

Risk-Adjusted Cross-Sectional Momentum¹

Myeong Hyeon Kim² and Inro Lee³

Abstract

This paper proposes a new ranking criterion for constructing momentum portfolios, namely risk-adjusted cross-sectional momentum. We propose to combine traditional cross-sectional momentum strategies with different volatility timing strategies in the form of the Sharpe ratio. Then, we show that the traditional momentum trading strategies are inferior to the risk-adjusted cross-sectional momentum. This finding is particularly pronounced in the presence of momentum crashes during the global financial crisis. Additionally, we highlight the role of the penny stocks and find that momentum strategies and crashes are significantly affected by the penny stocks. This finding provides an important implication for market practitioners.

Keywords: Momentum Strategies, Risk-Return Criteria, Volatility Timing

JEL classification: G11, G12, G14

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²Seoul National University of Science and Technology, 232 Gongneung-ro, Nowon-gu, Seoul, 01811, Korea; E-mail: mhkim@seoultech.ac.kr

³Corresponding Author, Address: The Bank of Korea, 39 Nadaemun ro, Jung-Gu, Seoul 04531, Republic of Korea. E-mail: leeinro@korea.ac.kr

1. Introduction

Momentum is an omnipresent phenomenon in almost all asset classes and markets. In their seminal paper, Jegadeesh and Titman (1993) find that constructing a zero investment portfolio by buying recent past winner stocks and selling recent past loser stocks can generate statistically significant systematic profits over various holding periods.

A newly surfaced criticism is the existence of momentum crashes. While investors of momentum strategies usually enjoy strong positive average returns, they also tend to suffer from significant negative skewed returns and excess kurtosis due to the crashes. Barroso and Santa-Clara (2015) document that the past-loser portfolio rose by 163%, while past winners' portfolio gained only 8% from March to May of 2009. The reason for momentum crashes varies. For instance, Daniel and Moskowitz (2016) attribute momentum crashes to the argument that loser firms are extremely levered at the risk of bankruptcy especially at turning points following large market declines. Grundy and Martin (2001) attribute to significant negative beta following bear markets. On the contrary, Daniel and Moskowitz (2016) show that relying on betas can not avoid the crashes. Novy-Marx (2015) shows that the strong comovement of recent winner stocks introduces significant risk to price momentum strategies, contributing volatility and negative skew that exposes the strategies to large drawdowns.¹

To reconcile with the inconsistency and to forestall momentum crashes, we propose to construct decile portfolios based on averages of past returns scaled by the inverse of their *expected* variance. The basic rationale is that if the variance does not forecast returns, the risk-return trade-off will deteriorate when the variance increases. That is, risk exposures decrease when the return variance is expected to be higher, and vice versa.² The concept of volatility-targeting or volatility-timing highlighted by Fleming et al. (2001, 2003), Kirby and Ostdiek (2012) and Hallerbach (2012) document that volatility-timing can result in desirable properties for the portfolio like lower turnover and larger Sharpe ratio. In this regard, by utilizing the substantial benefits of the volatility timing strategies, our method proposes to avoid big damages from the position of selling OTM puts during crisis periods.³

¹Another criticism may be rooted from the traditional portfolio theory in which employing realized cumulative returns as sole selection criterion with no risk component is not consistent with the theoretical derivation. For instance, the famous portfolio selection problem by Merton (1974) implies that investors should allocate their wealth into their risky assets by considering the first and second moments simultaneously. To be specific, a solution to the single-variable Merton problem, the optimal portfolio weight on the risky asset is given as $\alpha = \frac{1}{\gamma} \frac{\mu - r}{\sigma^2}$, where γ, μ, r and σ^2 are risk aversion, expected return, risk-free rate and volatility, respectively.

²Our proposed portfolio construction is motivated from a mean-variance investor's perspective in which the investor's objective is to maximize the trading profitability of taking a long position in the winner stocks adjusted by their risk proxies and to take a short position in the loser stocks adjusted by their risk proxies. In practice, more sophisticated investors tend to deploy the conditional volatilities.

³In terms of the payoff, traditional momentum strategies can be considered to have a similar payoff structure as selling out-of-the-money (OTM) puts. See; Brunnermeier et al. (2008) and Chernov et al. (2016)

To do so, we combine cross-sectional momentum strategies with different volatility timing strategies in the form of the Sharpe ratio. Specifically, we employ the *forward-looking* Sharpe ratio, $\frac{\hat{\mu}_t^{\text{MOM}}}{\hat{\Sigma}_{t+1}^{\text{GARCH}}}$ as our ranking criteria.⁴ When S_u is defined as a continuous compounding excess return, two individual stocks with a subscript i and j fall into different portfolio deciles with superscript A and B as follows:

$$\begin{aligned} \frac{dS_u}{S_u} &= \mu du + \sigma dW_u, \\ \text{decile}_t^A &:= \frac{1}{K} \sum_{k=1}^K \frac{\int_{t-k}^t \frac{dS_u^i}{S_u^i}}{E_t(\sigma_{i,t}^2)} > \frac{1}{K} \sum_{k=1}^K \frac{\int_{t-k}^t \frac{dS_u^j}{S_u^j}}{E_t(\sigma_{j,t}^2)} =: \text{decile}_t^B \end{aligned} \quad (1)$$

where A (B) decile is the winner (loser) portfolio and the *expected* variance $E_t(\sigma^2)$ is estimated using firm-level data for the corresponding ranking period. In terms of the volatility timing, equation (1) would be the near full utilization of Busse (1999)'s finding that many portfolio managers behave like volatility timers, reducing their market exposure during periods of higher expected volatility and Fleming et al. (2001, 2003)'s finding that the volatility timing strategies outperform the unconditionally static portfolios.

We make two distinctive contributions to the literature on momentum. Firstly, we analyze the performance of the risk-adjusted cross-sectional momentum strategies in the form of forward-looking Sharpe ratio. Our proposed ranking criterion is unique in the sense that loser portfolios with higher expected volatilities become *real* loser portfolios and winner portfolios with lower expected volatilities become *real* winner portfolios.⁵ Based on the proposed methodology of constructing momentum strategies, we naturally test the usefulness of the stochastic investment opportunities of dynamic and asymmetric properties by applying different types of volatility models to estimate conditional volatilities. Secondly, we highlight the role of the penny stocks in the performance analysis of the momentum strategies. The majority of time-series momentum and relevant momentum crash studies have focused on the analysis of the WML portfolios, while we document additional evidence that momentum crashes are closely associated with the presence of the penny stocks in the process of constructing momentum portfolios.

After verifying the existence of momentum crashes, we show that the performances of traditional cross-sectional momentum are inferior to those of the risk-adjusted cross-sectional momentum. To be specific, the traditional ranking criteria produce the final dollar values of \$6.77, compared to the final dollar value of \$71 for our proposed ranking criteria for the whole sample period January 1965 to December 2014. We also highlight

⁴The reason we consider the conditional framework is that unconditional alpha estimates are biased when a conditional beta covaries with volatility.

⁵That is, past winner stocks that have performed relatively well become real past winner stocks if past returns perform relatively well with lower expected volatility. On the contrary, past winner stocks with higher expected volatility would be allocated to inferior deciles. A similar argument does hold for the loser stocks, too.

the role of the penny stocks in the momentum trading performance. When the penny stocks are excluded, the final dollar value for the traditional momentum increases to \$194, compared to the final dollar value of \$273 for the proposed momentum trading strategies for the same period. We have verified that the difference between the final dollar value comes from the role of risk-adjusted momentum strategies' lowering loser portfolio returns. This result is most pronounced for the sample periods including the technology bubble-burst and the global financial crisis. From the result, the penny stocks and NASDAQ stocks are presumed to be the driver in the performance of risk-adjusted momentum strategies. Our results are robust after controlling Fama and French(1993) three factors. Our empirical finding has important implications to avoid so-called momentum crashes.

Combining the volatility timing with cross-sectional momentum at the firm level is rare in the finance literature. A notable exception is Rachev, Jasic, Stoyanov, and Fabozzi (2007) in which the authors apply several risk measures such as standard deviation, Value at Risk (VaR), and Expected Shortfall (ES) to form momentum portfolios.⁶ Our proposed approach is different from their methodology in two distinctive ways. Firstly, risk measures employed by Rachev et al. (2007) are backward-looking in the sense that their risk measures are calculated by using past returns where all past returns are treated as equal, thus extreme events are just as important to current estimates whether they occurred yesterday or a long time ago. A possible weakness of these risk measures resides in the implied assumption that investors invest in risky assets and adjust their portfolios by extrapolating the historical statistics to the future naively. Instead, motivated by the volatility timing literature, we apply several conditional heteroskedasticity models to extract forward-looking risk estimates *individually*. Our basic conditional volatility is based on the parsimonious form of GARCH(1,1). Secondly, the asset universe of Rachev et al. (2007) consists of a total of 517 stocks included in the S&P 500 index in the period January 1, 1996 to December 31, 2003. The main finding of Rachev et al. (2007) reporting cumulative return criterion provides the highest average monthly momentum profits may not be concrete in that they dodge the momentum crashes by not including the global financial crash and not employing NASDAQ and other penny stocks. We use a broader sample by extending the sample period from January 1965 to December 2014 to include several momentum crashes. Our analysis is benefited from a large amount of daily data newly available in CRSP dataset after Rachev et al. (2007)'s study.

The idea of constructing momentum strategies by employing the reward-risk stock selection criteria is closely related to both the emerging literature on risk-managed factor investing and the methods used in the time-series momentum literature. The recent literature on risk-managed factor investing proposes scaling exposure to factors as a function of estimates of volatility for each factor (see; Moreira and Muir (2017), Barroso and F. Maio (2016, 2017), and Grobys et al. (2017)) and the literature on the time-series momentum

⁶They find that the cumulative return criterion provides the highest average monthly momentum profits but the alternative ratios provide better risk-return profile.

proposes to use asset-specific volatility estimates as a scaling factor (see; Baltas (2015) and Baltas and Kosowski (2017)).⁷ For instance, Moskowitz et al. (2012) evaluate the performance of a strategy which dynamically adjusts the weight on the WML momentum strategy using the forecasted return and variance of the strategy and Barroso and Santa-Clara (2015) discuss of scaling the returns by their forecasted variance estimated at the portfolio level. Whereas, Baltas (2015) and Baltas and Kosowski (2017) construct a long-short trend-following strategy that makes use of risk-parity principles by extending the conventionally long-only risk-parity allocation at the individual asset classes.

Recent studies have documented a lower risk anomaly in the cross section where stocks with low betas or lower idiosyncratic volatility have high risk-adjusted returns. On the firm level, the positive relation has been well-documented by Malkiel and Xu (2006), Spiegel and Wang (2005), Fu (2009), and Huang et al. (2010). In addition, Gomes et al. (2003) develop a general equilibrium model in which the firm-level size and book-to-market ratio are correlated with the market beta. In this regard, our motivation by support for firm-level risk and expected return variations would also lend credit to the application of scaling firm stock returns with firm-level risk proxies, i.e., the cross-section of stock returns.⁸ Relative to this recent branch of literature, we share the insight of exploiting a potentially imperfect link between *expected* volatility and returns in the sense that this study uses instead asset(or firm) specific volatility estimates rather than using portfolio/factor level volatility to manage risk to form portfolios. That is, first comes scaling the volatilities individually, then next comes forming the portfolios.

The structure of our paper is as follows. Section 2 describes the data set and sample. Section 3 presents the empirical results and section 4 concludes with a summary of the main results.

2. Data and Sample

We use all firms listed in NYSE, AMEX, and NASDAQ provided by the CRSP dataset. Following Jegadeesh and Titman (1993), portfolios are constructed by sorting all stocks into one of five equally weighted portfolios per every month. We skip one month between portfolio formation periods and the holding periods to minimize microstructure

⁷Scaling stock returns with their risk proxies is in the same line with practical versions of the risk parity in which the investment weights are inversely proportional to the volatility (see; Wai (2011) and Denis Chaves and Shakernia (2011) among many). Recently, time-series momentum as alternative ranking criteria by Moskowitz et al. (2012) have received increasing attention after impressive diversification benefits during the recent financial crisis. A time-series momentum strategy, also known as a trend-following strategy, can be understood as an extension to the long-only volatility timing strategy of Equation (1) and involves both long and short positions.

⁸For portfolios sorted by idiosyncratic volatilities, Ang et al. (2006) find that portfolios with high idiosyncratic volatility in the current month yield low value-weighted returns in the following month and Ang et al. (2009) also confirm this negative relation in international markets. Bali and Cakici (2008), however, report that this negative relation is not robust under different choices of data frequency, weighting scheme, and breakpoints in the construction of idiosyncratic volatility-sorted portfolios.

problems. That is, momentum portfolios are constructed based on cumulative returns from $t-J-1$ to $t-1$ periods and held from t to $t+k$ periods ($J/1/K$). To estimate conditional volatilities, we use daily stock returns of each firm for the past six months based on GARCH(1,1) specification, then convert daily volatilities to monthly volatilities by multiplying square 30.⁹ After eliminating daily stock returns with zero trading volume per each day, we use all firm stock returns with the number of total trading days for the past six months being more than 100. This is to avoid potential liquidity biases. To test the role of the penny stocks in terms of turnover costs and bid-ask biases, we eliminate stocks with prices less than \$1 at the beginning of holding periods and we report the results in the separate tables. Following the portfolio construction convention and data availability of CRSP, we use closing prices and all returns are calculated using close prices. The one-month risk free rate (Treasury bill rate) and Fama and French(1993) three factors are obtained from Kenneth French’s website.¹⁰ Our sample period is ranging from January 1965 to December 2014. All firms meeting the requirements are then placed into one of five decile portfolios based on three ranking criteria.

3. Empirical Results

This section contains empirical results for our proposed momentum strategy, namely risk-adjusted cross-sectional momentum. Table 1 reports descriptive statistics of three trading strategies for different sample periods. The first momentum portfolios are constructed by buying recent past winner stocks and selling recent past loser stocks as in Jegadeesh and Titman (1993). Next momentum portfolios are constructed by employing Rachev et al. (2007) where the authors adjust cumulative excess returns with the sample second moment of the excess return. Finally, we propose our momentum portfolios based on the equation (1).¹¹

3.1. Main findings

We report the performance of three momentum strategies for different sample periods. The first column of Table 1 shows the average monthly returns of winner and loser portfolios as well as of the zero-cost, winner-minus-loser portfolios for our 6/1/6 month strategy for three momentum strategies; cumulative return (CR), cumulative return adjusted by the sample variance (RAR), and cumulative return adjusted by conditional volatilities (CRAR) criteria. Table 1 summarizes the effective performance of employing the risk-parity, or the volatility timing. Consistent with the existing literature, CR criterion yields a strong momentum premium over the period January 1965 to December 2014

⁹We have tested other specifications including GJR-GARCH based on the empirical performance suggested by Laurent et al. (2012). The results are invariant and available upon request.

¹⁰Kenneth French’s data library

¹¹The decisions based on the Sharpe ratio lead to optimal results if the returns are assumed to follow the Gaussian distribution.

Table 1: The performance of three momentum strategies					
Ranking	Portfolio	Summary Statistics			
		Mean	Std.	Skew.	Kurt.
Panel A: 1965-2014					
CR	Loser	1.13	9.68	1.35	7.6
	Winner	1.69	7.31	-0.37	2.39
	WML	0.56	6.37	-2.87	23.02
RAR	Loser	0.82	7.37	0.79	5.18
	Winner	1.65	6.3	-0.39	2.78
	WML	0.83	4.92	-1.43	16.32
CRAR	Loser	0.82	7.31	0.73	4.93
	Winner	1.66	6.25	-0.41	2.69
	WML	0.84	4.79	-1.45	16.66
Panel B: 1965-1999					
CR	Loser	0.91	8.45	0.77	3.96
	Winner	1.9	7.05	-0.67	2.57
	WML	0.98	4.92	-1.58	6.47
RAR	Loser	0.61	6.52	0.18	2.27
	Winner	1.83	6.06	-0.7	2.71
	WML	1.21	3.71	-0.44	1.12
CRAR	Loser	0.63	6.48	0.15	2.26
	Winner	1.82	6.03	-0.71	2.73
	WML	1.19	3.64	-0.45	1.21
Panel C: 2000-2014					
CR	Loser	1.63	12.08	1.65	7.69
	Winner	1.21	7.88	0.17	2.26
	WML	-0.42	8.81	-2.77	17.85
RAR	Loser	1.29	9.07	1.2	5.6
	Winner	1.24	6.83	0.15	2.98
	WML	-0.05	6.9	-1.31	12.47
CRAR	Loser	1.27	8.95	1.13	5.35
	Winner	1.27	6.75	0.12	2.71
	WML	0.01	6.7	-1.36	12.98

Note. This table reports the mean, standard deviation(Std.), skewness(Skew.), and excess kurtosis(Kurt.) of raw returns (in percent) on three momentum strategies; cumulative return (CR), cumulative return adjusted by the sample variance (RAR), and cumulative return adjusted by conditional volatilities (CRAR) . The sample period is from January 1965 to December 2014.

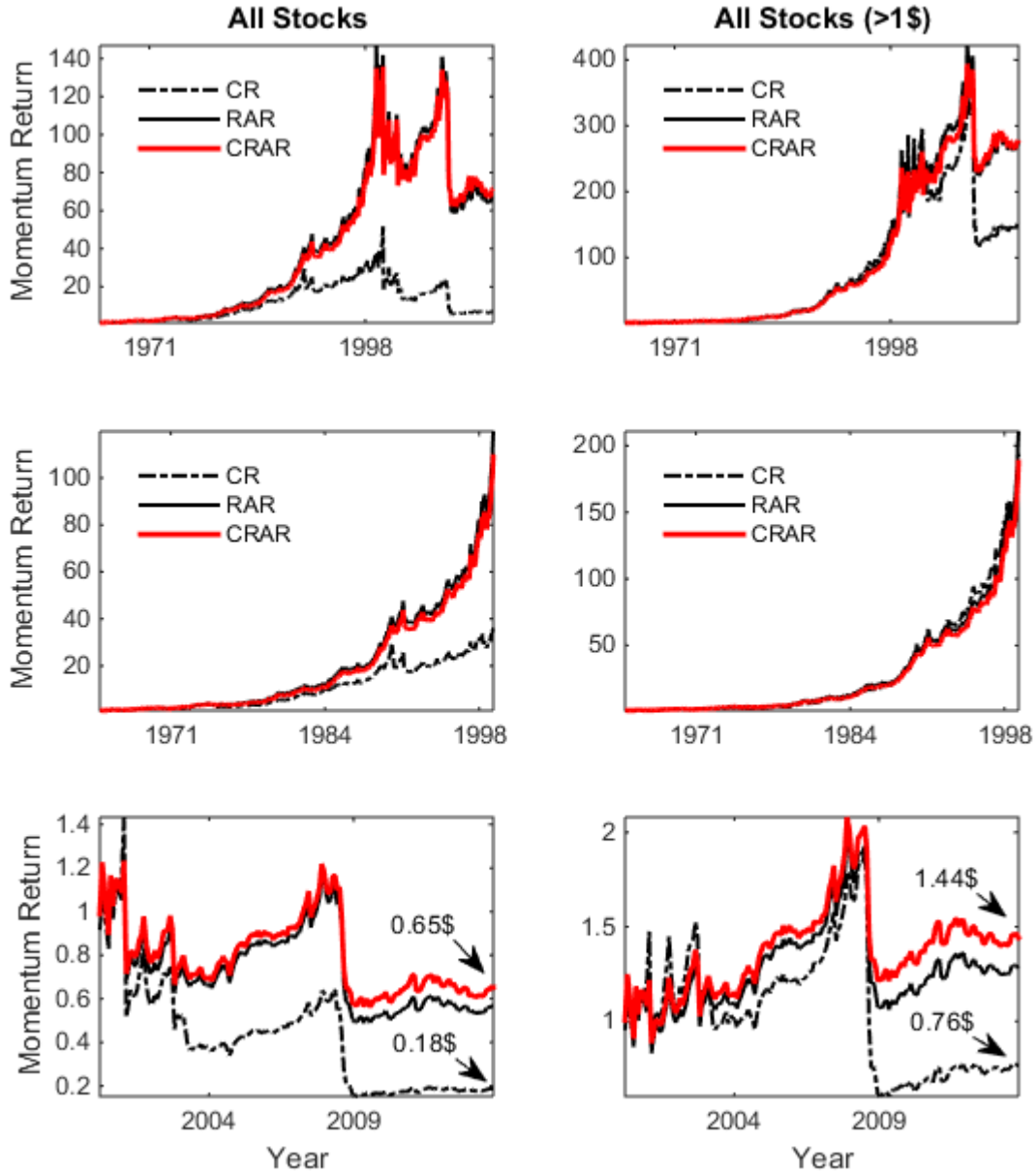
and January 1965 to December 1999. The winners significantly outperform the losers for those periods as shown in Panel A and B. Panel A presents the results for CR, RAR, and CRAR criteria over the period January 1965 to December 2014. The mean monthly returns in Panel A clearly demonstrate that both RAR and CRAR rules generate the larger returns than what CR can produce. In terms of the Sharpe ratio, the Sharpe ratio of RAR or CRAR (0.175) is twice greater than that of CR (0.087) criteria.

In addition, earning negative average monthly in the WML portfolios with severely negative skewness for the period January 2000 to December 2014 in Panel C is also consistent with the literature on momentum crashes. Panel A and B in Table 1 verify that the winner portfolios are considerably more negatively skewed than the loser portfolios. The loser portfolios strongly outperform the winner portfolios and the losers produce 34% higher profits than those of the winners for the momentum crash periods shown in Panel C. To summarize, the cumulative returns adjusted by risk measures (RAR and CRAR) obtain the largest average monthly momentum profits compared to the cumulative return (CR), and these strategies are less riskier than the traditional momentum strategy if measured on volatility or skewness of the WML portfolios. Managing the risk of momentum improves the mean return while reducing the standard deviation, by thus the Sharpe ratios of the risk adjusted cross-sectional momentum increase. Note that the results of our proposed criterion is as good as those of the criteria suggested by Rachev et al. (2007) in terms of a statistical distribution.

Figure 1 displays the cumulative monthly returns as measured in the final dollar values of \$1 for each of the three portfolios for three sub-sample periods. The final values are tabulated in the right of the plot under the assumption that investors are given a \$1 investment in January 1965 (the first two rows) and January 2000 (the last row) with no transaction costs. In addition to the results of Table 1, Figure 1 exhibits the effects of the penny stocks in forming momentum strategies. The first and the second columns exhibit the final dollar values of \$1 using all stocks listed in NYSE, AMEX, and NASDAQ and excluding the penny stocks whose value is less than \$1, respectively. Basically, the final dollar values are consistent with the results of Table 1 in the sense that we observe marginal differences between RAR and CRAR criteria but huge differences between CR and other two risk-adjusted criteria.

One notable finding is that it is the penny stocks that drag down the performance of momentum trading strategies significantly. For the whole sample period in the first row and column, CR ranking criterion produces the final dollar values of \$6.77, compared to the final dollar values \$67 and \$71 for RAR and CRAR ranking criteria. When the penny stocks are excluded as in the first row and second column, the final dollar values for CR increases to \$148 and those for RAR and CRAR to \$270 and \$273, respectively. A similar pattern is observed for the sample period January 1965 to December 1999 in the second row. CR ranking criterion produces the final dollar values of \$36, compared to the final dollar values of \$119 and \$110 for RAR and CRAR ranking criteria. When the penny stocks are excluded as in the first row and second column, the final dollar value for CR

Figure 1: The final dollar values of three momentum strategies



Note. This figure depicts cumulative realized profits for Cumulative Return (CR), Risk-Adjusted Return (RAR), and Conditional Risk-Adjusted Return (CRAR) criteria of the 6/1/6 month strategy. The profits are calculated as the final dollar values of \$1 for the three momentum portfolios for three sub-sample periods.

increases to \$194 and those for RAR and CRAR increase to \$210 and \$189, respectively.

What makes CRAR ranking criterion distinguishable from the RAR ranking criterion is observed in the last row of Figure 1. We emphasize that the difference between two risk proxies naturally resides in the weighting scheme. In calculating the sample variance, equal weights, that is $1/N$ for N observations, are given to the past squared returns for a chosen sample period, while weights are given by the estimated coefficients to the long-run average variance, the variance predicted, and newly arrived information in calculating conditional volatilities. Risk-adjusted momentum depends on ex-ante information, thus implementing these trading strategies is required to be in real time.¹²

For the sample period January 2000 to December 2014 in the last row, CR ranking criterion produces the final dollar values of \$0.18, compared to the final dollar values \$0.56 and \$0.65 for RAR and CRAR ranking criteria. When the penny stocks are excluded, the final dollar values for CR increases to \$0.76 and those for RAR and CRAR to \$1.28 and \$1.44, respectively. Our proposed momentum strategy manages to preserve the seed money and obtains the highest return in the 2000s. This compares favorably with the pure momentum strategy which loses 82% during the same period. Risk-adjusted momentum not only ends the decade up 28% and 44% giving rise to avoiding the crash but also capturing the positive returns of 2007-2008 when the penny stocks are excluded. When the volatility timing intertwined with momentum strategies, the benefits of using volatility timing strategies are especially important when momentum crashes surface as evidenced by Panel C in Table 1. The difference between the results with all stocks in the first column and stocks with price bigger than \$1 in the second column conforms to the findings of Duffee (1995) that individual firms stock return volatility rises after stock prices fall

Tables 2 verifies the abovementioned results. Panel A reports the average monthly returns of the winner and loser portfolios as well as of the zero-cost, WML portfolios for our 6/1/6 month strategy for three momentum strategies with all stocks, panel B, and C report the results under the restrictions that the penny stocks less than \$1 or NASDAQ stocks are excluded. A seemingly puzzling finding is that the average monthly returns by CR ranking criterion are greater than those by RAR and CRAR ranking criteria if NASDAQ stocks are excluded. However, this finding is consistent with the main result of Rachev et al. (2007) stating that cumulative return criterion provides the highest average monthly momentum profits for the period 1996 to 2003.

We also report the results for different holding periods H in Table A1 and A2 in the appendix. The results for different holding periods are also consistent with the findings of Table 1 and 2 as well as Figure 1. Momentum portfolios are formed by purchasing the 20% stocks with the highest cumulative returns over the fixed past 6 months and selling short the 20% stocks with the lowest cumulative returns over the past 6 months. Portfolios are then held for the subsequent H months. The reversals of the WML portfolios are

¹²We emphasize that the difference between two risk measures and Peterson and Smedema (2011)'s finding that realized and expected idiosyncratic volatility are separate on an equal footing.

Table 2: Average monthly returns for three momentum strategies

Portfolio	CR		RAR		CRAR	
	Mean	t-value	Mean	t-value	Mean	t-value
Panel A: All Stocks						
Loser	1.13	(2.86)	0.82	(2.71)	0.82	(2.75)
Winner	1.69	(5.67)	1.65	(6.41)	1.66	(6.49)
WML	0.56	(2.17)	0.83	(4.15)	0.84	(4.28)
Panel B: Exclusion of stocks less than \$1						
Loser	0.67	(1.82)	0.60	(2.12)	0.61	(2.17)
Winner	1.68	(5.62)	1.64	(6.38)	1.64	(6.45)
WML	1.01	(4.42)	1.04	(5.68)	1.04	(5.83)
Panel C: Exclusion of stocks listed in NASDAQ						
Loser	0.38	(1.23)	0.55	(2.18)	0.56	(2.21)
Winner	1.53	(5.73)	1.52	(6.59)	1.53	(6.66)
WML	1.15	(5.99)	0.97	(6.2)	0.97	(6.41)

Note. This table reports the mean and t-value of raw returns (in percent) for three momentum strategies; cumulative return (CR), cumulative return adjusted by the sample variance (RAR), and cumulative return adjusted by conditional volatilities (CRAR). Panel A includes all firms in NYSE, AMEX, and NASDAQ. Panel B and C eliminates stocks less than \$1 and in NASDAQ, respectively. The sample period is from January 1965 to December 2014.

observed as the holding periods become longer for all panels. Interestingly, the average monthly returns of winner and loser portfolios as well as of the zero-cost, WML portfolios for different holding periods decreasing monotonically. This pattern is observed for every sample period and Panel B of Table 2 in Wang and Wu (2011) gives credit to our results in terms of the risk-adjustment for momentum portfolios.

To summarize Table 1, 2 and Figure 1, the penny stocks are to be the source of crashes in the cross-sectional momentum portfolios and deploying volatility timing strategies counter the momentum crashes better than the sample variances. We associate our finding with the argument that the number of stocks included in the winner and loser portfolios varies with the state of the market. In this regard, the information in the momentum signals mostly comes from the tails of the return distribution generated by the behavior of the penny stocks.

3.2. Robustness checks

A possible criticism may arise regarding whether our proposed ranking criterion would produce additional returns compared with the results on the double-sorted portfolios on conditional volatilities and momentums. Can a simple form of the *forward-looking* Sharpe ratio, $\frac{\hat{\mu}_t^{\text{MOM}}}{\hat{\Sigma}_{t+1}^{\text{GARCH}}}$ as a ranking criterion create a marginal information, thus give rise to higher returns? This is the question we answer through Table 3 and 4. These tables report the mean returns for stock portfolios using 5×5 two-way sorts on conditional

volatilities ($\hat{\Sigma}_{t+1}^{\text{GARCH}}$) and momentums ($\hat{\mu}_t^{\text{MOM}}$) for all stocks and stocks bigger than \$1, correspondingly. We verify that momentum sorted portfolios are almost monotonically increasing from lower deciles to higher deciles as we observe in the momentum literature and the WML returns are similar to the CR results of Table 1 and 2.

The portfolio returns two-way sorted on conditional volatilities and momentums as described in Table 3 and 4 display several intriguing points.¹³ The portfolio with higher expected volatility tends to have higher returns than the portfolio with low expected volatility given fixed momentum deciles in Table 3. The equal-weighted portfolio returns increase monotonically except for the lowest decile portfolios. This evidence confirms the positive relation between conditional volatilities and firm stock returns. The results of Table 1 and 2 are generally consistent with the findings of Fu (2009) using portfolios formed on conditional idiosyncratic volatility.¹⁴ We emphasize that our proposed ranking criterion yields higher portfolio returns when compared with WML portfolio returns for all given expected volatility deciles except the fourth expected volatility decile in Panel A and B of Table 3.

Interestingly, the portfolio returns of the lowest decile with stocks bigger than \$1 in Table 4 exhibit little variation among the portfolio returns sorted on conditional volatilities. Relating to this, the effects of excluding the penny stocks are most pronounced for the portfolio returns with the highest conditional volatilities. The portfolio returns sorted on momentum with the highest conditional volatilities in Table 3 display no statistical significance in Panel A and 0.43% average monthly returns in Panel B, while the same portfolio returns with the same sorts in Table 4 exhibits more than two times higher returns reaching to 0.92%. This effect can be attributed to the reduced portfolio returns with highest conditional volatilities within loser deciles. This finding is in the same line with the story contained in Figure 1 describing the role of the penny stocks that drag down the performance of momentum trading strategies. Again, our proposed ranking criteria dominate over all WML portfolio returns for all given expected volatility deciles in Panel A and B of Table 4. To sum, a simple form of the *forward-looking* Sharpe ratio, $\frac{\hat{\mu}_t^{\text{MOM}}}{\hat{\Sigma}_{t+1}^{\text{GARCH}}}$ as a ranking criteria certainly can create additional information, thus yields higher returns.

For the sake of additional robustness check, we run Fama and French’s three-factor regression to find whether our results are consistent after controlling well-known risk factors (see, Fama and French (1997) and Jegadeesh and Titman (1993)). Previous studies have found that momentum profits are quite significant and in most cases even bigger than raw returns even after adjusting risk factors. We also report risk-adjusted returns and

¹³Since 6/1/6 momentum strategies have been employed in the main table, we apply the same strategy in Table 3 and 4. That is, raw returns are the average for 6 months holding periods sorted on expected volatilities estimated using firm stock returns for the past 6 months

¹⁴The author finds that the portfolio consisting of stocks with high expected idiosyncratic volatility has higher returns than the portfolio consisting of low expected idiosyncratic volatility stocks. Refer to Table 6 in the paper.

Table 3: All Stocks

		Cumulative Return (CR)					High-	All
		1(Low)	2	3	4	5(High)	Low	stocks
Panel A: 1965-2014								
Expected Volatility	1	0.87	1.04	1.11	1.19	1.39	0.52***	1.1
	(Low)	(3.92)	(5.82)	(6.76)	(7.43)	(7.82)	(3.3)	(7.11)
	2	0.8	1.1	1.22	1.31	1.52	0.71***	1.27
		(3.2)	(5.09)	(6.04)	(6.56)	(7.16)	(4.9)	(5.98)
	3	0.87	1.13	1.27	1.39	1.65	0.78***	1.27
		(3.05)	(4.48)	(5.23)	(5.78)	(6.49)	(5.07)	(5.13)
	4	0.83	1.19	1.31	1.42	1.72	0.89***	1.28
		(2.41)	(3.88)	(4.46)	(4.8)	(5.59)	(5.24)	(4.12)
	5	1.45	1.54	1.52	1.62	1.58	0.13	1.56
	(High)	(3.25)	(4.1)	(4.19)	(4.51)	(4.39)	(0.61)	(3.93)
P5-P1		0.58*	0.50*	0.41	0.42	0.19	-0.38**	0.46
		(1.66)	(1.76)	(1.47)	(1.54)	(0.74)	(-1.9)	(1.42)
All Stocks		1.09	1.17	1.24	1.35	1.59	0.50**	
		(3.19)	(4.73)	(5.66)	(6.16)	(5.87)	(2.41)	
Panel B: 1965-1999								
Expected Volatility	1	0.8	1.04	1.12	1.22	1.44	0.64***	1.13
	(Low)	(3.13)	(4.86)	(5.61)	(6.13)	(6.62)	(3.58)	(5.94)
	2	0.73	1.11	1.25	1.36	1.64	0.91***	1.31
		(2.57)	(4.37)	(5.2)	(5.59)	(6.44)	(5.97)	(5.17)
	3	0.71	1.13	1.32	1.46	1.79	1.08***	1.31
		(2.23)	(3.82)	(4.51)	(5.03)	(5.88)	(7.01)	(4.41)
	4	0.7	1.19	1.34	1.51	1.9	1.20***	1.3
		(1.82)	(3.36)	(3.87)	(4.34)	(5.26)	(7.37)	(3.62)
	5	1.3	1.59	1.6	1.7	1.73	0.43**	1.56
	(High)	(2.73)	(3.74)	(3.86)	(4.11)	(4.19)	(2.04)	(3.57)
P5-P1		0.5	0.55*	0.48	0.48	0.29	-0.21	0.44
		(1.37)	(1.77)	(1.57)	(1.6)	(1.01)	(-1.0)	(1.31)
All Stocks		0.94	1.17	1.28	1.41	1.75	0.80***	
		(2.58)	(4.06)	(4.82)	(5.3)	(5.53)	(4.16)	

Note. This table represents average raw returns for portfolios that are formed each month by sorting stocks on the past six month cumulative returns and expected volatility estimated by a GARCH(1,1) model. Since 6/1/6 momentum strategies are mainly employed throughout the paper, raw returns are average of subsequent realized returns for 6 month holding periods. The first portfolio (Low) consists of the 20% of stocks with the lowest expected volatility and the last portfolio (High) consists of the 20% of stocks with the highest expected volatility. Portfolios are updated monthly. ***, **, * in High-Low portfolio indicate significance at the 1, 5, 10 percent levels, respectively.

Table 4: Stocks (> \$1)

		Cumulative Return (CR)					High-	All
		1(Low)	2	3	4	5(High)	Low	stocks
Panel A: 1965-2014								
Expected Volatility	1	0.84	1.04	1.11	1.19	1.39	0.54***	1.1
	(Low)	(3.89)	(5.81)	(6.76)	(7.42)	(7.82)	(3.61)	(7.11)
	2	0.78	1.1	1.22	1.31	1.52	0.74***	1.21
		(3.12)	(5.08)	(6.04)	(6.56)	(7.16)	(5.17)	(5.97)
	3	0.83	1.12	1.26	1.38	1.65	0.82***	1.26
		(2.94)	(4.43)	(5.19)	(5.77)	(6.48)	(5.42)	(5.08)
	4	0.75	1.15	1.29	1.4	1.72	0.97***	1.24
		(2.21)	(3.78)	(4.4)	(4.76)	(5.58)	(5.94)	(4.02)
	5	0.82	1.29	1.33	1.49	1.52	0.70***	1.22
	(High)	(2.01)	(3.56)	(3.76)	(4.2)	(4.22)	(3.8)	(3.24)
P5-P1		-0.02	0.25	0.22	0.3	0.13	0.16	0.12
		(-0.0)	(0.93)	(0.83)	(1.1)	(0.52)	(0.93)	(0.41)
All Stocks		0.8	1.11	1.21	1.33	1.57	0.77***	
		(2.47)	(4.57)	(5.57)	(6.09)	(5.82)	(4.18)	
Panel B: 1965-1999								
Expected Volatility	1	0.77	1.04	1.12	1.22	1.44	0.67***	1.13
	(Low)	(3.07)	(4.87)	(5.61)	(6.13)	(6.61)	(4)	(5.94)
	2	0.72	1.11	1.25	1.36	1.64	0.92***	1.26
		(2.52)	(4.36)	(5.2)	(5.58)	(6.44)	(6.1)	(5.16)
	3	0.7	1.13	1.31	1.46	1.79	1.09***	1.3
		(2.19)	(3.8)	(4.5)	(5.03)	(5.88)	(7.17)	(4.4)
	4	0.65	1.18	1.34	1.51	1.9	1.26***	1.29
		(1.71)	(3.32)	(3.85)	(4.33)	(5.27)	(7.84)	(3.59)
	5	0.77	1.43	1.45	1.6	1.69	0.92***	1.31
	(High)	(1.74)	(3.45)	(3.57)	(3.88)	(4.09)	(4.94)	(3.1)
P5-P1		0.01	0.39	0.33	0.38	0.25	0.24	0.18
		(0.02)	(1.32)	(1.13)	(1.28)	(0.88)	(1.3)	(0.58)
All Stocks		0.71	1.14	1.26	1.4	1.74	1.02***	
		(2.03)	(3.97)	(4.77)	(5.26)	(5.51)	(5.74)	

Note. This table represents average raw returns for portfolios that are formed each month by sorting stocks on the past six month cumulative returns and expected volatility estimated by a GARCH(1,1) model. Since 6/1/6 momentum strategies are mainly employed throughout the paper, raw returns are average of subsequent realized returns for 6 month holding periods. The first portfolio (Low) consists of the 20% of stocks with the lowest expected volatility and the last portfolio (High) consists of the 20% of stocks with the highest expected volatility. Portfolios are updated monthly. ***, **, * in High-Low portfolio indicate significance at the 1, 5, 10 percent levers, respectively.

factor loadings in Table 5 using the following factor model.

$$R_{it}^e = \alpha_i + \beta_{i,b}(R_{mt} - R_{ft}) + \beta_{i,s}(R_{SMB,t}) + \beta_{i,h}(R_{HML,t}) + \epsilon_{it} \quad (2)$$

where R_{it}^e is the excess return for the winner or the loser portfolio, or the returns for the zero-cost WML portfolios, R_{mt} is the return for the equal-weighted CRSP market index, R_{ft} is the one-month Treasury bill rate, $R_{SMB,t}$ is the return on the zero-cost portfolio that buys large-capitalization stocks and sells small capitalization stocks, and $R_{HML,t}$ is the return on the zero-cost portfolio that buys high book-to-market stocks and sells low book-to-market stocks.

In Table 5, the intercept estimates and the estimates of the market, SMB, and HML denote abnormal returns (Jensen's α) and factor loadings (sensitivities) of the aforementioned factor model, respectively. Returns of the WML portfolios for CR ranking criterion is 0.83% with t-statistic of 3.18, meaning that the momentum anomaly is still strong even after adjusting three factors. Being consistent with Table 1, this table further proves that RAR and CRAR ranking criteria generate higher returns than CR ranking criteria from the zero-cost WML portfolios. Returns differentials between CR and CRAR are calculated as 0.22% (1.05% -0.83%) and 0.13%(1.35% -1.22%) in Panel A and B, respectively. However, when penny stocks are eliminated, CR criterion provides almost the same returns as CRAR criterion in Panel C and D.

These results are consistent with our main finding that the penny stocks are to be the source of risk-adjusted momentum profits by bearing the possibilities of momentum crashes. Interestingly, differences of the SMB factor loadings ($\beta_{i,s}$) in the CR and CRAR ranked portfolios are reported bigger than those of market and HML factor, leading to the conclusion that risk-adjusted momentum strategies can reduce the factor sensitivities on the SMB factors.¹⁵ The results reported in Table 5 show that three momentum strategies exhibit abnormal returns under the framework of Fama and French three-factor model because the risk-adjusted returns are uniformly larger and more significant than the raw returns. Not surprisingly, this evidence has always been cited in favor of a non-risk-based explanation of the momentum phenomenon.

4. Conclusions

This paper proposes a modified ranking criteria for constructing momentum portfolios to forestall the momentum crashes. By associating the traditional momentum trading strategies with the volatility timing strategies, we propose the *forward-looking* Sharpe ratio as the ranking criteria. Based on the criteria, we provide several interesting empirical findings. Firstly, we show that the traditional momentum trading strategies are inferior to the risk-adjusted cross-sectional momentum in terms of preventing momentum crashes.

¹⁵Since the empirical patterns over the period 2000-2014 are the same as our main finding, the results are shown in Table A3 in the appendix.

Table 5: Factor time-series regressions

		α	t-value	$\beta_{i,b}$	t-value	$\beta_{i,s}$	t-value	$\beta_{i,h}$	t-value
Panel A: All stocks over 1965-2014									
CR	Loser	-0.35	(-1.5)	1.28	(23.53)	1.35	(17.71)	0.24	(2.86)
	Winner	0.48	(4.92)	1.12	(48.7)	1.06	(32.91)	-0.07	(-1.92)
	WML	0.83	(3.18)	-0.16	(-2.65)	-0.29	(-3.4)	-0.30	(-3.26)
RAR	Loser	-0.52	(-3.33)	1.18	(32.12)	0.85	(16.58)	0.35	(6.2)
	Winner	0.53	(6.69)	1.05	(56.22)	0.78	(29.93)	-0.03	(-1.09)
	WML	1.05	(5.22)	-0.13	(-2.7)	-0.07	(-1.04)	-0.38	(-5.23)
CRAR	Loser	-0.51	(-3.31)	1.17	(32.25)	0.86	(16.9)	0.34	(6.22)
	Winner	0.54	(7.05)	1.05	(58.26)	0.77	(30.51)	-0.03	(-1.06)
	WML	1.05	(5.35)	-0.11	(-2.49)	-0.08	(-1.31)	-0.37	(-5.29)
Panel B: All stocks over 1965-1999									
CR	Loser	-0.67	(-3.41)	1.12	(23.17)	1.53	(22.66)	0.32	(4.14)
	Winner	0.56	(5.13)	1.11	(41)	1.03	(27.15)	-0.08	(-1.95)
	WML	1.22	(5.29)	-0.01	(-0.16)	-0.50	(-6.27)	-0.40	(-4.4)
RAR	Loser	-0.80	(-6.41)	1.05	(33.8)	0.98	(22.55)	0.30	(5.94)
	Winner	0.57	(7.02)	1.06	(53.02)	0.72	(25.62)	-0.04	(-1.22)
	WML	1.37	(7.7)	0.01	(0.26)	-0.26	(-4.25)	-0.33	(-4.74)
CRAR	Loser	-0.78	(-6.39)	1.04	(34.24)	0.99	(23.18)	0.3	(6.14)
	Winner	0.56	(7.19)	1.06	(54.41)	0.71	(26.03)	-0.04	(-1.4)
	WML	1.35	(7.78)	0.02	(0.39)	-0.28	(-4.63)	-0.34	(-4.98)
Panel C: Stocks (> \$1) over 1965-2014									
CR	Loser	-0.81	(-4.37)	1.30	(29.89)	1.25	(20.54)	0.27	(4.13)
	Winner	0.47	(4.82)	1.12	(49)	1.05	(32.83)	-0.08	(-2.22)
	WML	1.27	(5.59)	-0.18	(-3.35)	-0.20	(-2.66)	-0.35	(-4.28)
RAR	Loser	-0.73	(-5.72)	1.17	(38.96)	0.80	(18.97)	0.38	(8.38)
	Winner	0.52	(6.58)	1.05	(55.77)	0.78	(29.64)	-0.04	(-1.29)
	WML	1.26	(6.94)	-0.13	(-2.95)	-0.02	(-0.34)	-0.42	(-6.49)
CRAR	Loser	-0.72	(-5.73)	1.16	(39.38)	0.8	(19.51)	0.38	(8.39)
	Winner	0.53	(6.88)	1.05	(57.51)	0.77	(30.06)	-0.04	(-1.28)
	WML	1.25	(7.1)	-0.11	(-2.72)	-0.04	(-0.66)	-0.41	(-6.53)
Panel D: Stocks (> \$1) over 1965-1999									
CR	Loser	-1.02	(-6.67)	1.13	(29.75)	1.43	(26.95)	0.28	(4.67)
	Winner	0.56	(5.12)	1.12	(41.35)	1.02	(26.98)	-0.10	(-2.23)
	WML	1.58	(7.61)	-0.01	(-0.25)	-0.41	(-5.73)	-0.38	(-4.62)
RAR	Loser	-0.93	(-8.12)	1.06	(37.25)	0.94	(23.7)	0.30	(6.6)
	Winner	0.57	(7.04)	1.06	(52.71)	0.71	(25.27)	-0.05	(-1.41)
	WML	1.5	(8.74)	0.01	(0.15)	-0.23	(-3.82)	-0.34	(-5.06)
CRAR	Loser	-0.91	(-8.12)	1.05	(37.88)	0.95	(24.45)	0.3	(6.82)
	Winner	0.57	(7.21)	1.06	(54.09)	0.7	(25.67)	-0.05	(-1.58)
	WML	1.47	(8.84)	0.01	(0.23)	-0.24	(-4.22)	-0.35	(-5.31)

Note. This table presents abnormal returns and factor loadings in the time-series regression equation (2). α , $\beta_{i,b}$, $\beta_{i,s}$, $\beta_{i,h}$ denote abnormal returns, the slopes of market, SMB, and HML factors, respectively. The models are fitted to the portfolios sorted on three momentum strategies; cumulative return (CR), cumulative return adjusted by the sample variance (RAR), and cumulative return adjusted by conditional volatilities (CRAR). Samples are specified in each Panel.

We also highlight the role of the penny stocks in the momentum trading performance, which indicates that risk-adjusted strategies are effective for lowering loser portfolio returns, and the penny stocks and NASDAQ stocks may be working at the source of risk-adjusted momentum strategy. This result is most pronounced for the sample periods, including the technology bubble-burst and the global financial crisis.

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Table A1: All Stocks

		H=3		H=6		H=9		H=12	
		Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value
Panel A: 1965-2014									
CR	Loser	0.86	(2.31)	1.13	(2.86)	1.16	(3.05)	1.28	(3.43)
	Winner	1.52	(5.65)	1.69	(5.67)	1.59	(5.34)	1.46	(4.9)
	WML	0.66	(2.45)	0.56	(2.17)	0.44	(1.95)	0.18	(0.86)
RAR	Loser	0.70	(2.41)	0.82	(2.71)	0.86	(2.95)	0.97	(3.37)
	Winner	1.55	(6.64)	1.65	(6.41)	1.54	(6.02)	1.42	(5.58)
	WML	0.85	(4.21)	0.83	(4.15)	0.69	(3.94)	0.45	(2.85)
CRAR	Loser	0.70	(2.45)	0.82	(2.75)	0.87	(2.99)	0.98	(3.43)
	Winner	1.55	(6.71)	1.66	(6.49)	1.55	(6.07)	1.42	(5.62)
	WML	0.85	(4.44)	0.84	(4.28)	0.68	(4.01)	0.45	(2.87)
Panel B: 1965-1999									
CR	Loser	0.89	(2.09)	0.91	(2.22)	0.95	(2.36)	1.12	(2.76)
	Winner	1.89	(5.54)	1.90	(5.52)	1.81	(5.27)	1.66	(4.86)
	WML	1.00	(3.7)	0.98	(4.1)	0.86	(3.89)	0.54	(2.5)
RAR	Loser	0.60	(1.87)	0.61	(1.92)	0.66	(2.12)	0.80	(2.55)
	Winner	1.84	(6.24)	1.83	(6.18)	1.73	(5.84)	1.59	(5.43)
	WML	1.24	(6.18)	1.21	(6.71)	1.06	(6.24)	0.78	(4.82)
CRAR	Loser	0.62	(1.92)	0.63	(1.99)	0.69	(2.2)	0.82	(2.64)
	Winner	1.82	(6.2)	1.82	(6.19)	1.72	(5.83)	1.58	(5.43)
	WML	1.20	(6.14)	1.19	(6.71)	1.03	(6.17)	0.76	(4.73)
Panel C: 2000-2014									
CR	Loser	1.63	(1.75)	1.63	(1.81)	1.63	(1.93)	1.66	(2.06)
	Winner	1.33	(2.21)	1.21	(2.06)	1.08	(1.84)	0.99	(1.67)
	WML	-0.30	(-0.4)	-0.42	(-0.64)	-0.55	(-1.04)	-0.67	(-1.49)
RAR	Loser	1.28	(1.83)	1.29	(1.91)	1.31	(2.05)	1.36	(2.2)
	Winner	1.38	(2.63)	1.24	(2.43)	1.12	(2.22)	1.04	(2.05)
	WML	0.10	(0.17)	-0.05	(-0.1)	-0.19	(-0.46)	-0.32	(-0.88)
CRAR	Loser	1.25	(1.82)	1.27	(1.9)	1.29	(2.03)	1.34	(2.2)
	Winner	1.42	(2.75)	1.27	(2.53)	1.15	(2.3)	1.06	(2.12)
	WML	0.17	(0.29)	0.01	(0.02)	-0.13	(-0.33)	-0.28	(-0.79)

Note. This table reports the mean and t-value of of average monthly returns (in percent) for three momentum strategies with all stocks for different holding periods (H); cumulative return (CR), cumulative return adjusted by the sample variance (RAR), and cumulative return adjusted by conditional volatilities (CRAR). The WML portfolios are formed by purchasing the 20% stocks with the highest cumulative returns over the fixed past 6 months and selling short the 20% stocks with the lowest cumulative returns over the past 6 months. Portfolios are then held for the subsequent H months.

Table A2: Stocks(>\$1)

		H=3		H=6		H=9		H=12	
		Mean	t-value	Mean	t-value	Mean	t-value	Mean	t-value
Panel A: 1965-2014									
CR	Loser	0.59	(1.82)	0.67	(1.82)	0.72	(2.05)	0.87	(2.51)
	Winner	1.71	(5.62)	1.68	(5.62)	1.56	(5.26)	1.42	(4.81)
	WML	1.12	(4.42)	1.01	(4.42)	0.84	(4.33)	0.55	(3.16)
RAR	Loser	0.58	(2)	0.60	(2.12)	0.65	(2.37)	0.78	(2.84)
	Winner	1.69	(6.53)	1.64	(6.38)	1.53	(5.97)	1.40	(5.53)
	WML	1.11	(5.32)	1.04	(5.68)	0.87	(5.45)	0.63	(4.25)
CRAR	Loser	0.58	(2.04)	0.61	(2.17)	0.67	(2.44)	0.79	(2.91)
	Winner	1.69	(6.58)	1.64	(6.45)	1.53	(6.02)	1.40	(5.57)
	WML	1.10	(5.45)	1.04	(5.83)	0.86	(5.54)	0.62	(4.31)
Panel B: 1965-1999									
CR	Loser	0.46	(1.16)	0.53	(1.38)	0.59	(1.55)	0.76	(2)
	Winner	1.88	(5.51)	1.89	(5.5)	1.80	(5.23)	1.64	(4.81)
	WML	1.42	(5.9)	1.36	(6.37)	1.21	(6.24)	0.88	(4.76)
RAR	Loser	0.47	(1.5)	0.48	(1.55)	0.54	(1.75)	0.68	(2.2)
	Winner	1.84	(6.23)	1.83	(6.18)	1.72	(5.84)	1.58	(5.42)
	WML	1.36	(7.04)	1.35	(7.71)	1.19	(7.34)	0.91	(5.9)
CRAR	Loser	0.49	(1.55)	0.50	(1.62)	0.56	(1.83)	0.70	(2.29)
	Winner	1.82	(6.2)	1.82	(6.19)	1.72	(5.83)	1.58	(5.42)
	WML	1.33	(7)	1.32	(7.7)	1.16	(7.27)	0.88	(5.83)
Panel C: 2000-2014									
CR	Loser	0.88	(1.05)	0.98	(1.2)	1.03	(1.34)	1.11	(1.51)
	Winner	1.29	(2.15)	1.17	(2)	1.01	(1.74)	0.91	(1.56)
	WML	0.41	(0.62)	0.19	(0.34)	-0.02	(-0.03)	-0.20	(-0.52)
RAR	Loser	0.83	(1.33)	0.88	(1.45)	0.93	(1.61)	1.01	(1.79)
	Winner	1.35	(2.59)	1.20	(2.37)	1.06	(2.13)	0.98	(1.95)
	WML	0.53	(1)	0.32	(0.72)	0.13	(0.36)	-0.03	(-0.1)
CRAR	Loser	0.81	(1.33)	0.85	(1.44)	0.91	(1.61)	0.99	(1.79)
	Winner	1.39	(2.7)	1.23	(2.46)	1.09	(2.2)	1.00	(2.01)
	WML	0.58	(1.14)	0.38	(0.87)	0.18	(0.49)	0.01	(0.02)

Note. This table reports the mean and t-value of average monthly returns (in percent) for three momentum strategies with Stocks (>\$1) for different holding periods (H); cumulative return (CR), cumulative return adjusted by the sample variance (RAR), and cumulative return adjusted by conditional volatilities (CRAR). The WML portfolios are formed by purchasing the 20% stocks with the highest cumulative returns over the fixed past 6 months and selling short the 20% stocks with the lowest cumulative returns over the past 6 months. Portfolios are then held for the subsequent H months.

Table A3: Factor time-series regressions over 2000-2014

		α	t-value	$\beta_{i,b}$	t-value	$\beta_{i,s}$	t-value	$\beta_{i,h}$	t-value
Panel A: All stocks over 2000-2014									
CAR	Loser	0.63	(1.06)	1.68	(12.62)	0.93	(5.09)	-0.11	(-0.61)
	Winner	0.29	(1.42)	1.13	(24.84)	1.13	(18.03)	-0.03	(-0.46)
	WML	-0.34	(-0.53)	-0.55	(-3.76)	0.20	(0.98)	0.08	(0.41)
RAR	Loser	0.33	(0.8)	1.44	(15.6)	0.60	(4.74)	0.26	(2.02)
	Winner	0.41	(2.22)	1.03	(24.94)	0.91	(16.11)	0.02	(0.36)
	WML	0.08	(0.16)	-0.41	(-3.61)	0.31	(2)	-0.24	(-1.51)
CRAR	Loser	0.32	(0.78)	1.42	(15.55)	0.59	(4.75)	0.25	(1.94)
	Winner	0.45	(2.54)	1.03	(26.08)	0.89	(16.48)	0.03	(0.52)
	WML	0.13	(0.26)	-0.39	(-3.5)	0.3	(1.98)	-0.22	(-1.41)
Panel B: Stocks (>1\$) over 2000-2014									
CAR	Loser	-0.07	(-0.14)	1.69	(15.9)	0.87	(6.01)	0.04	(0.25)
	Winner	0.25	(1.24)	1.13	(24.87)	1.13	(18.17)	-0.03	(-0.51)
	WML	0.32	(0.57)	-0.56	(-4.45)	0.25	(1.48)	-0.07	(-0.4)
RAR	Loser	-0.10	(-0.32)	1.39	(19.7)	0.55	(5.72)	0.36	(3.67)
	Winner	0.37	(2.03)	1.02	(24.64)	0.91	(16.1)	0.02	(0.33)
	WML	0.47	(1.1)	-0.37	(-3.83)	0.36	(2.71)	-0.34	(-2.54)
CRAR	Loser	-0.1	(-0.33)	1.36	(19.71)	0.55	(5.79)	0.34	(3.52)
	Winner	0.41	(2.28)	1.02	(25.46)	0.89	(16.28)	0.03	(0.46)
	WML	0.51	(1.22)	-0.34	(-3.66)	0.34	(2.68)	-0.32	(-2.4)

Note. This table presents abnormal returns and factor loadings in the time-series regression equation (2). α , $\beta_{i,b}$, $\beta_{i,s}$, $\beta_{i,h}$ denote abnormal returns, the slopes of market, SMB, and HML factors, respectively. The models are fitted to the portfolios sorted on three momentum strategies; cumulative return (CR), cumulative return adjusted by the sample variance (RAR), and cumulative return adjusted by conditional volatilities (CRAR). Samples are specified in each Panel.