Momentum Crash Management

Mahdi Heidari [*]

Stockholm School of Economics

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Abstract

Momentum is the largest and most pervasive market anomaly, but despite high mean and Sharpe ratio, it suffers from large negative skewness that comes from momentum crash periods. These crashes happen in times of market stress and market rebound, thus the variables that capture these episodes, can be used as momentum predictor. I introduce three new momentum predictors and show that change in momentum volatility has the highest predictive power among other predictors in previous studies. Once momentum prediction has been proofed, the predictors can be employed in momentum risk management. I introduce a new method of momentum risk management with lower transaction cost than methods in previous studies, both in terms of turnover and price impact.

JEL Classification: G11, G12, G14, G17

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[*]Swedish House of Finance, Drottninggatan 98, 111 60 Stockholm
Email: mahdi.heidari@hhs.se

1 Introduction

Momentum as a tendency of assets performance continuation in short run, is one of the most pervasive market anomalies. Jegadeesh and Titman (1993) find that previous winners in the U.S. stock market outperform previous losers. Winner minus loser strategy has return by as much as 1.3 percent a month with a Sharpe ratio that exceeds the Sharpe ratio of market return, size, and value factors in sample of 1927 to 2013. Attempts to explain momentum returns with regular risk factors confront with even more challenges, so that controlling for Fama French factors, momentum has an excess return of 1.9 percent per month in the sample period.

Despite high average return and Sharpe ratio, momentum returns have very negative skewness and excess kurtosis and crashes from time to time. In 1932, the momentum strategy dropped 92 percent in just two months. In 2009, momentum experienced a crash of 73 percent in three months. Momentum crashes happen after overall down markets followed with rebound and high ex-ante volatility in the market. in this situation previous loser which have dropped a lot in down market, experience higher return in market rebound than previous winner which have had better return before. In a recent momentum crash, over the three-month period from March to May of 2009, the past-loser decile rose by 163% while the decile portfolio of past winners gained only 8%. This is closely related to the time-varying beta of momentum portfolio that has been shown in Kothari and Shanken (1992) and Grundy and Martin (2001) among the others. Therefore there is potential for predictability of momentum crashes.

There are number of studies which try to predict momentum return. Daniel and Moskowitz (2014) and Barroso and Santa-Clara (2014) use momentum volatility and market volatility as predictor while Cooper, Gutierrez and Hameed (2004) use state of the market and Avramov, Cheng and Hameed (2013) use market illiquidity for momentum prediction, but there is no comparison among the momentum predictors to show which variable have better prediction power and can survive with presence of other variables. In this paper, I introduce three new momentum predictors and compare them with other predictors that have been used separately in the literature and show that change in momentum volatility which is new to this study, has the highest predictive power for momentum return. Also I analyze momentum prediction in two subsample of crash and normal periods and show that most of the prediction power comes from crash periods and even some of the predictors have opposite sign in crash and normal period regression. Then I use this fact in momentum risk management method and introduce an alternative method of risk management that is more successful than previous method used in literature, both in terms of return and implementation cost.

The three momentum predictors in this study are cross sectional dispersion of stock returns, change in market return and change in momentum volatility. These variable are in same spirit as predictors in previous studies and can be rationalized with similar economic reasoning but they have higher predictive power and are more successful in capturing market rebound. As a result, these variables improve momentum risk management from previous counterpart predictors, so change in market return is a better risk management tool than market past return, market dispersion is superior to market volatility and change in momentum volatility improves momentum more than level of momentum volatility. Furthermore, risk managed momentum with change in momentum volatility has the highest return and Sharpe ratio among all dynamic momentum strategies.

In total, I use seven variables for predicting momentum return and categorize them in two groups: the first group are variables that are obtained from overall stock market and the second group is related to time series of momentum return. Market past return (which is correlated with state of the market in Cooper, Gutierrez and Hameed (2004)), change in the market return, volatility of the market, cross sectional dispersion of stock returns and market illiquidity are variables in the first group while volatility of momentum and change in momentum volatility come from momentum time series and are in second group. I show the predictability of each variables that verifies results in previous studies and shows the significance of new variables. Then I run a horse racing test and show that change in momentum volatility and change in market return stay significant when I include all the predictors as well as common risk factors.

Predictive power of momentum volatility has been shown in Daniel and Moskowitz (2014) and Barroso and Santa-Clara (2014) studies. I use change in momentum volatility as well that turns out to be a better predictor than level of momentum volatility. In one month ahead prediction of momentum return, change in momentum volatility has t statistics of -12 and R^2 of 12 percent which is four times larger than R^2 of level of momentum as a predictor. Also when I include all of the predictors in the regression, change in momentum volatility is the most important predictor and it has lower correlation with other predictors than level of momentum volatility. From first group of predictors, change in market return is the winner of the horse race regression and has higher predictive power than other variables.

Once momentum predictability has been shown, momentum risk management can be pursue in the next step by dynamically changing the weights in momentum portfolio base on the momentum predictors. Momentum is a zero investment strategy, i.e. goes one dollar long in past winner and one dollar short in past loser, so it can be weighted in each rebalancing period to construct dynamic risk managed momentum strategy. Daniel and Moskowitz (2014) and Barroso and Santa-Clara (2014) use inverse of momentum predictors as weight of momentum portfolio in each month. Barroso and Santa-Clara use the realized volatility of momentum return as predictor and improve the the Sharpe ratio of momentum return from 0.53 to 0.97 while the excess kurtosis drops from 18.24

to 2.68, and the left skewness improve from -2.47 to -0.42.

The inverse weighting method of Daniel and Moskowitz (2014) and Barroso and Santa-Clara (2014) in momentum risk management has two down sides: First, I show that most of the momentum predictors' power comes from crash periods which can be defined as months in which momentum drops more than 10 percent. There are 60 out of 1044 crash periods corresponding to this definition in my sample. Momentum volatility that both BS and DM use for momentum risk management, has negative and strongly significant coefficient in prediction model, both in crash periods and whole sample regression, but if I redo the test for normal periods, the sign of coefficient changes and it turns out that it's positively correlated with next period momentum return in normal periods. The results for other predictors are quite similar. Therefore using this predictors (momentum volatility in case of DM and BS) in each period for weighting winner and loser portfolio is not efficient and although it eliminates high exposure to static momentum strategy in bad states but it also unnecessarily changes the portfolio weights in normal period.

The second issue is that dynamic strategy method in DM and BS has high portfolio turnover that leads to higher transaction cost. One can show that because of relatively long ranking period with respect to holding period (12 against 1 month), most of the stocks remain in the winner or loser portfolio for several months and consequently they need slight adjustment of weight in portfolio each month that comes from change in market value and relative weights in the portfolio, but momentum predictors are quite volatile and using inverse of them for weighting the portfolio demands much higher turnover each month.

In this paper, instead of inverse weighting, I use "state" dummy for each predictor to distinguish between crash and normal periods. To implement this method, I use 90 percentile of each variables in the past 5 years as threshold. All of the predictors are negatively correlated with next month momentum return both in full sample and crash period subsample, so I define variable X's dummy equal to 1 if it's less than 90 percentile and 0 otherwise. Dynamic momentum strategy with respect to any predictor is defined as same as static strategy when state dummy of specific variable is equal to 1. When state dummy is 0, which means that the predictor is high compare to previous value (more than its 90 percentile), then dynamic strategy closes all of the positions in static momentum strategy.

The results of empirical analysis show that momentum risk management using state dummy weighting is successful in mitigating momentum crashes. Sharpe ratios of all of the dynamic strategies are higher than static winner minus loser strategy with improved left skewness or even slightly positive skewness. Sharpe ratios are from 0.68 in dynamic strategy using market lag return to 1.10 in the strategy that is constructed by using change in momentum volatility in weighting. The results verify two points: first, new predictors that are introduced in this study have more desirable risk managed momentum return than previous variables, so M-MktChg which is dynamic momentum return using change in market return as predictor, has better result than M-Mkt, M-Disp which is risk managed by market dispersion is superior to M-MktVol and M-MVolChg which is constructed by using change in momentum volatility improves static momentum more than momentum volatility in M-MomVol.

Second, risk management method using state dummy is more efficient than inverse weighting. When I use momentum volatility for risk management which is used in previous studies with inverse weighting , I get Sharpe ratio of 1.00 with skewness of 0.07 and kurtosis of 2.00 which all of the statistics are slightly better than BS risk managed result while portfolio turnover and accordingly cost of implementation of state dummy method is lower which results more desirable after transaction cost return.

Analyzing exact amount of transaction costs for each strategy is not doable with available data, but it can be estimated by portfolio's turnover which is related to bid ask spread and fees and size of the portfolio as proxy for price impact. The main part of transaction cost is proportional to portfolio's turnover in each strategy. The dynamic momentum strategies that I use in this paper have turnovers of between 84 to 104 percent of static momentum strategy's turnover. This is lower than turnover of momentum risk management by inverse weighting.

Also portfolio size in dynamic momentum using state dummy is always less than or equal to static strategy portfolio size. This means that comparing after transaction cost return of static and dynamic strategies with state dummy method will intensify risk management benefit while it can reduce or mitigate benefit of risk management with inverse weighting method.

The remaining of the paper is structured as follows. Section 2 reviews some of the more relevant previous studies, section 3 presents data and methodology that has been used for analysis. Momentum portfolio and momentum predictors' construction as well as turnover has been described in this section. Section 4 shows empirical results and analysis. Momentum return prediction models and results in whole sample, crash and normal period subsample and the prediction of winner and loser portfolio separately are discussed in this section. Section 5 that is main part of the paper, is devoted to momentum risk management result and analysis. Riskiness of risk managed strategies, performance of them in normal and crash periods, transaction costs of different strategies and economic analysis of them are investigated in this section. In section 6, I show prediction results in different sample period as robustness check. Finally, section 7 presents the conclusion.

2 Literature Review

Jegadeesh and Titman (1993) in the first well known study which introduced the old phenomenon of price momentum in the wall street to the academy, find that previous winners in the U.S. stock market outperform previous losers. Winner minus loser strategy has return by as much as 1.3 percent a month with a Sharpe ratio that exceeds the Sharpe ratio of market return, size, and value factors in sample of 1927 to 2013. Attempts to explain momentum returns with regular risk factors confront with even more challenges, so that controlling for Fama French factors, momentum has an excess return of 1.9 percent per month in the sample period.

Momentum is not just a U.S. equity market anomaly and is observed in international markets and the bulk of the literature suggests that momentum is widely present both geographically and across asset classes. (Chan, Hamao, and Lakonishok (1991); Fama and French (1998); Rouwenhorst (1998); Griffin, Ji, and Martin (2003); Chui, Titman, and Wei (2010); Asness, Moskowitz, and Pedersen (2013)).

Relative strength has been used by practitioners for many generations. George Chestnutt of the American Investors Fund began using it in the 1930s and said it had been in use by others for at least a generation before that. Grinblatt and Titman (1989, 1993) find that most mutual fund managers incorporate momentum of some sort in their investment decisions, thus relative strength strategies are widespread among practitioners.

Although high return of momentum strategy has been well accepted, the source of this profits is widely debated. Attempts to explain momentum returns with regular risk factors confront with even more challenges. Controlling for Fama French factors, momentum has an excess return of 1.89 percent per month from 1927 to 2013. Indeed, Fama and French (1996) acknowledge that momentum is “the main embarrassment of the three-factor model."

Several behavioral theories have been developed to explain the momentum in stock returns. Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999) each employ different behavioral or cognitive biases to explain this anomaly. Daniel, Hirshleifer, and Subrahmanyam (1998) assume that investors are overconfident about their private information and overreact to it. If investors also have a self-attribution bias, then when subsequent (public) information arrives, investors will react asymmetrically to confirming versus dis-confirming pieces of news. In other words, investors attribute successes to their own skill more than they should and attribute failures to external noise more than they should. The consequence of this behavior is that investors' overconfidence increases following the arrival of confirming news. The increase in overconfidence furthers the initial overreaction and generates return momentum.

Hong and Stein (1999) also develop a behavioral theory to explain momentum. Their model is based on initial under-reaction to information and subsequent overreaction, which eventually leads to stock price reversal in the long-run. Their model employs two types of investors: "news watchers" and "momentum traders." The news watchers rely exclusively on their private information; momentum traders rely exclusively on the information in past price changes. The additional assumption that private information diffuses only gradually through the marketplace leads to an initial under-reaction to news. The under-reaction and subsequent positive serial correlation in returns attracts the attention of the momentum traders whose trading activity results in an eventual overreaction to news.

This is closely related to the time-varying beta of momentum portfolio. The time variation in betas of return sorted portfolios was first documented by Kothari and Shanken (1992). Grundy and Martin (2001) also show the time-varying exposure of momentum to market risk factor. They argue that momentum portfolios have time-varying systematic risk, which is not captured in unconditional regressions and reason that after good returns in the stock market, winners naturally tend to be high beta stocks while the loser should mainly be low beta stocks. Hence the momentum portfolio, short on previous losers and long on previous winners, should have a high beta by design. By contrast in an extreme bear market, previous losers should be typically stocks with high betas, while the group of winner stocks would have low betas. Thus the momentum portfolio would have a negative beta by construction.

Using the time varying beta of momentum and relation of crash periods to the overall market behavior, momentum return can be predicted and momentum crash risk management can be implemented. Daniel and Moskowitz (2014; hereafter DM) find that momentum crashes tend to occur in times of market stress, when the market has fallen and ex-ante measures of volatility are high, coupled with an abrupt rise in contemporaneous market returns. They use market volatility and its interaction with market state as momentum predictor. Also Stivers and Sun (2010) show that the momentum premium is low when market volatility is high. Barroso and Santa-Clara (2014; hereafter BS) use the realized momentum return volatility to predict next month momentum return.

Cooper, Gutierrez and Hameed (2004) examine importance of the state of the market on profitability of momentum strategies. They define UP and DOWN states as non-negative and negative three-year lagged market return respectively. They find that momentum profit exclusively follow UP periods. Chordia and Shivakumar (2002) show that commonly used macroeconomic instruments for measuring market condition can explain large portion of momentum profit. Avramov, Cheng and Hameed (2013) argue that momentum profitability depends on the state of market illiquidity and the effect of market illiquidity on momentum subsumes the explanatory power of market volatility. They show that the momentum effect is strong (weak) when liquidity is high (low).

3 Data and Methodology

3.1 Momentum Portfolio Construction

I collect stock prices, returns, trading volume, and the short-term interest rate from the Center for Research in Security Prices (CRSP) for period of Jan 1926 to Dec 2013. The Fama and French (1993) factors as well as returns on portfolios formed on size and book-to-market are from Kenneth French.

My formulation of the momentum strategy is standard (Fama and French (1996); Carhart (1997); Asness, Moskowitz, and Pedersen (2013)). I start with all stocks listed on the NYSE, AMEX, and NASDAQ with share code 10 or 11. This eliminates closed-end funds, real estate investment trusts, American Depository Receipts, foreign companies, primes, and scores. I exclude stock with price less than 1 dollar to mitigate the impact of any micro-structure biases. At the beginning of each month t, stocks are sorted into 10 deciles based on their cumulative returns from month $t-12$ to $t-2$ (ranking period). I use one month gap between ranking period and holding period to avoid short term one month reversals documented by Jegadeesh (1990) and Lehmann (1990). Similar to DM, I use stock that have at least 8 month of return in 11 month of formation period and valid price and number of share outstanding at the formation date. The momentum strategy goes long a value-weighted portfolio of stocks in the top decile and sells short a value-weighted portfolio of stocks in the bottom decile. Table 2 shows 10 deciles portfolio average return as well as CAPM and Fama French 3 factors alpha. Average return and both alphas monotonically increase from portfolio 1 to portfolio 10. Furthermore, momentum (winner minus loser strategy) has negative exposure to the market.

Table 3 presents summary statistics of momentum return as well as market return and size (SMB) and value (HML) strategy returns. Momentum has higher average return than other strategies but with more negative skewness and much higher kurtosis. The minimum monthly return of momentum is -81 percent that is much lower than minimum of other portfolios. Table 1 shows 10 worse momentum returns in the past 87 years that demonstrate fat tail in momentum distribution and presents 10 worse crash periods of it.

3.2 Momentum Predictors

Momentum strategy has time-varying exposure to market risk by construction (Grundy and Martin, 2001), so momentum crashes happen after overall down markets followed with rebound in which previous loser that have dropped a lot in down market, experience higher return in market rebound than previous winner that have had better return before. Therefore if a variable can capture market rebound states, it can be used for momentum crash prediction. I use seven variables for predicting momentum return which some are used in previous studies and I arrange them in two sets. The first group are variables that are obtained from overall stock market and the second group is related to momentum return time series.

I use market past return (Mkt), change in the market return ($MktChg$), volatility of the market ($MktVol$), cross sectional dispersion of stock returns ($Disp$) and market illiquidity ($Illiq$) from the market in the first group. I also use momentum return volatility ($MomVol$) and change in momentum volatility ($MVolChg$) that come from momentum time series. DM and BS use momentum and market volatility, Cooper, Gutierrez and Hameed (2004) use state of the market that is correlated with past market return and Avramov, Cheng and Hameed (2013) use market illiquidity for momentum prediction and change in the market return, market dispersion and change in momentum volatility are new to this study. In this section I describe how these variables are constructed and in next section I briefly explain the reason for selecting them as momentum predictors.

3.2.1 Predictors from Market Variables

I have five variables in market group which are market lagged return, market return volatility, cross sectional stock returns dispersion and illiquidity. I also use change in market lag as another predictor. These variables are used to capture market rebound and change in market situation that will be described with more details in next section.

I use CRSP value weighted return including dividends as proxy for market return (Mkt) and use change in market return ($MktChg$) from $t-1$ to t. All of the predictors including market return should be known at time t that is formation date to predict momentum at $t+1$, so market return as predictor is different from contemporaneous market return of CAPM or Fama French which is risk factor.

Table 1 shows 10 worse momentum returns as well as market return and volatility in the same month and one month before (formation date). Market volatility in formation dates of almost all of the momentum crashes is more than twice of its mean, also market return rebound in most of the momentum crash events. When market falls, losers fall more than winners (as it's defined) and then when market rebounds, stocks that have experienced higher drop will go up more than the others and thus loser portfolio's return will be higher than winner. This can rationalize why momentum crashes happening in panic periods and how market volatility and return can be used for momentum prediction. Same argument can motivate prediction of market dispersion that is new to this study. Market dispersion is cross sectional volatility in the market and contain information about difference between stocks return. In panic periods dispersion of stock returns is higher and it can be used to predict momentum return.

For market volatility ($MktVol$), I use weekly return of CRSP value weighted return and calculate standard deviation of past 52 weeks (one year), then I get the average of weekly volatilities in each month to have monthly time series of market volatility. I use cross sectional volatility of stocks returns as a measure of market dispersion ($Disp$) which captures dispersion of return cross the market. I use daily stock returns and calculate variance of daily return cross all CRSP stocks, then I get the average of daily cross sectional variance in each month and call it market dispersion.

In order to obtain market illiquidity measure ($Illiq$), similar to Avramov, Cheng and Hameed (2013), I use Amihud (2002) measure of stock illiquidity. For each stock in each day, absolute daily return is divided by closing price times the number of traded stocks in that day, then the monthly average is taken for each stock. Definition of illiquidity can be presented as follow:

$$ILLIQ_{i,d} = \frac{1}{n} \sum_{d=1}^{n} \frac{|R_{i,d}|}{P_{i,d} \times N_{i,d}} \tag{1}$$

where n is the number of trading days in each month,$R_{i,d}$ is return of stock i on day d, $P_{i,d}$ is closing price and $N_{i,d}$ is number of shares traded during day d.

Market illiquidity ($Illiq$) is defined as the value weighted average of each stock monthly Amihud illiquidity measure. Similar to Atkins and Dyl (1997) because reporting mechanism for trading volume differs between NYSE/AMEX and NASDAQ stock exchange, I restrict my sample to NYSE and AMEX.

3.2.2 Predictors from Momentum Time Series

Similar to two close works to this paper, i.e. BS and DM, I also use momentum volatility as momentum predictor. In each month, I calculate standard deviation of past six month momentum return as a proxy for momentum volatility ($MomVol$). The last predictor that is new to this study, is change in momentum volatility ($MVolChg$) which has higher predictive power than level of momentum volatility and all other market variables. Summary statistics and correlation matrix of predictors has been shown in table 4. Correlation is positive for most of the pairs, but none of the variables is perfectly correlated to the others, thus I keep all of the predictors for regression analysis.

3.3 Transaction Cost

The cost of implementing any strategy is very crucial and profitability of before transaction cost strategy can diminish by its cost. To obtaining a measure of transaction cost to compare different strategies, I use DeMiguel, Garlappi and Uppal (2009) method. First to get a sense of amount of trading needed in each strategy, I compute portfolio turnover that is defined as the average sum of the absolute value of the trades across all stocks:

$$Turnover = \frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{N}(|w_{j,t+1} - w_{j,t^+}|) \tag{2}$$

where $w_{j,t+1}$ is weight of stock j at time $t+1$ in the winner or loser portfolio and w_{j,t^+} is its weight just before rebalancing of portfolio. N is number of stocks in winner and loser portfolio and T is number of months in dataset. As momentum strategy is combination of short and long portfolios, I sum up turnover of winner and loser portfolio to get total turnover of the strategy. Balduzzi and Lynch (1999) assume proportional transaction cost equal to 50 basis points per transaction, but as I need a comparison of transaction cost among different strategies that is proportional to turnover, I can use turnover itself to compare different strategies implementation cost.

3.4 Combo: Combination of Value and Momentum

Asness, Moskowitz, and Pedersen (2013) argue that Combination of Value and Momentum (Combo) portfolio that invest equally in momentum and value strategies, yields more persistent return with higher Sharpe ratio. I examine the predictability of Combo portfolio return to see whether the momentum risk management can improve Combo return or not. For value investing return, I use value weighted returns of 10 portfolios sorted on book equity to market equity from Kenneth French website, then I calculate high minus low (HML) strategy return by buying 10th decile portfolio and selling first decile portfolio.

Value and momentum have negative correlation and combination of them have better return, so I calculate equally weighted average of momentum and value and call it Combo:

$$Combo = \frac{1}{2}(Winner - Loser) + \frac{1}{2}(High - Low) \tag{3}$$

Table 5 shows summary statistics of Mom, HML and Combo as well as their correlation matrix. HML and Mom have correlation of -38% and Combo has positive correlation with both of them. Combo has also higher Sharpe ratio than both HML and Mom with less skewed returns.

4 Empirical Results and Analysis

In this section, I present results of several empirical tests. First I show momentum return prediction outcome, then I redo the analysis in crash and normal periods. I also test the predictability of winner and loser portfolios separately.

4.1 Momentum Return Prediction

In this section I examine the predictive power of momentum predictors that was described in section 3. First I analyze the following time series regression:

$$Mom_{t+1} = \alpha + \beta_i X_{i,t} + e_{t+1} \tag{4}$$

where Mom_{t+1} is momentum return at $t + 1$ and $X_{i,t}$ is predictor i at t (formation period). Panel A in table 6 shows regression results. All of the seven predictors have statistically and economically significant beta with negative sign. Change in volatility of the momentum return has the highest R^2 and t statistics. It can explain 12 percent of momentum return variation with t statistics equal to -11.9. Then I regress next month momentum return on all predictors in each group. Change in market return, dispersion and market illiquidity are significant while level of market return and volatility are no longer significant in first group regression. In the second group regression, both level and change of momentum volatility are significant with R^2 of 14 percent. In the last test, I rum the horse race regression in which change in momentum volatility, level of momentum volatility remain significant in 1 percent level and change in market return and illiquidity are significant in 5 percent level. Change in momentum volatility has the highest t statistics (-10.1).

In the next step, I add Fama French factors to the regression to see the predictive power of momentum predictors controlling for common risk factors:

$$Mom_{t+1} = \alpha + \beta_{mkt}Mkt + \beta_{smb}SMB + \beta_{hml}HML + \beta_i X_{i,t} + e_{t+1} \tag{5}$$

Panel B in table 6 present the results from this regressions. All of the predictors have significant beta controlling for risk factors. Again change in momentum volatility has the highest predictive power. In the last regression with all of the predictors, change in market return, momentum volatility and change in momentum volatility stay significant. Unlike the previous model, market illiquidity is no longer significant in this model that is in contrary to Avramov, Cheng and Hameed (2013) which claim that market illiquidity is main market state momentum predictor.

Grundy and Martin (2001) show the time varying exposure of momentum strategy to market risk. In the bull market, past winner most probably are high beta stocks while past loser are low or negative beta stocks, so the portfolio that goes long in past winner and short past loser will have high beta by construction. Same logic can be applied in bear market that means winner minus loser portfolio will have low or negative beta in the bear market. The variation of momentum portfolio exposure to market (and maybe other) risk factor(s) suggest that variables that show the change in market direction can predict momentum return. This can explain the results of momentum prediction in these tests.

4.2 Crash and Normal Periods Prediction

As mentioned before, momentum fat tail distribution which means it crashes from time to time. In context of momentum prediction, one can ask the following questions. First, how well momentum predictors can predict momentum return is crash periods? and second, does all of the predicting power of momentum predictors come from crash periods or they can also predict momentum return in normal periods?

To answer these questions, I redo the analysis of previous section for both subsamples of crash and normal periods. Crash periods are defined as months with momentum return less than -10 percent, which are 60 months out of 1044 months. The remaining of the sample called normal periods. Panel A in table 7 shows summary statistics of momentum return in both subsample. Panel B and C present regression results in crash and normal periods respectively. All of the coefficients in the models are negative and significant in crash periods as they are in whole sample. Momentum volatility itself can explain 70 percent of momentum variation. Adding change in momentum volatility increase R^2 to 85 percent. Market variables have also much higher R^2 in crash period regression than in whole sample. But in normal subsample, the predictors have less power, some with positive coefficient and some are insignificant, suggesting that momentum prediction comes from crash period prediction. I use this fact in momentum risk management method and try to use predictors for disentangling crash and normal period from each other.

4.3 Winner and Loser Portfolio's Prediction

Momentum strategy consists of two portfolios in each point in time. As mentioned before, momentum crashes are due to market rebound that past loser after large decline in the market turn back and experience higher return than past winner, therefore prediction of loser portfolio return is more important than winner portfolio. In this section, I use all seven predictors to predict winner and loser portfolios separately. As it shown in table 9 most of the predictive power comes from loser portfolio prediction. All of the predictors have significant coefficient with positive sign (as it should be) in loser portfolio regression while there is much less predictive power in winner portfolio with even wrong sign, i.e. lag market return and change in momentum volatility have positive correlation with winner portfolio but they are negatively correlate with momentum, showing that loser portfolio correlation is stronger and more profound. These results suggest that momentum prediction comes from loser portfolio prediction and it capture market rebound or crash period as we expect.

5 Momentum Risk Management

As mentioned before, despite high return and Sharpe ratio of momentum strategy, it has few very negative return that can be called momentum crash . As shown in previous section, because of inherent feature of momentum portfolio that comes from its construction method, momentum return can be predicted. Using momentum predictors, dynamic momentum strategy can be defined by conditionally changing of the exposure to the momentum portfolio. Dynamic strategy can improve momentum return distribution and eliminate crashes.

As momentum predictors are negatively correlated with next period momentum return, BS and DM use inverse of momentum predictors as weight of momentum portfolio in each month. This method is based on the fact that momentum is a zero investment strategy, i.e. goes one dollar long and one dollar short in the same time and it can be weighted in each rebalancing period to construct dynamic risk managed momentum strategy.

Using inverse of momentum predictor for weighting in dynamic strategy has two problems: First, as I showed in section 4.2, momentum predictors' power come from crash period prediction, for example, momentum volatility that both BS and DM use for weighting in dynamic momentum portfolio, is positively correlated with next period momentum return in normal period while in crash period and overall sample, the regression coefficient is negative and strongly significant. Hence using momentum volatility in each period for weighting long and short portfolios is not efficient. It means that in most of the times that the dynamic weighting is unnecessary (normal periods), they change momentum portfolio weights. The second reason is that this method of weighting leads to higher portfolio turnover than static strategy which consequently results higher transaction cost of dynamic strategy. We know that because of relatively long ranking period with respect to holding period (12 against 1 month), most of the stocks remain on winner or loser portfolio for several month in static momentum strategy and they only need slight adjustment in each month that comes from change in market value and relative weight in the portfolio, while momentum predictors have high volatility and using inverse of them for weighting the portfolio will need higher turnover each month.

Instead of inverse weighting, I use "state" dummy for each predictor to distinguish between normal and crash period. To implement this method, I use 90 percentile of each variables in past 5 years as threshold. All of the predictors have negative correlation with next period momentum return both in full sample and crash period subsample, so I define variable X's dummy equal to 1 if it's less than 90 percentile and 0 other wise. Dynamic momentum strategy with using any predictor is same as static strategy when state dummy of specific variable is equal to 1 and when the state dummy is 0, then dynamic strategy closes all of the positions in static momentum strategy. It mean that when the predictor is high compare to previous value (more than its 90 percentile) there is high probability of negative momentum return in next period and thus in dynamic strategy all of the positions will be closed.

Table 8 presents summary statistics of static and dynamic risk managed momentum strategies. Sharpe ratios of all of the dynamic strategies are higher than static winner minus loser strategy while skewness is higher. Sharpe ratios are from 0.68 in dynamic strategy using market lag return to 1.10 in the strategy that is constructed by using change in momentum return volatility in weighting. Also minimum return in all of the dynamic strategies is higher than static strategy and their distributions are less left skewed. Figure 1 shows the logarithm of cumulative return of different strategies. There is substantial improvement in return in all of the dynamic momentum strategies. Change in momentum volatility as predictor produce the highest cumulative return.

One of the main aspect of evaluation of different stock market strategies is the trading costs of implementing them. I analyze transaction cost of dynamic strategies and show that their transaction cost is either lower or close to static momentum strategy. This is one of the main privilege of using state dummy weighting rather than inverse weighting that has been used in previous studies.

In remaining of this section, I examine dynamic strategies' performance in crash period and describe transaction cost effect. At the end, I examine the predictability and risk management performance in combination of value and momentum strategy and also analyze the economic preferences of all strategies by using certainty equivalent of each strategy's return moment.

5.1 Dynamic Strategies Performance in Crash Periods

The main idea of momentum risk management is to mitigate huge drops in crash periods. To examine the success of dynamic strategies which are introduced in this study in improvement of crash periods returns , I show 10 worse returns of static and risk managed momentum strategies in table 8. In all of the dynamic strategies, worse returns are higher than static strategy, so dynamic weighting can mitigate crashes in momentum return.

5.2 Transaction Cost

Introducing transaction cost can destroy benefit of trading strategy, especially if the strategy involve massive portfolio rebalancing. This is more concern in momentum strategy that involve both long and short positions and need monthly rebalancing. Dynamic strategy that is based on state dummy weighting of static strategy is more prone to large transaction cost, so taking to account the transaction cost may weaken or eliminate benefit of risk management. To examine the effect of transaction costs on risk managed momentum strategies, I use DeMiguel, Galappi and Uppal (2013) method as described in previous section and calculate turnover of strategies as a proxy for transaction cost. Table 10 shows different strategies' turnover and the ratio of dynamic strategies' turnover to the static momentum. Turnover of dynamic strategies are 92 to 104 percent of static strategy, suggesting that they don't have higher transaction cost and the effect of risk management can survive taking to account transaction cost. Comparing static and dynamic strategies, in some cases (MktVol, Disp) the benefit of risk management can be even higher considering transaction cost effect.

To compare turnover of state dummy weighting with inverse weighting of BS and DM, I use their method for dynamic strategies construction and calculate the turnover of their risk managed portfolios. Portfolio turnover of inverse weighting is about 50 percent higher than static strategy in some cases that means transaction cost can mitigate benefit of momentum risk management.

There are other sources of transaction cost in the form of spreads or price impact that is not proportional to the trades. The price impact models imply that abnormal returns to portfolio strategies decline with portfolio size. Korajczyk and Sadka (2004) investigate several trading cost models and momentum portfolio strategies and find that the estimated excess returns of some momentum strategies disappear after an initial investment of 4.5 to over 5 billion dollar is engaged (by a single fund) in such strategies. They argue that the statistical significance of these excess returns disappears after 1.1-2.0 billion dollar is engaged in such strategies. Frazzini, Israel, and Moskowitz (2013) which use trades data from a large institutional investor (AQR Capital) over a long period of time containing more than a trillion dollars of live trades from 1998 to 2013 across 19 developed equity markets, estimate what real-world trading costs are for momentum strategy. Their conclusion is that per dollar trading costs for momentum are quite low, and thus, despite the higher turnover, momentum easily survives transactions costs.

If I consider investment size as a proxy of non-proportional trading cost, all dynamic strategies that use 0 or 1 weighting scheme can easily survive transaction costs because they have smaller than or equal to static momentum's fund size. Again inverse weighting scheme can have larger fund size. I use inverse weighting method for market and momentum volatility. In the strategy that uses market volatility for weighting, average weight is 1.43 with median 1.32 and it can rise up to 5.12 or drop to 0.17. Also momentum volatility weights have average and median of 1.53 and 1.39 with maximum of 8.68 and minimum of 0.21. Thus, these two strategies can have higher trading costs in the forms of spread or price impact. I can't examine whether the amount of trading costs in these strategies are higher than their benefit or not but as Frazzini, Israel, and Moskowitz (2013) mention, trading cost can be ten time lower for institutional investors than average investors. They argue that trading patiently by breaking orders up into small sizes and setting limit order prices that provide, not demand, liquidity, and allowing some tracking error to a theoretical style portfolio can significantly reduce trading costs without changing the nature of the strategy. Therefore I can't reject the profitability of BS and DM risk managed momentum strategies after transaction cost but I can argue that 0 or 1 weighting scheme that is used in this study has much less cost of implementation considering turnover or portfolio size as proxy for transaction costs.

5.3 Value and Momentum: Combo

As mentioned before, Asness, Moskowitz, and Pedersen (2013) show that Combo portfolio (equally weighted portfolio of momentum and value strategies) yields more persistent return with higher Sharpe ratio. Table 5 presents this results. In this section, I examine the predictability of momentum predictors for Combo and then use the same method of weighting as I use in dynamic momentum strategy to improve Combo return.

Table 11 shows Combo regression results. Change in market return, momentum volatility and change in the momentum volatility have predictive power for Combo as well. Panel B shows Combo risk managed strategies that are constructed in a same way as dynamic momentum returns. There is slight improvement in Sharpe ratio and all of the risk managed Combo strategies have higher maximum return with almost same or higher minimum return. These results show that momentum risk management method can be useful even after diversification and combination of momentum with value that are negatively correlated and can produce higher return together.

5.4 Economic Analysis

As Barroso and Santa-Clara (2013) argue, momentum strategy offers a trade-off between desired and undesired features which are high Sharpe ratio (desirable) and high kurtosis and left skewness (undesired). To assess this trade-off and compare different dynamic strategies with static strategy, I use BS method of certainty equivalent calculation. In this model the utility of return is in the form of power utility function:

$$U(r) = \frac{(1+r)^{1-\gamma}}{1-\gamma} \tag{6}$$

where γ is constant coefficient of relative risk aversion (CRRA). I use relatively low risk aversion of 3. The certainty equivalent from the utility of return can be obtained as follow:

$$CE(r) = \{(1-\gamma)E[U(r)]\}^{\frac{1}{1-\gamma}} - 1 \tag{7}$$

This indicates the welfare that the investor gets from a series of returns in terms of an equivalent risk free annual return expressed in a unit of percentage points per year. Taylor series approximation for expected utility around its mean can be done as follow:

$$\begin{aligned} E[U(r)] = U(E(r)) + \frac{1}{2}\, U''(E(r))\ E(r-E(r))^2 + \frac{1}{6}\, U^{(3)}(E(r))\ E(r-E(r))^3 \\ + \textit{higher order approximation} \end{aligned} \tag{8}$$

where higher order approximation is the reminders corresponding to the utility from moments with order greater than four. From this approximation, certainty equivalent due to each moment can be obtained as follow:

$$CE(\mu_1) = \{(1-\gamma)U(E(r))\}^{\frac{1}{1-\gamma}} - 1 \tag{9}$$

$$CE(\mu_2) = \{(1-\gamma)[U(E(r)) + \frac{1}{2}U''(E(r))E(r-E(r))^2]\}^{\frac{1}{1-\gamma}} - CE(\mu_1) - 1 \tag{10}$$

$$\begin{aligned} CE(\mu_3) = &\{(1-\gamma)[U(E(r)) + \frac{1}{2}U''(E(r))E(r-E(r))^2 + \frac{1}{6}U^{(3)}(E(r))E(r-E(r))^3]\}^{\frac{1}{1-\gamma}} \\ &- CE(\mu_1) - CE(\mu_2) - 1 \qquad (11) \\ &\ldots \end{aligned}$$

I use overlapping yearly return of market, static and dynamic momentum strategies and calculate certainty equivalent of first four moments of them and then compare summation of these certainty equivalents of different strategies. Table 13 presents the results. Certainty equivalent of first four moments of market portfolio is around 4 percent while despite higher CE of first moment, static momentum strategy has certainty equivalent of 3 percent. All of the dynamic strategies have certainty equivalent of between 3 to 4 times of the static momentum which shows substantial improvement of certainty equivalent in dynamic momentum strategies.

6 Robustness Check

There is a fair concern that prediction results are driven by few crash periods and it cannot generalize to whole periods and also the results come from in sample analysis. It's hard to find a real out of sample test for these kind of analysis and one may argue that even testing in other markets or countries is not out of sample because of correlation between the markets. I can't completely mitigate this concern in this study but I show standard subsample tests in this section. I divide time series to 3 periods: 1927 to 1955, 1956 to 1984 and 1985 to 2013. Table 12 shows regression results in each period. All of the coefficients have correct sign although not always being significant. Market lag return, momentum volatility and change in momentum volatility have negative and significant coefficient in all subsamples.

7 Conclusion

Momentum has predictable crash periods that happen in times of market stress, high market volatility and market rebound. The time varying exposure of momentum portfolio to systematic risk factors can justify momentum return behavior. Momentum predictability has been show in previous studies. I collect momentum predictors in literature and add three new variables that are stock return dispersion, change in market return and change in momentum volatility and verify the predictability of each variable and show that when I include all predictors in a horse race test, change in momentum volatility has the highest predictive power which can explain about 12 percent of momentum return variation in whole sample.

Then I show that almost all of the predictive power in the whole set of momentum predictors comes from crash periods while there is no predictability in normal periods. In some cases, regression coefficient of momentum predictors in normal period are significant but with opposite sign which furthermore verifies the importance of crash periods in momentum prediction. Using this fact and taking to account implementation cost, I introduce a state dummy method of momentum risk management which is different from inverse weighting that has been used in previous studies. I show that this method of dynamic momentum risk management has less transaction cost both in terms of portfolio turnover and price impact than inverse weighting scheme with more desirable results of risk managed momentum return. Among different strategies, dynamic momentum using change in momentum volatility has the highest Sharpe ratio (1.1) with higher skewness than static strategy. I analyze certainty equivalent of dynamic and static momentum strategies which verifies the results.

Therefore, I argue that momentum crashes can be mitigated with simple dynamic setting which implies that momentum is even more strong and pervasive anomaly that momentum crashes cannot destroy it. The results of the paper has also portfolio management implication.

References

[1] Yakov Amihud, *Illiquidity and stock returns: cross-section and time-series effects*, Journal of financial markets **5** (2002), no. 1, 31–56.

[2] Clifford S Asness, Tobias J Moskowitz, and Lasse Heje Pedersen, *Value and momentum everywhere*, The Journal of Finance **68** (2013), no. 3, 929–985.

[3] Allen B Atkins and Edward A Dyl, *Market structure and reported trading volume: Nasdaq versus the nyse*, Journal of Financial Research **20** (1997), no. 3, 291–304.

[4] Doron Avramov, Si Cheng, and Allaudeen Hameed, *Time-varying momentum payoffs and illiquidity*, Tech. report, Working paper, 2013.

[5] Pierluigi Balduzzi and Anthony W Lynch, *Transaction costs and predictability: Some utility cost calculations*, Journal of Financial Economics **52** (1999), no. 1, 47–78.

[6] Pedro Barroso and Pedro Santa-Clara, *Momentum has its moments*, Available at SSRN 2041429 (2013).

[7] Mark M Carhart, *On persistence in mutual fund performance*, The Journal of finance **52** (1997), no. 1, 57–82.

[8] Louis KC Chan, Yasushi Hamao, and Josef Lakonishok, *Can fundamentals predict japanese stock returns?*, Financial Analysts Journal (1993), 63–69.

[9] Tarun Chordia and Lakshmanan Shivakumar, *Momentum, business cycle, and time-varying expected returns*, The Journal of Finance **57** (2002), no. 2, 985–1019.

[10] Andy CW Chui, Sheridan Titman, and KC John Wei, *Individualism and momentum around the world*, The Journal of Finance **65** (2010), no. 1, 361–392.

[11] Michael J Cooper, Roberto C Gutierrez, and Allaudeen Hameed, *Market states and momentum*, The Journal of Finance **59** (2004), no. 3, 1345–1365.

[12] Kent Daniel, David Hirshleifer, and Avanidhar Subrahmanyam, *Investor psychology and security market under-and overreactions*, the Journal of Finance **53** (1998), no. 6, 1839–1885.

[13] Victor DeMiguel, Lorenzo Garlappi, and Raman Uppal, *Optimal versus naive diversification: How inefficient is the 1/n portfolio strategy?*, Review of Financial Studies **22** (2009), no. 5, 1915–1953.

[14] Eugene F Fama and Kenneth R French, *Common risk factors in the returns on stocks and bonds*, Journal of financial economics **33** (1993), no. 1, 3–56.

[15] ______, *Multifactor explanations of asset pricing anomalies*, The journal of finance **51** (1996), no. 1, 55–84.

[16] ______, *Value versus growth: The international evidence*, The Journal of Finance **53** (1998), no. 6, 1975–1999.

[17] John M Griffin, Xiuqing Ji, and J Spencer Martin, *Momentum investing and business cycle risk: Evidence from pole to pole*, The Journal of Finance **58** (2003), no. 6, 2515–2547.

[18] Mark Grinblatt and Sheridan Titman, *Mutual fund performance: An analysis of quarterly portfolio holdings*, Journal of business (1989), 393–416.

[19] ______, *Performance measurement without benchmarks: An examination of mutual fund returns*, Journal of Business (1993), 47–68.

[20] Bruce D Grundy and J Spencer Martin, *Understanding the nature of the risks and the source of the rewards to momentum investing*, Review of Financial Studies **14** (2001), no. 1, 29–78.

[21] Harrison Hong and Jeremy C Stein, *A unified theory of underreaction, momentum trading, and overreaction in asset markets*, The Journal of Finance **54** (1999), no. 6, 2143–2184.

[22] Ronen Israel, Andrea Frazzini, Tobias J Moskowitz, and Clifford S Asness, *Fact, fiction and momentum investing*, Available at SSRN (2014).

[23] Narasimhan Jegadeesh, *Evidence of predictable behavior of security returns*, The Journal of Finance **45** (1990), no. 3, 881–898.

[24] Narasimhan Jegadeesh and Sheridan Titman, *Returns to buying winners and selling losers: Implications for stock market efficiency*, The Journal of Finance **48** (1993), no. 1, 65–91.

[25] Robert A Korajczyk and Ronnie Sadka, *Are momentum profits robust to trading costs?*, The Journal of Finance **59** (2004), no. 3, 1039–1082.

[26] Shanker P Kothari and Jay Shanken, *Stock return variation and expected dividends: A time-series and cross-sectional analysis*, Journal of Financial Economics **31** (1992), no. 2, 177–210.

[27] Bruce Lehmann, *Fads, martingales, and market efficiency*, 1990.

[28] K Geert Rouwenhorst, *International momentum strategies*, The Journal of Finance **53** (1998), no. 1, 267–284.

[29] Chris Stivers and Licheng Sun, *Cross-sectional return dispersion and time variation in value and momentum premiums*, (2010).

Figure 1: Base and Risk Managed Momentum Strategies' Cumulative Return

This figure shows how the logarithm portfolio value of base and dynamic momentum strategies changes over time. All portfolios start with 1 dollar investment in 1927.

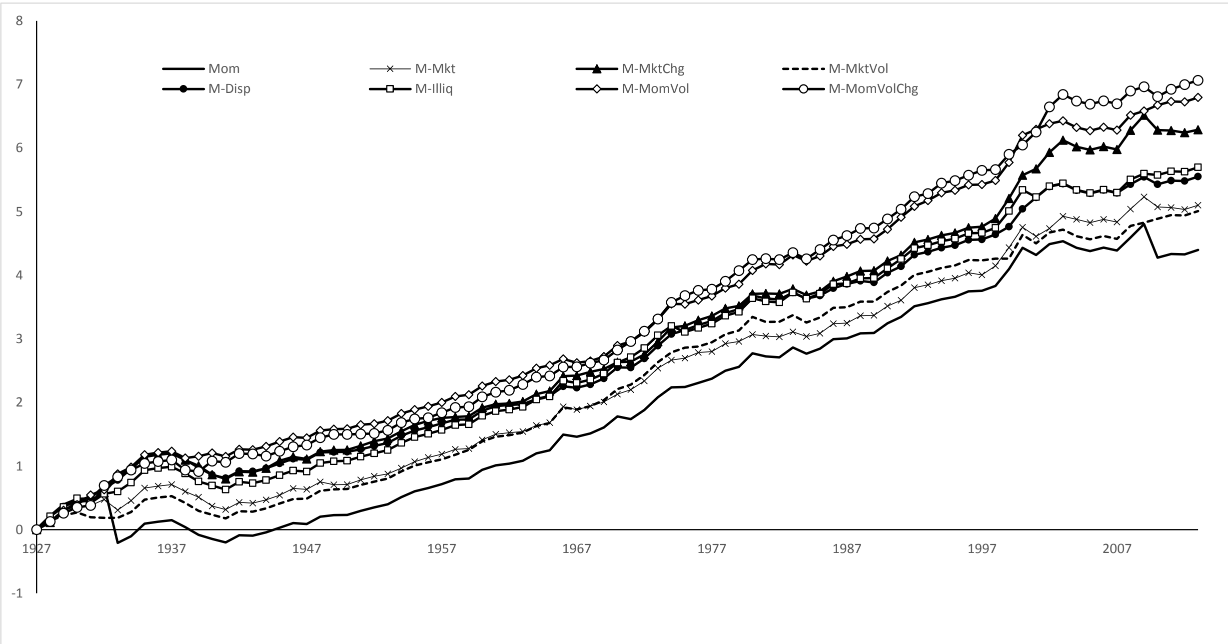

Table 1: 10 Worse Momentum Returns Periods and Market Return and Volatility

This table present 10 worse momentum returns (momentum crashes) and market return and volatility in the same months and one month before. Loser portfolio return has average return of 0.3% but it gains much higher return than Winner portfolio is crash periods. Its contemporaneous with high market volatility and market return compare to their means.

Date	Mom(t)	Winner(t)	Loser(t)	MktVol(t-1)	MktVol(t)	Mkt(t-1)	Mkt(t)
1932m8	-81.40%	20.60%	102.00%	2.20%	3.10%	33.60%	36.50%
1932m7	-61.90%	21.50%	83.40%	3.00%	2.20%	-0.70%	33.60%
2009m4	-47.00%	0.10%	47.20%	3.10%	2.00%	9.00%	10.20%
2001m1	-42.20%	-6.70%	35.50%	1.90%	1.70%	1.70%	3.70%
1939m9	-40.80%	13.10%	54.00%	1.40%	2.20%	-6.60%	17.00%
1938m6	-33.70%	12.00%	45.60%	1.40%	1.70%	-3.80%	23.70%
2002m11	-28.90%	3.20%	32.10%	2.20%	1.50%	8.00%	6.10%
2009m3	-28.70%	4.00%	32.80%	2.20%	3.10%	-10.10%	9.00%
1931m6	-27.00%	8.80%	35.80%	1.40%	2.60%	-13.10%	13.90%
2001m10	-24.70%	1.80%	26.60%	2.20%	1.20%	-9.00%	2.70%

Table 2: Descriptive Statistics for Momentum Portfolios

This table presents summary statistics of 10 portfolios that are constructed base on past returns. In each month t, all stocks are sorted base on their cumulative return from $t-12$ to $t-1$ in 10 portfolios and kept for 1 month. This table shows moments and risk adjusted return of these 10 portfolios from 1927 to 2013. Mean and standard deviation (Std) are monthly and Sharpe ratio is annual. Mean return, CAPM alpha and Fama French 3-factor alpha increase monotonically from portfolio 1 (past loser) to portfolio 10 (past winner). Numbers in parenthesis are t-statistics. P10-P1 is winner minus loser strategy that buys portfolio 10 and short sells portfolio1 in each month.

	1	2	3	4	5	6	7	8	9	10	P10-P1
Mean	0.25%	0.55%	0.68%	0.85%	0.87%	0.89%	1.08%	1.15%	1.31%	1.63%	1.38%
Std	9.99%	8.26%	7.46%	6.41%	6.01%	5.77%	5.75%	5.63%	6.03%	7.14%	8.10%
Sharpe	0.09	0.23	0.32	0.46	0.5	0.53	0.65	0.71	0.75	0.79	0.59
α_{capm}	0.07%	0.43%	0.58%	0.77%	0.79%	0.82%	1.02%	1.10%	1.25%	1.58%	1.68%
	(-0.22)	(-1.68)	(-2.52)	(-3.89)	(-4.24)	(-4.58)	(-5.73)	(-6.3)	(-6.65)	(-7.1)	(-6.97)
α_{ff}	0.03%	0.38%	0.53%	0.74%	0.74%	0.79%	0.99%	1.08%	1.23%	1.56%	1.88%
	(-0.09)	(-1.47)	(-2.3)	(-3.7)	(-3.99)	(-4.42)	(-5.54)	(-6.14)	(-6.52)	(-6.99)	(-8.1)
Skewness	1.89	1.29	1.59	1.17	1	0.16	0.24	0.1	-0.17	-0.08	-2.12

Table 3: Momentum strategy compare to Value and Size

This table shows Momentum (WML) returns moments as well as HML and SMB and market. Momentum has higher monthly return and Sharpe ratio than HML and SMB, but it suffer from huge negative return from time to time. Minimum of momentum return (-81%) is much lower than HML (-13%), SMB (-16%) and market (-29%)

	Mean	Std. Dev.	Sharpe	Skewness	Kurtosis	Min	Max
WML	1.38%	8.09%	0.59	-2.11	20.29	-81.4%	34.4%
Mkt	0.92%	5.41%	0.59	0.12	10.5	-29.1%	38.6%
SMB	0.24%	3.24%	0.25	2.05	23.46	-16.4%	37.5%
HML	0.40%	3.51%	0.39	1.92	18.68	-12.7%	34.1%
Winner	1.64%	7.15%	0.79	-0.07	6.81	-30.5%	50.0%
Loser	0.24%	10.01%	0.08	1.89	20.84	-41.1%	102.0%

Table 4: Descriptive Statistics and Correlation of Momentum Predictors

Panel A presents momentum predictors summary statistics.Mkt is average market lag return. MktChg is change in market return from previous period. MktVol and MomVol are standard deviation of market and past momentum returns and MVolChg is change in momentum volatility. Illiq is Amihud illiquidity measure for market and Disp is cross sectional volatility of the market. Panel B shows correlation matrix of predictors. The overall correlation are positive but they are not perfectly correlated, Dispersion has higher correlation than others.

Panel A	Mkt	MktChg	MktVol	Disp	Illiq	MomVol	MVolChg
Mean	0.93%	0.00%	2.18%	0.12%	0.006	6.50%	0.00%
Std	5.42%	7.23%	1.16%	0.11%	0.015	4.88%	2.06%
Skew	0.12	0.45	2.08	2.72	6.48	3.21	-1.41
Kurt	7.52	4.22	5.06	10.28	68.36	16.37	45.03
Min	-29.14%	-39.53%	0.72%	0.02%	0	1.10%	-27.64%
Max	38.62%	38.40%	7.48%	0.87%	0.237	45.75%	16.27%

Panel B	Mkt	MktChg	MktVol	Disp	Illiq	MomVol	MVolChg
Mkt	1						
MktChg	0.67	1					
MktVol	-0.01	0.02	1				
Disp	0	0.08	0.61	1			
Illiq	-0.04	0.09	0.6	0.4	1		
MomVol	0.05	0.03	0.59	0.57	0.39	1	
MVolChg	0	0.08	-0.04	0.12	0.11	0.21	1

Table 5: Descriptive Statistics and Correlation of Combo

Panel A shows momentum, value and combination (Combo) strategies summary statistics. Combo is constructed by equally weighted averaging of momentum and value strategy. Because of negative correlation between momentum and value, Combo has higher Sharpe ratio and is less skewed. Panel B presents correlation matrix of value, momentum and Combo strategy. Correlation between momentum and value is -38% while momentum and Combo have correlation of 68%.

Panel A	Mean	Std	Ann Mean	Ann Std	Sharpe	Skew	Kurt	Min	Max
HML	0.0053	6.53%	6.42%	22.61%	0.28	2.74	23.74	-22.67%	71.54%
Mom	1.38%	8.10%	16.59%	28.05%	0.59	-2.12	17.24	-81.43%	34.66%
Combo	0.96%	4.13%	11.50%	14.31%	0.8	-0.22	2.91	-20.02%	20.46%

Panel B	HML	Mom	Combo
HML	1		
Mom	-0.38	1	
Combo	0.42	0.68	1

Table 6: Momentum Return Prediction

Panel A presents momentum return regression on each of six predictors. Mom is monthly winner minus loser return. All of the coefficients are negative and statistically significant. Panel B shows same regression controlling for Fama French risk factors. Again all of the coefficients are negative and significant. t statistics in parentheses

Panel A	(1) Mom(t+1)	(2) Mom(t+1)	(3) Mom(t+1)	(4) Mom(t+1)	(5) Mom(t+1)	(6) Mom(t+1)	(7) Mom(t+1)	(8) Mom(t+1)	(9) Mom(t+1)	(10) Mom(t+1)
Mkt(t)	-0.195***							-0.0989		-0.0991*
	(-4.25)							(-1.61)		(-1.70)
MktChg(t)		-0.188***						-0.117**		-0.101**
		(-5.48)						(-2.53)		(-2.29)
MktVol(t)			-0.611***					0.326		0.0402
			(-2.83)					(1.06)		(0.13)
Disp(t)				-8.708***				-5.901**		2.184
				(-3.73)				(-2.03)		(0.75)
Illiq(t)					-0.816***			-0.763***		-0.420**
					(-5.00)			(-3.72)		(-2.16)
MomVol(t)						-0.346***			-0.235***	-0.211***
						(-6.88)			(-4.82)	(-3.26)
MVolChg(t)							-1.367***		-1.250***	-1.211***
							(-11.93)		(-10.78)	(-10.12)
Constant	0.0156***	0.0138***	0.0271***	0.0243***	0.0190***	0.0363***	0.0138***	0.0196***	0.0291***	0.0276***
	(6.19)	(5.58)	(5.09)	(6.47)	(7.07)	(8.88)	(5.87)	(3.46)	(7.40)	(5.12)
Observations	1044	1043	1044	1044	1044	1044	1043	1043	1043	1043
R^2	0.017	0.028	0.008	0.013	0.023	0.043	0.120	0.053	0.140	0.165
Adjusted R^2	0.016	0.027	0.007	0.012	0.022	0.043	0.120	0.048	0.138	0.159

Panel B	(1) Mom(t+1)	(2) Mom(t+1)	(3) Mom(t+1)	(4) Mom(t+1)	(5) Mom(t+1)	(6) Mom(t+1)	(7) Mom(t+1)	(8) Mom(t+1)	(9) Mom(t+1)	(10) Mom(t+1)
Mkt(t)	-0.118***							-0.0143		-0.0246
	(-2.71)							(-0.25)		(-0.44)
MktChg(t)		-0.137***						-0.125***		-0.113***
		(-4.29)						(-2.90)		(-2.72)
MktVol(t)			-0.551***					-0.252		-0.341
			(-2.77)					(-0.87)		(-1.13)
Disp(t)				-5.762***				-2.585		4.022
				(-2.66)				(-0.95)		(1.46)
Illiq(t)					-0.423***			-0.194		0.00837
					(-2.75)			(-0.99)		(0.04)
MomVol(t)						-0.286***			-0.210***	-0.209***
						(-6.15)			(-4.57)	(-3.42)
MVolChg(t)							-1.043***		-0.943***	-0.956***
							(-9.42)		(-8.44)	(-8.29)
Mkt-RF	-0.339***	-0.335***	-0.345***	-0.343***	-0.335***	-0.339***	-0.273***	-0.334***	-0.278***	-0.271***
	(-7.45)	(-7.39)	(-7.58)	(-7.53)	(-7.34)	(-7.56)	(-6.14)	(-7.35)	(-6.29)	(-6.17)
SMB	-0.0858	-0.0912	-0.109	-0.110	-0.123	-0.0938	-0.111	-0.0659	-0.0853	-0.0445
	(-1.11)	(-1.21)	(-1.45)	(-1.45)	(-1.64)	(-1.26)	(-1.53)	(-0.86)	(-1.19)	(-0.60)
HML	-0.611***	-0.605***	-0.618***	-0.604***	-0.588***	-0.591***	-0.543***	-0.586***	-0.531***	-0.528***
	(-9.14)	(-9.10)	(-9.26)	(-9.02)	(-8.70)	(-8.97)	(-8.38)	(-8.62)	(-8.26)	(-8.11)
Constant	0.0197***	0.0185***	0.0307***	0.0256***	0.0212***	0.0371***	0.0179***	0.0283***	0.0315***	0.0340***
	(8.41)	(8.03)	(6.26)	(7.39)	(8.54)	(9.87)	(8.04)	(5.31)	(8.51)	(6.62)
Observations	1044	1043	1044	1044	1044	1044	1043	1043	1043	1043
R^2	0.171	0.180	0.171	0.171	0.171	0.194	0.231	0.187	0.246	0.260
Adjusted R^2	0.168	0.177	0.168	0.168	0.168	0.191	0.228	0.181	0.243	0.253

Table 7: Momentum return prediction in Crash and Normal periods

These tables show the same results as previous tables but for two subsample: Crash and Normal periods. Crash period are defined as periods with momentum return less than -10 percent. 60 month out of total 1044 month are in this subsample. The remaining are normal periods. Panel A present summary statistics of two subsamples and Panel B (C) shows crash (normal) period regression result. The results are very different for two subsample and momentum volatility and change in volatility have highest predictive power in crash period.

Panel A	Mean	Std	Ann Mean	Ann Std	Sharpe	Skew	Kurt	Min	Max
Normal	2.61%	5.76%	31.3%	20.0%	1.57	0.86	2.15	-9.75%	34.66%
Crash	-18.78%	12.84%	-225.4%	44.5%	-5.07	-2.96	10.32	-81.43%	-10.07%

Panel B: Crash Periods Prediction

	(1) Mom(t+1)	(2) Mom(t+1)	(3) Mom(t+1)	(4) Mom(t+1)	(5) Mom(t+1)	(6) Mom(t+1)	(7) Mom(t+1)	(8) Mom(t+1)	(9) Mom(t+1)	(10) Mom(t+1)
Mkt(t)	-0.458**							-0.362		-0.0364
	(-2.09)							(-1.43)		(-0.24)
MktChg(t)		-0.468***						0.0813		-0.0613
		(-3.02)						(0.41)		(-0.55)
MktVol(t)			-4.704***					-0.615		-0.373
			(-4.34)					(-0.54)		(-0.54)
Disp(t)				-43.82***				-27.15***		7.904
				(-5.26)				(-2.99)		(1.31)
Illiq(t)					-2.355***			-1.691***		-0.282
					(-6.04)			(-3.96)		(-1.06)
MomVol(t)						-1.578***			-1.152***	-1.095***
						(-11.85)			(-10.44)	(-5.99)
MVolChg(t)							-2.395***		-1.405***	-1.437***
							(-8.86)		(-7.56)	(-6.69)
Constant	-0.181***	-0.175***	-0.0466	-0.0899***	-0.161***	0.0217	-0.105***	-0.0859***	0.0139	0.00639
	(-10.91)	(-10.81)	(-1.30)	(-3.87)	(-11.51)	(1.09)	(-7.26)	(-2.73)	(0.97)	(0.33)
Observations	60	60	60	60	60	60	60	60	60	60
R^2	0.070	0.136	0.245	0.323	0.386	0.708	0.575	0.541	0.854	0.867
Adjusted R^2	0.054	0.121	0.232	0.311	0.376	0.703	0.568	0.499	0.849	0.849

Panel C: Normal Periods Prediction

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)
Mkt(t)	-0.136***							-0.115**		-0.125***
	(-3.94)							(-2.50)		(-2.74)
MktChg(t)		-0.0820***						-0.0235		-0.0144
		(-3.13)						(-0.68)		(-0.42)
MktVol(t)			0.581***					0.188		0.0540
			(3.57)					(0.78)		(0.21)
Disp(t)				10.58***				10.47***		8.218***
				(5.77)				(4.57)		(3.49)
Illiq(t)					0.193			-0.251		-0.277
					(1.38)			(-1.39)		(-1.55)
MomVol(t)						0.237***			0.239***	0.164***
						(5.78)			(5.85)	(3.18)
MVolChg(t)							0.301***		0.315***	0.345***
							(2.70)		(2.86)	(3.10)
Constant	0.0273***	0.0260***	0.0137***	0.0140***	0.0249***	0.0117***	0.0267***	0.0126***	0.0122***	0.00904**
	(14.77)	(14.18)	(3.51)	(5.05)	(12.33)	(3.80)	(14.46)	(2.98)	(3.97)	(2.12)
Observations	984	983	984	984	984	984	983	983	983	983
R^2	0.016	0.010	0.013	0.033	0.002	0.033	0.007	0.050	0.041	0.071
Adjusted R^2	0.015	0.009	0.012	0.032	0.001	0.032	0.006	0.045	0.039	0.064

Table 8: Descriptive Statistics of Static and Dynamic Momentum Returns

Panel A presents summary statistics of static momentum return as well as dynamically weighted momentum strategies. Mom is base strategy return, M-MktVol and M-MomVol are constructed by using market and momentum return volatility in state dummy weighting scheme respectively. In each month the dummy variable is equal to 1 if the corresponding predictor is less than its 90 percentile in past 5 years and 0 otherwise. Dynamic momentum is simply static momentum times state dummy. M-Mkt, M-MktChg, M-Disp, M-Illiq and M-MVolChg are constructed by 0 or 1 weighting of static momentum with using market past return, change in market return, market disperison, illiquidity and change in momentum volatility as predictor respectively. Average returns and Sharpe ratios of all the dynamic strategies are higher than static strategy while their return is less skewed and have higher minimum returns.
Panel B shows 10 worse momentum returns in base and risk managed strategies. All of the dynamic strategies have higher minimum returns than static strategy; M-MVolChg has the higher minimum return which is -23% while the static strategy has minimum return of -81%. Other strategies drop for around 42% in the worst case.

Panel A	Mom	M-Mkt	M-MktChg	M-MktVol	M-Disp	M-Illiq	M-MomVol	M-MVolChg
Mean	1.38%	1.41%	1.62%	1.30%	1.43%	1.50%	1.67%	1.69%
Std	8.10%	7.18%	6.63%	6.05%	6.24%	6.75%	5.78%	5.31%
Sharpe	0.59	0.68	0.84	0.74	0.79	0.77	1	1.1
Skew	-2.12	-1.18	-0.36	-0.62	-0.48	-0.65	0.12	0.07
Kurt	17.24	10.17	4.88	6.51	5.5	5.52	3.93	2
Min	-81.43%	-61.86%	-40.82%	-40.82%	-40.82%	-42.20%	-28.95%	-23.13%
Max	34.66%	34.66%	34.66%	34.66%	34.66%	34.66%	34.66%	24.28%

Panel B	Mom	M-Mkt	M-MktChg	M-MktVol	M-Disp	M-Illiq	M-MomVol	M-MVolChg
1	-81.4%	-61.9%	-40.8%	-40.8%	-40.8%	-42.2%	-28.9%	-23.1%
2	-61.9%	-42.2%	-33.7%	-33.7%	-33.7%	-40.8%	-24.7%	-17.8%
3	-47.0%	-40.8%	-28.7%	-28.9%	-28.9%	-33.7%	-21.7%	-17.0%
4	-42.2%	-33.7%	-27.0%	-27.0%	-27.0%	-28.9%	-20.8%	-16.2%
5	-40.8%	-28.7%	-24.7%	-24.7%	-24.7%	-24.7%	-20.8%	-15.3%
6	-33.7%	-27.0%	-24.7%	-23.1%	-20.8%	-23.1%	-16.4%	-14.7%
7	-28.9%	-24.7%	-21.7%	-21.7%	-19.8%	-21.7%	-16.2%	-14.7%
8	-28.7%	-24.7%	-20.8%	-20.8%	-19.2%	-20.8%	-15.8%	-14.7%
9	-27.0%	-23.1%	-18.8%	-19.8%	-18.3%	-20.8%	-14.9%	-14.1%
10	-24.7%	-21.7%	-18.3%	-18.8%	-17.8%	-19.8%	-14.7%	-13.6%

Table 9: Prediction of Winner and Loser Portfolio's Return

These two tables show winner and loser portfolio's prediction with momentum predictors. It can be seen that most of the prediction power comes from Loser portfolio prediction. As momentum negative results are mainly due to high returns of short positions, loser portfolio return are predicted with positive coefficients and all of them are statistically significant. There is much less prediction power for predicting winner portfolios return.

	(1) Winner(t+1)	(2) Winner(t+1)	(3) Winner(t+1)	(4) Winner(t+1)	(5) Winner(t+1)	(6) Winner(t+1)	(7) Winner(t+1)
Mkt(t)	0.0845**						
	(2.08)						
MktChg(t)		0.0294					
		(0.96)					
MktVol(t)			-0.0982				
			(-0.51)				
Disp(t)				1.855			
				(0.90)			
Illiq(t)					0.285*		
					(1.96)		
MomVol(t)						-0.0161	
						(-0.36)	
MVolChg(t)							0.319***
							(2.98)
Constant	0.0155***	0.0162***	0.0185***	0.0141***	0.0145***	0.0174***	0.0162***
	(6.94)	(7.35)	(3.91)	(4.22)	(6.06)	(4.72)	(7.37)
Observations	1044	1043	1044	1044	1044	1044	1043
R^2	0.004	0.001	0.000	0.001	0.004	0.000	0.008
Adjusted R^2	0.003	-0.000	-0.001	-0.000	0.003	-0.001	0.007

	(1) Loser(t+1)	(2) Loser(t+1)	(3) Loser(t+1)	(4) Loser(t+1)	(5) Loser(t+1)	(6) Loser(t+1)	(7) Loser(t+1)
Mkt(t)	0.279***						
	(4.95)						
MktChg(t)		0.217***					
		(5.13)					
MktVol(t)			0.513*				
			(1.92)				
Disp(t)				10.56***			
				(3.67)			
Illiq(t)					1.102***		
					(5.48)		
MomVol(t)						0.330***	
						(5.27)	
MVolChg(t)							1.686***
							(11.93)
Constant	-0.0000775	0.00243	-0.00866	-0.0102**	-0.00449	-0.0189***	0.00241
	(-0.02)	(0.80)	(-1.31)	(-2.21)	(-1.36)	(-3.72)	(0.83)
Observations	1044	1043	1044	1044	1044	1044	1043
R^2	0.023	0.025	0.004	0.013	0.028	0.026	0.120
Adjusted R^2	0.022	0.024	0.003	0.012	0.027	0.025	0.119

Table 10: Turnover of Static and Dynamic Momentum Strategies

This table presents average turnover of base and dynamic momentum strategies. Turnover is defined similar to DeMiguel, Galappi and Uppal (2013) and can be used as a proxy for transaction cost. Risk managed strategies have less or very close turnover to base strategy, suggesting that they can all survive transaction costs.

	Mom	M-Mkt	M-MktChg	M-MktVol	M-Disp	M-Illiq	M-MomVol	M-MVolChg
Turnover	0.81	0.83	0.84	0.68	0.76	0.78	0.74	0.83
Proportion to base strategy	100%	103%	104%	84%	94%	96%	92%	103%

Table 11: Value and Momentum Combination (Combo)

Panel A presents value and momentum combination strategy (Combo) prediction. Combo is constructed by equally weighting value and momentum strategies in each month. Change in market return, momentum volatility and change in the momentum volatility have predictive power for Combo as well, when I control for Fama French factors in panel B, then market illiquidity and market lag return have also statistically significant coefficients.
Panel C shows Combo risk managed strategies that are constructed in a same way as dynamic momentum returns. There is slight improvement in Sharpe ratio and all of the risk managed Combo strategies have higher maximum return with almost same or higher minimum return.

Panel A	(1) Combo(t+1)	(2) Combo(t+1)	(3) Combo(t+1)	(4) Combo(t+1)	(5) Combo(t+1)	(6) Combo(t+1)	(7) Combo(t+1)	(8) Combo(t+1)	(9) Combo(t+1)	(10) Combo(t+1)
Mkt(t)	-0.0120							0.0651**		0.0709**
	(-0.51)							(2.04)		(2.24)
MktChg(t)		-0.0504***						-0.0863***		-0.0851***
		(-2.86)						(-3.57)		(-3.57)
MktVol(t)			-0.0967					-0.265*		-0.247
			(-0.87)					(-1.66)		(-1.44)
Disp(t)				0.379				2.069		5.039***
				(0.32)				(1.37)		(3.20)
Illiq(t)					-0.0237			0.0870		0.183*
					(-0.28)			(0.82)		(1.73)
MomVol(t)						-0.0893***			-0.0621**	-0.113***
						(-3.43)			(-2.36)	(-3.21)
MVolChg(t)							-0.334***		-0.303***	-0.306***
							(-5.44)		(-4.83)	(-4.72)
Constant	0.00965***	0.00950***	0.0116***	0.00908***	0.00969***	0.0153***	0.00951***	0.0116***	0.0135***	0.0143***
	(7.44)	(7.45)	(4.27)	(4.70)	(6.99)	(7.24)	(7.53)	(3.94)	(6.37)	(4.89)
Observations	1044	1043	1044	1044	1044	1044	1043	1043	1043	1043
R^2	0.000	0.008	0.001	0.000	0.000	0.011	0.028	0.014	0.033	0.053
Adjusted R^2	-0.001	0.007	-0.000	-0.001	-0.001	0.010	0.027	0.009	0.031	0.047

Panel B	Combo	Com-Mkt	Com-MktChg	Com-MktVol	Com-Disp	Com-Illiq	Com-MomVol	Com-MVolChg
Mean	0.95%	0.97%	1.07%	0.91%	1.01%	0.98%	1.10%	1.11%
Std	4.13%	4.17%	4.18%	4.05%	4.20%	4.05%	4.07%	3.94%
Sharpe	0.8	0.8	0.89	0.78	0.83	0.84	0.94	0.98
Skew	-0.21	0.49	0.71	0.74	0.53	0.72	0.93	1.25
Kurt	2.91	7.59	7.48	8.08	7.17	7.98	8.85	9.73
Min	-20.02%	-20.02%	-19.13%	-19.13%	-20.02%	-19.13%	-19.13%	-15.29%
Max	20.46%	35.77%	35.77%	35.77%	35.77%	35.77%	35.77%	35.77%

Table 12: Robustness Check

These tables show prediction power of momentum predictors in three sub-periods: first sample is from 1927 to 1955, second sample is from 1956 to 1984 and the last sample is from 1985 to 2013. Although there is variation in predictive power but similar results can be seen in all three sub periods and the results are not driven by specific period (crash period)

First period: 1927 to 1955

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)
Mkt(t)	-0.201***							-0.235**		-0.177**
	(-2.92)							(-2.56)		(-1.97)
MktChg(t)		-0.169***						0.00552		-0.0187
		(-3.24)						(0.08)		(-0.27)
MktVol(t)			-0.407					1.198**		0.835*
			(-1.31)					(2.46)		(1.70)
Disp(t)				-9.200**				-0.378		4.049
				(-2.54)				(-0.07)		(0.73)
Illiq(t)					-1.023***			-1.652***		-1.061***
					(-4.78)			(-4.98)		(-3.19)
MomVol(t)						-0.380***			-0.282***	-0.237**
						(-4.85)			(-3.70)	(-2.28)
MVolChg(t)							-1.221***		-1.080***	-0.910***
							(-6.82)		(-6.00)	(-4.89)
Constant	0.0126**	0.0106**	0.0212**	0.0211***	0.0287***	0.0369***	0.0106**	0.0113	0.0302***	0.0212**
	(2.56)	(2.17)	(2.24)	(3.30)	(4.71)	(5.11)	(2.28)	(1.18)	(4.32)	(2.27)
Observations	348	347	348	348	348	348	347	347	347	347
R^2	0.024	0.029	0.005	0.018	0.062	0.064	0.119	0.113	0.153	0.199
Adjusted R^2	0.021	0.027	0.002	0.015	0.059	0.061	0.116	0.100	0.148	0.182

Second period: 1956 to 1984

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)
Mkt(t)	-0.161**							-0.181*		-0.149
	(-2.09)							(-1.67)		(-1.46)
MktChg(t)		-0.0515						0.0409		0.00554
		(-0.91)						(0.51)		(0.07)
MktVol(t)			-1.247**					-1.526**		-2.030***
			(-2.33)					(-2.04)		(-2.78)
Disp(t)				-7.405				11.92		27.88**
				(-0.79)				(0.92)		(2.18)
Illiq(t)					-2.598			-2.563		-1.094
					(-0.76)			(-0.74)		(-0.33)
MomVol(t)						-0.356***			-0.213*	-0.162
						(-3.22)			(-1.94)	(-1.27)
MVolChg(t)							-1.349***		-1.242***	-1.367***
							(-6.05)		(-5.42)	(-5.90)
Constant	0.0178***	0.0165***	0.0387***	0.0220***	0.0199***	0.0356***	0.0166***	0.0397***	0.0280***	0.0435***
	(5.39)	(5.06)	(3.84)	(2.86)	(3.60)	(5.27)	(5.35)	(3.72)	(4.22)	(4.24)
Observations	348	348	348	348	348	348	348	348	348	348
R^2	0.013	0.002	0.015	0.002	0.002	0.029	0.096	0.030	0.105	0.140
Adjusted R^2	0.010	-0.001	0.013	-0.001	-0.001	0.026	0.093	0.016	0.100	0.123

Third period: 1985 to 2013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)	Mom(t+1)
Mkt(t)	-0.208**							0.149		0.0542
	(-2.03)							(1.09)		(0.42)
MktChg(t)		-0.353***						-0.415***		-0.321***
		(-4.73)						(-4.06)		(-3.31)
MktVol(t)			-0.909*					-0.371		-0.665
			(-1.75)					(-0.66)		(-1.04)
Disp(t)				-11.62**				-7.579		2.452
				(-2.49)				(-1.50)		(0.46)
Illiq(t)					16.74			17.67		-6.035
					(0.26)			(0.28)		(-0.10)
MomVol(t)						-0.301***			-0.172*	-0.104
						(-3.20)			(-1.91)	(-0.80)
MVolChg(t)							-1.619***		-1.533***	-1.496***
							(-7.50)		(-6.97)	(-6.58)
Constant	0.0164***	0.0144***	0.0339***	0.0345***	0.0131*	0.0359***	0.0143***	0.0327**	0.0266***	0.0317**
	(3.44)	(3.16)	(2.81)	(3.70)	(1.92)	(4.39)	(3.29)	(2.26)	(3.42)	(2.34)
Observations	348	348	348	348	348	348	348	348	348	348
R^2	0.012	0.061	0.009	0.018	0.000	0.029	0.140	0.078	0.149	0.194
Adjusted R^2	0.009	0.058	0.006	0.015	-0.003	0.026	0.137	0.065	0.144	0.177

Table 13: The Economic Performance of Different Strategies

This table presents the economic performance of market portfolio, base momentum strategy and risk managed momentum strategies for a representative investor with constant relative risk aversion (CRRA) utility which has risk aversion of 3. Colum 1, 2, 3 and 4 show contribution of first, second, third and fourth moments in certainty equivalent respectively that are calculated by using Taylor approximation of utility function around mean returns. Last column represents summation of first 4 columns. The certainty equivalent of moments are calculated using overlapping annual returns. Certainty equivalent return of base momentum strategy is less than market and all risk managed strategies. All of the dynamic momentum returns have much higher summation of certainty equivalent compare to market and base strategy but there is no big difference between them.

	CE(μ_1)	CE(μ_2)	CE(μ_3)	CE(μ_4)	$\sum$ CE
Mkt	11.80%	-5.78%	0.26%	-2.00%	4.28%
Mom	16.87%	-9.13%	-0.33%	-4.40%	3.00%
M-Mkt	16.79%	-6.74%	1.31%	-2.07%	9.29%
M-MktChg	21.06%	-8.62%	2.60%	-3.40%	11.64%
M-MktVol	16.06%	-5.56%	0.80%	-1.42%	9.89%
M-Disp	17.99%	-7.00%	1.78%	-2.81%	9.96%
M-Illiq	18.41%	-6.81%	1.30%	-2.07%	10.84%
M-MomVol	22.26%	-7.92%	3.54%	-5.01%	12.87%
M-MVolChg	23.49%	-9.25%	4.47%	-6.24%	12.46%