Momentum Crashes: Evidence from the A-share Market

Wang, Weiming

UNIVERSITÉ DE GENÈVE GENEVA FINANCE RESEARCH INSTITUTE

Momentum Crashes: Evidence from the A Share Market

Dissertation Submitted to

The University of Geneva

in partial fulfillment of the requirement

for the professional degree of

Doctorate of Advanced Professional Studies in Applied Finance, with Specialization in Wealth Management

by

Weiming Wang
(FCO N° 61910)

Dissertation Supervisor: Professor Rajna GIBSON BRANDON
University of Geneva

September, 2022

Disclaimer

I declare that I have read the plagiarism information and prevention documents issued by the University of Geneva.

I certify that this work is the result of personal work and has been written independently. The work is the responsibility of the author, in no way does the work engage the responsibility of the University of Geneva, nor of the supervising Professors.

I declare that all sources of information used are cited in a complete and accurate manner, including sources on the Internet. Other individuals and groups that have contributed to the research work involved in this paper have been clearly identified in the paper.

I am aware that the fact of not citing a source or not quoting it correctly is plagiarism and that plagiarism is considered a serious fault within the University, punishable by penalties.

In view of the above, I declare on my honor that the present work is original.

Signature：Weiming Wang Date： September, 2022

Abstract

Daniel and Moskowitz (2016) document the momentum crashes in the US stock market: the returns to momentum experience infrequent but persistent strings of negative returns. Based on their findings, this paper investigates the phenomenon of momentum crashes in A share market. We confirm the existence of the momentum effect and the crash of momentum strategy in A Share market using weekly data. The crash happens together with, if not slightly before the decline of the whole market. When the market starts to decrease after a long period of expansion, the beta of the winner portfolio (high beta) remains high, and the beta of the loser portfolio (low beta) remains low. The momentum strategy of buying historical winners and selling historical losers is equivalent to buying a high-beta portfolio and selling a low-beta portfolio. When the market decreases, the high-beta portfolio will decrease more than the low-beta portfolio, and the momentum strategy will suffer a great loss. The crash can be avoided if we allow an investor to dynamically allocate her assets between a risky asset and a risk-free asset based on an optimization problem that maximizes the Sharpe ratio of the portfolio.

Key words: Momentum Crashes; Time Varying Beta; Portfolio Optimization

Table of Contents

List of Tables

List of Figures

Momentum Crashes: Evidence from the A Share Market

Introduction

In the first half of 2018, the A-share market began a period of decline, with the Shanghai Composite Index falling 22.4% from a high of 3,587 at the start of June to 2,782 at the end of June. Along with the market decline, many “buy and hold” strategies performed poorly, but hedging strategies performed relatively well. Unlike the US market, the A-share market has not shown a long-term upward trend, despite the high economic growth in China over the past few decades. As a result, it is difficult for “buy and hold” strategies to obtain excess returns in such a volatile market, and quantitative hedging strategies generally perform better.

However, quantitative hedging strategies don’t always perform well in A share market. Take 2017 as an example, when the market index out-performed 80% of the individual stocks, the hedging strategy rarely achieved positive returns. Unlike the “buy and hold” strategy which depends on the subjective judgment of the investor, quantitative hedging investment is the process of using computer technology and certain mathematical models. Why is model-based strategy unstable? Is there any way to avoid a significant drawdown of a quantitative hedging strategy? Using momentum strategy and A-share market data, this paper provides an in-depth analysis of these two questions.

Particularly, this paper considers a widely adopted momentum strategy (i.e., Daniel and Moskowitz, 2016), which can be summarized as follows.

Step 1: To form the momentum portfolios, we first rank stocks based on their cumulative returns from J periods before to one period before the formation date (i.e., the t-J to t-1-period returns), where, consistent with the literature (Jegadeesh and Titman, 1993; Asness, 1994; Fama and French, 1996; Daniel and Moskowitz, 2016), we use a one period gap between the end of the ranking period and the start of the holding period to avoid the short-term reversals documented by Jegadeesh (1990) and Lehmann (1990).

Step 2: All firms in our data sample are then placed into one of ten decile portfolios based on this ranking, where portfolio 10 represents the “Winners” (those with the highest past returns) and portfolio 1 represents the “Losers”. The equally-weighted holding period returns of the decile portfolios are computed. At time t, the investor buys the winner portfolio and sells the loser portfolio, and holds the “Winner minus loser (WML)” portfolio for the next K periods.

The cumulative return of this momentum strategy (Blue line in Figure 1) performs well for most of the sample period. For example, in the first half of 2018, the A-share market began a period of decline, with the market index falling 14.7% from a high of 3,007 at the beginning of January to 2,564 at the end of June. Meanwhile, the momentum strategy generates a positive return of 6.7%. The whole sample return of the momentum strategy also outperforms that of the market. Starting with an initial value of 1 in March 2001, the cumulative return of the momentum strategy reaches the highest value of 5.91 in May 2015, which is equivalent to an annual growth rate of 13.5%. Meanwhile, the maximum cumulative return of the market only exceeds 3 (Red line in Figure 1). However, the momentum strategy also experiences substantial downturns in June 2015 as indicated in Figure 1. From June 2015 to April 2016, the momentum strategy generates a negative return of 59.22%, while the cumulative return of the market is -32.47%. Based on these findings, we conduct a series analysis with respect to the momentum strategy. The research questions discussed in this paper can be summarized as follows.

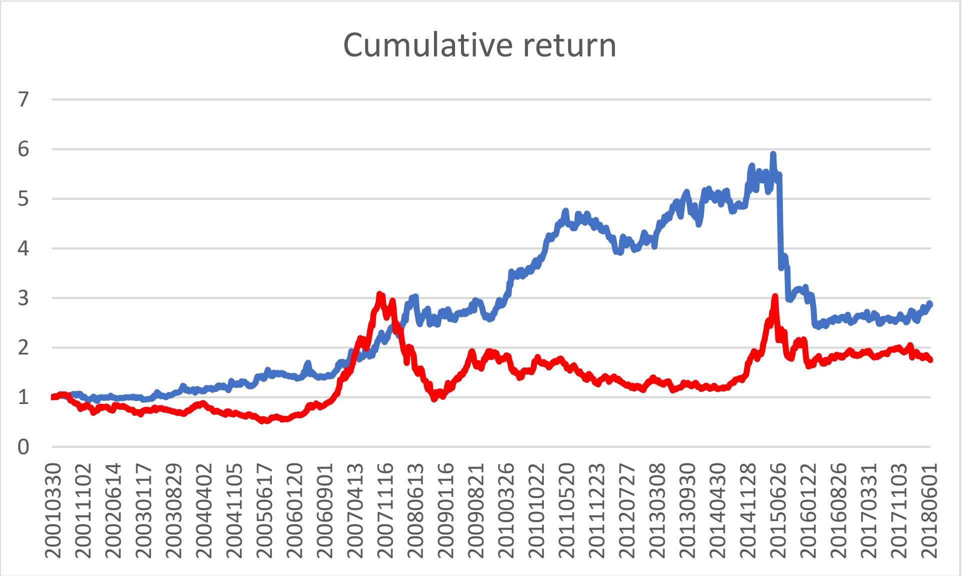
Q1: Is momentum effect significant in A share market?

Q2: Does the problem of momentum crashes exist in the A share market?

Q3: What causes the momentum crashes in the A share market?

Q4: What are the variables that can be used to predict the momentum crashes?

Q5: How to avoid the problem of momentum crash while forming a trading strategy?



Notes: the blue line represents the cumulative return generated by the momentum strategy, while the red line represents the cumulative return generated by the market.

Figure 1: *Cumulative Returns of The Momentum Strategy, 2001.3-2018.6*

Literature Review

Literature on Momentum Strategy

Stock prices tend to continue the original direction of movement. Stocks that have good/poor performance in the past will perform well/poorly in the future. The momentum effect was first proposed by Jegadesh and Titman (1993). Using data from 1965 to 1989, they found that the monthly returns of the past "winner" stocks were 1.49% higher than the those of the "loser" stocks. The Momentum strategy of buying winners and selling losers produces a higher Sharp ratio than the market. Momentum effect exists in many markets (Rouwenhorst, 1998), and it cannot be explained by the Fama-French 3-factor model. Therefore, momentum has been identified as another risk factor in addition to the Fama-French three factors (Carhart 1997).

There are many studies on the momentum effect of China's A-share market. For example, Zhou Linjie (2002) found that the return of the momentum strategy is sensitive to the duration of the formation period and the holding period. Some researchers use monthly or annual data to study the momentum effects, and the results are mostly negative. Instead, they find that the A-share market has a significant reversal effect in the medium to long term, i.e., 2–3 years (Wang Yonghong and Zhao Xuejun, 2001; Wu Shinong, and Wu Chaopeng, 2003; Xiao Jun, and Xu Xinzhong, 2004; Liu Bo and Pi Tianlei, 2007; Pan Li and Xu Jianguo, 2011, etc.). However, some researchers reach the opposite conclusions. For example, Lu Zhen and Zou Hengfu (2007) find that China's stock market has a significant momentum effect of six months. There are also studies documenting the momentum effect using weekly stock data (i.e., Zhu Zhanyu, et al., 2003; Shen Keting and Liu Yuhui, 2006; Gao Qiuming, Hu Conghui and Yan Xiang, 2014).

Although scholars have not reached an agreement on the momentum effect of the A-share market, the strategy has been widely implemented in the industry of asset management. Nearly 90% of the funds choose momentum strategy as a priority (Huang Jing and Gao Fei, 2005).

Literature on the Mechanism of Momentum Effects

Traditional finance theory believes that the excess returns of momentum strategies come from more risk-taking. Fama and French (1993, 1996) argue that the momentum effect is not the evidence of market ineffectiveness. In asset pricing models, market beta is not sufficient to capture all the risks. As long as new risk factors are added to the factor model, the excess gains may disappear.

Behavioral finance believes that momentum effect is related to the behavior bias of investors when processing information. Barberis, Shleffer and Vishny (BSV, 1998), for example, argue that stocks exhibit price inertia in the short run because investors under-react to information in the short term. In the long run, with the spread of information, investors tend to over-react to information, and eventually the stock price reverses. Daniel, Hirsheifer and Subramanyam (DHS, 1998) explain the momentum effect from the perspective of overconfidence and attribution bias. Investors often overestimate their ability to forecast, and underestimate their forecasting errors. They also overestimate the value of private information, while underestimate the value of public information. In DHS model, overconfident investors are those who overestimate the accuracy of signals emitted by private information and underestimate the accuracy of signals sent by public information. Overconfidence leads to higher weights on private signals, causing stock price to over-react. When public information arrives, the invalid deviation of the price is partially corrected. As more and more public information arrives, the over-reacted prices tend to reverse.

From the point of view of investor heterogeneity, Hong and Stein (1999) believe that there are two types of traders in the market, information observer and momentum trader. Information observers do not observe all information at once, and with the spread of information, the price of stocks presents a certain momentum effect. In general, the faster the information diffuses, the shorter the duration of momentum effect. In order to better describe the spread of information, Balsara et al. (2006) introduce the idea of disease transmission into the model of Hong and Stern (1999). They conclude that the degree of information diffusion is affected by both the speed of information dissemination and the degree of information absorption. The former is an objective indicator related to turnover rates, volatility, etc., while the latter depends on some subjective factors.

There are also scholars who explain the momentum effect from the point of view of Knight's uncertainty. For example, Lewellen and Shanken (2002) argue that the predictability of stock price is related to parameter uncertainty in the pricing model. When decision makers are uncertain about the prior distribution of future cash flows, they gradually update their beliefs through Bayesian learning. The learning process leads to the positive auto-correlation of stock prices. Similarly, Ford, Kelsey and Pang (2013) point out that when there are signs of uncertainty in the market, momentum effect will present if both market makers and investors show optimism (pessimism). Gerdjikova (2006) argues that, given Knight's uncertainty, if stock price stays within a reasonable range, investors will trade the stock frequently in pursuit of more returns, creating a momentum effect.

Literature on Momentum Crashes

While momentum strategies provide investors with a higher Sharpe ratio than other risk factors, they also experience significant downturns over a period of time. Many studies have documented the large drawdowns of momentum strategies. For example, Barroso and Santa-Clara (2012) show that in 1932, the momentum strategy of buying a winner portfolio and selling a loser portfolio experienced a loss of 91.59% in just two months. In 2009, the loss of momentum strategy also reached 73.42% in three months. Daniel and Moskowitz (2016) have reached similar conclusions. The return for the historical loser portfolio reaches 232% from July 1932 to August 1932, compared with 32% for the historical winner portfolio. Similar results are found from March 2009 to May 2009. In both periods, the momentum strategy suffers a big loss. In addition, many studies have documented momentum crashes in different markets, such as Cooper, Gutierrez and Hameed (2004), Grundy and Martin (2001), and so on.

Daniel and Moskowitz (2016) demonstrate that the momentum crashes occur during times when the market rebounds from a long-term decline. The year of 1932 and 2009 are such examples when the market rebounds from the Great Depression and the financial crisis. Before the rebound of the market when the market is still declining, the winner portfolio tends to be the one with low market beta. Because only the low-beta portfolio will keep rising or experience slight downturn during the time when the market falls. Similarly, the loser portfolio tends to be the one with high beta, because the high beta portfolio will have significant negative returns when the market falls. Correspondingly, the momentum strategy of buying historical winners and selling historical losers is equivalent to buying a low-beta portfolio and selling a high-beta portfolio. When the market rebounds, the low-beta portfolio will rebound less than the high beta portfolio, and the momentum strategy will suffer a great loss as a result.

Momentum crashes in the A share market has been studied by some Chinese scholars who follow the work of Daniel and Moskowitz (2016). However, none of them explores the reasons for the crashes. They simply take it for granted that the crash is similar to the U.S. market (e.g., Shan Zhuo, 2014). However, our study shows that the pattern of momentum crash in the A-share market is completely different from that of the U.S. market. The crash of the U.S. market occurs when the market rebounds after a long time of decline, while the crash in the A share market occurs at the peak of the market. In addition, we try to provide explanations for the pattern difference in the two markets. There are more individual investors in the A share market than in the US market. The herding behavior of the individual investors is one of the causes of the pattern difference between the two markets.

Methodology and data

Methodology

This paper investigates the following 5 research questions:

Q1: Is momentum effect significant in A share market?

Q2: Does the problem of momentum crashes exist in the A share market?

Q3: What causes the momentum crashes in the A share market?

Q4: What are the variables that can be used to predict the momentum crashes?

Q5: How to avoid the problem of momentum crash while forming a trading strategy?

Different methodologies are used to address different research questions. For the evaluation of the performance of the momentum strategy, and the pattern of the momentum crashes (Questions 1 and 2), we adopt the widely used procedure to construct the momentum strategy for A share market. Specifically, it takes the following steps to form a momentum strategy.

Step 1: To form the momentum portfolios, we first rank stocks based on their cumulative returns from J periods before to one period before the formation date (i.e., the t-J to t-1-period returns), where, consistent with the literature (Jegadeesh and Titman, 1993; Asness, 1994; Fama and French, 1996; Daniel and Moskowitz, 2016), we use a one period gap between the end of the ranking period and the start of the holding period to avoid the short-term reversals documented by Jegadeesh (1990) and Lehmann (1990).

Step 2: All firms in our sample are then placed into one of ten decile portfolios based on this ranking, where portfolio 10 represents the “Winners” (those with the highest past returns) and portfolio 1 the “Losers.” The equally-weighted holding period returns of the decile portfolios are computed. At time t, investors buy the winner portfolio and sell the loser portfolio, and hold the “Winner minus loser (WML)” portfolio for the next K periods.

After identifying the momentum effects and crashes in A share market, we use the idea of time varying beta to explain the crashes (Question 3). The estimation of betas follows Daniel and Moskowitz (2016). Particularly, the betas are estimated by running a set of 52 weeks (about 1 year) rolling regressions of the momentum portfolio returns on the contemporaneous excess market return and 4 (weekly) lags of the market return.

Model: $r_{i,t} = \beta_0 r_{m,t} + \beta_1 r_{m,t-1} + \cdots \beta_4 r_{m,t-4}, \beta = \beta_0 + \beta_1 + \cdots \beta_4$ (1)

where $r_{i,t}$ denotes the return of past winner/loser portfolios, $r_{m,t}$ denotes the market return.

We use bull market indicators and market volatility to predict momentum crashes (Question 4). These variables are chosen because in the A share market, momentum crashes tend to occur in times of market boom, when the market has risen and ex-ante measures of volatility are high, coupled with an abrupt decrease in contemporaneous market returns.

$$r_{wml,t} = \gamma_0 + \gamma_1 I_{B,t-1} + \gamma_2 \sigma^2_{m,t-1} + \gamma_3 I_{B,t-1} \sigma^2_{m,t-1} + \epsilon_t \qquad (2)$$

where $r_{wml,t}$ denotes the return of winner minus loser portfolio, $I_{B,t-1}$is the bull market indicator and $\sigma^2_{m,t-1}$ is the variance of the weekly returns on the market, measured over the 52 weeks preceding the start of week t. The bull-market indicator equals 1 if the cumulative market return in the past 26 weeks is positive, and zero otherwise.

To avoid the crash of the momentum strategy, we assume an investor who allocates her assets between a risky asset and a risk-free asset. The objective function of the investor is to maximize the full sample Sharpe ratio of a portfolio where, each period, the risky assets can be traded in or out with no cost. The optimization problem of the investor can be found in Appendix A. As shown in Daniel and Moskowitz (2016), the optimal behavior of the investor yields the following weights on the risky asset

$$w_t = \frac{1}{2\lambda} \frac{\mu_t}{\sigma^2_t} \qquad (3)$$

where μ_t is the conditional expected return of the risky asset (winner minus loser portfolio, WML portfolio) obtained from Equation (2), σ^2_t is the conditional variance of the WML portfolio return, which can be obtained by applying the GARCH model proposed by Glosten, Jagannathan, and Runkle (1993, GJR) to the WML return series. Consistent with Daniel and Moskowitz (2016), the value of λ is chosen so that the in-sample volatility of the strategy return equals that of the market return over the full sample. This choice of λ is to make the strategy return comparable with the market return.

Data Sources

The Chinese stock market was established in 1990. The data used in this paper includes all firms listed on the Shanghai Stock Exchange (SHSE) and Shenzhen stock exchange (SZSE). The initial sample interval goes from January 1991 to June 2018. Weekly return data is used in this paper unless indicated otherwise.

In the early 1990s when the Chinese stock market was just established, the number of stocks was small, and the stock price was easily manipulated and volatile. Therefore, the performance of the momentum strategy was easily affected by the movement of one single stock. In order to get robust results, we only consider the sample periods when the number of tradable stocks exceeded 1,000 while forming the momentum portfolio. With this constraint, the new sample period starts from March 2001[1]. Suspended stocks are automatically removed when forming the portfolio. After the holding period, if stocks are suspended, we use the most recent closing price to compute the holding period return. Following convention, all prices are closing prices, and all returns are from close to close.

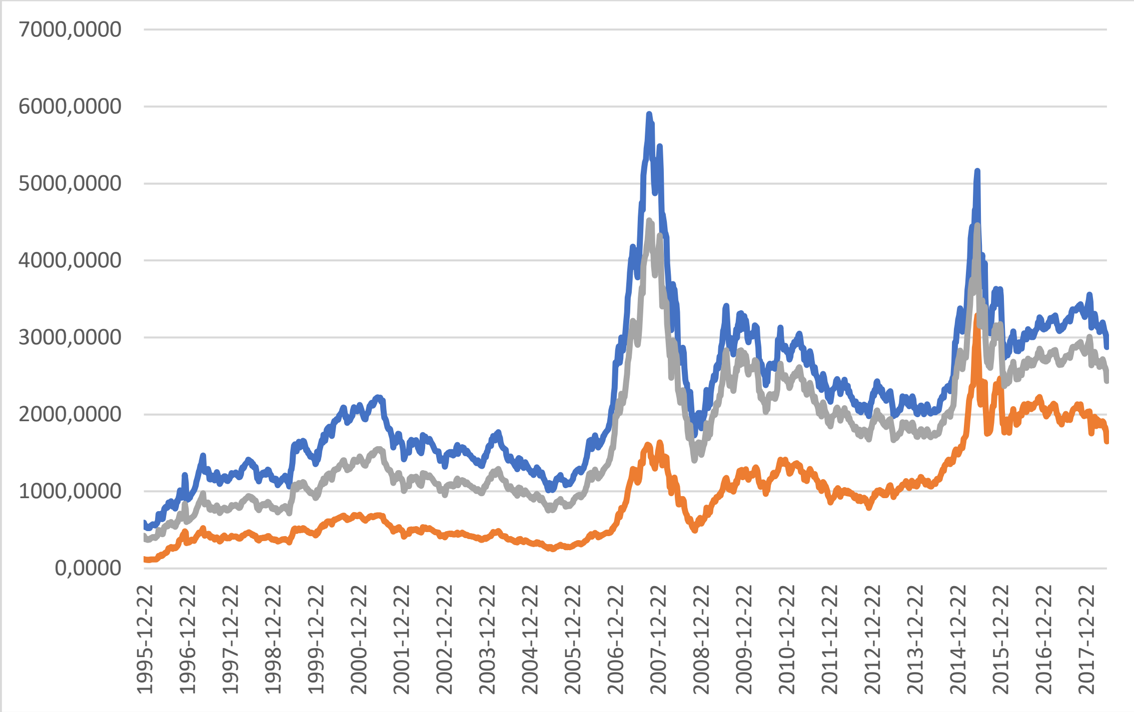
We use return data for all individual stocks in the A share market in this paper. Besides, market returns, and risk-free rates are also used. All the data is collected from WIND database, the data information system created by the Shanghai-based company called WIND Co. Ltd., the Chinese version of Bloomberg.

Market return is computed from the market index, which is the value-weighted average of Shanghai Composite Index and the Shenzhen A-Share Index (Figure 2). It should be noted here that the Shenzhen A-Share Index is different from the familiar Shenzhen Component Index. Shenzhen Component Index is a free-float market cap-weighted index. The constituents consisted of the 40 largest and most liquid A-share stocks listed and traded in SZSE, when the index was first launched on May 5, 1995. The index was developed with a base value of 1000 as of July 20, 1994. On May 20, 2015, the number of members changed from 40 to 500. While Shenzhen A-Share Index is constructed based on all individual stocks listed in Shenzhen Stock exchange. The index was first launched on October 4, 1992. Because we use all individual stocks in our paper, it is more appropriate to use Shenzhen A-Share Index which covers all individual stocks.

Figure 2 shows that all three indices are highly correlated. The correlation coefficient between Shanghai Composite Index and the Shenzhen A-Share Index is 0.84. The correlation coefficient between Shanghai Composite Index and the constructed market index is 0.99. The correlation coefficient between Shenzhen A-Share Index and the constructed market index is 0.89.

---

[1] The momentum effect is not significant during the year between 1991 to 2001.



Notes: The blue line represents the Shanghai Composite Index. The orange line represents the Shenzhen A-Share Index. The gray line represents the constructed market index which is a value-weighted average of the Shanghai Composite Index and the Shenzhen A-Share Index.

Figure 2:*Market Performance, 1995–2018*

Analysis

In this chapter, we try to provide answers to the following 5 questions, using the methodologies described above:

Q1: Is momentum effect significant in A share market?

Q2: Does the problem of momentum crashes exist in the A share market?

Q3: What causes the momentum crashes in the A share market?

Q4: What are the variables that can be used to predict the momentum crashes?

Q5: How to avoid the problem of momentum crash while forming a trading strategy?

Each question is discussed in the subsequent analysis.

Is Momentum Effect Significant in A Share Market?

We test the momentum effect in A share market using both monthly stock return data and weekly stock return data. Each momentum strategy is characterized by two variables, the formation period J, and the holding period K. Let $R_{wml}(J, K)$ denote the return of the momentum portfolio that is formed based on previous J period information and held for the next K period.

Using monthly data, we construct 36 different momentum strategies based different values of J and K, and compute the holding period return for each strategy. The results in Table 1 show that momentum effect barely exists in A share market at monthly frequency. 35 out of 36 strategies generate negative returns. The only exception is the strategy with $J =$ 9 month and $K = 6$ month. However, the t value is only 0.03 for this strategy, and the momentum effect is not significant.

Monthly data	K=1	2	3	6	9	12
	$R_{wml}(J, K)$ (%)					
J=1	-0.19 (-0.67)	-0.38 (-0.84)	-0.53 (-0.94)	-1.25 (-1.47)	-1.50 (-1.31)	-1.41 (-0.97)
2	-0.77 (-2.30)	-1.19 (-2.50)	-1.10 (-1.80)	-1.47 (-1.84)	-0.51 (-0.50)	-1.33 (-0.93)
3	-0.93 (-2.59)	-1.13 (-1.95)	-1.72 (-2.42)	-1.23 (-1.31)	-0.48 (-0.38)	-1.57 (-1.07)
6	-0.67 (-1.58)	-0.95 (-1.58)	-0.90 (-1.21)	-0.06 (-0.05)	-0.40 (-0.28)	-2.35 (-1.51)

9	-0.27 (-0.64)	-0.44 (-0.72)	-0.47 (-0.62)	0.04 (0.03)	-1.56 (-1.01)	-3.25 (-1.92)
12	-0.32 (-0.70)	-0.48 (-0.71)	-0.80 (-0.92)	-1.41 (-1.10)	-2.74 (-1.69)	-4.42 (-2.38)

Notes: t-statistics are in parentheses.

***Table 1**: Monthly Performance of Momentum Portfolio for Different J and K*

This finding is consistent with the existing literature on the momentum effect in A share market (Wang Yonghong and Zhao Xuejun, 2001; Gao Qiuming, Hu Conghui and Yanxiang, 2014). There are several reasons for the missing momentum effect in A Share market at monthly frequency. Firstly, the turnover ratio is high in A Share market. In 2015, the year when the momentum crash takes place, the annual turnover ratio in A Share market reaches the highest level of 556.9%, more than 3 times that of the United States (Figure 3). Hong and Stein (1999) argue that the persistence of the momentum effect is positively related to the trader's holding period. Therefore, a high turnover ratio may dampen the persistence of the momentum effect, and no momentum effect is found at monthly frequency. Besides, the proportion of individual investors in A share market is high. The herding behavior of the individual investors may cause the stock price to overreact in the short run, and the long-run correction of the overreacted price weakens the momentum effect in the long run.

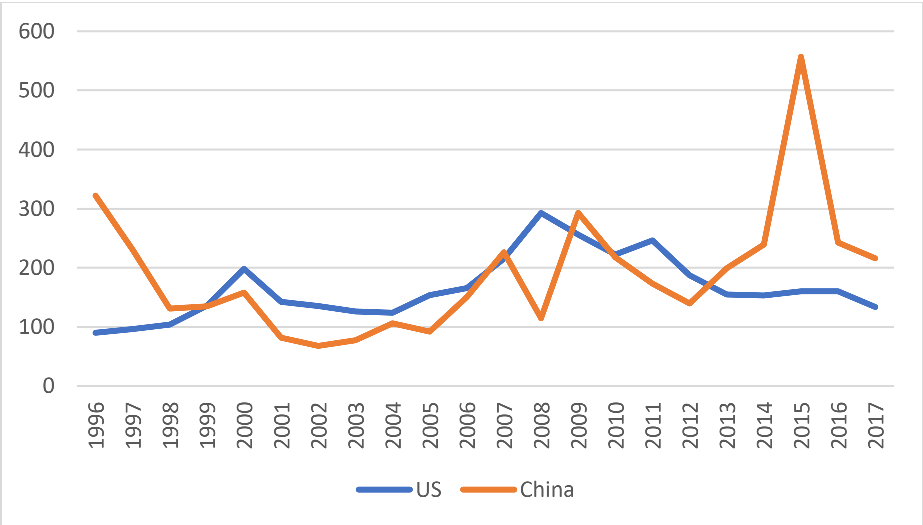


Figure 3: Stock Market Turnover Ratio (Value Traded/Capitalization) for United States and China, Percent, Annual
(Source: Federal Reserve Bank of St. Louis)

High turnover ratio and high proportion of individual investors in A share market may explain the missing momentum effect in the long run, but they cannot rule out the existence of the momentum effect in the short run. We reinvestigate the momentum effect using weekly data, and the results are reported in Table 2. Several pieces of information can be drawn from Table 2. Firstly, significant momentum effect is found for a very short formation period and holding period, i.e. (J=1 week, K=1 week), (J=1 week, K=2 weeks), and (J=2 weeks, K=1 week). As the formation period and the holding period increase, the momentum effect turns to reversal effect. Secondly, for a given value of the formation period J, the return of the WML portfolio decreases with the horizon of the holding period K. Finally, for a given value of the holding period K, the return of the WML portfolio decreases with the horizon of the formation period J. These findings are consistent with the literature that documents the existence of short-term momentum effect and long-term reversal effect in the A share market. There are 3 different momentum strategies with positive returns. Without loss of generality, we focus on the case with J=2 weeks, and K=1 week in the following analysis. Robustness checks are given at the end of this section. Our results also apply to the other two cases.

Weekly data	K=1	2	3	5	6	7
	$R_{wml}(J,K)$ (%)					
J=1	0.24 (2.96)	0.23 (2.05)	-0.00 (-0.03)	-0.58 (-3.13)	-0.63 (-3.24)	-0.64 (-3.16)
2	0.16 (1.81)	-0.06 (-0.50)	-0.48 (-3.1)	-1.14 (-5.62)	-1.18 (-5.40)	-1.14 (-4.93)
3	-0.11 (-1.17)	-0.51 (-3.81)	-1.03 (-6.08)	-1.62 (-7.34)	-1.66 (-7.06)	-1.69 (-6.85)
5	-0.36 (-3.55)	-0.82 (-5.74)	-1.28 (-7.21)	-1.79 (-7.71)	-1.86 (-7.43)	-1.95 (-7.31)
6	-0.37 (-3.69)	-0.83 (-5.63)	-1.26 (-6.87)	-1.72 (-7.24)	-1.82 (-7.15)	-1.91 (-7.12)
7	-0.37 (-3.59)	-0.81 (-5.33)	-1.21 (-6.49)	-1.75 (-7.25)	-1.87 (-7.27)	-2.01 (-7.33)

Notes: t-statistics are in parentheses.

Table 2: Weekly Performance of Momentum Portfolio for Different J and K

To get a better understanding of the return of the momentum portfolio, we compute the average return for each momentum decile portfolio. The results in Table 3 show that the average return of past losers (Decile 1) is -0.07%, and the average return of past winners (Decile 10) is 0.09%. Therefore, the average return of the “Winners minus losers” portfolio (WML) is 0.16%, which is higher than the market return (0.08%). The Sharpe ratio of the WML portfolio is 0.06, and that of the market is 0.02. It is worth emphasizing that the mean return does not increase monotonically as we go from Decile 1 to Decile 10. In fact, Decile 6 and Decile 7 deliver the highest returns. Stocks with moderate returns in the past two weeks tend to outperform other stocks in the next week. One possible explanation is that even 1 week is too long for past winners to remain their high returns, due to the high turnover ratio and high proportion of individual investors in A share market. A detailed explanation of this phenomenon is beyond the scope of this paper.

The market beta of the WML portfolio is -0.04 (t-stat = -1.71), while all other decile portfolios have positive betas. The unconditional CAPM alpha of the WML portfolio is 0.15 (t-stat = 1.81). Given the high alpha, the WML portfolio has a Sharpe ratio triple that of the market.

It is worth emphasizing that the winner portfolios are more negatively skewed than the loser portfolios. The skewness is -0.14 for the loser portfolios and -0.23 for the winner portfolios. While on average the winners outperform the losers, they tend to generate extreme negative values, which may cause crashes of the momentum strategy. The discussion of momentum crashes will be given in the next subsection.

	Momentum Decile Portfolios											
	1	2	3	4	5	6	7	8	9	10	Wml	Mkt
$\bar{r}(\%)$	-0.07	0.15	0.14	0.19	0.19	0.20	0.20	0.14	0.03	0.09	0.16	0.08
σ	4.62	4.41	4.36	4.26	4.26	4.26	4.20	4.07	4.06	4.33	2.59	3.41
Sharpe ratio	-0.02	0.03	0.03	0.04	0.05	0.05	0.05	0.03	0.01	0.02	0.06	0.02
α	-0.15	0.07	0.06	0.11	0.11	0.12	0.12	0.06	-0.04	0.01	0.15	0
$t(\alpha)$	-1.60	0.83	0.72	1.35	1.43	1.49	1.55	0.82	-0.52	0.08	1.81	-
β	1.09	1.04	1.05	1.02	1.04	1.05	1.03	0.99	0.98	1.04	-0.04	1
$t(\beta)$	39.27	40.1	43.1	42.7	44.5	45.5	45.6	44.2	42.9	42.0	-1.71	-
Skewness	-0.14	-0.11	-0.29	-0.17	-0.30	-0.36	-0.29	-0.23	-0.38	-0.23	-1.16	-0.02

Notes: Decile 1 represents the portfolio with the lowest past returns and decile 10 represents the portfolio with the highest past returns. Wml represents the winners minus loser's portfolio. The mean return, standard deviation and α are in percent (not annualized). The α, $t(\alpha)$, and β are estimated from a full-period regression of each decile portfolio's return on the market return.

Table 3: Momentum Portfolio Characteristics, 2001:03~2018:06

In this subsection we confirm the existence of momentum effect in A share market at weekly frequency. For the following analysis, we explore the phenomenon of momentum crashes for the momentum strategy with J = 2 weeks and K = 1 week. Robustness checks are given at the end of this section.

Does the Problem of Momentum Crashes Exist in the A Share Market?

Although the momentum strategy generates substantial profits over time, there are also periods when the strategy suffers a great loss. As indicated in Figure 1 in the previous section, from May 29th, 2015 to September 11th 2015 (15 weeks), the momentum strategy generates a negative return of around 50%, while the cumulative return of the market is -31%. This is the largest downturn of the momentum strategy, and the crash takes place right at the top of the market. On May 29, the cumulative return of the momentum strategy reached the highest level of 5.91. Two weeks later, the market return reached the highest level of 3.04, and started a long-term decrease until June 2018, the end of our sample period.

Does it mean that the crash of momentum strategy in A Share market happens together with, if not slightly before the decline of the whole market? We provide more evidence on this question in Table 4. We list the top 5 momentum crashes in A share market over 2001:03~2018:06. All of the 5 biggest crashes occur when the lagged two-year market return is positive. 3 crashes occur in the month where the market decreases contemporaneously, and 4 crashes occur in the month where the next month return of the market is negative. Take July 2015 as an example, the momentum strategy generates a negative return of 29.31% in that month. The cumulative return of the market from 2 years ago to July 2015 is 81.67%, and the market decreases by 13.02% in July and, by another 11.93% in August. Therefore, it is safe to reach the conclusion that the crash of momentum strategy in A Share market takes place right at the top of the market, when the market is or about to the decline.

Month	WML (t-1m,t)	MKT (t-1m,t)	MKT (t, t+1m)	MKT (t-2y,t)
2015:07	-29.31%	-13.02%	-11.93%	81.67%
2016:03	-20.26%	7.86%	-1.22%	48.47%
2015:09	-17.21%	-5.69%	11.77%	40.91%
2008:09	-9.01%	-4.28%	-24.71	49.39%
2008:07	-8.49%	4.30%	-16.00%	80.44%

Notes: This table lists the top 5 momentum crashes in A share market over 2001:03~2018:06. Also tabulated are the contemporaneous market returns, MKT (t-1m,t), the market returns in one month MKT (t, t+1m), and the market returns lagged by two years, MKT (t-2y,t).

Table 4: Worst Monthly Momentum Returns in A share market

A detailed comparison shows that the momentum crashes in the A share market is totally different from those in the US market. Daniel and Moskowitz (2016) studies the momentum crashes in the US market. The return for the historical loser portfolio reaches 232% from June 1932 to August 1932, compared with 32% for the historical winner portfolio. Similar results are found from March 2009 to May 2009. In both periods, the momentum strategy suffers a big loss. They argue that the momentum crashes occur during times when the market rebounds from a long-term decline (Table 5). The year of 1932 and 2009 are such examples when the market rebounds from the Great Depression and the financial crisis.

Month	WML (t-1m,t)	MKT (t-1m,t)	MKT (t-2y,t)
1932:08	-74.36	36.49	-67.77
1932:07	-60.98	33.63	-74.91
2001:01	-49.19	3.66	10.74
2009:04	-45.52	10.20	-40.62
1939:09	-43.83	16.97	-21.46

This table lists the top 5 momentum crashes in the US market over 1927:01~2013:03. Also tabulated are the contemporaneous market returns, MKT (t-1m, t), and the market returns lagged by two years, MKT (t-2y,t).

Table 5: Worst Monthly Momentum Returns in the US Market
(Source: Daniel and Moskowitz, 2016, Table 2)

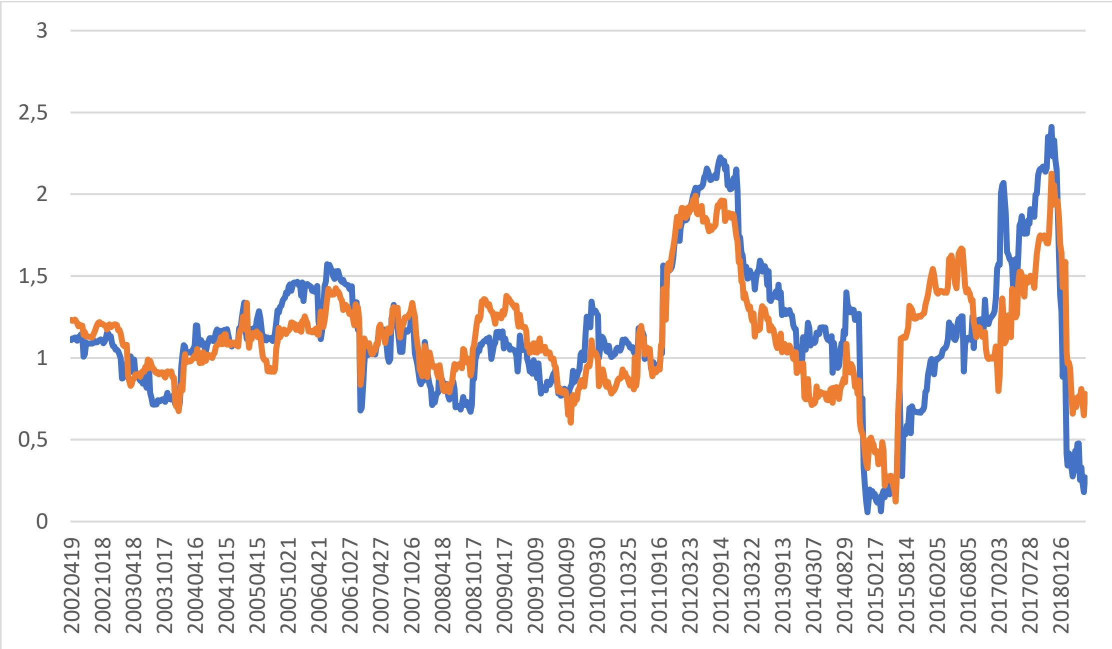
They also explain what causes the momentum crashes. Before the rebound of the market when the market is still declining, the winner portfolio tends to be the one with low market beta. Because only the low-beta portfolio will keep rising or experience slight downturn during the time when the market falls. Similarly, the loser portfolio tends to be the one with high beta, because the high beta portfolio will have significant negative returns when the market falls. Correspondingly, the momentum strategy of buying historical winners and selling historical losers is equivalent to buying a low-beta portfolio and selling a high-beta portfolio. When the market rebounds, the low-beta portfolio will rebound less than the high beta portfolio, and the momentum strategy will suffer a great loss as a result.

In the next subsection, we adopt similar argument proposed by Daniel and Moskowitz (2016) to explain the momentum crashes in China, and shed light on the mechanisms that cause the pattern difference of the crashes in the two markets.

What Causes the Momentum Crashes in the A Share Market?

Following Daniel and Moskowitz (2016), we use the argument of time varying beta to explain the crashes of the momentum strategies. We compute the market betas for the winner and loser portfolios. Market betas are estimated using 52 weeks (around 1 year) rolling regressions with weekly data (Equation 1). The model equation includes the market return at time t, $t-1$, $t-2$, $t-3$ and $t-4$ as the independent variables. Significant coefficients on lagged terms suggest that market-wide information is incorporated into the prices of many of the firms in these portfolios over the span of multiple periods.

Figure 4 plots the betas for the winner and loser momentum deciles for the full sample period. The betas move around substantially. The volatility of the betas for the loser decile (standard deviation = 0.42) is higher than that for the winner decile (standard deviation = 0.33). The two groups of betas are highly correlated, with a correlation coefficient of 0.8.



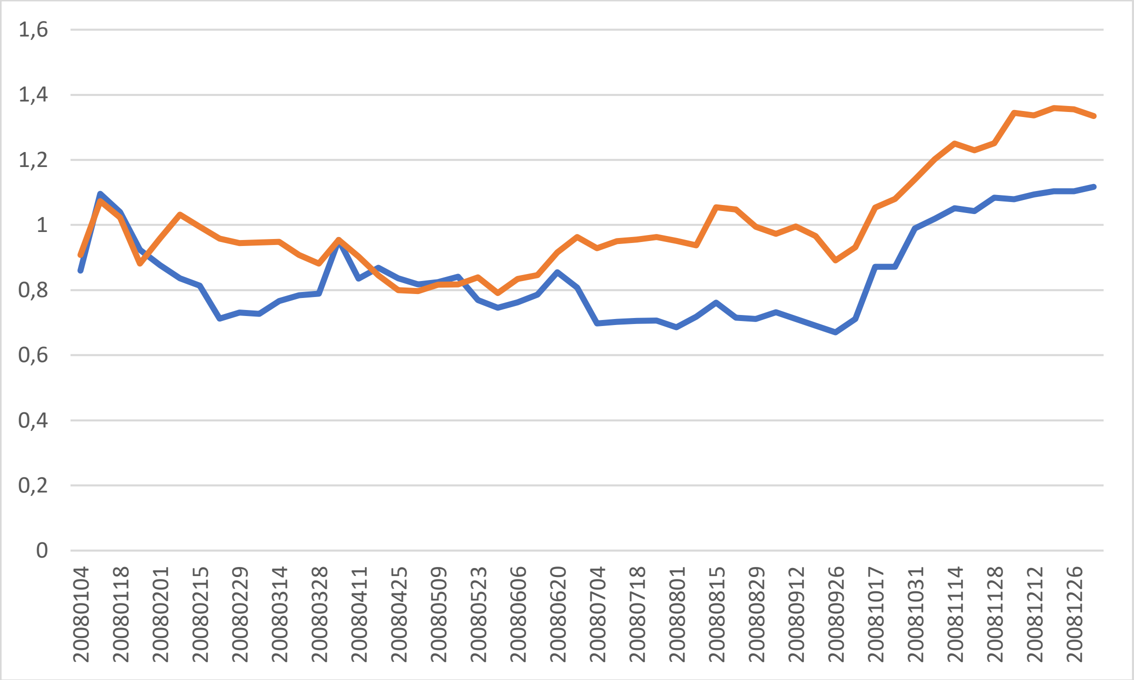
Notes: The blue line represents the market beta for the loser decile and the orange line represents the market beta for the winner decile. The betas are estimated by running a set of 52-week rolling regressions of the momentum portfolio returns on the contemporaneous market return and 4 (weekly) lags of the market return, and summing the betas.

***Figure 4: Market* Betas *of* Winner *and* Loser Decile Portfolios**

How can the movement of betas for different portfolios explain the momentum crashes in A share market? Recall that the crashes take place when the market enjoys a long term of expansion and is or about to decline. Assume that the market is still on the rise at time t, but starts to decline at time $t+1$. At time t when the market is still rising, the winner portfolio tends to be the one with high market beta. Because only the high-beta portfolio will deliver a high return during the time when the market rises. Similarly, the loser portfolio tends to be the one with low beta, because the low beta portfolio will perform badly when the market rises. When the investor forms a momentum strategy at time t, she buys historical winners (high beta) and sells historical losers (low beta). At time $t+1$, when the market starts to decrease, the return of past winners (high beta) will decrease more than that of past losers (low beta). Therefore, the momentum strategy suffers a great loss.

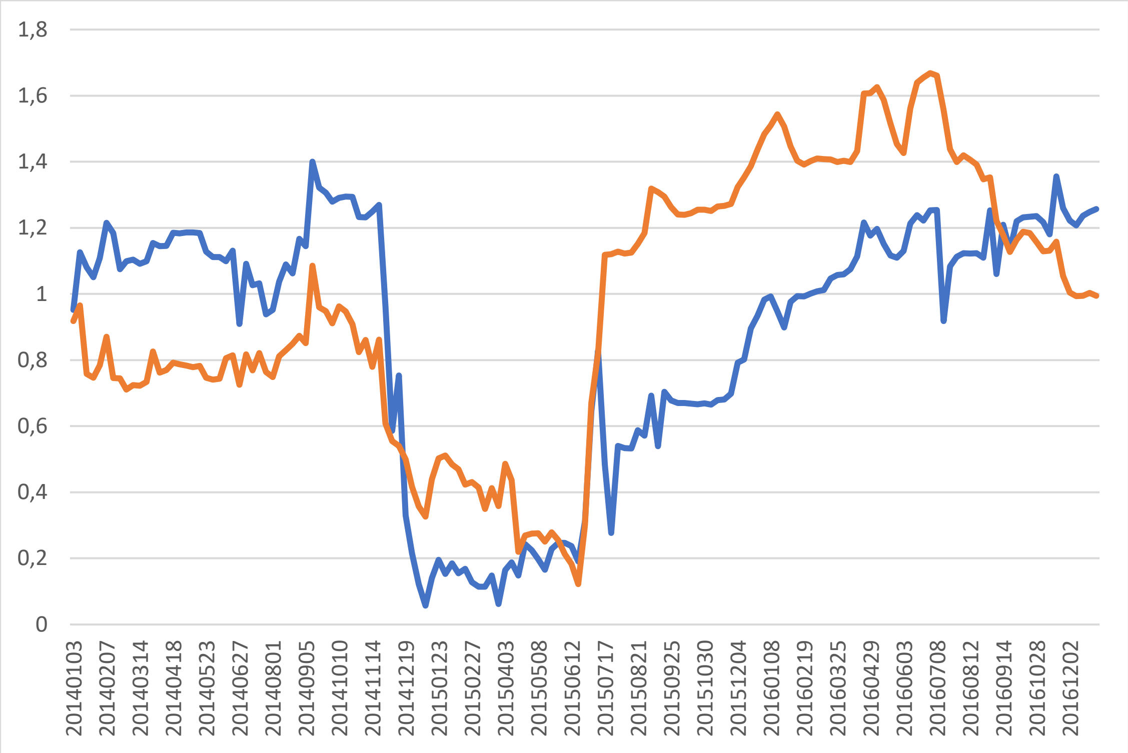
So far, our analysis relies on one condition that the beta of the winner (loser) portfolios will remain high (low) when the market changes from rising to falling. If the value of beta of the winner (loser) portfolios decreases (increases) as the market decreases, the return of past winner portfolios may still outperform that of past loser portfolios. The momentum strategy may still perform well.

Figure 5 and Figure 6 plot the market betas for the winner (loser) portfolio for the two sample periods when the crash of the momentum strategy takes place. For 2008:07~2008:09, and 2015:07~2016:03, the beta of the winner portfolios exceeds that of the loser portfolios. It is worth emphasizing that after 2015:07, the movement of market betas for the two deciles diverges considerably. The high value of market betas of the winner portfolios explains the crashes of the momentum strategy in A share market. In the next subsection, we will use regression analysis to show that the beta of the loser portfolio will be more negatively affected than the winner portfolio when the market changes from rising to declining.



Notes: The blue line represents the market beta for the loser decile and the orange line represents the market beta for the winner decile. The betas are estimated by running a set of 52-week rolling regressions of the momentum portfolio returns on the contemporaneous market return and 4 (weekly) lags of the market return, and summing the betas. The sample period goes from 2008:01 to 2008:12

Figure 5: Market* Betas *of* Winner *and* Loser Decile Portfolios *(2008)



Notes: The blue line represents the market beta for the loser decile and the orange line represents the market beta for the winner decile. The betas are estimated by running a set of 52-week rolling regressions of the momentum portfolio returns on the contemporaneous market return and 4 (weekly) lags of the market return, and summing the betas. The sample period goes from 2014:01 to 2016:12

*Figure **6: Market Betas of Winner and Loser Decile Portfolios (2014~2016)***

The pattern of the momentum crashes in the US market differs from that in the A share market. The former takes place when the market starts to rebound after a long period of decline, while the latter takes place when the market starts to decrease after a long period of expansion. Despite the pattern difference, the same logic applies to both markets. As long as the beta value of the high (low) beta portfolio remains high (low) during the time when the market changes, either from rising to falling or from falling to rising, it is likely for momentum strategy to suffer a loss. Based on different market conditions, the explanation of momentum crashes can be summarized by the following two cases.

Case 1: When the market starts to decrease after a long period of expansion, the beta of the winner portfolio (high beta) remains high, and the beta of the loser portfolio (low beta) remains low. The momentum strategy of buying historical winners and selling historical losers is equivalent to buying a high-beta portfolio and selling a low-beta portfolio. When the market decreases, the high-beta portfolio will decrease more than the low-beta portfolio, and the momentum strategy will suffer a great loss as a result.

Case 2: When the market starts to rebound after a long period of decline, the beta of the winner portfolio (low beta) remains low, and the beta of the loser portfolio (high beta) remains high. The momentum strategy of buying historical winners and selling historical losers is equivalent to buying a low-beta portfolio and selling a high-beta portfolio. When the market rebounds, the low-beta portfolio will rebound less than the high-beta portfolio, and the momentum strategy will suffer a great loss as a result.

Obviously, Case 1 can be used to explain the momentum crashes in the A share market, and Case 2 can be used to explain the momentum crashes in the US market. Please note that we do not find momentum crashes in A share market during the period when the market starts to rebound. This indicates that the beta of high (low) beta portfolio may no longer remain at high (low) value during that period. Similar argument holds for the US market. Therefore, it is interesting to ask the following question: Why does the beta value of high (low) beta portfolios remains high (low) when the market starts to decline in the A share market, but remains high (low) when the market starts to rebound in the US market? Here we only provide some intuition for this question, and further exploration of this question is beyond the scope of this paper. The high turnover ratio and high proportion of individual investors in A share market might be the reasons. The number of individual investors increases in the bull market, and reaches a high level at the end of the bull market. Individual investors pay more attention to past winners. Therefore, more attention is given to the winner stocks than the loser stocks, which increases the beta of the winner stocks and makes the winner stocks fluctuates more than the market index. When the markets start to decrease, individual investors are not able to detect the change of the market, and keep purchasing past winners. As a result, the beta of past winners (high beta) portfolios remains high. Our regression analysis partially confirms this argument. The regression analysis in Table 7 shows that the beta of the loser portfolio decreases substantially when the market starts to fall, while the beta of the winner portfolio is much less affected. Future research may focus on this question.

What Are the Variables That Can Be Used to Predict The Momentum Crashes?

In this subsection, we further explore the factors that affect the return of WML portfolios, and form predictors that can be used to forecast the momentum crashes.

We first run a set of weekly time-series regression; the results are presented in Table 6. The variables used in the regression are:

$r_{wml,t}$: the WML return in week t.

$r_{mkt,t}$: the market return in week t.

$I_{B,t-1}$: an ex-ante bull-market indicator that takes the value of 1 if the cumulative market return in the past 52 weeks (1 year) is positive.

$I_{D,t}$: a dummy variable that is used to capture the change of the market from increase to decrease. If the market return is negative at time t or in any of the future 3 weeks (i.e., $t+1$, $t+2$, $t+3$), the variable takes the value of 1.

Coef.	Variable	Reg.（1）	Reg.（2）	Reg.（3）
α_0	1	0.0016* (1.8305)	0.0014 （1.1168）	0.0014 （1.1191）
α_B	$I_{B,t-1}$		0.0004 （0.2250）	0.0004 （0.2490）
β_0	$r_{mkt,t}$	-0.0439* (-1.7061)	-0.1013** （-2.6090）	-0.1013** （-2.6144）
β_B	$I_{B,t-1} \cdot r_{mkt,t}$		0.1018** （1.9651）	0.0230 （0.3626）
$\beta_{B,D}$	$I_{B,t-1} \cdot I_{D,t} \cdot r_{mkt,t}$			0.1463** （2.1360）

This table presents the time series regression results from 2001:03 to 2018:06. In all 3 regressions, the dependent variable is the return of the WML portfolio. The independent variables are a constant, an indicator for the bull market, $I_{B,t-1}$,the market return, $r_{mkt,t}$, and a dummy variable $I_{D,t}$.

Table 6: Regression Results for WML Portfolio Returns

Regression (1) in Table 6 takes the following form

$$r_{wml,t} = \alpha_0 + \beta_0 r_{mkt,t} + \epsilon_t. \tag{4}$$

The negative market beta (-0.0439) is consistent with the results in the literature. The intercept (0.16% per week) is both economically large and statistically significant.

Regression (2) in Table 6 includes the bull market indicator as one more variable, and the regression equation takes the following form

$$r_{wml,t} = \left(\alpha_0 + \alpha_B I_{B,t-1}\right) + (\beta_0 + \beta_B I_{B,t-1}) r_{mkt,t} + \epsilon_t \tag{5}$$

This specification captures both expected return and market beta differences in bull markets. The intercept in bull markets is not significantly different from that in the whole market. However, in bull markets the market beta of the WML portfolio is 0.1018 higher, with a t-statistic of 1.9651. This result is equivalent to a lower beta of the WML portfolio in bear markets, which is consistent with Grundy and Martin (2001), and Daniel and Moskowitz (2016).

Regression (3) in Table 6 includes the dummy variable that is used to capture the change of market as one more variable, and the regression equation takes the following form

$$r_{wml,t} = \left(\alpha_0 + \alpha_B I_{B,t-1}\right) + [\beta_0 + I_{B,t-1}(\beta_B + I_{D,t}\beta_{B,D})] r_{mkt,t} + \epsilon_t \tag{6}$$

β_B remains positive but no longer significant, and $\beta_{B,D}$ is positive and significant at the 5% level. This means the higher beta in the bull markets are earned by the periods when the market is or about to decrease. After a long period of market expansion ($I_{B,t-1} > 0$), with the market now at the turning point from rising to decreasing ($I_{D,t} > 0$， $r_{mkt,t} < 0$), the momentum strategy will suffer a great loss ($I_{B,t-1}I_{D,t}\beta_{B,D}r_{mkt,t} < 0$). This regression explains the momentum crashes in the A share market.

Daniel and Moskowitz (2016) point out that if $\beta_{B,D}$ is significantly different from 0, this suggests that the WML portfolio exhibits option behavior relative to the market. In our case, a positive $\beta_{B,D}$ would mean that, in bull markets, the momentum portfolio is effectively short a put option on the market. If the market is still on a rise ($I_{D,t} = 0$), the point estimate of the WML portfolio beta is -0.0783 ($\beta_0 + \beta_B$). If the market starts to decrease ($I_{D,t} = 1$), the point estimate of the WML portfolio beta is 0.068 ($\beta_0 + \beta_B + \beta_{B,D}$). The higher value of market beta implies that the WML portfolio generates a negative return, as the market return $r_{mkt,t}$ is negative. This is equivalent to short a put option when the market falls.

The main source of this optionality comes from the loser portfolio. Table 7 presents the result of regression (3) (Equation 6) for both the loser portfolio and the winner portfolio. When the market starts to decrease, it has a negative impact on the market beta of the loser portfolio ($\beta_{B,D}$=-0.2419), and the beta value of the loser portfolio ($\beta_0 + \beta_B + \beta_{B,D}$ =0.9017) is smaller than that of the winner portfolio ($\beta_0 + \beta_B + \beta_{B,D}$ =0.9752). This finding is equivalent to the argument made in the analysis above. For momentum crashes to happen during the time when the market starts to decrease after a long time of expansion, we need the beta value of the winner portfolio to remain high. The high (low) beta of the winner (loser) portfolio makes its return decrease more (less) when the market falls. Therefore, the momentum strategy suffers a loss.

	Variable	Loser portfolio	Winner portfolio	WML
α_0	1	-0.0017	-0.0004	0.0014
α_B	$I_{B,t-1}$	0.0004	0.0008	0.0004
β_0	$r_{mkt,t}$	1.1701	1.0688	-0.1013
β_B	$I_{B,t-1} \cdot r_{mkt,t}$	-0.0211	0.0019	0.0230
$\beta_{B,D}$	$I_{B,t-1} \cdot I_{D,t} \cdot r_{mkt,t}$	-0.2419	-0.0955	0.1463

This table presents the time series regression results from 2001:03 to 2018:06. The dependent variables are the return of the loser portfolio, the return of the winner portfolio and the return of the WML portfolio, respectively. The independent variables are a constant, an indicator for the bull market, $I_{B,t-1}$,the market return, $r_{mkt,t}$, and a dummy variable $I_{D,t}$.

Table 7: Regression Results for Different Portfolio Returns

The option-like payoff associated with the WML portfolio further suggests that the value of this option should be a function of the future variance of the market. Put it in other ways, the value of the option (the return of the WML portfolio) should be predictable. Specifically, we use weekly market return data to construct an ex-ante estimate of the market volatility over the next week, and use this market variance estimates together with the bull-market indicator $I_{B,t-1}$ to predict future WML returns. That is, we use the following equation, which has been proposed in the methodology section and rewritten here, to predict future WML returns.

$$r_{wml,t} = \gamma_0 + \gamma_B I_{B,t-1} + \gamma_{\sigma_m^2} \sigma_{m,t-1}^2 + \gamma_{int} I_{B,t-1} \sigma_{m,t-1}^2 + \epsilon_t \quad (7)$$

where $I_{B,t-1}$ is the bull market indicator and $\sigma_{m,t-1}^2$ is the variance of the weekly returns of the market over the time t-27 to t-1 (around half a year).

The results show that the volatility of market returns has significant predictive power over future WML returns (significant value of $\gamma_{\sigma_m^2}$ in Regression 3), and the predictability comes from the bull market volatility (significant value of γ_{int} in Regression 5).

	Reg.（1）	Reg.（2）	Reg.（3）	Reg.（4）	Reg.（5）
γ_0	0.0011 （0.8514）	0.0037*** （2.7420）	0.0034** （1.9975）	0.0026*** （2.4476）	0.0017 （0.9266）
γ_B	0.0009 （0.5163）		0.0005 （0.2854）		0.0046* （1.6787）
$\gamma_{\sigma_m^2}$		-1.9089** （-2.0928）	-1.8796** （-2.0467）		-0.5453 （-0.4772）
γ_{int}				-2.0070* （-1.7428）	-3.7475* （-1.9572）

This table presents the time series regression results from 2001:03 to 2018:06. The dependent variable is the return of the WML portfolio. The independent variables are a constant, an indicator for the bull market, $I_{B,t-1}$, and the volatility of market returns.

Table 8: Regression Results for WML Portfolio Returns

In this subsection, we use various regressions to explain the performance of WML portfolio in the bull markets and demonstrate the option-like payoffs associated with the WML portfolio. The regression results help us determine the variables that can be used to predict future returns of the WML portfolio. The predicted values of future returns are used to form a trading strategy which does not suffer the problem of crashes. Details of the trading strategy can be found in next subsection.

How To Avoid The Problem of Momentum Crash While Forming A Trading Strategy?

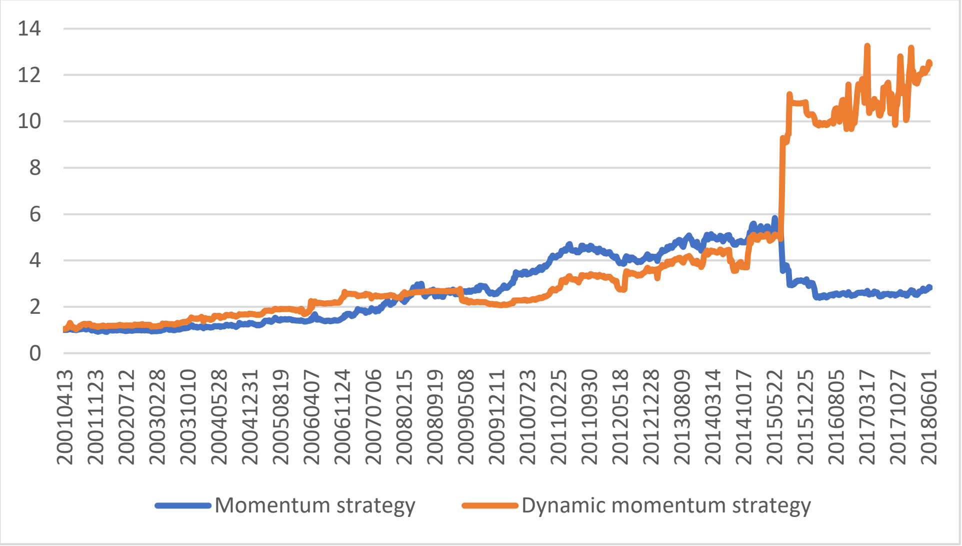
Based on the findings from previous sections, we form a trading strategy which dynamically adjusts the weight on the WML momentum strategy using the predicted return and variance of the strategy.

We assume an investor who allocates her assets between a risky asset and a risk-free asset. The objective is to maximize the Sharpe ratio of a portfolio where, each period, we can trade in or out of the risky asset with no cost. As shown in Daniel and Moskowitz (2016), the optimal behavior of the investor yields the following weights on the risky asset (WML portfolio).

$$w_t = \frac{1}{2\lambda}\frac{\mu_t}{\sigma_t^2} \qquad (8)$$

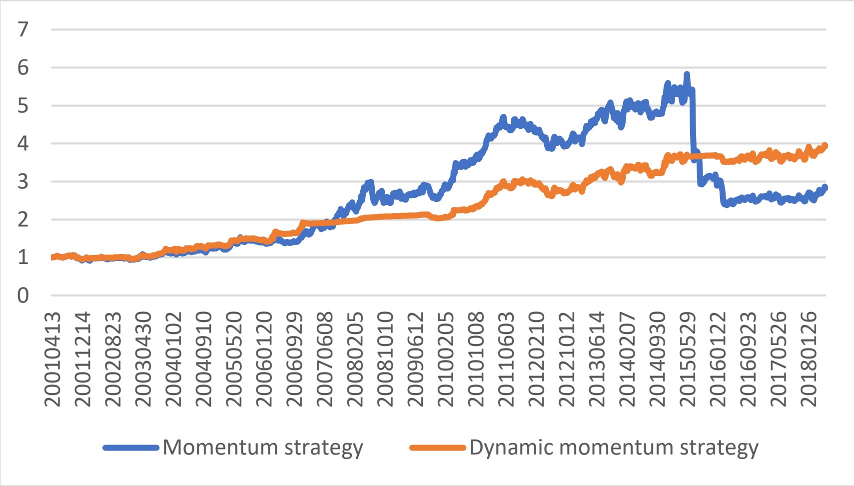
where μ_t is the conditional expected return of the WML portfolio obtained from Equation (7), σ_t^2 is the conditional variance of the WML portfolio return, which can be obtained by applying the GARCH model proposed by Glosten, Jagannathan, and Runkle (1993, GJR) to the WML return series. The specification and estimation of the GARCH model are given in Appendix B.

Starting from an initial value of 1, Figure 7 and Figure 8 plot the cumulative returns for the momentum strategies. In Figure 7, there is no restriction imposed on the dynamic weights. In Figure 8, the dynamic weights are restricted between 0 and 1. In both figures, the blue line represents the cumulative returns for the traditional momentum strategy, and the orange lien represents the cumulative returns for the dynamic momentum strategy. It is obvious that the dynamic strategy successfully avoids the crash in 2015. When no restriction is imposed on the dynamic weights, the cumulative return can reach a high level of almost 13.3. The crash is replaced by a profit jump in 2015, due to a negative weight assigned to the WML portfolio. When $0 \leq w_t \leq 1$, the performance of the dynamic momentum strategy still outperform that of traditional one, with a higher profit and lower volatility.



Notes: the blue line represents the cumulative return generated by the momentum strategy, while the orange line represents the cumulative return generated by the dynamic momentum strategy. There is no restriction on the value of w_t.

Figure 7: Cumulative Returns of the Momentum Strategy Without Restriction on the Weights



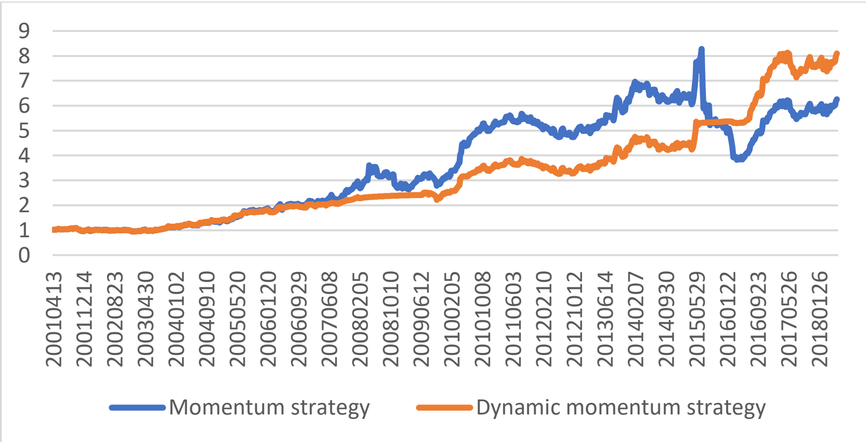
Notes: the blue line represents the cumulative return generated by the momentum strategy, while the orange line represents the cumulative return generated by the dynamic momentum strategy. Restrictions are set on the dynamic weights so that $0 \leq w_t \leq 1$.

Figure 8: Cumulative Returns of the Momentum Strategy with restrictions on The Weights

Robustness Check

Robustness check is conducted in this subsection. As shown in previous analysis, significant momentum effect is found for very short formation period and holding period, i.e. (J=1 week, K=1 week), (J=1 week, K=2 weeks), and (J=2 weeks, K=1 week) in A share market. We have reported the results for J=2 weeks and K=1 week in previous analysis, now we report the results for J=1 week, and K=1 week as the robustness check.

Figure 9 confirms the momentum crash in 2015 (blue line) and the improvement made by the dynamic momentum strategy (orange line). Therefore, the results in previous analysis are robust.



Notes: the blue line represents the cumulative return generated by the momentum strategy, while the orange line represents the cumulative return generated by the dynamic momentum strategy. Restrictions are set on the dynamic weights so that $0 \leq w_t \leq 1$. The results are reported for J=1 week and K=1 week.

Figure 9: Robustness Check

Conclusion

This paper provides a detailed analysis on the momentum effect in A share market. Particularly, we provide answers to the following questions.

Q1: Is momentum effect significant in A share market?

Q2: Does the problem of momentum crashes exist in the A share market?

Q3: What causes the momentum crashes in the A share market?

Q4: What are the variables that can be used to predict the momentum crashes?

Q5: How to avoid the problem of momentum crash while forming a trading strategy?

For Question 1, we confirm the existence of momentum effect in A share market at weekly frequency. But no momentum effect is found at monthly frequency.

For Question 2, we find that the crash of momentum strategy in A Share market happens together with, if not slightly before the decline of the whole market. This pattern differs from that in the US market where the crash of the momentum strategy happens when the market rebound from the bottom.

For Question 3, we find that time varying beta can be used to explain the momentum crashes in A share market. When the market starts to decrease after a long period of expansion, the beta of the winner portfolio (high beta) remains high, and the beta of the loser portfolio (low beta) remains low. The momentum strategy of buying historical winners and selling historical losers is equivalent to buying a high-beta portfolio and selling a low-beta portfolio. When the market decreases, the high-beta portfolio will decrease more than the low-beta portfolio, and the momentum strategy will suffer a great loss as a result.

For Question 4, we find that market volatility and a bull market indicator can be used to predict the crash of the WML portfolio.

For Question 5, we assume an investor who allocates her assets between a risky asset and a risk-free asset. When the dynamic weights are adopted, the performance of the momentum strategy is improved substantially.

The contribution of this paper is twofold. The first is the systematic analysis on the momentum effect in A share market, including the confirmation of the existence of the momentum effect at weekly frequency, the documentation of the momentum crashes in 2008 and 2015, and the way to avoid the crashes. To our knowledge, this is the most complete analysis on the momentum effect in the A share market. The second is that we find the pattern difference on the crashes between the US market and the A share market. The crash of the U.S. market occurs when the market rebounds after a long time of decline, while the crash in the A share market occurs at the peak of the market. We argue that the herding behavior of the individual investors in the A share market might cause the pattern difference between the two markets. Future research may focus on this area.

References

Balsara, N. J., Zheng, L., Vidozzi, A. et al. 2006. Explaining Momentum Profits with an Epidemic Diffusion Model. *Journal of Economics and Finance*, 30(3): 407–422.

Barberis, N., Shleifer, A. and Vishny, R. 1998. A Model of Investor Sentiment. *Journal of Financial Economics*, 49(3): 307–343.

Barroso, P., and Santa-Clara, P., 2012. Managing the Risk of Momentum. Nova School of Business and Economics, Working Paper.

Carhart, M.1997. On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1): 57–82.

Cooper, M. J., Gutierrez, R. C., and Hameed, A. 2004. Market States and Momentum. *The Journal of Finance*, 59(3): 1345–1365.

Daniel, K., Hirshleifer, D., and Subrahmanyam, A. 1998. Investor Psychology and Security Market Under- and Overreactions. *The Journal of Finance*, 53(6): 1839–1885.

Daniel, K., and Moskowitz, T. J. 2016. Momentum Crashes. *Journal of Financial Economics*, 122 (2): 221–247

Fama, E. F., and French, K. R. 1993. Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics*, 33(1): 3–56.

Fama, E. F., and French, K. R. 1996. Multifactor Explanations of Asset Pricing Anomalies. *Journal of Finance*, 51(1): 55–84.

Ford J. L., Kelsey D., and Pang W. 2013. Information and Ambiguity: Herd and Contrarian Behaviour in Financial Markets. *Theory and Decision*, 75:1–15.

Gao, Qiuming 高秋明, Hu, Conghui 胡聪慧, and Yan, Xiang 燕翔. 2014. Zhongguo Agu shichang dongliang xiaoying de tezheng he xingcheng jili yanjiu 中国 A 股市场动量效应的特征和形成机理研究. *Caijing yanjiu* 财经研究, 40(2): 97-107.

Grundy, B. D., and Martin, J. S. 2001. Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing. *The Review of Financial Studies*, 14:29–78.

Guerdjikova, A. V. 2004. Case-Based Decision Theory and Financial Markets. Doctoral Thesis. Heidelberg University, Heidelberg, Germany. DOI: 10.11588/heidok.00005176

Huang, Jing 黄静, and Gao, Fei 高飞. 2005. Jijing touzi xingwei yu touzi jixiao shizheng yanjiu 基金投资行为与投资绩效实证研究. *Zhengquan shichang daobao* 证券市场导报, 2:25–29.

Hong, H., and Stein, J. C. 1999. A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *Journal of Finance*, 54(6): 2143–2184.

Jegadeesh, N., and Titman, S.1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 48(1): 65–91.

Lewellen, J., and Shanken, J. 2002. Learning, Asset-Pricing Tests, and Market Efficiency. *The Journal of Finance*, 57(3): 1113–1145.

Liu, Bo 刘博, and Pi, Tianlei 皮天雷. 2007. Guanxing celue he fanzhuan celue: Laizi zhongguo hushen Agu shichang de xinzhengju 惯性策略和反转策略：来自中国沪深 A 股市场的新证据. *Jinrong yanjiu* 金融研究, 8(A): 154–166.

Lu, Zhen 鲁臻, and Zou, Hengfu 邹恒甫. 2007. Zhongguo gushi de guanxing yu fanzhuan xiaoying yanjiu 中国股市的惯性与反转效应研究. *Jingji yanjiu* 经济研究, 9: 145-155.

Pan, Li 潘莉, and Xu, Jianguo 徐建国. 2011. Agu gegu huibaolv de guanxing yu fanzhuan A 股个股回报率的惯性与反转. *Jinrong yanjiu* 金融研究, (001) :149-166.

Rouwenhorst, K. G., 1999. Local Return Factors and Turnover in Emerging Stock Markets. *Journal of Finance*, 54(4):1439–1464.

Shan, Zhuo 单卓. 2014. Wenjian dongliang jiaoyi celue de shizheng yanjiu-jiyu Agu shichang de zhengju 稳健动量交易策略的实证研究—基于 A 股市场的证据，Master Thesis. University of International Business and Economics (UIBE), Beijing, China.

Shen, Keting 沈可挺, and Liu, Yuhui 刘煜辉. 2006. Zhongguo gushi Zhong guanxing yu fanxiang touzi celue de huoli moshi 中国股市中惯性与反向投资策略的获利模式. *Guanli kexue xuebao* 管理科学学报, 6:47–56.

Wang, Yonghong 王永宏, and Zhao, Xuejun 赵学军. 2001. Zhongguo gushi “guanxing celue” he ’fanzhuan celue’de shizheng fenxi 中国股市 “惯性策略” 和 “反转策略”的实证分析. *Jingji yanjiu* 经济研究, 6: 56-61.

Wu, Shinong 吴世农, and Wu, Chaopeng 吴超鹏. 2003. Woguo gupiao shichang ’jiage guanxing celue’he ’yingyu guanxing celue’de shizheng yanjiu 我国股票市场"价格惯性策略"和"盈余惯性策略"的实证研究. *Jingji kexue* 经济科学, (04): 43–52.

Xiao, Jun 肖军, and Xu, Xinzhong 徐信忠. 2004. Zhongguo gushi jiazhi fanzhuan touzi celue youxiaoxing shizheng yanjiu 中国股市价值反转投资策略有效性实证研究. *Jingji yanjiu* 经济研究, 3: 55-64.

Zhou, Linjie 周琳杰. 2002. Zhongguo gupiao shichang dongliang celue yinglixing yanjiu 中国股票市场动量策略赢利性研究. *Shijie jingji* 世界经济, 025 (008): 60–64.

Zhu, Zhanyu 朱战宇, Wu, Chongfeng 吴冲锋, and Wang, Chenyi 王承炜,. 2003. Butong jianyan zhouqixia zhongguo gushi jiage dongliang de yinglixing yanjiu 不同检验周期下中国股市价格动量的盈利性研究. *Shejie jingji* 世界经济, 8: 62-67.

Appendix A: Optimization Problem of the Investor

The derivation of the optimal weights assigned to the WML portfolio follows Daniel and Moskowitz (2016). We rewrite it here for the completeness of the paper.

Assume the return of the risky asset $r_{t+1}$is normally distributed with conditional mean μ_t， and conditional variance σ_t^2

$$\mu_t = E_t r_{t+1} \qquad \text{（A1）}$$

$$\sigma_t^2 = E_t(r_{t+1} - \mu_t)^2 \qquad \text{(A2)}$$

The agent's objective function is to maximize the full period Sharpe ratio of a managed portfolio. At the beginning of each period, a fraction w_t is allocated to risky asset (the WML portfolio in our analysis), and a fraction (1-w_t) to the risk-free asset.

The full sample Sharpe ratio takes the form

$$\text{SR} = \frac{E(\frac{1}{T}\sum_{t=1}^{T} r_{p,t})}{\sqrt{E\frac{1}{T}\sum_{t=1}^{T}(r_{p,t} - \frac{1}{T}\sum_{t=1}^{T} r_{p,t})^2}}. \qquad \text{(A3)}$$

Daniel and Moskowitz（2016）show that maximizing the Sharpe ratio is equivalent to solving the constrained maximization problem

$$\max_{\omega_0,\dots,\omega_{T-1}} E(\frac{1}{T}\sum_{t=1}^{T} r_{p,t}), \ \text{s. t. } E\frac{1}{T}\sum_{t=1}^{T}(r_{p,t} - \frac{1}{T}\sum_{t=1}^{T} r_{p,t})^2 = \sigma_p^2. \qquad \text{(A4)}$$

They also prove that the resulting optimal weight on risky asset at time t takes the following representation.

$$w_t = \frac{1}{2\lambda}\frac{\mu_t}{\sigma_t^2} \qquad \text{(A5)}$$

where λ is the Lagrangian multiplier. The value of λ is chosen so that the in-sample volatility of the strategy return equals that of the market return over the full sample.

Appendix B: Estimation of the Garch Model

The Garch model proposed by Glosten，Jagannathan and Runkle (1993) takes the following form:

$$r_{wml,t} = \mu + \epsilon_t \quad \text{(B1)}$$

$$\epsilon_t \sim N\ (0,\ \sigma_t^2) \quad \text{(B2)}$$

$$\sigma_t^2 = \delta + \beta\sigma_{t-1}^2 + (\alpha + \gamma I(\epsilon_{t-1} < 0))\epsilon_{t-1}^2 \quad \text{(B3)}$$

where $I(\epsilon_{t-1} < 0)$ is an indicator variable that equals to one if $\epsilon_{t-1} < 0$， and 0 otherwise. We use the Eviews 8.0, a statistical software to estimate this model.

The maximum likelihood estimates and t-statistics are:

parameter	μ	δ	β	α	γ
ML_est	0.002185	3.83E-05	0.772859	0.287806	-0.184056
z_stat	(2.976443)	(6.066737)	(34.25951)	(6.533158)	(-4.637243)

This table presents the time series regressions results of the GJR Garch model. The sample goes from 2001:03 to 2018:06. The dependent variable is the return of the WML portfolio.

Table 9: Regression results of the GJR Garch model

The estimated time series of σ_t^2 is plotted in the figure below.

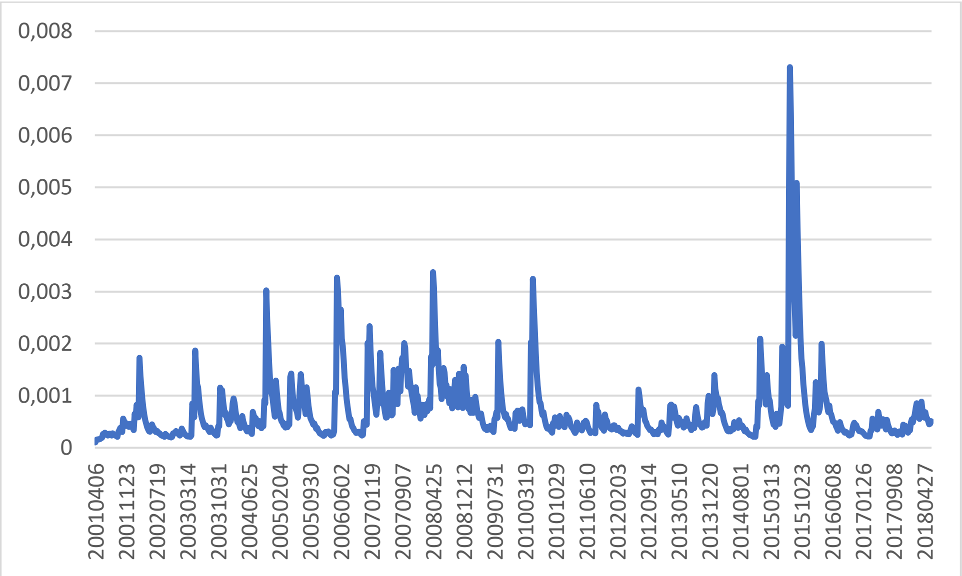


Figure 10: Model estimates of the variance of WML returns

Resume of the Author

<table>
<tr><td>Name</td><td>Weiming Wang</td><td>Sex</td><td>Male</td><td>Date Of Birth</td><td>Oct.16 1962</td></tr>
<tr><td colspan="2">Nationality</td><td colspan="2">P.R. China</td><td>Origins</td><td>Wujing, Jiangsu Province</td></tr>
<tr><td colspan="3">Professional Title</td><td colspan="3">Senior engineer, National first class registered architect</td></tr>
<tr><td colspan="2">Full Time Education</td><td colspan="2">B.A.</td><td>Economics and Management</td><td>Qiqihaer University</td></tr>
<tr><td colspan="2">On-The-Job Education</td><td colspan="2">Phd</td><td>Doctor of Business Administration</td><td>W.P. Carey School of Business
Arizona state university</td></tr>
<tr><td>Current Position</td><td colspan="5">Chairman, Weiye Financial Holding Group</td></tr>
<tr><td>Social Position</td><td colspan="5">Member of the CPPCC (China People's Political Consultative Conference) National Committee, Qinghai Province
Deputy director of the Economic Committee of the CPPCC, Qinghai Province
Vice-President of the Federal Association of Industry and Commerce， Qinghai Province
President of Jiangsu Chamber of Commerce, Qinghai Province
President of Association of Enterprise Credit, Qinghai Province</td></tr>
<tr><td>Education & Affiliations</td><td colspan="5">Education:
• BA, Economics and Management, Qiqihaer University, China 1994-1997
• EMBA, Joint program by The University of Hong Kong and Fudan University, 2006-2012
• EMBA, Cheung Kong Graduate School of Business, 2009-2012
• DBA, W.P. Carey School of Business, Arizona state university 2014-2017
• Affiliations:
• Manager, The third company of Wujin Construction Engineering Corporation, China, 1979-1985
• General Manager, The third company of Wujin Construction Engineering Corporation, China, 1985-1999
• General Manager, Qianhuang Real Estate Company,1999-2002
• Chairman, Weiye Financial Holding Group,2002-present</td></tr>
</table>

Chairman Profile	As an entrepreneur, Mr. Wang has rich experience in the fields of real estate, engineering, and finance. He has strong leadership ability, and can quickly adapt to the changing market. He also innovatively refines his management styles, in order to improve the operating efficiency of the company, and expand the reputation of the company. Meanwhile, Mr. Wang has always maintained a continuous pursuit of academic achievement. He currently holds a master degree from Cheung Kong Graduate School of Business, a doctor degree from Arizona State University, etc. Since 2016, Mr. Wang has made a strategic decision to explore oversea market, make full use of domestic and foreign resources to form a ‘two wheel drive’ of the company, and focus on multiple fields of real estate, construction, finance, technology, and international trade. Under the leadership of Mr. Wang, the development of the company has entered the fast lane.
Company Profile	Weiye Financial Holding Group Co., Ltd. is located in Hongqiao, Shanghai, China. The company has 3 secondary group companies (Jiangsu Weiye Construction Group, Jiangsu Weiye International Investment Group and Western Weiye Investment Group), and 42 wholly-owned subsidiaries (business units) in China, the United States, Canada, Pakistan, India, Zambia, Congo (DRC) and other countries. The company has a total registered capital of more than 2.8 billion yuan, more than 2,000 employees, and a total asset of nearly 15 billion yuan. The main business of the company includes real estate, construction, municipal transportation, decoration project, financial investment, high-tech investment, cement and building material, exploitation of mineral resources, and international trade. The "Shangri-La•City Garden" real estate brand launched by the company has won various rewards, including "Guangsha Award", the highest award in national real estate industry, and "Luban Award", the highest honor in the construction industry. Weiye Construction Group has been praised by former President Hu Jintao, and other government officials. In 2019, the company initiates a new real estate project in Nanxun, Huzhou, an ancient town with a history of 1,000 years. The project is located in the center of the city, which enjoys the prosperity of the CBD and the scary resources of the ecosystem.

<table>
<tr>
<td>Rewards</td>
<td>
Company Rewards:

In 2005, Former President Hu Jintao, Accompanied By Government Officials Li Yuanchao And Liang Baohua, Visited One Of The Projects Of The Company, “Gangnan Huayuan District”, And Expressed Positive Evaluation.
In 2008, Weiye Group Won The Title Of “Top Ten Enterprises With Comprehensive Strength In China's Commercial Concrete Industry”
In 2009, Xining Weiye Real Estate Development Co., Ltd. Won The Rewards Of “China Real Estate Integrity Enterprise (2007-2008)”
In 2018, Weiye Real Estate Development Co., Ltd. Won The Rewards Of “Advanced Enterprise Of Real Estate Development And Operation In Qinghai Province”

Personal Rewards:

China Charity Outstanding Contribution Award, 2014. (This Award Is Granted Every Five Years And Is The Highest Award For Chinese Charity By The Ministry Of Civil Affairs Of The People’s Republic Of China)
Best Individual Reward In Global Jiangsu Chamber Of Commerce, 2017
Best Individual Reward In Real Estate Development In Qinghai Province, 2019.

</td>
</tr>
</table>