocks with high transaction costs especially when I use CNY volume as a proxy for transaction costs. This argument is supported by Jordan's (2009) study that shows that transaction costs limit arbitrage opportunities and reversal profits disappear once transaction cost are included.

My findings that suggest that IV is not related to momentum and reversal returns are robust to the exclusion of low and small size stocks. However, the results of the robustness tests that use other proxies to measure IV and sorting methods indicate that the choice of the proxy used for IV, the sorting methods and number of portfolios (tercile versus quintile) play critical roles in determining the existence and significance of a relationship between IV and momentum or reversal. The reversal returns difference between high and low IV portfolios becomes larger and statistically significant when I use the IV-MM to estimate IV. I also find that the difference across reversal returns of high and low IV firms becomes statistically significant when I sort stocks into IV terciles and reversal deciles. My findings suggest that there is no robust relationship between IV and momentum or reversal. These findings also appear to be consistent with Bali and Cakici (2008) who find an insignificant relationship between IV and expected returns when they account for the data frequency used to estimate IV, weighting-scheme used to calculate portfolio returns (equal or value-weighted), breakpoints used to sort stocks into portfolio and the use of low and small price filters.

Barberis et al. (1998), Daniel et al. (1998) and Hong and Stein (1999) argue that momentum and reversal are part of the same phenomenon since momentum creates the subsequent reversal. However, I find that momentum and reversal are each strongest in different types of stock; momentum returns (6-month holding period) are strongest in the smallest and two largest size quintiles but weak in the second and non-existent in the third size quintiles. Momentum returns (6-month holding period) are also strongest in the low, second and high IV quintiles but comparatively weak in the other two IV quintiles. Reversal (6-month holding period), on the other hand, is strong in all size-based quintiles except in the high size quintile and also arises in all five of the IV quintiles. Therefore, my findings are consistent with McLean's (2010) study that suggests that momentum and reversal are generated by different underlying processes and are not part of the same phenomenon.

My study contributes to the existing finance literature by highlighting the fact that the findings of McLean (2010) and Arena et al. (2008) for U.S. stocks cannot be fully generalized to the other markets, especially emerging markets, since I find that IV is not related to either momentum or reversal in the world's largest emerging market. My results indicate that there is no significant robust relationship between IV and momentum or reversal when I account for different IV measures, sorting methods and number of portfolios (tercile or quintile portfolios). This chapter also finds that reversal and momentum are not part of the same phenomenon and suggests that each effect is strongest in different kinds of stocks. It also finds that both momentum and reversal are profitable in the world's largest emerging market and, therefore, investors could have earned profits using these strategies for investment. Another contribution of my study is that reversal profits are greatest among stocks with the highest transaction costs and therefore future research could emphasize this aspect of reversal.

Table 4.1
Descriptive Statistics

This table reports the summary statistics for the arbitrage cost variables used in this study. Panel A reports the statistics for the entire sample and Panel B shows the correlation matrix (Spearman Correlation Coefficients). Panels C, D and E report mean values across momentum, long-term reversal and IV quintiles. The momentum (reversal) quintiles are formed each month by sorting stocks on past returns from *t*-6 to *t*-1 (*t*-36 to *t*-7) months. Idiosyncratic volatility (IV-M) is the standard deviation of the monthly residuals from using market model over the past 36 months (see section 4.3.4 for a detailed description). IV-FF is the standard deviation of the monthly residuals from using the Fama-French model regression over the past 36 months (see section 4.3.4 for a detailed description). IV-MM is the standard deviation of the residuals from using the daily returns over the past 12 months (see section 4.3.4 for a detailed description). Total Volatility is the standard deviation of monthly returns over the past 36 months. Size is the natural logarithm of firm market value at the end of the previous month. CNY VOLUME is the average daily volume traded in the previous month, multiplied by the closing share prices. Firm PRICE is the monthly closing stock price at the end of the previous month. Total volatility (TOTV) is the standard deviation of monthly returns over the past 36-months. The sample period is from November 1994 to November 2010. The *t*-statistics are in parentheses.

Panel A: Sample Summary Statistics						
Variable	N	Mean	Std. Dev.	Median	25P	75P
IV-M	107344	10.82	6.13	10.11	7.61	12.88
IV-FF	107344	10.56	6.05	9.79	7.48	12.53
IV-MM	107344	3.00	1.20	2.90	2.30	3.60
TOTV	107344	14.95	7.07	14.04	10.49	18.00
Size	107344	7.72	1.48	7.80	7.13	8.51
Price	107344	10.28	9.05	8.20	5.32	12.55
CNY Volume	107344	19.68	1.69	19.72	18.46	20.95

Panel B: Correlation Matrix							
Variable	IV-M	IV-FF	IV-MM	T.V	Size	Price	CNY.Volume
IV-M	1.00						
IV-FF	0.98	1.00					
IV-MM	0.68	0.64	1.00				
TOTV	0.85	0.83	0.71	1.00			
Size	0.18	0.25	0.06	0.10	1.00		
Price	0.31	0.36	0.08	0.20	0.57	1.00	
CNY Volume	0.43	0.45	0.51	0.41	0.68	0.45	1.00

Panel C: Characteristics of Momentum Portfolios: Mean Values						
Past 6-month Return	P1(Losers)	P2	P3	P4	P5 (Winners)	P5-P1
IV-M	11.26	10.34	10.22	10.46	11.44	0.18 (0.90)
IV-FF	11.12	10.16	10.00	10.26	11.31	0.19 (1.15)
IV-MM	2.93	2.78	2.80	2.85	3.01	0.08 (2.55)
TOTV	16.30	16.10	15.70	16.00	17.10	0.80 (2.08)
Size	7.42	7.53	7.55	7.64	7.81	0.39 (7.65)
Price	8.68	9.02	9.38	10.26	12.47	3.79 (12.74)
CNY Volume	18.88	18.90	19.03	19.24	19.62	0.74 (14.89)

TABLE 4.1: Continued

Panel D: Characteristics of Reversal Portfolios: Mean Values						
Past 36-month Return	P1(Losers)	P2	P3	P4	P5 (Winners)	P5-P1
IV-M	11.00	9.80	10.30	11.00	12.40	1.40 (7.64)
IV-FF	10.70	9.40	10.00	10.80	12.40	1.70 (10.02)
IV-MM	2.97	2.78	2.78	2.80	2.82	-0.15 (-3.89)
TOTV	15.40	14.10	14.70	15.40	17.10	1.70 (5.55)
Size	7.12	7.39	7.48	7.62	7.88	0.76 (10.00)
Price	7.44	8.57	9.37	10.61	13.31	5.77 (15.14)
CNY Volume	18.85	19.02	19.18	19.34	19.58	0.73 (12.14)

Panel E: Characteristics of IV Portfolios: Mean Values						
Idiosyncratic Volatility	Low	2	3	4	High	H-L
IV-M	7.10	8.80	10.20	12.00	16.70	9.60 (26.91)
IV-FF	6.90	8.60	10.00	11.80	16.50	9.60 (26.66)
IV-MM	2.26	2.59	2.82	3.06	3.67	1.41 (64.82)
TOTV	13.80	14.90	15.40	17.20	20.80	7.00 (15.03)
Size	7.74	7.70	7.64	7.58	7.55	-0.19 (-14.69)
Price	8.27	9.12	9.94	10.42	11.06	2.79 (12.92)
CNY Volume	19.03	19.26	19.31	19.28	19.36	0.33 (10.25)

Table 4.2
Momentum and Reversal Portfolios via Alternative Weighting Schemes

This table reports average monthly return of equal-weighted, value-weighted, IV-weighted and size-based quintiles of momentum and long-term reversal portfolios. Idiosyncratic volatility (IV-M) is the standard deviation of the monthly residuals from using MARKET MODEL over the past 36 months (see section 4.3.4 for a detailed description). Size is defined as the market capitalization of each stock at the portfolio formation date. The momentum (reversal) portfolios are formed each month by sorting stocks on past returns from *t*-6 to *t*-1 (*t*-36 to *t*-7) months. The momentum (reversal) portfolios are held for the next 3-, 6-, 9- and 12-months (6-months), skipping month t. The momentum portfolio returns (P5-P1) are calculated by buying the high past returns quintile (winners) and selling the low past returns quintile (losers). The reversal portfolio returns (P1-P5) are calculated by buying the low past returns quintile (losers) and selling the high past returns quintile (winners). Both the raw and Fama-French adjusted returns (alpha) are reported in per cent and *t*-statistics provided in parentheses. Alpha refers to the Fama-French three factor model alpha using the average monthly returns for momentum and reversal portfolios. The sample period is from 1994 to 2010.

Panel A: Equal-weighted Momentum Portfolios				
Holding Period	3	6	9	12
P1 (Losers)	1.46	1.42	1.52	1.61
	(4.03)	(4.35)	(5.09)	(5.78)
P5 (Winners)	2.02	2.04	2.03	1.97
	(6.14)	(6.66)	(7.28)	(7.75)
P5-P1	0.57	0.62	0.51	0.36
	(3.61)	(4.46)	(4.35)	(3.66)
Alpha	0.66	0.68	0.53	0.35
	(4.05)	(4.77)	(4.43)	(3.45)

Panel B: Value-Weighted Momentum Portfolios				
Holding Period	3	6	9	12
P1 (Losers)	1.13	0.96	0.99	1.15
	(2.48)	(2.63)	(3.24)	(4.20)
P5 (Winners)	1.73	1.65	1.70	1.63
	(3.75)	(4.74)	(5.78)	(5.91)
P5-P1	0.60	0.69	0.71	0.48
	(3.08)	(4.32)	(6.01)	(4.34)
Alpha	0.65	0.70	0.69	0.47
	(3.74)	(5.06)	(6.72)	(4.54)

TABLE 4.2: Continued

Panel C: IV-Weighted Momentum Portfolios				
Holding Period	3	6	9	12
P1 (Losers)	1.76	1.65	1.70	1.78
	(4.71)	(4.88)	(5.56)	(6.24)
P5 (Winners)	1.94	2.00	2.17	2.14
	(5.71)	(6.36)	(7.50)	(8.09)
P5-P1	0.18	0.35	0.47	0.35
	(0.96)	(2.26)	(3.76)	(3.39)
Alpha	0.29	0.41	0.50	0.35
	(1.55)	(2.61)	(3.83)	(3.18)

Panel D: Long-Term Reversal Portfolio				
Weighting	P1 (Losers)	P5 (Winners)	P1-P5	Alpha
Equal	2.14	1.42	0.72	0.62
	(6.16)	(4.58)	(5.78)	(4.90)
Value	1.55	1.19	0.35	0.29
	(4.89)	(3.85)	(2.31)	(1.97)
IV	2.26	1.47	0.79	0.70
	(6.47)	(4.62)	(6.07)	(5.25)

Panel E: Momentum Returns Based on Size Quintiles (%)					
	S1	S2	S3	S4	S5
P1 (Losers)	1.77	1.96	1.60	1.20	1.19
	(4.78)	(5.88)	(5.08)	(3.89)	(3.62)
P5 (Winners)	2.96	1.67	1.79	1.81	1.76
	(7.19)	(5.50)	(5.71)	(5.77)	(5.49)
P5-P1	1.19	-0.30	0.20	0.61	0.57
	(4.70)	(-2.99)	(1.97)	(4.77)	(3.74)

Panel F: Reversal Returns Based on Size Quintiles (%)					
	S1	S2	S3	S4	S5
P1 (Losers)	3.23	1.84	1.74	2.08	1.37
	(5.86)	(4.25)	(4.06)	(5.05)	(3.65)
P5 (Winners)	2.40	1.61	1.39	1.50	1.08
	(5.16)	(4.00)	(3.54)	(3.81)	(2.60)
P1-P5	0.83	0.23	0.35	0.59	0.29
	(4.83)	(2.67)	(4.20)	(5.72)	(1.87)

Table 4.3
Momentum and Reversal Portfolios Cross-Sorted on IV

This table reports the equal-weighted average monthly returns and Fama-French 3-factor alphas of momentum and reversal portfolios that are cross-sorted into IV quintiles. The past returns and IV are sorted independently. Idiosyncratic volatility (IV-M) is the standard deviation of the monthly residuals from using MARKET MODEL over the past 36 months (see section 4.3.4 for a detailed description). The momentum (reversal) portfolios are formed each month by sorting stocks on past returns from *t*-6 to *t*-1 (*t*-36 to *t*-7) months. The momentum (reversal) portfolios are held for the next 3-, 6-, 9- and 12-months (6-months), skipping month t. The momentum portfolio returns (P5-P1) are calculated by buying the high past returns quintile (winners) and selling the low past returns quintile (losers). The reversal portfolio returns (P1-P5) are calculated by buying the low past returns quintile (losers) and selling the high past returns quintile (winners). Both the raw and Fama-French adjusted returns (alpha) are reported in per cent and *t*-statistics provided in parentheses. Alpha refers to the Fama-French three factor model alpha using the average monthly returns for momentum and reversal portfolios. The sample period is from 1994 to 2010.

Panel A: Momentum Returns Cross-Sorted on IV (%)						
(J=3)	LOW	2	3	4	High	High-Low
P1 (Losers)	1.68	1.53	1.53	1.43	1.29	
	(4.02)	(3.86)	(3.67)	(3.25)	(3.13)	
P5 (Winners)	2.39	2.39	1.97	1.97	1.98	
	(6.13)	(6.27)	(5.13)	(4.97)	(4.99)	
P5-P1	0.70	0.85	0.43	0.54	0.69	-0.01
	(2.29)	(3.91)	(1.89)	(2.45)	(3.45)	(-0.06)
Alpha	0.56	0.79	0.43	0.47	0.67	0.11
	(1.79)	(3.53)	(1.78)	(2.06)	(3.25)	(0.48)
(J=6)	LOW	2	3	4	High	High-Low
P1 (Losers)	1.60	1.44	1.47	1.48	1.26	
	(4.18)	(3.88)	(3.99)	(3.70)	(3.25)	
P5 (Winners)	2.39	2.47	1.88	2.05	1.99	
	(6.64)	(6.68)	(5.41)	(5.56)	(5.36)	
P5-P1	0.79	1.02	0.42	0.57	0.72	-0.07
	(2.81)	(5.05)	(2.14)	(2.85)	(3.81)	(-0.34)
Alpha	0.69	0.95	0.38	0.54	0.69	0.00
	(2.40)	(4.65)	(1.89)	(2.59)	(3.50)	(-0.01)
(J=9)	LOW	2	3	4	High	High-Low
P1 (Losers)	1.74	1.58	1.57	1.52	1.36	
	(4.96)	(4.60)	(4.63)	(4.17)	(3.76)	
P5 (Winners)	2.42	2.28	1.88	1.95	1.86	
	(7.33)	(6.86)	(5.86)	(5.74)	(5.58)	
P5-P1	0.68	0.70	0.31	0.43	0.50	-0.18
	(3.00)	(3.98)	(1.93)	(2.52)	(3.18)	(-0.98)
Alpha	0.61	0.63	0.27	0.40	0.46	-0.14
	(2.60)	(3.52)	(1.63)	(2.26)	(2.83)	(-0.76)
(J=12)	LOW	2	3	4	High	High-Low
P1 (Losers)	1.89	1.74	1.66	1.63	1.49	
	(5.64)	(5.39)	(5.19)	(4.77)	(4.43)	
P5 (Winners)	2.27	2.11	1.87	1.88	1.74	
	(7.24)	(6.95)	(6.39)	(6.08)	(5.76)	
P5-P1	0.39	0.37	0.21	0.25	0.25	-0.14
	(1.98)	(2.57)	(1.61)	(1.78)	(1.87)	(-0.81)
Alpha	0.32	0.33	0.19	0.23	0.23	-0.09
	(1.63)	(2.27)	(1.39)	(1.61)	(1.68)	(-0.53)

TABLE 4.3: Continued

Panel B: Long-term Reversal Returns Cross-Sorted on IV (%)						
	LOW	2	3	4	High	High-Low
P1 (Losers)	1.60	1.75	1.77	1.94	1.79	
	(3.41)	(3.52)	(3.57)	(3.88)	(3.54)	
P5 (Winners)	1.01	0.92	1.18	1.00	0.85	
	(2.36)	(2.23)	(2.81)	(2.13)	(1.88)	
P1-P5	0.59	0.83	0.60	0.94	0.94	0.35
	(2.91)	(4.74)	(4.33)	(5.62)	(5.42)	(1.57)
Alpha	0.72	0.66	0.52	0.96	0.79	0.24
	(3.00)	(3.92)	(3.88)	(4.95)	(4.54)	(1.05)

Table 4.4
Momentum and Reversal Portfolios Cross-Sorted on IV (with exclusions)

This table reports the equal-weighted average monthly returns and Fama-French 3-factor alphas of momentum and reversal portfolios that are cross-sorted into IV quintiles. Panels A and C report momentum and reversal returns excluding stocks priced below CNY1. Panels B and D report momentum and reversal returns with excluding stocks either priced below CNY1, or have market capitalization that places them in the lowest size decile. Stocks are sorted on past returns and IV independently. Idiosyncratic volatility (IV-M) is the standard deviation of the monthly residuals from using MARKET MODEL over the past 36 months (see section 4.3.4 for a detailed description). The momentum (reversal) portfolios are formed each month by sorting stocks on past returns from *t*-6 to *t*-1 (*t*-36 to *t*-7) months. The momentum and reversal portfolios are held for the next 6-months (t+1 to t+6), skipping month t. The momentum portfolio returns (P5-P1) are calculated by buying the high past returns quintile (winners) and selling the low past returns quintile (losers). The reversal portfolio returns (P1-P5) are calculated by buying the low past returns quintile (losers) and selling the high past returns quintile (winners). Both the raw and Fama-French adjusted returns (alpha) are reported in per cent and *t*-statistics provided in parentheses. Alpha refers to the Fama-French three factor model alpha using the average monthly returns for momentum and reversal portfolios. The sample period is from 1994 to 2010.

Panel A: Momentum Returns (%) by IV Excluding Stocks Priced below CNY1 Exclusion						
	LOW	2	3	4	High	High-Low
P1 (Losers)	1.66	1.38	1.56	1.57	1.40	
	(4.34)	(3.72)	(4.2)	(3.93)	(3.60)	
P5 (Winners)	2.39	2.55	1.90	2.06	2.02	
	(6.49)	(6.76)	(5.38)	(5.60)	(5.37)	
P5-P1	0.73	1.16	0.35	0.49	0.62	-0.11
	(2.53)	(5.56)	(1.81)	(2.56)	(3.50)	(-0.54)
Alpha	0.63	1.08	0.33	0.47	0.58	-0.05
	(2.15)	(5.19)	(1.68)	(2.37)	(3.21)	(-0.22)

Panel B: Momentum Returns (%) by IV with CNY1 and Lowest Size Decile Exclusion						
	LOW	2	3	4	High	High-Low
P1 (Losers)	1.81	1.49	1.70	1.86	1.55	
	(4.62)	(3.99)	(4.57)	(4.55)	(3.98)	
P5 (Winners)	2.42	2.66	1.96	2.15	2.11	
	(6.48)	(7.02)	(5.53)	(5.77)	(5.66)	
P5-P1	0.61	1.16	0.26	0.28	0.56	-0.05
	(2.05)	(5.59)	(1.35)	(1.40)	(3.28)	(-0.20)
Alpha	0.49	1.08	0.24	0.26	0.55	0.06
	(1.63)	(5.16)	(1.22)	(1.23)	(3.07)	(0.24)

TABLE 4.4: Continued

Panel C: Reversal Returns (%) by IV with CNY1 Exclusion						
IV	LOW	2	3	4	High	High-Low
P1 (Losers)	1.60	1.77	1.85	2.04	1.82	
	(3.41)	(3.55)	(3.69)	(4.02)	(3.61)	
P5 (Winners)	1.01	0.92	1.18	1.00	0.85	
	(2.36)	(2.23)	(2.81)	(2.13)	(1.89)	
P1-P5	0.60	0.85	0.67	1.04	0.96	0.37
	(2.92)	(4.85)	(4.61)	(5.46)	(5.60)	(1.68)
Alpha	0.55	0.64	0.62	0.91	0.82	0.26
	(2.56)	(3.80)	(4.20)	(4.61)	(4.72)	(1.15)

Panel D: Reversal Returns (%) by IV with CNY1 and Lowest Size Decile Exclusion						
IV	LOW	2	3	4	High	High-Low
P1 (Losers)	1.62	1.92	2.01	2.08	2.06	
	(3.14)	(3.67)	(3.91)	(4.06)	(3.96)	
P5 (Winners)	0.96	0.95	1.19	1.12	1.05	
	(2.13)	(2.14)	(2.71)	(2.25)	(2.13)	
P1-P5	0.66	0.97	0.82	0.93	1.01	0.34
	(3.11)	(6.26)	(6.49)	(7.17)	(7.87)	(1.56)
Alpha	0.69	0.84	0.76	0.93	0.98	0.28
	(3.10)	(5.64)	(6.05)	(6.85)	(7.44)	(1.24)

Table 4.5
Momentum and Reversal Portfolios Cross-Sorted on Alternative IV-measures

This table reports the equal-weighted average monthly returns and Fama-French 3-factor alphas of momentum and reversal portfolios that are cross-sorted into IV quintiles. The past returns and IV are sorted independently. Panel A (B) reports momentum (reversal) returns by using the IV measure estimated with Fama-French model regression over the past 36 months. Panel C (D) reports momentum (reversal) returns by using the IV measure estimated with market-model regression over the past 12 months. Panel E (F) reports momentum (reversal) returns using total volatility (TOTV. TOTV is the standard deviation of monthly returns over the past 36 months. The details of IV-measures and TOTV are given in section 4.3.4. The momentum (reversal) portfolios are formed each month by sorting stocks on past returns from t-6 to t-1 (t-36 to t-7) months. The momentum and reversal portfolios are held for the next 6 months (t+1 to t+6), skipping month t. The momentum portfolio returns (P5-P1) are calculated by buying the high past returns quintile (winners) and selling the low past returns quintile (losers). The reversal portfolio returns (P1-P5) are calculated by buying the low past returns quintile (losers) and selling the high past returns quintile (winners). Both the raw and Fama-French adjusted returns (alpha) are reported in per cent and *t*-statistics provided in parentheses. Alpha refers to the Fama-French three factor model alpha using the average monthly returns for momentum and reversal portfolios. The sample period is from 1994 to 2010.

Panel A: Momentum Returns by Fama-French Three-factor IV (%)						
	LOW	2	3	4	High	High-Low
P1 (Losers)	1.65	1.40	1.40	1.47	1.24	
	(4.25)	(3.65)	(3.78)	(3.82)	(3.14)	
P5 (Winners)	2.40	2.38	2.01	2.00	1.97	
	(6.43)	(6.45)	(5.58)	(5.59)	(5.27)	
P5-P1	0.75	0.98	0.61	0.53	0.73	-0.02
	(3.16)	(4.87)	(3.02)	(2.85)	(3.71)	(-0.11)
Alpha	0.64	0.90	0.57	0.49	0.71	0.07
	(2.61)	(4.36)	(2.69)	(2.55)	(3.45)	(0.40)

Panel B: Reversal Returns by Fama-French Three-factor IV (%)						
	LOW	2	3	4	High	High-Low
P1 (Losers)	1.78	1.79	1.82	2.43	1.84	
	(3.73)	(3.62)	(3.79)	(4.85)	(3.72)	
P5 (Winners)	1.06	0.94	1.10	1.14	0.93	
	(2.64)	(2.30)	(2.63)	(2.62)	(2.09)	
P1-P5	0.72	0.85	0.66	1.29	0.91	0.19
	(3.32)	(4.58)	(5.65)	(6.01)	(5.18)	(0.88)
Alpha	0.62	0.59	0.57	1.01	0.71	0.09
	(2.72)	(3.28)	(4.88)	(4.69)	(3.97)	(0.39)

TABLE 4.5: Continued

IV	LOW	2	3	4	High	High-Low
			Panel C: Momentum Returns using IV-MM (%)			
P1 (Losers)	1.32	1.08	1.41	1.51	1.66	
	(3.45)	(3.11)	(3.97)	(4.05)	(4.07)	
P5 (Winners)	1.73	1.91	1.83	1.92	2.23	
	(5.35)	(5.75)	(5.38)	(5.30)	(5.54)	
P5-P1	0.41	0.84	0.41	0.41	0.57	0.17
	(2.56)	(8.13)	(3.67)	(2.99)	(2.24)	(0.73)
Alpha	0.47	0.89	0.48	0.43	0.49	0.02
	(2.87)	(8.45)	(4.24)	(3.00)	(1.85)	(0.09)

IV	LOW	2	3	4	High	High-Low
			Panel D: Reversal Returns using IV-MM (%)			
P1 (Losers)	1.82	2.30	1.93	2.12	2.51	
	(3.97)	(4.65)	(4.13)	(4.49)	(4.58)	
P5 (Winners)	1.42	0.94	0.91	1.25	1.17	
	(3.34)	(2.24)	(2.11)	(2.71)	(2.60)	
P1-P5	0.40	1.39	1.02	0.87	1.34	0.94
	(3.67)	(10.88)	(9.73)	(6.14)	(4.68)	(3.83)
Alpha	0.33	1.30	0.93	0.70	0.98	0.65
	(2.99)	(10.15)	(8.83)	(4.99)	(3.47)	(2.65)

	LOW	2	3	4	High	High-Low
			Panel E: Momentum Returns by TOTV (%)			
P1 (Losers)	1.01	1.22	1.53	1.54	1.14	
	(3.38)	(3.30)	(4.02)	(3.83)	(2.80)	
P5 (Winners)	1.85	1.75	1.37	1.75	2.31	
	(5.29)	(5.36)	(4.07)	(4.80)	(5.20)	
P5-P1	0.84	0.53	-0.19	0.21	1.17	0.33
	(3.02)	(3.48)	(-1.18)	(1.14)	(4.12)	(1.54)
Alpha	0.74	0.54	-0.18	0.25	1.12	0.38
	(2.92)	(3.43)	(-1.09)	(1.33)	(4.29)	(1.60)

	LOW	2	3	4	High	High-Low
			Panel F: Reversal Returns by TOTV (%)			
P1 (Losers)	2.03	1.92	2.24	2.46	2.37	
	(3.73)	(3.35)	(3.76)	(3.94)	(3.83)	
P5 (Winners)	0.84	1.16	1.43	1.96	1.40	
	(1.88)	(2.24)	(2.80)	(3.52)	(2.54)	
P1-P5	1.19	0.68	0.68	0.50	0.97	-0.22
	(5.25)	(3.01)	(4.89)	(2.18)	(3.29)	(-0.74)
Alpha	1.00	0.59	0.59	0.27	0.77	-0.23
	(4.41)	(2.55)	(4.32)	(1.18)	(2.59)	(-0.74)

Table 4.6
Momentum and Reversal Portfolios based on IV (Alternative sorting and portfolio Schemes)

This table reports the equal-weighted average monthly returns and Fama-French 3-factor alphas of momentum and reversal portfolios cross-sorted into IV quintiles. Idiosyncratic volatility (IV-M) is the standard deviation of the monthly residuals from using MARKET MODEL over the past 36 months (see section 4.3.4 for a detailed description). Panel A (B) reports momentum (reversal) returns using dependent-sorting approach. In Panel A (B), first, I sort stocks into quintiles based on IV, and then each IV quintile is sorted into five groups based on the past returns. Panel C (D) reports momentum (reversal) returns using the IV terciles and momentum (reversal) deciles. In Panels C and D, I sort stocks into IV terciles and past-return deciles; these sortings are done independently. Panel E (F) reports momentum (reversal) returns by using the IV terciles and momentum (reversal) quintiles. In Panels E and F, I sort stocks into IV terciles and past-return quintiles; these sortings are done independently. The momentum (reversal) portfolios are formed each month by sorting stocks on past returns from *t*-6 to *t*-1 (*t*-36 to *t*-7) months. The momentum and reversal portfolios are held for the next 6-months (t+1 to t+6), skipping month t. The momentum portfolio returns (P5-P1) are calculated by buying the high past returns quintile (winners) and selling the low past returns quintile (losers). The reversal portfolio returns (P1-P5) are calculated by buying the low past returns quintile (losers) and selling the high past returns quintile (winners). Both the raw and Fama-French adjusted returns (alpha) are reported in per cent and *t*-statistics provided in parentheses. Alpha refers to the Fama-French three factor model alpha using the average monthly returns for momentum and reversal portfolios. The sample period is from 1994 to 2010.

Panel A: Momentum Returns by IV (%) with Dependent Sorting						
	Low	2	3	4	High	High-Low
P1 (Losers)	1.60	1.61	1.54	1.54	1.54	
	(4.47)	(4.46)	(4.42)	(3.98)	(4.09)	
P5 (Winners)	2.28	2.45	1.93	2.02	2.14	
	(7.03)	(7.17)	(5.89)	(5.76)	(5.76)	
P5-P1	0.69	0.85	0.39	0.48	0.60	-0.09
	(4.30)	(4.65)	(2.23)	(2.31)	(2.84)	(-0.64)
Alpha	0.66	0.82	0.36	0.46	0.55	-0.11
	(3.98)	(4.36)	(2.02)	(2.13)	(2.53)	(-0.75)

Panel B: Reversal Returns by IV(%) with Dependent Sorting						
	Low	2	3	4	High	High-Low
P1 (Losers)	2.28	2.07	2.03	2.51	2.15	
	(4.77)	(4.40)	(4.45)	(5.19)	(4.47)	
P5 (Winners)	2.09	1.25	1.52	1.27	0.92	
	(4.95)	(3.25)	(3.89)	(3.03)	(2.11)	
P1-P5	0.19	0.82	0.50	1.24	1.23	1.04
	(1.32)	(4.61)	(4.43)	(7.26)	(4.66)	(3.55)
Alpha	0.21	1.06	0.49	0.92	1.12	0.91
	(1.35)	(5.12)	(3.80)	(5.29)	(4.29)	(2.97)

TABLE 4.6: Continued

Panel C: Decile Momentum Returns by IV Terciles				
	Low	2	High	High-Low
P1 (Losers)	1.28	1.49	1.31	
	(3.14)	(3.98)	(3.15)	
P10 (Winners)	2.91	2.18	2.24	
	(7.72)	(5.88)	(5.90)	
P10-P1	1.63	0.69	0.93	-0.70
	(4.78)	(2.89)	(3.88)	(-3.54)
Alpha	1.49	0.62	0.89	-0.60
	(4.27)	(2.53)	(3.56)	(-3.01)

Panel D: Decile Reversal Returns by IV Terciles				
	Low	2	High	High-Low
P1 (Losers)	1.62	1.58	2.00	
	(2.84)	(2.63)	(3.39)	
P10 (Winners)	1.12	0.85	0.66	
	(2.19)	(1.69)	(1.23)	
P1-P10	0.51	0.44	1.34	0.83
	(1.57)	(1.81)	(4.81)	(2.48)
Alpha	0.62	0.45	1.44	0.83
	(1.91)	(1.79)	(5.05)	(2.39)

Panel E: Quintile Momentum Returns by IV Terciles				
	Low	2	High	High-Low
P1 (Losers)	1.60	1.63	1.57	
	(4.36)	(4.57)	(4.03)	
P5 (Winners)	2.58	1.96	2.12	
	(7.41)	(5.59)	(6.00)	
P5-P1	0.98	0.32	0.55	-0.44
	(4.72)	(1.72)	(2.86)	(-3.81)
Alpha	0.94	0.28	0.54	-0.40
	(4.35)	(1.43)	(2.72)	(-3.39)

Panel F: Quintile Reversal Returns by IV Terciles				
	Low	2	High	High-Low
P1 (Losers)	2.32	2.36	2.45	
	(5.03)	(4.97)	(5.18)	
P5 (Winners)	1.14	1.68	1.30	
	(3.10)	(3.96)	(3.06)	
P1-P5	1.18	0.68	1.15	-0.03
	(5.65)	(4.67)	(7.50)	(-0.15)
Alpha	1.00	0.52	0.96	-0.04
	(4.75)	(3.63)	(6.37)	(-0.19)

Table 4.7
Fama-MacBeth Regressions

This table reports the results of Fama-MacBeth cross-sectional regressions. The dependent variable is the average monthly return over a six-monthly (t+1 to t+6) holding period. The independent variables are the natural logarithm of SIZE, the natural logarithm of the book-to-market ratio (BTM), the past 6-month (t-6 to t-1) stock return (MOM), and the past t-36 to t-7 months stock return (REV). Idiosyncratic volatility (IV-M) is the standard deviation of the monthly residuals from using MARKET MODEL over the past 36 months (see section 4.3.4 for a detailed description). High IV is equal to one if the firm is in the highest IV quintile. SMALL SIZE is equal to one if a firm is in the lowest size quintile. PRICE is the monthly closing stock price at the end of the previous month. LOW PRICE is equal to one if a firm is in the lowest price quintile. CNY VOLUME is measured as the average daily volume traded in the previous month, multiplied by the closing share prices. CNY VOLUME is equal to one if a firm is in the lowest CNY quintile. In Panel A, MOM is interacted with the IV, SIZE, PRICE and CNY VOLUME. In Panel B, REV is interacted with the IV, SIZE, PRICE and CNY VOLUME. The numbers in the parentheses represent t- statistics, where standard errors are adjusted for overlap with the method of Newey and West (1987). The sample period is from 1994 to 2010.

Panel A: Momentum Interactions					
	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
Intercept	0.073	0.078	0.074	0.079	0.094
	(2.84)	(3.34)	(3.29)	(3.63)	(3.83)
SIZE	-0.004	-0.004	-0.003	-0.003	-0.002
	(-2.35)	(-2.58)	(-2.47)	(-2.49)	(-1.83)
BTM	0.003	0.002	0.002	0.001	0.002
	(2.14)	(1.89)	(1.84)	(1.14)	(1.93)
MOM	0.041	0.064	0.062	0.071	0.072
	(1.81)	(2.44)	(2.36)	(2.89)	(2.76)
REV	-0.084	-0.083	-0.084	-0.044	-0.080
	(-2.04)	(-2.01)	(-2.09)	(-1.11)	(-2.03)
IV		-0.159	-0.158	-0.179	-0.112
		(-1.25)	(-1.25)	(-1.38)	(-0.88)
MOM*HIGH IV		-0.055	-0.059	-0.057	-0.062
		(-3.12)	(-3.50)	(-3.43)	(-3.80)
MOM*SMALL SIZE			0.016		
			(0.63)		
PRICE				0.028	
				(1.67)	
MOM*LOW PRICE				0.019	
				(0.79)	
CNY VOLUME					-0.002
					(-3.10)
MOM*LOW CNY VOLUME					0.004
					(0.20)

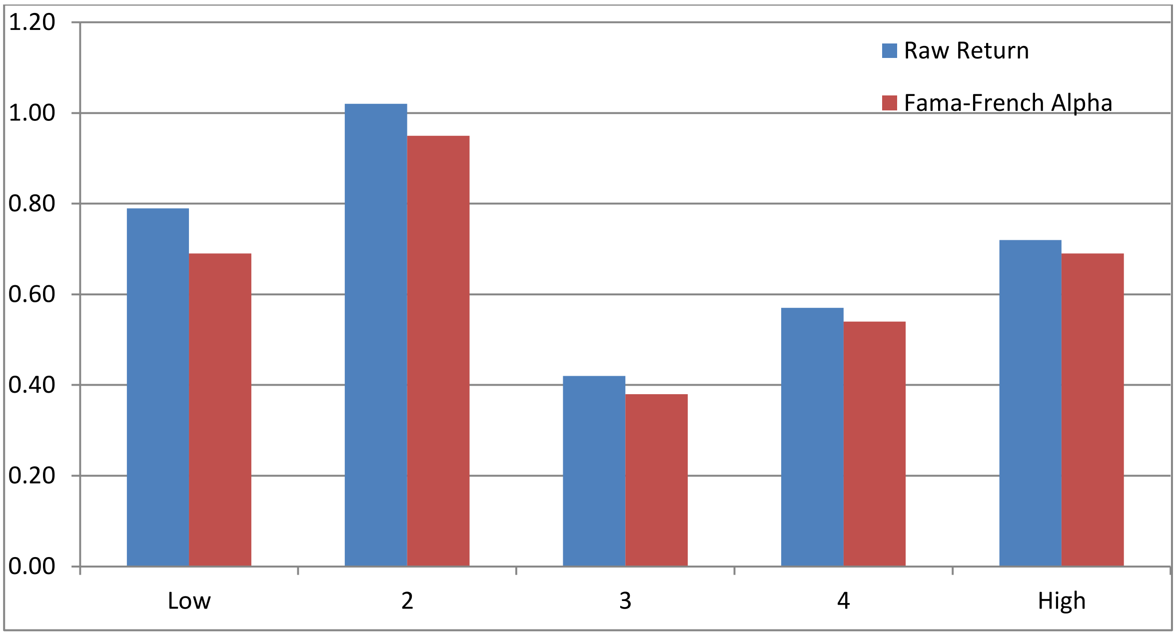
TABLE 4.7: Continued

Panel B: Reversal Interactions					
	Regression 1	Regression 2	Regression 3	Regression 4	Regression 5
Intercept	0.073	0.079	0.073	0.080	0.092
	(2.84)	(3.33)	(3.11)	(3.56)	(3.70)
SIZE	-0.004	-0.004	-0.003	-0.003	-0.003
	(-2.35)	(-2.65)	(-2.40)	(-2.58)	(-2.08)
BTM	0.003	0.002	0.002	0.001	0.002
	(2.14)	(1.77)	(1.77)	(1.02)	(1.82)
MOM	0.041	0.047	0.047	0.054	0.051
	(1.81)	(1.95)	(1.93)	(2.37)	(2.11)
REV	-0.084	-0.097	-0.094	-0.030	-0.063
	(-2.04)	(-2.28)	(-2.18)	(-0.72)	(-1.57)
IV		-0.119	-0.105	-0.157	-0.090
		(-0.94)	(-0.84)	(-1.25)	(-0.78)
REV*HIGH IV		0.026	0.024	0.036	0.024
		(0.71)	(0.67)	(0.46)	(0.64)
REV*SMALL SIZE			-0.081		
			(-1.47)		
PRICE				0.031	
				(1.92)	
REV*LOW PRICE				-0.054	
				(-1.44)	
CNY VOLUME					-0.002
					(-2.99)
REV*LOW CNY VOLUME					-0.155
					(-3.78)

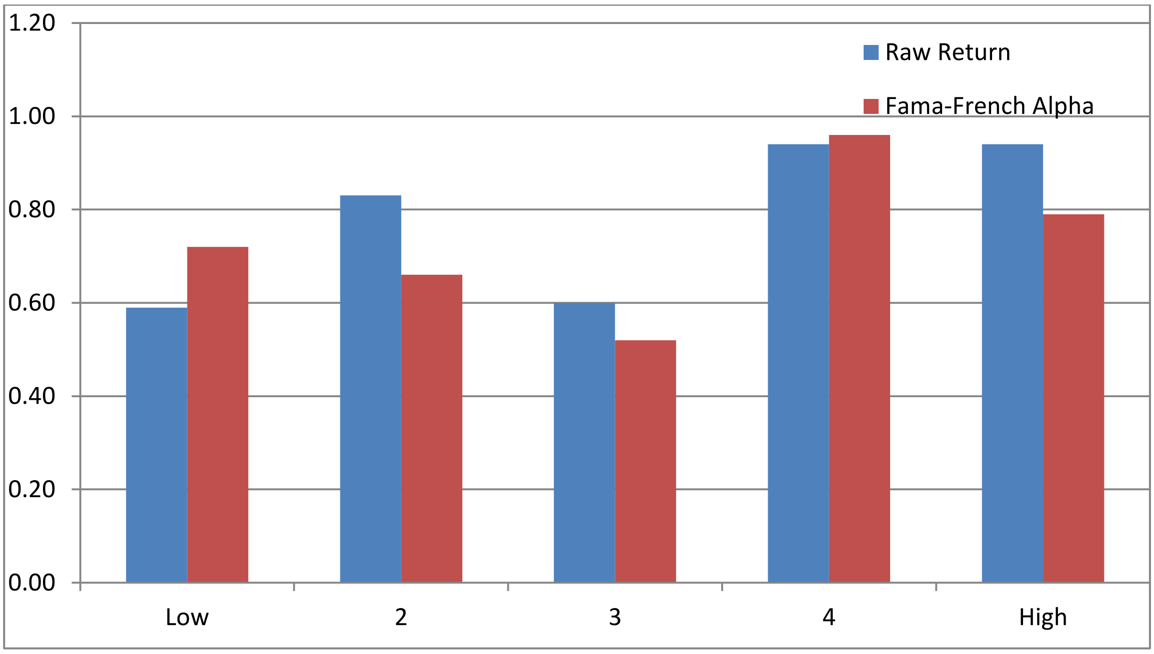
Figure 4.1 Momentum and Reversal Returns Sorted into IV Quintiles

Figure 4.1 displays the average monthly returns of the momentum and reversal portfolios sorted into IV quintiles. The returns are measured over a 6-month holding period as both raw returns and as Fama-French Alpha. The returns are reported in percentages.

Graph A: Momentum Portfolio Average Monthly Returns by IV Quintiles



Graph B: Reversal Portfolio Average Monthly Returns by IV Quintiles



Chapter 5

Conclusions, Summary and Directions for Future Research

The results presented in this thesis provide evidence from China, the world's largest emerging market about the relationship of momentum returns and market state, the Global financial crisis and information uncertainty, and the relationship of idiosyncratic volatility (IV) and momentum and reversal. Chapter 2 provides evidence that momentum is not related to market state, which contradicts the results in Cooper et al.'s (2004) study of the U.S. market. Instead of market state, I find that there is a strong relationship between momentum returns and business cycle because momentum returns are greater before the Global financial crisis but they turn into losses during the Global financial crisis period (2007-2010), especially in the months when the market conditions started to improve. This trend is loosely consistent with some behavioural findings since investors are fearful during market downturns and avoid loser stocks.[55] When the market improves, these loser stocks experience large gains because their losses were the result of fear instead of bad performance. The strong gains of loser stocks then result in losses for the momentum trading strategy.

Chapter 3 provides evidence that information uncertainty (IU) is positively correlated with future returns when IU is defined in terms of volume and firm size, which contradicts the results of Jiang et al.'s (2005) study for U.S. stocks. Using portfolio-level analysis and Fama and MacBeth (1973) cross-sectional regressions, I find that no robust relationship exists between momentum returns and the level of IU, which contradicts the results of Zhang (2006) and Jiang et al. (2005) for U.S. stocks. My findings suggest that it might be the activities of retail investors that result in momentum returns because China is dominated by retail investors.

Chapter 4 indicates that that the choice of the proxy used for IV, sorting method and portfolio size (tercile versus quintile) play critical roles in determining the existence and significance of a relationship between IV and momentum or reversal. Portfolio-level analysis based on four different measures of IV, and firm-level Fama and MacBeth (1973) cross-sectional regressions, indicate that no robust relationship exists between IV and momentum, which is consistent with McLean (2010). I also provide evidence that IV is not related to reversal,

[55] See Loewenstein (2000), Loewenstein et al. (2001) and Sunstein and Zeckhauser (2008)

which contradicts the results of McLean (2010) for the U.S. market. My findings, along with those in related studies, suggest that transaction costs are the binding costs that limit arbitrage for long-term reversal. In addition, I find that momentum and reversal are separate phenomena since momentum and reversal are each strongest in different types of stock, which is consistent with the suggestion of McLean (2010) but contrary to the claims of Barberis et al. (1998) and Daniel et al. (1998).

The fact that some of my findings do not conform to those found in developed markets highlights the importance of verifying relationships and anomalies initially evident in developed markets to see if they also apply to emerging markets. However, there are a few aspects of momentum trading strategy that I left unexplored. First, I could not test the relationship of momentum returns and macro-economic variables since I could not find some of macroeconomic variables' data like default spread and term spread for China.[56] Second, I could not test the relationship of momentum returns with either retail investors or the credit rating of the firms because of non-availability of data. Third, instead of the bid-ask spread I used price, size and volume as transaction cost proxies to test that transaction costs limit arbitrage opportunities for momentum and reversal.

Since I could not test some other aspects of momentum trading strategy, therefore I would suggest further research to explore those aspects. The future research should mainly address the following issues:

1. Future research needs to further explore the effect of economic activity on momentum returns by using macroeconomic variables. It might be difficult to find the exact macroeconomic variable data for China as used by Chordia and Shivakumar (2002) for the U.S. market. However, it is possible to use some other macroeconomic variables like interest rates, inflation, etc.

2. Another direction for future research is to explore the effect of institutional and retail investors on the profitability of momentum-based trading strategies. We need caution while dealing with the Chinese market not to add the state shareholding as institutional shareholding.

[56] Default spread is the defined as the difference between the average yield of A and B rated bonds. Term spread is the defined as the difference between the average yield of government bonds with more than 10 years to maturity and average yield of Treasury bills with three months maturity (for details see Chordia and Shivakumar, 2002).

3. It would be interesting to explore the relationship between the credit rating of firms and momentum returns. I could not find any specific data for the credit rating of Chinese firms; however, it is possible to find the credit rating of each firm individually.

4. I used different data frequencies to estimate IV so with different models, therefore, it would be interesting to test the impact of data frequency (daily versus monthly) with same model on the relationship of IV with momentum and reversal.

5. I would suggest using actual transaction costs like bid-ask spread to test the impact of transaction costs on the profitability of momentum and reversal trading strategies.

6. I find higher momentum returns following lagged 36-month and lagged 24-month DOWN markets; therefore, I would suggest testing them in other markets since it appears that momentum returns might be related to investors' fears following DOWN markets.

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APPENDIX

Following the description of the Fama-French factors given in Kenneth R. French's data library, I construct six value-weighted portfolios formed on size and book-to-market ratio.

SMB (small minus big) is the average return on the three small portfolios minus the average return on the three big portfolios:

SMB = 1/3 (small value + small neutral + small growth) - 1/3 (big value + big neutral + big growth)

HML (high minus low) is the average return on the two value-weighted portfolios minus the average return on the two growth portfolios:

HML = 1/2 (small value + big value) - 1/2 (small growth + big growth)

$R_m - R_f$, the excess return on the market, is the value-weighted monthly return for the All China Index, SSE Index, SZSE index and Hang Seng index minus the one-month risk-free return.

Beta is estimated for each stock using the Capital Asset Pricing model (CAPM) equation. I use monthly returns in the calendar year before the portfolio formation date for each stock and market index for the calculation of beta.