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Momentum crashes in Korean stock market
모멘텀 붕괴현상 한국 유가증권시장 연구

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경영학과 재무금융 전공

Rui Pinghai

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지도교수 박소정

이 논문을 경영학석사학위논문으로 제출함

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Rui Pinghai의 석사학위논문을 인준함

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위 원 장 _____ (인)

부 위 원 장 _____ (인)

위 원 _____ (인)

Abstract

Momentum crashes in Korean stock market

Rui Pinghai

College of Business Administration

The Graduate School

Seoul National University

This study investigates momentum crashes in Korean stock market following up the Kent Daniel (2016) paper. We find that the momentum crashes always happen during the bear market states with high market volatility. Especially, during the market upswings period, the loser portfolio has better performance than winner portfolio. Moreover, the momentum crashes themselves are predictable. When we apply the bear market indicator and ex ante estimated volatility to compute the conditional mean and conditional variance of momentum strategy. Those two elements help us build a dynamic weighting strategy to improve the momentum strategy performance. The results show that the Shape ratio of dynamic strategy is twice bigger than the constant volatility strategy. In the spanning test, the dynamic strategy market model alpha and constant volatility model alpha are both significant and positive.

Keywords: Momentum crashes, dynamic weighting, constant volatility

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1. Introduction

Momentum strategy is a kind of investment strategy betting on the past winners and shorting on the past losers. Both the past literatures and practical evidences support that the past winners will continue to maintain the increasing trend during the next 3 to 12 months which shows that momentum strategy is effective. Basing on the processing information theories, even though the information itself can be transferred immediately to the whole investors, the time of each investor fully understanding the exact impact of information and then reflecting to the market price can be more diverse and longer than market expectation. Therefore, the arbitrager takes the price moves themselves as information to trade. Beyond the rational explanation of good performance of momentum strategy, there are still some behavioral theories trying to give supports to momentum strategy, such as self-contribution biases and trend chasing theory.

On the other side, Daniel and Moskowitz (2016) shows that in the U.S. stock market, there are some crashes period of time, when the momentum strategy has significant and constant negative performance. Further, Daniel and Moskowitz (2016) prove that the momentum crashes themselves can be predicted and improved through dynamic adjustment. Also, in the Korean stock market, we find that from 2000 to 2016, the monthly average momentum portfolio return is 0.31% and the Sharpe ratio of momentum strategy is 0.10 and market model alpha is significantly positive. What's more, the Korean stock market has also been observed momentum crashes phenomenon. The worst momentum performance is in August 2004 which returns is -127.73%. In this month, the loser portfolio return

is 137.97% and winner portfolio return is 10.24% which is close to market return 9.28%. The second worst month is October 1998 with -112% return. The loser portfolio return is 140.58% and winner portfolio return is only 28.58% when the market return is 30%. Post the 2008 financial crisis period, the worst performance is in the April 2009 with -26.96% return. The loser portfolio return is 40.25% and the winner portfolio return is only 13.29% when the market return is 14.36%. Seemingly, due to in the momentum crashes period, the winner market returns are always close to market returns which can be understand as the low beta portfolio compared to the loser portfolio which is consist of high beta stocks.

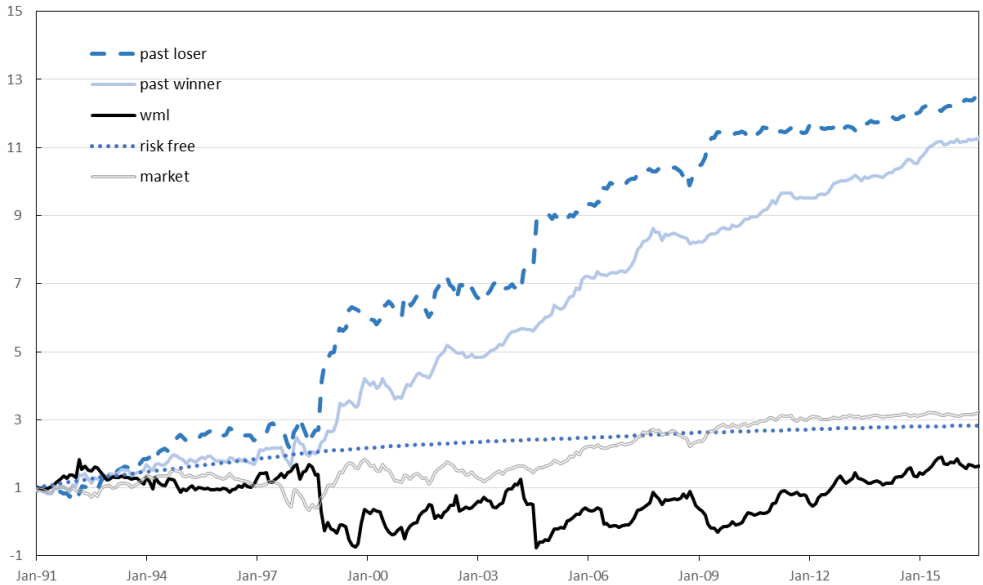
To study the characteristics of momentum crashes, we follow the Cooper et al. (2004) paper to test the relationship between market state and momentum return at first. And through the market timing analysis, we investigate the market stress and moment crashes connection. Cooper et al. (2004) state that previous years market return and market volatility have impact on the momentum premium. Cooper provides behavioral theory to explain the reason of momentum crashes. Cooper et al. (2004) said that intuitively the market rebounds are contemporaneous with much more mispriced risk than any other time period. During the crisis periods contemporaneous with high uncertainty of whole market, the stock price therefore might be heavily mispriced with fluctuant market volatility. In short, the momentum crashes will happen with market stress in much higher probability.

Further, basing on the worst momentum performance, the difference between loser portfolio and winner portfolio market betas might be significant. From the previous studies, Grundy and Martin (2001) states that the firms that fell in tandem with the

market were and are high beta firms, and those that performed the best were low beta firms. What's more, more volatile firms will drop heavily during the crisis time and will shoot up when the market rebounds again. Hence, in the bear market, the loser portfolio which is consist of many high beta firms will perform well accompanying the market recovery. When the market rebounds quickly, momentum strategies will crash because they have a conditionally large beta.

The structure of this paper is as follows, the section 1 has introduced the previous literature and the section 2 describes the Korea equity data and momentum crashes phenomenon. Section 3 is consists of the analysis of time-varying betas. Section 4 addresses the empirical studies on the market timing and momentum portfolio optionality. Section 5 covers the hedged strategy and dynamic weighting of the momentum portfolio. Section 6 concludes the whole paper.

Cumulative gains from investment, 1991:01-2016:09



Cumulative gains from investment, 2000:01-2016:09

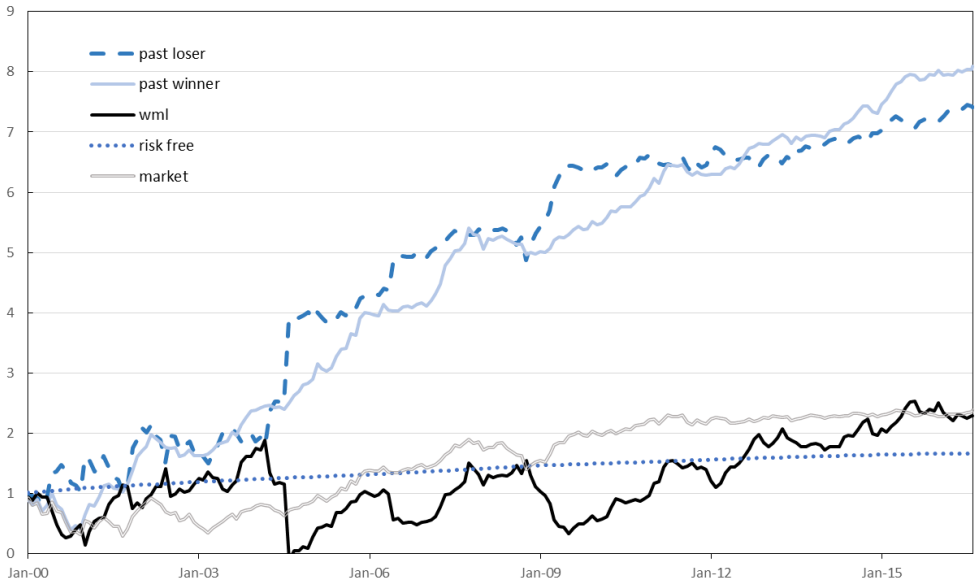


Figure 1. Winners and losers 1991:01-2016:09 and 2000:01-2016:09

1) risk-free asset; 2) past loser portfolio; 3) momentum portfolio; 4) past winner portfolio; 5) market index

2. Korea equity momentum

2.1 Data and portfolio formation

Table 1

Momentum portfolio summary statistics, 1991-2016 and 2000-2016

After the portfolio formation process, we divide monthly stock return into ten deciles according to the past one year cumulative returns. Decile 1 means the portfolio contains the past one year lowest 10% stocks, which is called losers' portfolio. Decile 10 means the portfolio is consist of past one year highest 10% stocks. Momentum portfolio represents the zero cost winner minus loser portfolio. Market return is the KOSPI index monthly returns. We compute the total number of month and portfolio excess return in the first two lines. SR means the Sharpe ratio of each decile and market. SK is the skewness of ten deciles, momentum portfolio, and market.

Panel A

	Momentum decile portoflios, from 1991 to 2016											
p/f	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**mom**	**mkt**
N	308	308	308	308	308	308	308	308	308	308	308	308
r-rf	3.12	1.34	1.57	1.49	1.24	1.52	1.70	1.57	1.86	2.74	-0.38	0.12
S.D.	17.75	10.97	11.07	10.31	9.77	10.13	9.66	9.86	10.06	11.35	16.95	8.35
SR	0.18	0.12	0.14	0.14	0.13	0.15	0.18	0.16	0.19	0.24	-0.02	0.01
SK	3.39	0.66	1.67	1.37	1.31	1.54	1.09	2.47	1.28	1.14	-2.47	0.71

Panel B

	Momentum decile portoflios, from 2000 to 2016											
p/f	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**mom**	**mkt**
N	200	200	200	200	200	200	200	200	200	200	200	200
r-rf	2.88	1.25	1.26	1.24	1.25	1.28	1.68	1.75	2.02	3.19	0.31	0.34
S.D.	16.46	9.44	8.81	7.62	7.66	7.54	8.12	7.84	8.10	9.27	15.63	6.85
SR	0.17	0.13	0.14	0.16	0.16	0.17	0.21	0.22	0.25	0.34	0.02	0.05
SK	3.33	0.32	0.75	0.19	0.42	0.01	0.19	-0.05	0.05	0.12	-3.26	-0.26

Following the Kent Daniel and Tobias J. Moskowitz (2016) portfolio formation method, at the end of each month, we constructs 10 value weighted portfolios according to the preceding return from 12 months to 2 month. And then, we will hold one month to catch the trend benefit. Between the formation period and

holding period, there is one month gap aiming to reduce the short-term reversal effect and get rid of bid-ask effect in some degree. As the momentum portfolio tradition, first we calculate the formation period cumulative return and rank the return from highest to lowest. Further, we choose the top 10 percent firms as the winner portfolio and we pick the bottom 10 percent firms to be the loser decile. Basing on the long short strategy, we purchase the winner portfolio stocks and borrow and then sell the loser portfolio stocks. In the end, we will rebalance the ranking portfolio monthly with overlapping.

We use the firms listed on KSE from January 1990 to September 2016. At the end of each month, we rebalance the portfolio when we use the monthly data and daily data. As the risk-free rate proxy, we select the daily and monthly currency stabilization security 364 rate.

2.2 Momentum portfolio performance

Figure 1 plots the cumulative gains from past loser portfolio, past winner portfolio, momentum portfolio, and risk-free asset portfolio from 1990-2016 and 2000-2016.

Summary statistics information is listed on the Table 1, Panel A from 1990-2016 and Panel B from 2000-2016. Decile 1 means the portfolio contains the past one year lowest 10% stocks, called losers' portfolio. Decile 10 means the portfolio is consist of past one year highest 10% stocks as winners' portfolio. Momentum portfolio represents the zero cost winner minus loser portfolio. In the full period, from 1990 to 2016, the momentum portfolio monthly mean is -0.38%, while from 2000 to 2016, we show that the momentum portfolio is profitable, the monthly average is equal to 0.31% significantly. And the standard deviation of momentum

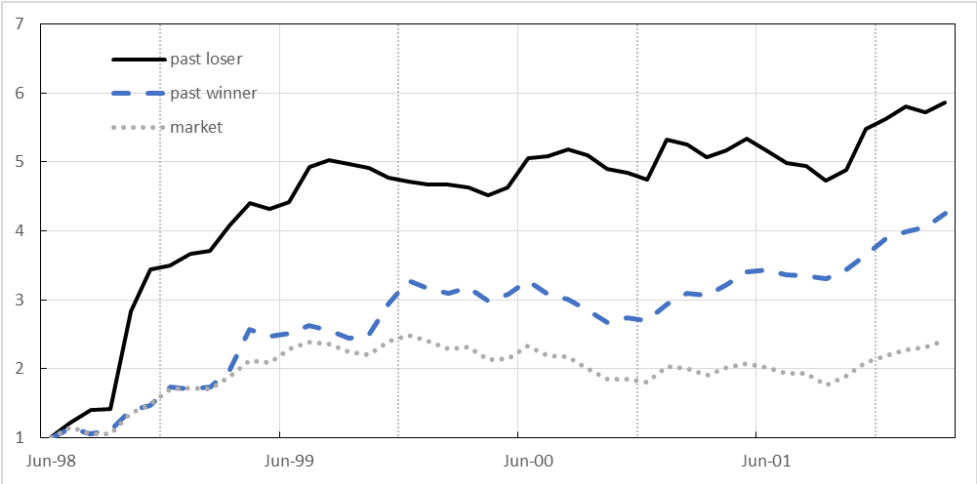
portfolio is 15.63%. As our expectation, the skewness of momentum is -3.26 from 2000 to 2016 and -2.49 during the full period from 1990 to 2016. Market return is the KOSPI index monthly returns. We compute the total number of month and portfolio excess return in the first two lines. SR means the Sharpe ratio of each decile and market. The Sharpe ratio of momentum portfolio during the 2000 to 2016 is equal to 0.11 annually.

2.3 Momentum crashes

Basing on the existence of momentum crashes in US stock market, firstly we want to use Korean stock market to check whether this phenomenon also happened in there. There are some numbers to support that Korean stock market does have momentum crashes.

First, it might be hard to do this kind of guess, but we are going to test if the high beta firms are covered by loser portfolio and low beta firms are covered by winner portfolio in the momentum crashes period. What's more, we want to have a look at the whole period beta value in the winner and loser portfolios.

Cumulative gains from investment, Jun, 1998 – Mar, 2002



Cumulative gains from investment, Oct, 2008 – Nov, 2010

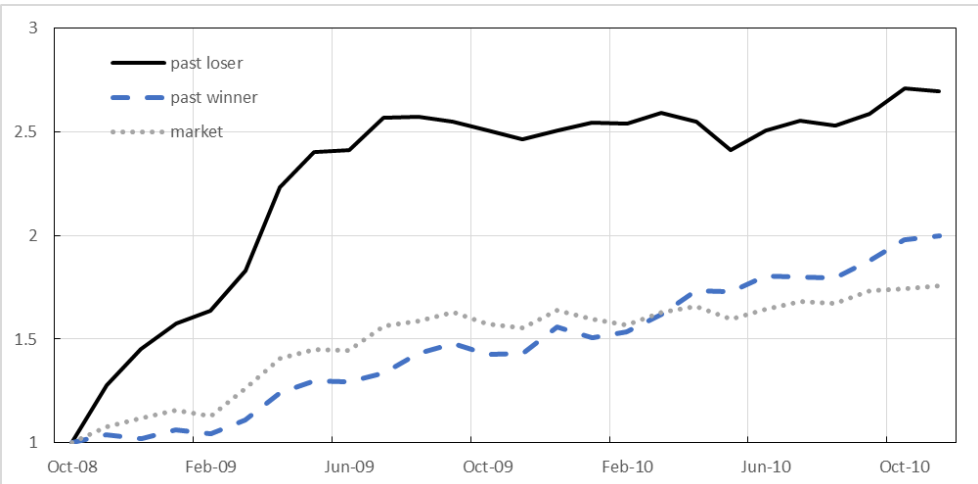


Figure 2. Momentum crashes, following the Korean financial crisis and the 2008-2009 financial crisis. 1) past loser portfolio 2) past winner portfolio 3) market index, especially during the Jun, 1998 – Mar, 2002 and Oct, 2008 – Nov, 2010.

Table 2

Worst monthly momentum returns

This table lists the worst 20-month momentum (WML) returns from 1991 to 2016. We also list the each month market return and previous one year market return to proxy the market condition (bear market or bull market). These months are concentrated on the post of 1997 Korean financial Crisis, 2000 dot come bubble period, and 2008 financial crisis time.

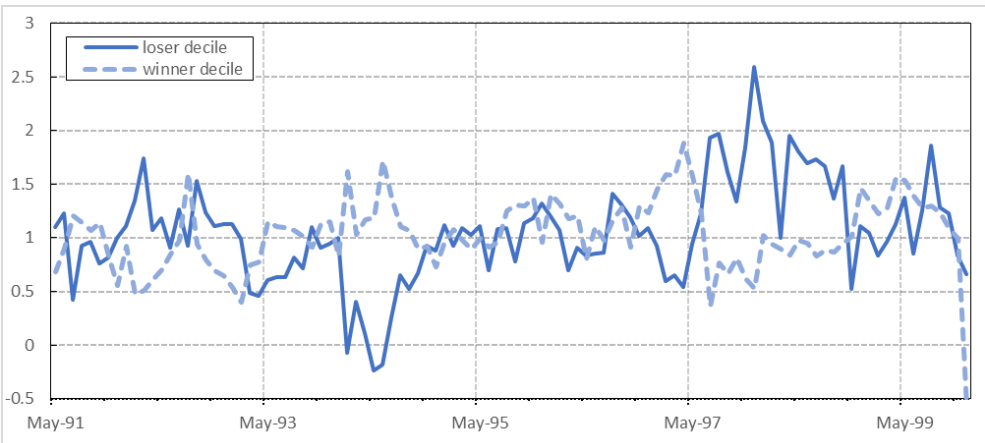
Rank	Month	Loser	Winner	WML	MKT	MKT-1y
1	Aug-04	137.97	10.24	-127.73	9.28	-4.69
2	Oct-98	140.58	28.58	-112.00	30.01	-42.32
3	Nov-98	61.57	6.14	-55.42	12.01	-6.85
4	Mar-98	29.76	-16.30	-46.06	-13.94	-27.87
5	Nov-01	58.98	21.70	-37.28	20.61	-3.10
6	Jan-01	58.27	23.83	-34.44	22.45	-49.56
7	Apr-09	40.25	13.29	-26.96	14.36	-20.39
8	May-97	25.20	-2.11	-27.30	7.61	-20.94
9	Aug-98	17.95	-7.36	-25.31	-9.66	-56.80
10	Nov-08	27.83	4.12	-23.71	7.70	-38.69
11	Nov-14	14.87	-8.37	-23.24	2.86	-1.39
12	Jul-00	3.04	-20.53	-23.56	-14.03	-12.27
13	Jun-00	42.96	19.92	-23.05	18.80	-18.90
14	Jan-12	20.26	0.36	-19.89	7.12	-9.27
15	Dec-08	17.32	-2.20	-19.52	4.50	-36.14
16	Jan-99	17.52	-2.23	-19.75	1.59	-1.68
17	Sep-15	9.60	-7.95	-17.56	1.30	-2.30
18	Jun-03	20.37	2.74	-17.63	5.76	-21.46
19	Aug-00	10.22	-6.77	-16.98	-2.46	-22.02
20	Feb-16	7.90	-8.29	-16.19	0.24	-3.95

The Korean stock market has also been observed momentum crashes phenomenon. The worst momentum performance is in August 2004 which returns is -127.73%. In this month, the loser portfolio return is 137.97% and winner portfolio return is 10.24% which is close to market return 9.28%. The second worst month is October 1998 with -112% return. The loser portfolio return is 140.58% and winner portfolio return is only 28.58% when the market return is 30%. Post the 2008 financial crisis period, the worst performance is in the April 2009 with -26.96% return. The loser portfolio return is 40.25% and the winner portfolio return is only 13.29% when the

market return is 14.36%. Seemingly, due to in the momentum crashes period, the winner market returns are always close to market returns which can be understand as the low beta portfolio compared to the loser portfolio which is consist of high beta stocks.

3. Time-varying beta and option-like payoffs

1991:05-1999:12



2000:06-2016:09

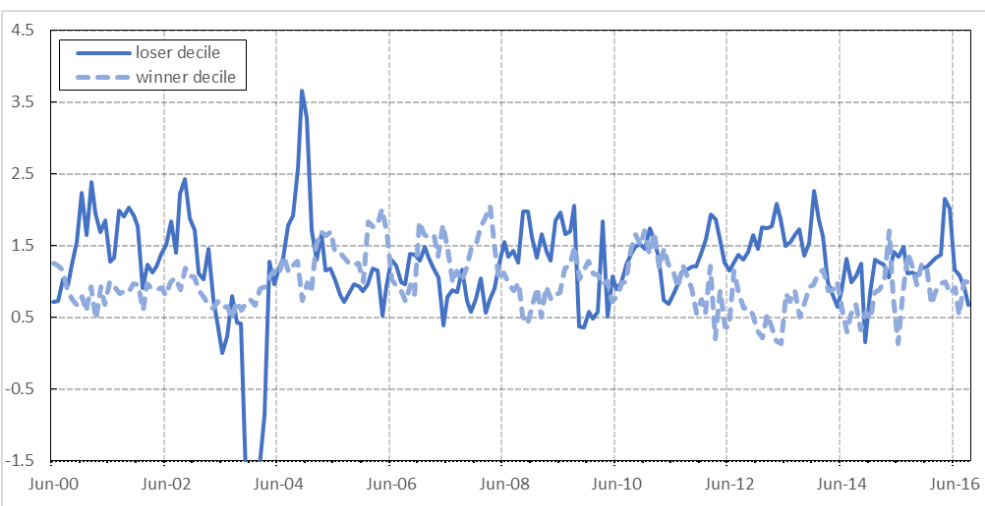


Figure 3. Market betas of winner and loser decile portfolios. The specification daily

regression model: 126-day rolling regression on the 10 lag market excess returns,

$$\tilde{r}_{i,t}^{e} = \beta_0 \tilde{r}_{m,t}^{e} + \beta_1 \tilde{r}_{m,t-1}^{e} + \cdots + \beta_{10} \tilde{r}_{m,t-10}^{e} + \tilde{\epsilon}_{i,t}$$

The monthly market beta is the sum of 10 lag market excess return betas, equal to $\hat{\beta}_0 + \hat{\beta}_1 + \cdots + \hat{\beta}_{10}$. This two independent non-overlapping sub-sample periods are 1991:05- 1999:12 and 2000:06- 2016:09.

To study the difference of market betas of winner and loser portfolios, we use the rolling regression model to estimate the time-varying market betas and try to find the evidence of two portfolios' asymmetric behavior. To be more specific, in this investigation, we use the 126-day rolling regression to estimate on 10 lag market excess returns according to independent loser portfolio and winner portfolio. The result shows that 1) Loser portfolios' market beta are more volatile than winners'. Most of market betas of winner portfolio are located in between 0.5 to 1.5, which are close to 1. However, the market beta of loser portfolio reach to 2.5 during the 1998 post Korean financial crisis period, also during the round 2001 post dot com bubble period, and even during the March 2009, which is market swing period, the beta is not significant higher than other period, comparing with winner portfolio, the market betas of loser portfolio are still more volatile and higher in some extents. To formally understand the relationship between the market betas and bear market with market upswings, we need investigate the marketing timing and other empirical tests.

3.1 Market states and momentum

Cooper et al. (2004) illustrates that momentum return relays on the market states. The mean profit of momentum in up market is positive and significant, whereas the

mean profit of momentum in down market is negative and insignificant. By the way, Cooper et al. (2004) uses prior 3 years market return to proxy the market states and they also show that prior 1 year and 2 years proxy are also robust to clarify the relation between market states and momentum profits. These asymmetric profit pattern of momentum strategy makes following studies get insight into relationship between momentum crashes and market states.

In this study, we use prior 1 year market return to proxy market states. To be more specific, if the prior 1 year market return is negative, then we define the market state as down market, while if the prior 1 year market return is positive, then we consider the market states4 as up market. Depending on the full sample analysis, we state the total 285 months momentum pattern. 193 months are up market and the rest of months (total 92 months) are down market. When we hold momentum strategy only one month, the monthly mean profit of momentum in up market is 2.08% and t-statistic value is 3.82. However, when we use the same holding strategy, the monthly mean profit of momentum in down market is only -0.41% but the t-statistic value is -0.35, which is not significant. When we hold momentum strategy in next 6 months, the monthly average return in up market is 1.55% and t-statistic value is 3.14. The same asymmetric story happen to the down market, the return is -0.16% and insignificant.

Due to the Korean stock market data specificity, we will make our study focus on the after 2000 performance. From 2000, the Korean stock market started to generate momentum profits, which is widely accepted by scholars. Hence, the monthly mean profit of momentum strategy during the up market is 2.85% and

t-statistic is significant, which is higher than the full sample result. Further, when we apply the CAPM model to analyze momentum performance, we get the alpha, 2.37% significantly. Even we test the different holding period, from one month, six months to twelve months, all the alphas are significant, 2.37%, 2.10%, and 1.54%. On the other side, the down market momentum performance is insignificantly negative and the CAPM alpha is also not significant.

Table 3:

Market states and momentum, both from 1993 and from 2000

From 2000

	month 1	month 1-6	month 1-12
Panel A: UP			
N	149	149	149
Mean profit	2.85%	2.54%	1.94%
t-statistic	5.6	5.6	4.74
CAPM alpha	2.37%	2.10%	1.54%
t-statistic	4.79	4.74	3.82
Panel B: DOWN			
N	52	52	52
Mean profit	-0.14%	0.63%	0.32%
t-statistic	9.11	0.64	0.39
CAPM alpha	-0.54%	0.26%	-0.03%
t-statistic	-0.48	0.28	-0.04

From 1993

	month 1	month 1-6	month 1-12
Panel A: UP			
N	193	193	193
Mean profit	2.08%	1.55%	1.08%
t-statistic	3.82	3.14	2.75
CAPM alpha	1.35%	1.03%	0.87%
t-statistic	2.56	2.33	2.21
Panel B: DOWN			
N	92	92	92
Mean profit	-0.41%	-0.16%	-0.04%
t-statistic	-0.35	-0.02	-0.35
CAPM alpha	-1.33%	-0.75%	-0.20%
t-statistic	-1.22	-0.88	-1.01

3.2 Market timing of momentum strategy

Model 1:

$$\tilde{R}_{WML,t} = \alpha_0 + \beta_0 \tilde{R}_{m,t} + \tilde{\epsilon}_t \qquad (1)$$

This is an unconditional market model to test the market timing issue of momentum return. We want to test the market timing of momentum strategy from January 1991 to September 2016. The first model we used is about to explain momentum return on excess market return. In this case, the market beta is about

4.58, but which is not significantly impacting on the momentum return. The intercept term is 1.49% significantly which is similar to our hypothesis (t-statistics: 2.32).

Model 2:

$$\tilde{R}_{WML,t} = [\alpha_0 + \alpha_B I_{B,t-1}] + [\beta_0 + \beta_B I_{B,t-1}]\tilde{R}_{m,t} + \tilde{\epsilon_t} \qquad (2)$$

Basing on the model 1 analysis, we consider the bear market indicator in model 2. $I_{B,t-1}$, is the bear indicator, which is estimated by past one year excess market return before month t. $I_{B,t-1}$, is equal to 1 if past one year excess market is positive, otherwise the bear market indicator equals to 0. There is an interaction term which combines the bear market indicator and market excess return. Under the CAPM as the widely accepted theory, the model 2 illustrates that both the bear market indicator and interaction term are significantly negative. In this case, the market beta in bear market is equal to -0.62 lower and quite highly significant (t-statistics=-5.95). Further, the momentum return alpha is 6.46% with 4.93 t-statistics in bear market. Therefore, beyond independent consideration of up and down market effect on momentum strategy, bear market indicator itself and interaction with excess market return can explain the momentum return in some degrees.

Model 3:

$$\tilde{R}_{WML,t} = [\alpha_0 + \alpha_B I_{B,t-1}] + [\beta_0 + I_{B,t-1}(\beta_B + \widetilde{I_{U,t}}\beta_{B,U})]\tilde{R}_{m,t} + \tilde{\epsilon_t} \qquad (3)$$

In order to understand momentum crashes market timing issue, this study insert market rebound indicator to illustrate momentum crashes feature. Just as the market beta pattern shows, when the market rebounds, the momentum strategy will

under-performance and will be easy to emerge momentum crashes. Hence, basing on the model 2, we add the interaction term combining up market indicator, $I_{U,t}$, and bear market indicator with excess market return. We use the monthly market return as market rebound variable. If the market return is positive, the up market indicator is equal to 1, otherwise market indicator will be zero. The regression result shows that the bear market and market rebound interaction terms has influence on the momentum return. In the bear market, the market beta, when the market return is negative, is -0.2 (=$\widehat{\beta_0} + \widehat{\beta_B}$). If the bear market contemporaneous with positive market return, the market beta is declined to -0.44(=$\widehat{\beta_0} + \widehat{\beta_B} + \widehat{\beta_{B,U}}$). Hence, according to the explanation Daniel and Moskowitz (2015), the momentum strategy shows an option-like behavior which means that in the bear market, basing on the market return level, the market beta of momentum strategy is significantly different. In addition, in model 3, we find that even though both the excess market return and two interaction terms is significant, the bear indicator itself is not significant any more. In the end, we try to eliminate the bear indicator itself to run the regression. And the regression's R square is the largest among the four regression models. What's more, the bear market indicator with market return and bear market indicator with recovery indicator are both significantly negative, which prove the hypotheses.

Table 4

Market timing regression results

$$\tilde{R}_{WML,t} = [\alpha_0 + \alpha_B I_{B,t-1}] + [\beta_0 + I_{B,t-1}(\beta_B + \widetilde{I_{U,t}}\beta_{B,U})]\tilde{R}_{m,t} + \widetilde{\epsilon_t} \qquad (3)$$

$I_{B,t-1}$, is the bear indicator, which is estimated by past one year excess market return before month t. $I_{B,t-1}$, is equal to 1 if past one year excess market is positive, otherwise the bear market indicator equals to 0. Up market indicator, $I_{U,t}$, if the market return is positive, is equal to 1, otherwise market indicator will be zero. We test above four models using the KOSPI market data from 1990:01 to 2016:09.

		Estimated Coefficients *(t-statistics in parenthese)*			
Coef.	Variable	(1)	(2)	(3)	(4)
$\widehat{\alpha_0}$	1	1.49	3.76	3.76	2.95
		(2.32)	(5.09)	(5.09)	(3.80)
$\widehat{\alpha_B}$	IB, t-1		-6.42	-5.55	
			(-4.93)	(-1.56)	
$\widehat{\beta_0}$	Rm, t	4.58	0.36	0.36	0.30
		(0.85)	(4.69)	(4.69)	(3.88)
$\widehat{\beta_B}$	IB, t-1*Rm, t		-0.62	-0.56	-0.28
			(-5.95)	(-4.70)	(-3.07)
$\widehat{\beta_{B,U}}$	IB, t-1*IU, t*Rm, t			-0.24	-0.72
				(-1.01)	(-3.50)
R-sqr adj		0.1	0.18	0.18	0.21

Table 5

Momentum portfolio optionality

$$\tilde{R}_{i,t} = \alpha_0 + \left[\beta_0 + I_{B,t-1}\left(\beta_B + \widetilde{I_{U,t}}\beta_{B,U}\right)\right]\tilde{R}_{m,t} + \widetilde{\epsilon_t} \qquad (4-1)$$

Using the table 4 model 4 to test the optionality of bear market. $\tilde{R}_{m,t}$ is the market excess return, $\tilde{R}_{WML,t}$, is the ten decile portfolios' return, $I_{B,t-1}$ is the bear market indicator, and $I_{U,t}$ is the market rebound indictor in Panel A from 1990:01 to 2016:09.

$$\tilde{R}_{i,t} = \alpha_0 + \left[\beta_0 + I_{L,t-1}\left(\beta_L + \widetilde{I_{U,t}}\beta_{L,U}\right)\right]\tilde{R}_{m,t} + \widetilde{\epsilon_t} \qquad (4-2)$$

In Panel B, instead of bear market indicator, we consider the other side, bull market indicator to test if there is asymmetry performance in each ten decline. $I_{L,t-1}$, is bull market indicator, which is defined as$(1 - I_{U,t})$. The test period is equal to the Panel A, from 1990:01 to 2016:09.

	Momentum Decile Portfolios - Monthly Excess Returns (t-statistics in parentheses)										
	1	2	3	4	5	6	7	8	9	10	WML
Panel A: Optionality in Bear Markets											
$\widehat{\alpha_0}$	2.839	4.652	4.871	4.678	5.047	5.382	5.477	5.447	5.256	5.358	2.520
	4.2	8.3	9.6	10.0	11.8	13.1	12.8	13.5	12.1	12.6	3.8
$\widehat{\beta_0}$	0.400	0.539	0.549	0.547	0.587	0.593	0.625	0.620	0.667	0.696	0.295
	5.2	8.4	9.5	10.2	11.9	12.6	12.7	13.3	13.4	12.6	3.9
$\widehat{\beta_B}$	0.161	0.066	0.058	0.026	-0.005	-0.015	-0.055	-0.041	-0.123	-0.117	-0.278
	1.8	0.9	0.8	0.4	-0.1	-0.3	-0.9	-0.8	-2.1	-1.8	-3.1
$\widehat{\beta_{B,U}}$	**0.835**	**0.616**	**0.443**	**0.402**	**0.422**	**0.285**	**0.281**	0.220	**0.263**	0.113	**-0.723**
	4.0	**3.5**	**2.8**	**2.8**	**3.2**	**2.2**	**2.1**	1.7	**2.0**	0.8	**-3.5**
Panel B: Optionality in Bull Markets											
$\widehat{\alpha_0}$	4.625	5.645	5.347	5.139	5.367	5.512	5.575	5.489	5.246	5.166	0.541
	6.0	8.8	9.3	9.7	11.0	11.9	11.5	12.1	10.8	9.6	0.7
$\widehat{\beta_0}$	0.716	0.706	0.669	0.631	0.636	0.611	0.602	0.602	0.570	0.582	-0.134
	10.7	12.6	13.4	13.7	14.9	15.1	14.2	15.2	13.4	12.4	-2.1
$\widehat{\beta_L}$	-0.162	-0.094	-0.097	-0.059	-0.043	-0.025	0.013	0.006	0.075	0.081	0.243
	-1.6	-1.1	-1.3	-0.9	-0.7	-0.4	0.2	0.1	1.2	1.2	2.5
$\widehat{\beta_{L,U}}$	**-0.525**	-0.183	0.017	0.002	0.101	0.122	0.140	0.131	0.194	0.201	**0.726**
	-2.0	-0.8	0.1	-0.1	0.6	0.8	0.8	0.8	1.2	1.1	**2.8**

3.3 Momentum portfolio optionality

$$\tilde{R}_{WML,t} = \alpha_0 + \left[\beta_0 + I_{B,t-1}\left(\beta_B + \widetilde{I_{U,t}}\beta_{B,U}\right)\right]\tilde{R}_{m,t} + \widetilde{\epsilon_t} \qquad (4)$$

After considering the market states and bear market with market rebound effect, we want to continue to check whether there is asymmetric effect of market rebound. In other words, this is because we have proved both bear market and market rebound have negative effect on the momentum return, and then we want to provide some evidences about during the bull market, the market rebound does not have prediction power of momentum return. Instead of bear market indicator, we insert bull market indicator to test our hypothesis. Panel A shows 10 portfolios' regression results using model 4. The outcome illustrate that across 10 portfolios, the interaction term combining the bear market indicator and up market indicator. However, when we check the interaction term combining the bull market indicator and up market indicator, the result shows that almost all of 10 portfolios' interaction term is not significant, which means that unlike the bear market, the bull market interaction element cannot predict the momentum return.

In the Table 4 Panel A, the market beta of bear market contemporaneous with market rebound in the loser portfolio is equal to 1.396(=$\widehat{\beta_0} + \widehat{\beta_B} + \widehat{\beta_{B,U}}$), while in the winner portfolio (0.113).

3.4 Market stress and momentum returns

After analysis of market timing and momentum optionality, we are trying to prove the option-like hypothesis. If the loser portfolio performs like a call option, the loser portfolio return should have connection with market volatility due to the option value is positively related to the volatility level. Further, the momentum portfolio is similar to the short call option strategy which will have negative

relationship with market volatility. Hence, we introduce the market variance variable to proxy the market volatility and try to find the connection between the momentum return and market volatility.

Table 6

Momentum Returns and Estimated Market Variance

Monthly time-series regression specification:

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_B \cdot I_{B,t-1} + \gamma_{\sigma_m^2} \cdot \hat{\sigma}_{m,t-1}^2 + r_{int} \cdot I_{B,t-1} \cdot \hat{\sigma}_{m,t-1}^2 + \tilde{\epsilon}_t$$

We use the sign of prior one year market return to proxy the bear market indicator, $I_{B,t-1}$, which is also robust when we use the past 3 years and past 2 years proxies to test the relation between momentum returns and estimated market variance. $\hat{\sigma}_{m,t-1}^2$ is the daily market variance measured from previous 126-day to the day before t month. It shows the five different models' estimated coefficients and t-statistics in the parentheses from 2000:06 to 2016:09 (N: 196). $\hat{\gamma}_0$ and $\hat{\gamma}_B$ are percent per month.

	(1)	(2)	(3)	(4)	(5)
$\widehat{\gamma_0}$	1.846	4.032	4.358	1.591	4.753
	(1.03)	(1.87)	(2.00)	(0.97)	(1.61)
$\widehat{\gamma_B}$	−7.141		−3.924		−4.694
	(−2.25)		(−1.11)		(−0.89)
$\widehat{\gamma_{\sigma_m^2}}$		−0.188	−0.149		−0.172
		(−2.80)	(−1.97)		(−1.23)
$\widehat{\gamma_{int}}$				−0.165	0.332
				(−2.72)	(0.20)

$I_{B,t-1}$, is the bear indicator, which is estimated by past one year excess market

return before month t. $I_{B,t-1}$, is equal to 1 if past one year excess market is positive, otherwise the bear market indicator equals to 0, which is also robust when we use the past 3 years and past 2 years proxies to test the relation between momentum returns and estimated market variance. $\hat{\sigma}^2_{m,t-1}$ is the daily market variance measured from previous 126-day to the day before t month.

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_B \cdot I_{B,t-1} + \gamma_{\sigma^2_m} \cdot \hat{\sigma}^2_{m,t-1} + r_{int} \cdot I_{B,t-1} \cdot \hat{\sigma}^2_{m,t-1} + \tilde{\epsilon}_t \qquad (5)$$

In the first two models, we only test the bear market indicator and market volatility independently. During the high market stress periods, which are captured by interaction term, $I_{B,t-1} \cdot \hat{\sigma}^2_{m,t-1}$, it has negative impact on the future momentum return.

4. Dynamic weighting of the momentum portfolio

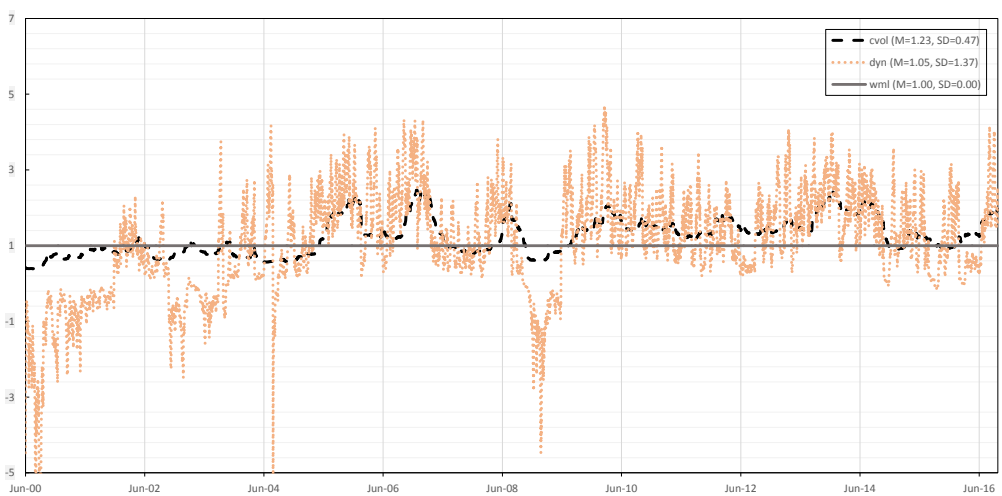


Fig 4 Dynamic strategy weights on WML

According to the previous sections analysis, we prove that even though the average of momentum strategy is effective to gain positive return in full time period, during the bear market period, we still suffer and even face huge losses if we carry out

momentum strategy without any adjustment. Since the momentum crashes are highly related to the market stress, we try to introduce an improved strategy to reduce the negative impact of the bear market and take advantage of the bull market performance. Based on the failure of beta as a predictor, we follow the idea of table 6, to use market volatility information to maximize the Sharpe ratio of dynamic strategy, in order to guarantee the dynamic momentum strategy performance.

Instead of consideration of the constant volatility solely, in this paper, we are trying to maximum Sharpe ratio of dynamic strategy. Basing on the evidences from the table 6, the momentum crash always accomplishes with high market volatility in bear market condition. Hence, while we attempt to make a tradeoff decision between risky asset and risk-free asset, we consider that the optimal weights on the risky asset should have positive relationship with risky asset mean and have negative relationship with the risky asset standard deviation which is used to proxy to market volatility. After the intuitive analysis, we have to show the numerical supports as follows,

Risky asset (original momentum strategy) mean and variance:

$$\mu_t = E_t\ [\tilde{r}_{t+1}]\ and\ \sigma_t^2 = \mathrm{E}_t\ [(\tilde{r}_{t+1} - \mu_t)^2]$$

The target of the dynamic strategy is to maximize the Sharpe ratio of the full period and we will use w_t to show the weight on the risky asset, original momentum strategy, and hence straightforward $1 - w_t$ is the proportion on the risk-free asset.

The whole period Sharpe ratio can be stated as,

$$SR = \frac{E\left[\frac{1}{T}\sum_{t=1}^{T}\tilde{r}_{p,t}\right]}{\sqrt{E\left[\frac{1}{T}\sum_{t=1}^{T}\left(\tilde{r}_{p,t}-\overline{r_p}\right)^2\right]}}$$

$\overline{r_p}$ is the sample average per period excess return $\frac{1}{T}\sum_{t=1}^{T}\tilde{r}_{p,t}$.

Therefore, we construct a constrained optimization objection,

$$\max[w_0, w_1, \cdots, w_{T-1}]:\ E\left[\frac{1}{T}\sum_{t=1}^{T}\tilde{r}_{p,t}\right]\ s.t.\ E\left[\frac{1}{T}\sum_{t=1}^{T}\left(\tilde{r}_{p,t}-\overline{r_p}\right)^2\right] = \sigma_p^2$$

Using the Lagrangian function, we can solve the maximize problem.

$$w_t^* = \left(\frac{1}{2\varphi}\right)\frac{\mu_t}{\sigma_t^2}$$

1) φ, is the Lagrangian parameter, which is constant and shows the unconditional risk and return of the dynamic portfolio. In our sample, we use the market volatility 15.63% to proxy this time-invariant parameter.

2) μ_t, is computed basing on the fitted regression, $E[\tilde{R}_{WML,t}] = \gamma_0 + r_{int} \cdot I_{B,t-1} \cdot \hat{\sigma}_{m,t-1}^2$, which follows the idea of table 5 model 4, where $I_{B,t-1}$ is the bear market indicator and $\hat{\sigma}_{m,t-1}^2$ is the past 126-day market variance proxy the market volatility. We use the interaction term of bear market indicator and market volatility proxy to compute the expected mean in the weights formula.

3) σ_t^2, follows the GJR GARCH model

A. What is GJR GARCH model

Following the GJR GARCH model, the momentum portfolio mean process is,

$$R_{WML,t} = \mu + \epsilon_t$$

where $\epsilon_t \sim N(0, \sigma_t^2)$ and variance σ_t^2 process is,

$$\sigma_t^2 = w + \beta\sigma_{t-1}^2 + (\alpha + \gamma I(\epsilon_{t-1} > 0))\epsilon_{t-1}^2$$

where, $I(\epsilon_{t-1} > 0)$ is a dummy variable which is equal to 1 when the mean

function residuals is positive, otherwise equal to 0.

B. Why we choose GJR-GARCH model

Even though, some of study such as Barroso and Santa-Clara (2012) use AR process to mimic the volatility process, our study decides to select GARCH model is due to the assumption of asymmetries in conditional variance that depends on the new information. Glosten, Jagannathan, and Runkle (1993) finds support for a negative relation between conditional expected monthly return and conditional variance of monthly return, using a GARCH-M (GJR-GARCH) model, which focused on the intertemporal relation between risk and return.

We use maximum likelihood to estimate the parameter set $(\mu, w, \alpha, \gamma, \beta)$ depending on the whole sample periods. To predict the volatility we fit a GJR GARCH process to the daily momentum returns, which follows the equations (6) and (7).

Table 7

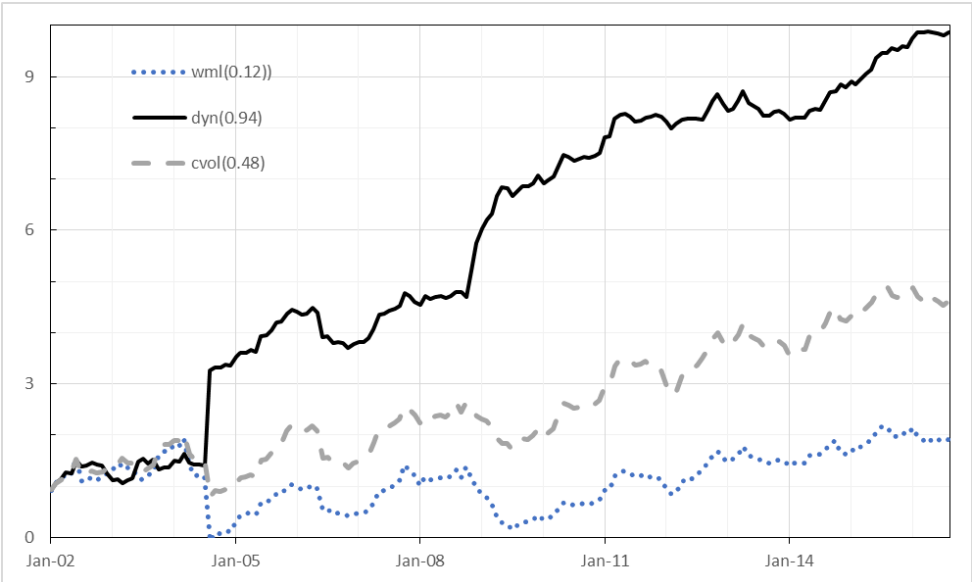
parameter:	$\hat{\mu}$	$\hat{\omega}$	$\hat{\alpha}$	$\hat{\gamma}$	$\hat{\beta}$
ML-est	0.98×10^{-3}	1.68×10^{-5}	0.152	0.026	0.81
z-stat	(4.42)	(13.43)	(17.73)	(2.33)	(114.18)

From the view of checking the efficiency of the parameters, we regression the future realized 22-day WML return volatility $\widehat{\sigma_{22,t+1}}$ on the GARCH estimated variance ($\widehat{\sigma_{GARCH,t}}$) and preceding 126-day WML return volatility ($\widehat{\sigma_{126,t}}$), and add the constant term. Based on the OLS estimation, we get the coefficients and t-statistics,

coefficient:	$\hat{\alpha}$	$\widehat{\sigma_{GARCH,t}}$	$\widehat{\sigma_{126,t}}$
coef. Est.	0.0002	0.41196	0.1908
t-stat	(17.13)	(39.97)	(15.11)

The adjustment R square of this regression is 35.02%. And then the fitted estimation of $\widehat{\sigma_{22,t+1}}$ is used to compute the weights of the dynamic momentum strategy. The autocorrelation of dependent variable is large and statistically significant, which suggests that dependent variable has forecastable proportions. At the same time, the lag one residual autocorrelation is -0.005(t-statistics=-0.41), which is uncorrelated to the forecast variables. Therefore, the both components contribute the forecasting future daily realized volatility. The coefficient of preceding 126-day variance, 0.1908 is smaller than the GARCH coefficient, 0.41196. The preceding 126-day variance has a longer-lived component of future realized volatility.

Figure 5 plots the three strategies' weight. They are original momentum strategy, constant volatility strategy and dynamic strategy which is given by the weight equation. The average weights of each strategy are 1.05(dynamic), 1.23(constant), and 1(momentum). The standard deviations are 1.37(dynamic), 0.47(constant), and 0(momentum).



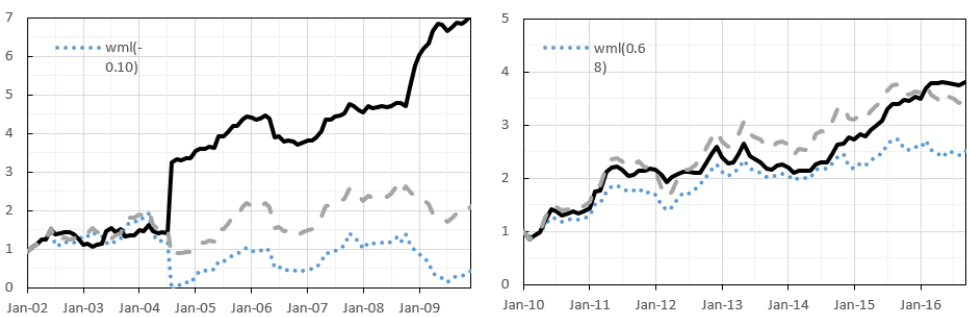


Fig. 5. Dynamic momentum strategy performance

4.1 Dynamic strategy performance

The first graph in Fig.6, plots the three strategy's full period performance. The solid line is the dynamic momentum strategy, the grey middle long potted line is the constant volatility strategy, and the blue potted line is the basic momentum strategy. The first feature is the market stress period performance of dynamic strategy is better than the others, in the March 2009 and around 2001. Just as the figure 5 weight graph shows that the constant volatility strategy has the same

pattern direction with the basic momentum strategy. To sum up, dynamic strategy can mitigate the momentum crashes and hence outperforms. In this graph, we use the market volatility, 15.63% and constant volatility is also scaled to 15.63%.

4.2 Sub-sample dynamic strategy performance

The other four graphs show the sub-sample three strategy performance, from 2000~2004, 2005~2009, 2010~2013, 2014~2016. And the pattern of each performances are similar to the full period performance. We apply the same market volatility to the each four figures and prove the momentum crashes can be mitigated only by dynamic strategy.

Expanding window regression coefficients

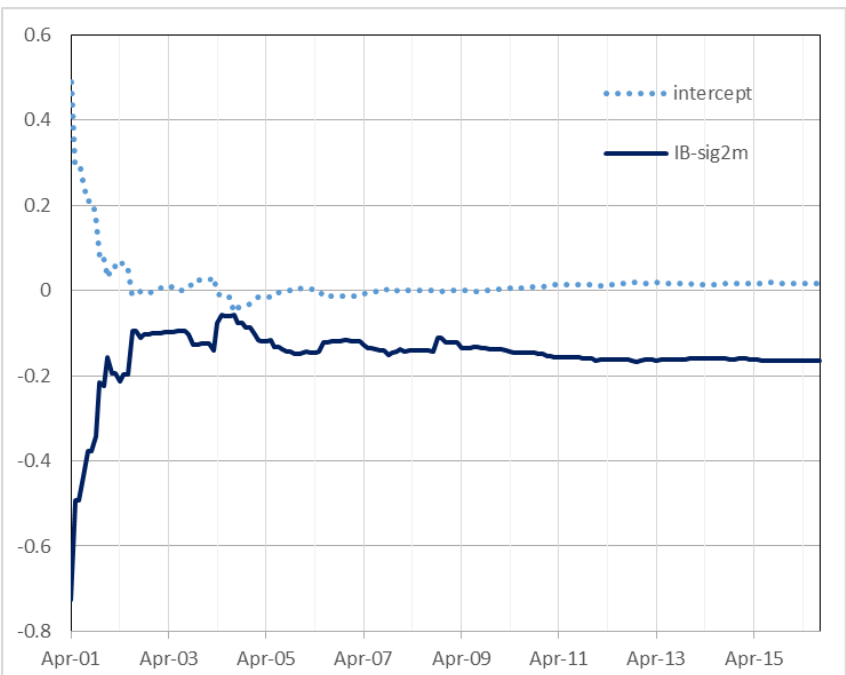


Fig 6 Mean forecast coefficients: expanding window. Instead of using full period date to estimate the parameters. We use the fitted regression $E_{t-1}[\tilde{R}_{WML,t}] =$

$\widehat{\gamma_{0,t-1}} + \widehat{r_{int,t-1}} \cdot I_{B,t-1} \cdot \hat{\sigma}^2_{m,t-1}$ from the start (2000:06) of the full dataset to the month t-1, to estimate the time-series estimated parameters. $\hat{\sigma}^2_{m,t-1}$, is the daily market variance measured from preceding 126-day to the day before t month.

4.3 Out-of-sample performance

Completed in-sample analysis, in this section, we try to relax the assumption that all parameters are estimated by full periods. Too much rely on the parameters will reduce the effectiveness of the models, hence, in the out-of-sample analysis, we still use the table 5 model 4 to compute the weights information and use it to do the fitted-regression to estimate the parameter in the t-1 information set.

$$\mu_{t-1} = E_{t-1}[\tilde{R}_{WML,t}] = \widehat{\gamma_{0,t-1}} + \widehat{r_{int,t-1}} \cdot I_{B,t-1} \cdot \hat{\sigma}^2_{m,t-1}$$

Firstly, we detect from figure 7, in the market stress period, the interaction coefficient has a slightly increase compared to the other periods, especially in the 2000:06 and 2009:03. The range of interaction coefficient is -1.5~-0.5. Through the time periods, the intercept is closing to the 0.

4.4 Out-of-sample dynamic strategy performance

Table 8

Strategy performance comparison

This table presents the annualized Sharpe-ratios of four zero-investment portfolio strategies, based on the monthly returns of these strategies over the 2001:04 to 2016:09 times period. 1) Basic momentum strategy; 2) Constant volatility: Scaled by the realized variance of the daily WML returns over the preceding 126 trading

days; 3) Out-of-sample dynamic: Scaled by the realized variance of the daily WML returns over the preceding 126 trading days. AR is Appraisal Ratio of the strategy, relative to the strategy in the preceding row.

Strategy	SR	AR
momentum	0.1	
constant volatility	0.48	0.0670
dyn, out-of-sample	0.71	0.0632
dyn, in-sample	0.89	0.0136

Table 9

Spanning tests of the dynamic momentum portfolio

Panel A tests the daily dynamic momentum return regression on market return and static momentum return in the model 1. The conditional regression means that we interact the market stress indicator, $I_{B\sigma^2}$ to estimate the conditional daily regressions in the model 2. In the model 3 and 4, the independent variables contain the market return and constant volatility portfolio return to try to explain the dynamic momentum strategy. Panel B follows the similar idea of Panel A, the only difference is in the model 3 and model4. In these case, we use the dynamic portfolio return and market return to study the alpha or the intercept of the constant volatility portfolio returns.

Panel A: Dependent variable = returns to dynamic (dyn) momentum portoflio

	(1)	(2)	(3)	(4)
Model	Mkt+WML	Mkt+WML conditional	Mkt+cvol	Mkt+cvol conditional
α	0.2351	0.2175	0.1893	0.1804
t(α)	6.31	5.72	5.5	5.25

Panel B: Dependent variable = returns to constant volatility (cvol) momentum portoflio

	(1)	(2)	(3)	(4)
Model	Mkt+WML	Mkt+WML conditional	Mkt+dyn	Mkt+dyn conditional
α	0.0628	0.1221	0.0276	0.1408
t(α)	5.19	3.82	0.95	4.45

To build the formal test for supporting dynamic momentum portfolios performance, we use the spanning tests to check the dynamic results. Panel A tests the daily dynamic momentum return regression on market return and static momentum return in the model 1. The conditional regression means that we interact the market stress indicator, $I_{B\sigma^2}$ to estimate the conditional daily regressions in the model 2. In the model 3 and 4, the independent variables contain the market return and constant volatility portfolio return to try to explain the dynamic momentum strategy. Panel B follows the similar idea of Panel A, the only difference is in the model 3 and model4. In these case, we use the dynamic portfolio return and market return to study the alpha or the intercept of the constant volatility portfolio returns.

5. Conclusion

The momentum portfolio has positive gains since 2000 in Korean stock market, however there are some momentum crash periods, which have persistent influence on the longer horizon, such as in the 1998 and 2009. We firstly find that the momentum crashes always happen during the bear market states with high market volatility. Especially, during the market upswings period, the loser portfolio has better than winner's performance. Moreover, the momentum crashes themselves are predictable. When we apply the bear market indicator and ex ante estimated volatility to compute the conditional mean and conditional variance of momentum strategy. Those two elements help us build a dynamic weighting strategy to improve the momentum strategy especially during the momentum crashes period. The results show that the Shape ratio of dynamic strategy is twice bigger than the

constant volatility strategy. In the spanning test, they dynamic strategy market model alpha and constant volatility model alpha are both significant and positive.

Basing on the solid empirical results, we try to find some theories to explain the momentum crash problems. One understanding is based on the loser portfolio's call option-like behavior. Consistent with market upswings period, the loser portfolio is consist of high beta firms when the market volatility is high in the bear market states. Hence, the expected return of loser portfolio is high and momentum strategy will probably face crashes. From the viewpoint of behavioral studies, the crashes are accompanied by fearfulness only focusing on losses.

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요약(국문초록)

본 논문의 주제는 한국 유가증권시장 모멘텀 붕괴현상 연구입니다. 한국시장에서 모멘텀 붕괴현상은 시장 panic 상태에만 일어나고 market upswings 와 동반하여 발생합니다. Bear market indicator 과 ex ante estimated volatility 을 이용하여 구성된 동적 weighting 모멘텀 개선 전략은 기존 constant volatility 전략에 비해 Sharpe ratio 은 2 배 늘어났고 시장모델의 알파도 유의하게 나타납니다.

주요어: 모멘텀 붕괴, dynamic weighting, constant volatility

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