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Managing Momentum Crashes in Real Time

US Stock Market

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Abstract

Though, profitable, momentum is punctuated with crashes which make the strategy risky and unfavourable for an investor who dislikes long tails. Volatility management is one approach that has been introduced to deal with the momentum crashes. Volatility managed portfolios are portfolios that take less risk when volatility is high and high risk when volatility is low. The volatility managed strategy, though implementable, uses ex-post information which can make the results bias and impractical. We propose two tweaks in the volatility management process to make it practical. Firstly, we use cumulative statistics up to the formation month instead of the whole sample to manage the portfolio. Secondly, we use statistics of prior 10-year period to manage the volatility of the next ten years. We find that using prior information instead of ex-post information as in the two modifications do not positive results as claimed and therefore the results of Barroso and Santa-Clara (2015) are biased. We find that the kurtosis, which is an important component of managing momentum crashes, increases rather.

Also, combo portfolio, a portfolio that combines value and momentum, is another method of dealing with momentum crashes. The combo portfolio reduces the standard deviation, kurtosis and skewness of momentum strategy while increasing the Sharpe ratio. We further manage the combo portfolio such that we decrease exposure when volatility is high and increase exposure when volatility is low. We find that the Sharpe ratio of the volatility managed combo portfolio of about 1.13 is higher than unmanaged combo portfolio of 0.80. The volatility managed portfolio yields positive large alpha of 0.78 per month even after controlling for exposure to the Fama-French risk factors and the unmanaged portfolio.

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1 Introduction

Momentum strategy was introduced by Jagadeesh and Titman (1993) who formed the portfolio by sorting stocks based and ranking them into deciles according to their past twelve month cumulative returns. Momentum strategy outperforms the market and produces positive significant alphas even after controlling for the Fama and French factors – market, size and value – in the US stock market[1]. Momentum is pervasive: it has been found in multiple time periods, many stock markets and in many other asset classes[2].

However, the high positive returns and Shape ratio of momentum come with occasional crashes. These crashes take long periods to recover. It would take about thirty-one years for an investor who invested $1 in momentum strategy in 1932 to recover from the crash. Daniel and Moskowitz (2013) found that in the period of 1927 – 2013 momentum in the US market had two noticeable crashes. In July and August 1932, the past-loser decile returned -232% while the past-winner decile returned just 32%. Also, in March to May of 2009, the past-loser decile gained 163% while the past-winner decile only gained 8%. This is worrying for investors because the large returns of the momentum strategy do not compensate for such crashes which can take more than a decade to recover from.

There have been many attempts to solve this problem. Kothari and Shanken (1992) found that momentum has a time-varying beta and this is partly responsible for the crashes. They show that during bear markets, momentum strategy has a significant negative beta. That is following negative returns of the overall market, winners are low beta stocks and losers are

[1] Cahart (1997) used momentum as one of the risk factors in evaluating mutual funds' performance.

[2] See Rouwenhorst (1998) for international evidence, Asness, Liew and Stevens (1997) for country stock indices and Asness, Moskowitz and Pedersen (2013) for evidence across asset classes

high beta stocks which makes the winners-minus-losers strategy have a negative beta. Their findings show that momentum crashes are predictable and hence avoidable.

This led Grundy and Martin (2001) to argue that the performance of momentum is greatly improved and returns are stable by hedging the time-varying market exposure to the market. Daniel and Moskowitz (2013) show that the hedge portfolio of Grundy and Martin (2001) is constructed using forward-looking betas and is therefore biased and cannot be implemented in real time. They go further to show that using betas in real time do not avoid the crashes. Some other methods such as volatility management introduced by Barroso & Santa-Clara (2015) and Moreira & Muir (2016) which adjusts the exposure to the strategy by scaling the returns by its past or realised volatility and, therefore, increases exposure in low volatility periods and decreases exposure in high volatility periods and a hedge combination of value and Momentum introduced by Asness, Moskowitz and Pedersen (2013) have been proposed.

In this paper, we examine some of the some of the proposed solution. We start with volatility management and then a combination of value and momentum. Though all the authors claim that their proposed solutions are practical and can be implemented, we find these claims not entirely factual. There are some hidden details in the procedures that make the solutions either un-implementable in real life of or difficult to justify economically. We suggest possible ways to implement the strategies in practice.

Our analysis builds on work by Barroso and Santa-Clara (2015), Moreira and Muir (2016) and Asness, Moskowitz and Pedersen (2013). Asness, Moskowitz and Pedersen (2013) though not explicitly trying to solve the problem of momentum crashes find that value strategies are positively correlated to other value strategies across unrelated markets and same for momentum. However, momentum and value are negatively correlated with each not just in stocks but across markets and other assets. For the sample from 1972:01 to 2011:07 the correlation between value and momentum for US market was – 0.53. Though this does not represent a perfect hedge it shows that it can provide some hedge for each. They then show that a combo portfolio which is a 50-50 combination of value and momentum yields a Sharpe ratio of 0.63 which is higher than value (0.29) and momentum (0.33) within the sample period.

Asness, Moskowitz and Pedersen (2013) construct their value and momentum portfolio in an unconventional way. Instead of the ranking the stocks into deciles according to the general specification, they instead divide it into three and create the factors as a long position in the top 33.33% and a short position in the bottom 33.33%. This does not, however, change the main conclusion when looking at conventional factors as found on Kenneth French website which gives a correlation between value and momentum of – 0.41 from 1927:01 – 2011:12.

Barroso and Santa-Clara (2015) find that managing exposure to momentum by scaling it by the inverse of its six-month realised volatility results in improvements in its returns and Sharpe ratio. They show that the managed momentum has a Sharpe ratio of 0.97 compared to 0.53 for the unmanaged. Also, the standard deviation, skewness and kurtosis are greatly improved and therefore avoids crashes. This finding is striking because they use a very simple approach in estimating variance and also use only past information which makes it implementable in real time.

While the approach uses only past information and is easy to implement, they scale the portfolio with a target ex-post standard deviation of 12%. They, however, give no reason for this choice. We find this choice of volatility target curious because it assumes that the investor maintains the same target for the entire period. It is rational to think that investors may want to take more risk in bull markets and less risk in bear markets. Investors risk preference may vary over time especially during good time and bad times.

Moreira and Muir (2016) improve on the volatility managed portfolios by scaling the portfolio such that the ex-post standard deviation of the managed portfolio is the same as that of the unmanaged portfolio. This choice is rational because it assumes that the investor takes the same risk as if he invested in the unmanaged portfolios. They also use the past variance instead of the realised variance in managing the portfolios. Their approach produces positive monthly alpha of 0.73 for market, 0.71 for size, 0.65 for value and 0.59 for momentum.

The choice of the ex-post volatility target leads to some potential biases because in order to scale such that the two standard deviations are the same, they use future information. The approach assumes that the standard deviation for the whole sample period is known at the beginning of the sample period which is obviously not like. They, therefore, use future information in the scaling of the portfolios.

One major issue on volatility management is the choice of target volatility. Barroso and Santa-Clara (2015) choose a target of 12% which they provide no reason for. We see this choice of volatility target to be unjustified because it implies in that all investors have the same level of risk preference. Moreira and Muir (2016) on the other hand take a more practical approach by choosing a target such that the ex post volatility of momentum is the same as that of the unmanaged.

While this choice is more justifiable, there is a small detail which can potentially bias the results. The target is calculated using information of the entire sample which implies that the investor knows that volatility for the entire sample no matter when he/she is in the sample. Example an investor who starts investing mid sample period will know that volatility for the entire sample and will therefore scale the returns as such.

We introduce two modifications to deal with the impracticality and bias due that may arise from the use of ex-post information. First, we construct the target volatility using cumulative variance. That is, we calculate the variance of the portfolio of the months prior to the formation month, we then scale the returns of the formation month with the variance of the previous month and use the variance of all previous months in calculating the target. This ensures that no future or present information is used in scaling the portfolios. This modified volatility managed momentum strategy produces a Shape ratio of 0.93. Though the Sharpe ratio is slightly lower than that of Moreira and Muir (2016) of 1.08, it is still far better than that of the unmanaged portfolio of 0.59. The higher moments have mixed improvements. Skewness is improved from -1.09 to -0.17. However, the kurtosis of 22.68 is significantly worse that the unmanaged portfolio of 12.77.

The first solution does not achieve goal of improving all the risk characteristics of momentum strategy. This can be explained by the variations in the target volatility with which to scale the portfolio. The target volatility changes every month depending on the cumulative variance. This makes it difficult to track and control the volatility of the portfolio. To tackle this issue, we propose another solution in which we estimate the target volatility using past information for a sample period and use it to manage the returns of the following period. For example, we use a 10-year period to estimate the target volatility and then use that to manage the portfolio for the next 10 years. That is, we target volatility which is equal to the volatility of the preceding window (previous 10 years). The target volatility changes once in ten years which makes it more stable and reduces the variability of the target volatility. The second modification produces a Sharpe ratio of 1.06 which is similar to that of Moreira and Muir (2016) of 1.08. The skewness of this approach is greatly improved. It changes from negative to positive (-1.97 to 1.15). There is, however, no significant improvement in the kurtosis which changes from 12.77 to 11.82.

Our findings show that using past information instead of future and present information improves the Sharpe ratio and skewness but does not improve the kurtosis much and therefore using the volatility management approach to avoid momentum crashes is not enough. We introduce the combo portfolio which is a 50-50 combination of value and momentum. We create this portfolio by equally weighting the value and momentum strategies. The returns of the combo portfolios are calculated as below:

$$r_t^{COMBO} = 0.5r_t^{HML} + 0.5r_t^{WML}$$

We applied our modifications of the volatility management to the combo portfolio and find that it performs better than the managed momentum in terms of all risk characteristics of momentum - Sharpe ratio, skewness and kurtosis. One major finding is that the managed combo portfolio performs better that the average of managed momentum and value. Specifically, the Sharpe ratio of the managed combo portfolio is higher than the average of Sharpe ratios of the separately managed value and momentum.

This paper proceeds as follows. Section 2 describes the sources and types of data we use in our analysis. Section 3 shows our empirical results related to the performance and crashes of momentum compared to the Fama-French factors, the volatility managed portfolio and the combo portfolio. Section 4 discusses why volatility management works and in section 5 we test the robustness of the finding across subsamples. Finally, in section 6 we state the conclusions and implications of our results.

2 Data Description

This section describes the types and sources of data we used in our analysis. We use momentum, value and also a combination of value and momentum portfolios. In addition, the individual portfolios will be described in detail. We also point out some difference between momentum portfolio as created by two different researchers (Kent Daniel and Kenneth French)

We obtain two sets of data. The first is daily and monthly data of the returns of the Market (MKT), Size (SMB), Value (HML) and Momentum (WML) from Kenneth French's data library from January 1927 to December 2016. We also obtain updated data of Daniel and Moskowitz (2013) which are daily and monthly returns for ten value-weighted portfolios sorted on previous momentum from Kent Daniel's website. The data set is from January 1927 to December 2016. MKT represents the value weighted returns of all stocks on NYSE Amex and Nasdaq from Center for Research in Security (CRSP), SMB represents the size factor that takes a long position in small firms and shorts big firms, WML represents the momentum factor which goes long on past winners and short on past losers and HML represents the value factor which goes long on high book to market and short on low Book to market ratio.[3]

HML is created by ranking all stocks on the US market according to the ratio of its book value of equity to its market value of equity. The stocks are then classified into deciles according to NYSE cut-offs which ensures that each bucket has the same number of NYSE stocks. The HML strategy is to short the lowest decile and take a long position on the highest decile. WML is created by ranking all stocks on the US market (Amex, Nasdaq and NYSE) according to returns from month t – 12 to t – 2. They are then sorted into deciles according to NYSE cut-offs such that each bin has equal number of NYSE stocks. WML strategy shorts the

[3] https://wrds-web.wharton.upenn.edu/wrds/ds/crsp/stock_a/msf.cfm?navId=128

lowest decile and buys the highest decile. This is the similar to how Jagadeesh and Titman (1993) created their momentum portfolio.

Even though the general approach to creating the momentum portfolio (WML) is identical, there are some differences in the details of the construction. Whereas, Daniel and Moskowitz (2015) sorts stocks on only prior returns, Fama and French (1992) double-sorts based on size and prior returns. The differences in the momentum portfolios are very striking as indicated by the p-value in table 1.

See Kenneth French's website[4] and Kent Daniel's website[5] for more detailed description of how the factors are formed. Table 1 shows a descriptive analysis of momentum portfolio from the two sources and the Fama-French factors. We find that, though, there are significant differences in the momentum portfolio as created by Daniel and Moskowitz (2015) or Fama and French (1992), our results from volatility management is not significantly different whether we use either portfolio. Therefore, where necessary we focus on that of Daniel and Moskowitz (2015) since it is generally accepted in the literature.

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[5] http://www.kentdaniel.net/data.php

3 Empirical Results

This section details the results of our various analysis. First, we address the problem of momentum crashes in detail. We show the two periods that have the most pronounced momentum crashes as well as the effect of those crashes on momentum returns in the long run (subsection 3.1). Next, we explain that momentum has a time-varying risk that is dependent on the risk of the market in subsection 3.2. Subsection 3.3 details the volatility management approach of dealing with the crashes of momentum. Next, we introduce our modification to volatility management to make it practical and implementable in real time (subsection 3.4). In subsection 3.5 we introduce the combo portfolio and also apply the modified volatility management.

3.1 Momentum Portfolio Performance

Table 1 compares momentum with the three Fama-French risk factors using a sample period from January 1927 to December 2016. There are two momentum portfolios that are obtained from the two different ways the momentum strategy is implemented by Kent Daniel (KD WML) and Kenneth French (KF WML). There is a significant difference between the returns of the two momentum strategies as indicated by their descriptive statistics and specifically the P-value from a t-test of the two portfolios in Panel A. Comparing momentum to the other factors, the momentum strategy provided large returns of 14.47% for Kent Daniel and 8.29% for Kenneth French per annum compared to that of the market with 7.79%, 2.61% for size and 4.81% for value. The Sharpe ratio of momentum is also higher than that of market, size and value.

The abnormal performance of momentum is surprising because it does not correspond to higher exposure to risk which is a blow to the risk-return theory of finance. This is can be shown as an ordinary least square regression of WML on Fama-French factors yields a significant positive alpha of 2.07% per month or 24.84% per year. Momentum also has a negative loading on the risk factors which implies that momentum provided some diversification.

These characteristics of momentum make it look like money without any risk. However, Daniel and Moskowitz (2013) show that momentum crashes. Momentum has excess kurtosis of 12.77 and a very high negative skewness of -1.97. This means that momentum has a very fat left tail and momentum returns can plummet rapidly leading to investors losing all the gains and even losing their invested capital. These crashes are also persistent and can take decades to recover from.

The two most pronounced momentum crashes occurred in decades 1930 to 1939 and 2000 to 2009. Fig 1 shows how momentum performed in these crash periods. The worst returns in the first period occurred in July 1932 with returns of -61.02% and August 1932 with returns of -43.94% -respectively. In April and May 2009 which were the worst years in the second period had returns of -42.32 and -34.39. These crashes are not just sudden but also persistent. In Fig 1, we see that investor who invests a dollar at the beginning of the two periods does not recover in that decade. It would take until April 1963 before the dollar invested in January 1932 is recovered not accounting for inflation.

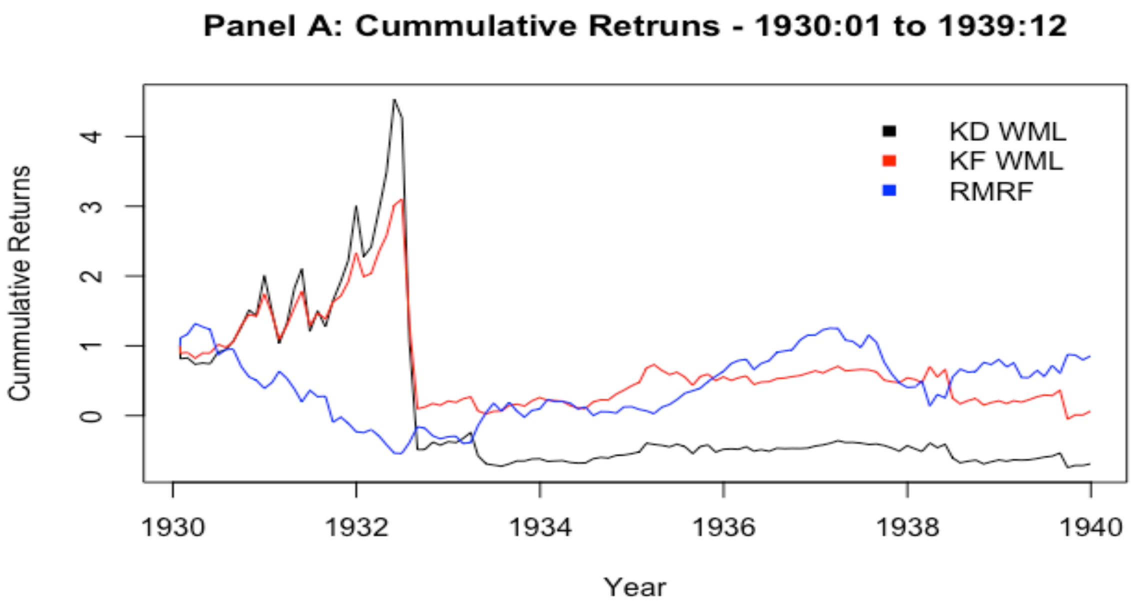
Table 1: **Descriptive statistics of momentum, market, size and value.**

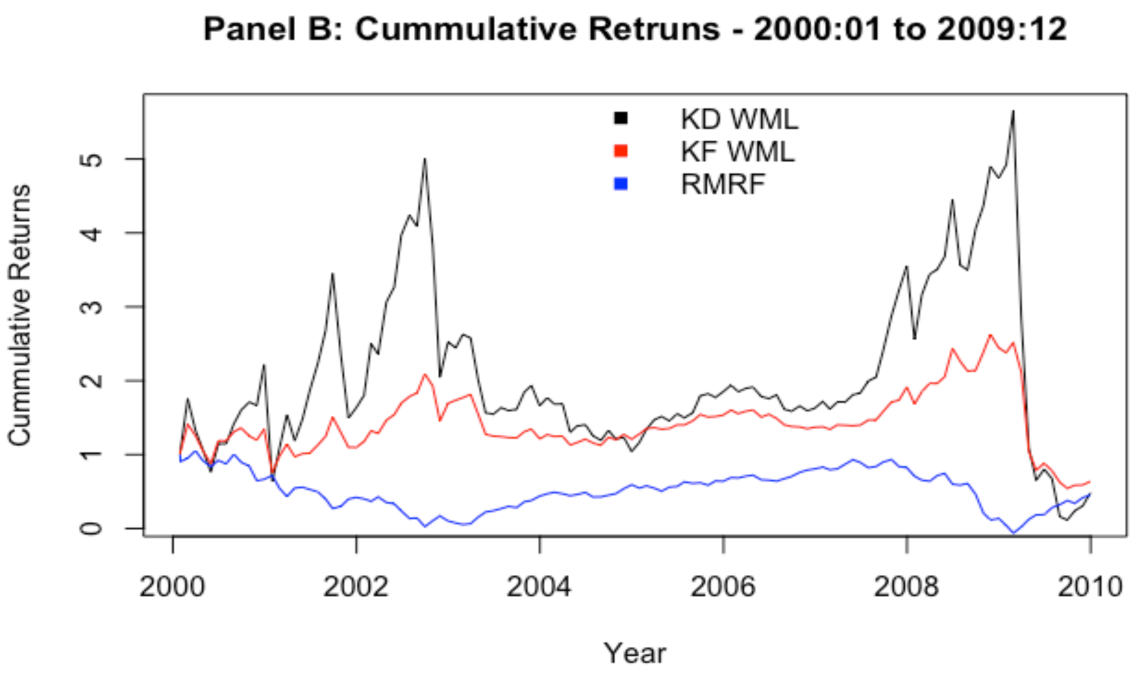
This table shows a comparison between momentum (WML) and Fama-French's three risk factors: market (RMRF), size (SMB) and value (HML). Panel A shows a comparison between the momentum factor as constructed Kent Daniel and Kenneth French. All statistics are calculated with monthly returns. Subscripts KF and KD for WML represent data from Kenneth French and Kent Daniel respectively. Reported are the maximum and minimum of the factors of each data set in the sample, the annualized mean average excess return, annualized standard deviation, the kurtosis and skewness of each factor. The P-value is from a T test comparing the two momentum strategies. The sample returns are from 1927:01 to 2016:12.

Portfolio	Maximum	Minimum	Mean	Standard deviation	Sharpe ratio	Kurtosis	Skewness	P-value
Panel A: Comparison of momentum from the two sources								
WML_{KD}	34.17	-75.12	17.57	29.88	0.59	12.77	-1.97	–
WML_{KF}	18.36	-52.26	7.94	16.63	0.48	27.51	-3.05	0.007
Panel B: Market, Size and Value								
RMRF	38.85	-29.13	7.79	18.64	0.42	7.72	0.19	–
SMB	36.70	-16.88	2.61	11.14	0.23	19.21	1.93	–
HML	35.46	-13.28	4.81	12.15	0.40	19.00	2.17	–

Fig. 1: **Momentum crash periods**.

The figure shows the cumulative returns of the momentum portfolios as created by Kent Daniel (KD WML) and Kenneth French (KF WML) as well the market (RMRF) in the two decades with the most pronounced momentum crashes. We track the progress of a $1 investment at the beginning of the decade till the end of the decade. Panel A shows the results for the period 1930 to 1930 while panel B shows the results for 2000 to 2009.





3.2 Time varying momentum risk

The time varying market betas of momentum is well known and documented characteristics of momentum (Grundy and Martin, 2001; Daniel and Moskowitz, 2013). They show that momentum, especially the beta of the loser portfolio, varies substantially because it tends to increase during volatile period. This is simple to understand because in normal or bull markers the losers have low betas while winners have high betas. This is reversed in downward or bear markets.

This coupled with the fact that momentum performs worse during market upswings (table 3) partly explains why momentum crashes. Thirteen out of the fifteen worst momentum returns have negative returns in the two-year prior returns and all but one has a positive market returns in the formation month. The time varying beta and negative market returns prior the formation period make momentum crashes predictable. Therefore, a strategy that accurately predicts crashes and hedge or avoids it will make momentum a sure money without risk.

Grundy and Martin (2001) propose a hedge momentum such that the conditional market and size exposure is zero. The problem with this approach as shown by (Daniel and Moskowitz, 2013) is that this approach uses ex poste betas which biases the results. The improvement vanishes if ex ante betas are used. Daniel and Moskowitz (2013) then go on to proposed their dynamic strategy approach which is dynamically adjusting the weight on momentum portfolio using forecasted variance and return of the portfolio. They forecast variance using the generalized conditional autoregressive conditional heteroscedasticity (GARCH) model proposed by (Glosten, Jagannathan and Runkle, 1993). Even though this approach works, the results hangs on the effectiveness of the forecast method. As we know, it is difficult to accurately predict returns of stock and hence a simpler approach to will be more practical than this.

Barroso and Santa-Clara (2015) and Moreira and Muir (2016) propose a much simpler and effective way of doing this. They propose that momentum portfolio is scale by weights that are determined by its past realised volatility or past variance. We analyse the volatility managed portfolios approach next.

Table 2: **Worst Monthly returns of Momentum**

The table reports the fifteen worst monthly returns of momentum portfolio (WML) for the sample period 1927:01 to 2016:12. Also reported are the market returns (MKT) and the two-year market returns (MKT-2y) leading up to the formation date of the momentum portfolio. All figures are in percentages.

Rank	Date	WML_t	MKT_t	MKT-2y
1	1932-08-31	-75.12	37.06	-56.54
2	1932-07-30	-61.02	33.84	-93.3
3	2001-01-31	-49.19	3.13	2.21
4	2009-04-30	-45.62	10.19	-45.48
5	1939-09-30	-45.05	16.88	17.96
6	1933-04-29	-44.00	38.85	-14.29
7	2009-03-31	-42.33	8.95	-52.18
8	2002-11-29	-37.04	5.96	-30.01
9	1938-06-30	-33.44	23.87	-3.65
10	2009-08-31	-30.59	3.33	-27.26
11	1931-06-30	-28.90	13.9	-55.75
12	1933-05-31	-27.35	21.43	20.38
13	2001-11-30	-25.31	7.54	-24.07
14	2001-10-31	-24.98	2.46	-28.24
15	1974-01-31	-24.04	-0.17	-17.18

3.3 Volatility-managed portfolios

We construct volatility managed portfolios in two approaches. In the first approach, we estimate realised variance (RV) using daily returns in the previous 21 days for each month. The realised variance is the sum of the squared daily returns of the previous 21 days starting from the preceding date of the last trading date of the month. We then scale the monthly returns of the factors by the inverse of its realised variance. We scale exposure to the portfolios such that it has a constant risk over time. This procedure is similar to the risk-managed portfolios used by Barroso and Santa-Clara (2015). The most significant difference is that we use one month in calculating the realised variance whereas they use six months. The realised variance and scaled factors are computed as:

$$RV_t^2 = \sum_{i=0}^{20} f_i^2 \tag{1}$$

$$f_{t+1}^* = \frac{\sigma_{target}}{RV_t^2} * f_{t+1} \tag{2}$$

Eqn 1 represents the realised variance where RV_t^2 is the realised variance and f_i is the daily returns of the factor. Eqn 2 represents the managed factor where RV_t^2 is the realised variance for month t, f_{t+1} is the monthly return of the factor for the following month and σ_{target} is the target volatility uses to scale the factor to have a constant risk over time. We choose an arbitrary target volatility of 12%.

The second approach is similar to that of Moreira and Muir (2016). We use the variance of the daily returns in each month instead of the realised variance. Also, instead of choosing an arbitrary target, we choose a σ_{target} such that the managed portfolios have the same unconditional standard deviation as the non-managed portfolios.

The managed portfolios are calculated as:

$$f_{t+1}^{*} = \frac{\sigma_{target}}{\sigma_{f_t}^{2}} * f_{t+1} \quad (3)$$

where f_{t+1} is the un-managed factor and $\sigma_{f_t}^{2}$ is the variance daily returns for the previous month. The target volatility divided by the variance of the factor represents the weight. In both approaches, the portfolios are rebalanced each month according to either the previous month's realised variance or variance respectively.

Fig 2 shows that the realised volatility and past variance have similar co-movements. They are at their highest during the two crash decades earlier indicated. The top twenty-five highest realised volatility and past variance are within one of the two worst decades of momentum. These high realised volatility and past variance periods are accompanied with low weights as seen in Fig 3. This means that there is less exposure during high volatility periods and more exposure during low volatility periods. We also emphasize the common co-movement in the volatility and weights across the portfolios. The volatility for the all portfolios increase in turbulent markets such as the crash periods and the weights reduce accordingly.

Fig 2: **Time-series of volatility.**

Panel A plots the time-series of annualised monthly realised volatility of momentum (both Kenneth French – KF WML – and Kent Daniel – KD WML) and value (HML). Panel B plots the monthly variance. The sample period is from 1927:02 to 2016:12.

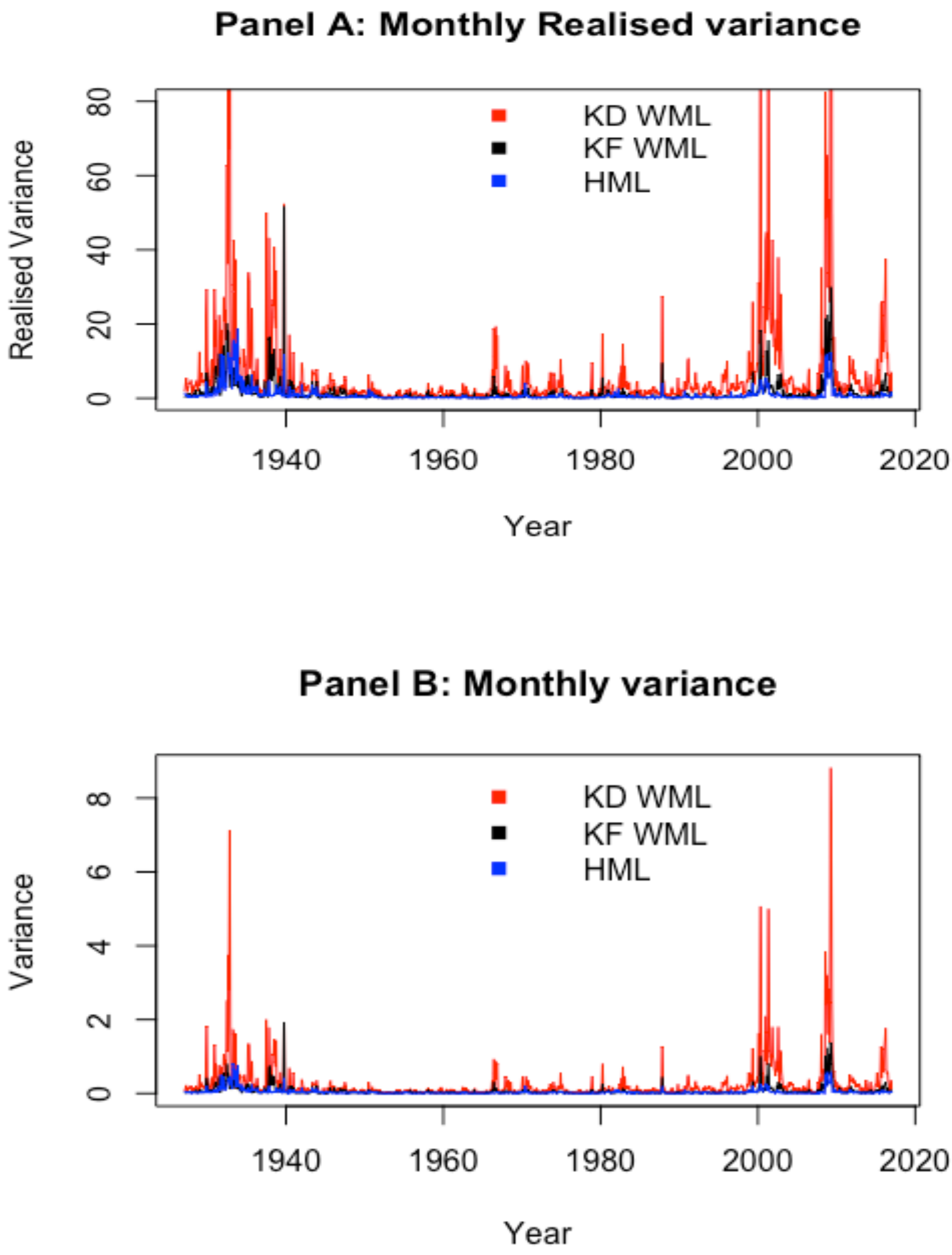
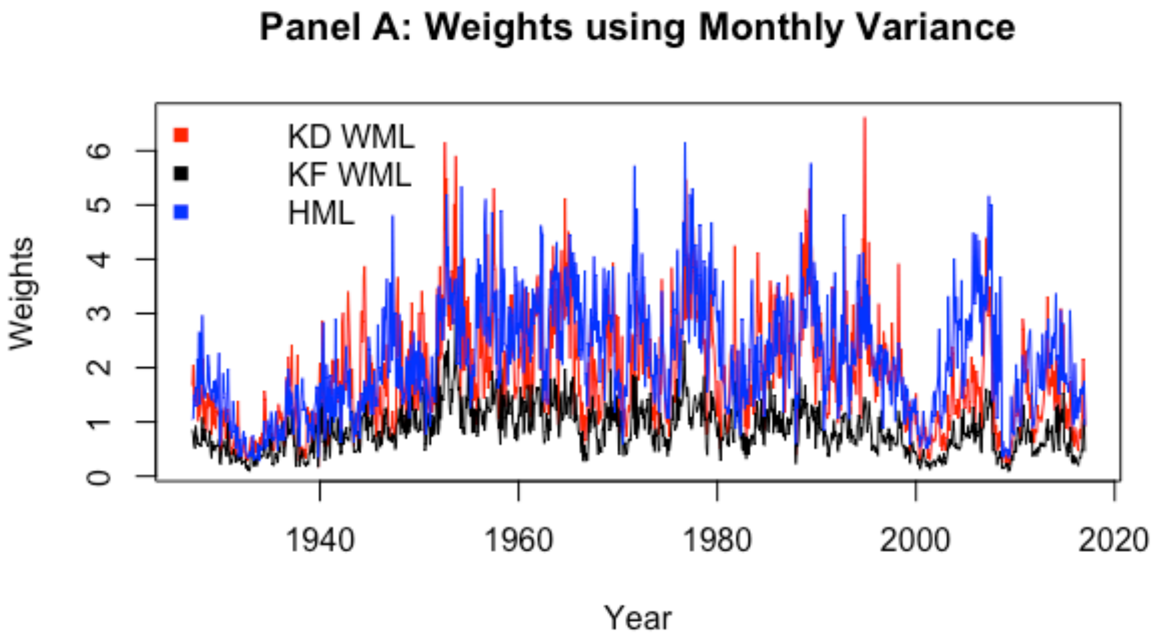
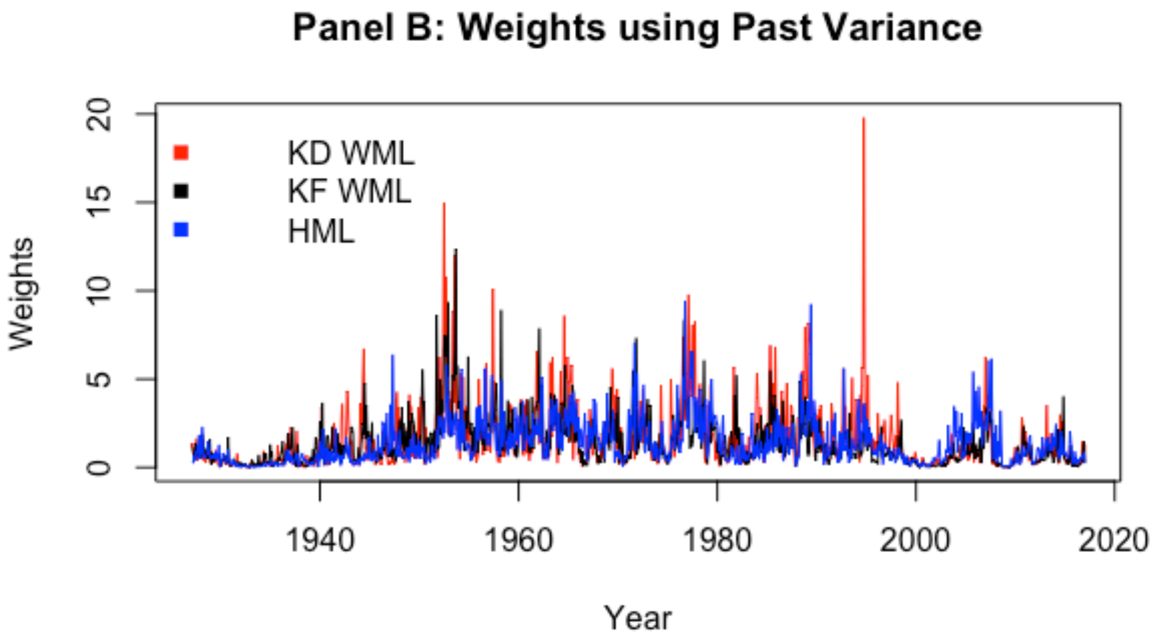


Fig 3: **Time series of weights used to scale the portfolios.**

Panel A shows the weights calculated using past realised variances and scaling with an unconditional standard deviation of 12%. Panel B shows weights calculated using past monthly variance and scaling such that the standard deviation of the managed portfolio equals the that of the managed portfolio.





Weights are calculated with realised variance as in formula (2 and 3) and we choose a target equals to the annualised volatility of 12% as did Barroso and Santa-Clara (2015). The annualised standard deviation for monthly returns is higher because of the autocorrelation of daily returns which makes it incomparable to those of other lower frequencies. This choice of a target is based on the assumption that the investor maintains the same risk exposure for the entire period which is very unlikely.[6]

The reason for volatility managing the momentum portfolio differs for both authors. Barroso and Santa-Clara (2015) manage the momentum factor in order to deal with its high excess kurtosis and the high negative skewness. They show by volatility managing momentum factor improves its skewness and its kurtosis reduces greatly which this is good for investors who like the excess return of the momentum strategy but dislikes its high negative skewness and excess kurtosis. They also show that since the crashes of the momentum factor can be predicted volatility managing momentum is highly beneficial.

Moreira and Muir (2016) on the other hand manage many other factors including market, size, value, investment, return on equity, carry and foreign exchange. They find that the volatility managed factors produce significant positive alphas in a univariate regression with the original factors with the exception of size which gives a negative alpha.

[6] We try different targets and find that the mean and standard deviation increase but its Sharpe ratio, kurtosis and skewness remain the same.

This goes against conventional wisdom in two ways. First, conventional wisdom suggests that investors should hold constant their investments for the investment horizon and secondly, by reducing exposure when volatility is high and increasing exposure when volatility is low indicates that the traditional risk-return story does not hold. That is past volatility predicts future volatility but does not predict future returns.

The two approaches produce identical results. Both improve the performance of the unmanaged portfolio. The Sharpe ratio of the managed momentum portfolio increases by about 80% and 100% for Ken Daniel and Kenneth French respectively and that of value increases by about 10%. This implies that volatility management helps to reduce risk (measured by the second moment of returns) while earning good returns.

There are also improvements in the kurtosis and skewness. The portfolios managed with the past realised variance reduces the negative skewness of momentum from -1.97 to -0.36 and kurtosis from 12.77 to 1.4.2. This is good news for investors who do not like the negative skewness and high excess kurtosis.

Comparing the results for the two volatility management approaches so far, we see that there is no clear winner. Each of the approaches has its strengths and weakness. The Sharpe ratio for each approach is similar. However, the realised variance approach has worse skewness compared to the variance approach. Both momentum portfolios have negative skewness (though greatly reduced) for the realised variance approach while the variance approach manages to change the skewness to positive. The opposite is true for kurtosis where the variance approach has a higher excess kurtosis.

Table 3: **Performance of volatility managed portfolios**

In Panel A, the managed portfolios are calculated using realised variance of the previous month. In Panel B, we show the results for portfolios managed using past variance. The mean, standard deviation and Sharpe ratio are annualised. The table reports statistics from the managed momentum (WML) portfolio from Ken Daniel (KD) and Kenneth French (KF), managed value (HML) as well the combo (COM) portfolio of value and the two momentum portfolios.

Portfolio	Maximum	Minimum	Mean	Standard deviation	Sharpe ratio	Kurtosis	Skewness
			Panel A: Managed with past realised variance				
WML^{σ}_{KD}	19.52	-20.17	18.46	17.37	1.06	1.42	-0.11
WML^{σ}_{KF}	20.05	-28.14	17.72	18.40	0.96	1.84	-0.36
HML^{σ}	36.22	-22.73	8.21	18.62	0.44	2.85	0.56
			Panel B: Managed with past variance				
WML^{σ}_{KD}	60.40	-58.37	32.43	29.88	1.08	7.99	1.00
WML^{σ}_{KF}	28.93	-35.09	16.20	16.39	0.99	8.68	0.74
HML^{σ}	22.69	-20.57	4.47	12.15	0.37	6.24	0.44

3.4 Modifications to volatility management

In calculating the target volatility in eqn (2) and (3), we use the variance of the entire sample. This indicates that we know the variance for the entire sample at the beginning of the sample. This is obviously not accurate since we do not know future returns for the portfolios when we are in the middle of the sample. This means we do not know variance of the entire sample until after the end of the sample. We are, therefore, using ex post information to calculate the target volatility. This is a potential source of bias that can affect the validity and practicality of our results[7]. We, therefore introduce two modifications to the volatility management approach that uses only past information and not present or future information. In both modifications, we suggest ways of calculating the target volatility such that it does not use ex post information.

In the first modification, we use the past cumulative variance instead of the sample variance. That is, we calculate variance cumulatively for the entire period and use that in calculating σ_{target}. The advantage of this modification is that only previous information is used since we use the cumulative variance as at the immediate prior month. One major disadvantage is that since the variance changes every month the σ_{target} also changes every month. This is affects its practicality. Investors may want to have stable risk exposure and not a varying exposure.

The second modification addresses the shortfalls of the first. We use a window of ten years to get the estimate for the target portfolio. That is, we calculate the target portfolio using information from the previous ten years and scale the returns of the next ten years with a target volatility that is equal to that of the previous ten years. This modification improves the first by

[7] There are other practicality issues such as transaction costs that are not addressed in this paper. Daniel and Moskowitz (2013) and Moreira and Muir (2015) address this issue and show that transaction cost is not a problem. They however do it for the managed portfolios in isolation and not the combo portfolios.

reducing the variations in the target. In fact, the target changes once in ten years compared to the first modification which changes every month. This stability in risk exposure makes this modification more practicable. One disadvantage of this modification is that the target is dependent on the market dynamics of the previous decade. Therefore, in the decades following severe crash decades will have less exposure because of the scares of the previous decade and vice versa.

Table 4: **Performance of modified managed portfolios**

The table shows the descriptive statistics of momentum and value strategies. Subscripts KD and KF represent the momentum strategy as created by Kent Daniel and Kenneth French respectively. Panel A shows the results of the first modification which uses information for all the months prior to the current month. Hence the target volatility changes every month. Panel B shows the results for the modification that information from the previous decade to manage the returns of the next decade and hence the target volatility changes once in ten years. Mean, standard deviation and Sharpe ratio are annualised in percentage terms.

Portfolio	Maximum	Minimum	Mean	Standard deviation	Sharpe ratio	Kurtosis	Skewness
Panel A: Managed with monthly varying target (c)							
WML_{KD}^{σ}	49.38	-74.92	21.29	23.00	0.93	22.68	-0.17
WML_{KF}^{σ}	22.48	-43.97	10.13	13.41	0.75	26.36	-1.59
HML^{σ}	50.50	-15.67	4.61	13.13	0.35	36.54	2.95
Panel B: Managed with decade varying (c)							
WML_{KD}^{σ}	67.57	-57.60	29.54	27.90	1.06	11.82	1.15
WML_{KF}^{σ}	59.82	-73.01	18.19	21.85	0.83	20.24	-0.63
HML^{σ}	16.70	-37.02	2.54	12.06	0.21	18.72	-1.21

Table 4 shows the results of using the two modifications to volatility management on the momentum and value portfolios. The Sharpe ratios are reduced when compared to the previous unmodified managed portfolios in Table 3. However, when compared to the Sharpe ratios of the unmanaged portfolios in Table 1, we see that the modified managed momentum portfolio is better. This is not the case for the value. The modified managed value portfolio has a worse Sharpe ratio of 0.35 compared to that of the unmanaged of 0.40. Therefore, using only past information to manage the returns of the value strategy does not provide any extra benefits than the unmanaged value portfolio which is a very important finding.

Also, one very important implication of the results is that using both modification, which uses only past information to managed the portfolios, provides no significant improvement to the kurtosis and in some cases, such as the value strategy the kurtosis is actually worse. This implies that the using ex post information in managing momentum as in Barroso and Santa-Clara (2016) & Moreira and Muir (2015) biases the results.

These two are very important observations because as we will see later in the next two sections, even though managing value in isolation provided no benefit, managing a portfolio that combines value and momentum provides extra benefits over and above the results of the average of the two separately managed portfolios and is also a very effective method of avoiding momentum crashes.

3.5 Combo Portfolio

One approach proposed to deal with the crashes of momentum is the combo portfolio. This was first introduced by Asness, Moskowitz and Pedersen (2013) who created a combo portfolio by combining momentum and value such that it takes a 50% position in momentum and a 50% position in value. Value and momentum have negative correlation which implies that they can be used as a hedge for each other. The correlation, however, does not provide a perfect hedge. For the sample period from 1927:01 to 2016:12, the correlation between value and momentum is about -0.41. This is consistent with the results of Asness, Moskowitz and Pedersen (2013). Nonetheless, the combo portfolio produces results that are better than momentum and value alone.

Table 5 provides a summary of the performance of the combo portfolio for the period 1927 - 2016. Looking at Kent Daniel's momentum and the combo portfolio created with value and Kent Daniel's momentum, the combo portfolio has a lower average return of 11.19 percentage points per year compared to that of momentum of 17.57. However, the risk characteristics are improved. There is a huge reduction in standard deviation for the combo portfolio as compared to the momentum and portfolio. The standard deviation for the combo portfolio is 13.95 which is lower that of momentum 29.88. As a result, the Sharpe ratio of the combo portfolio of 0.8 is significantly higher than that of momentum of 0.59.

We are, however, more interested in reducing the higher moments of momentum. We see improvements in the kurtosis and skewness as well. Kurtosis for the combo portfolio is 6.19 which is significantly lower than the 12.77 kurtosis of momentum. The left skewness is also reduced from -1.97 to -1.09. This reduces the crash risk of momentum. Fig 2 shows the density function of momentum and combo portfolios. Momentum has a very long left tail while the combo portfolio has a much-reduced left tail.

The combo portfolio performs very well in the crash decades as shown in Fig 3. In the 1930, the combo portfolio finishes the decade 12% up compared to momentum strategy which loses 94%. In the 2000s the combo portfolio finishes 156% up compared to momentum which lost 51%. The benefit of combining the portfolio is especially seen in the 2000s. As seen in Fig 3: panel B, the combo portfolio manages to stay above both momentum and value for significant part of that period.

Table 5: **Performance of combo portfolio**

This table shows the descriptive statistics of the combo portfolio. The combo portfolio formed by combining value and momentum. Specifically, it is a 50-50 combination of value and momentum. The first row is the combo portfolio of value and the Kent Daniel's momentum portfolio and the second row is combo formed with Kenneth French's momentum portfolio. All statistics are calculated with monthly data. Mean, standard deviation, Sharpe ratio are annualized.

Portfolio	Maximum	Minimum	Mean	Standard deviation	Sharpe ratio	Kurtosis	Skewness
COM_{KD}	20.17	-27.04	11.19	13.95	0.80	6.19	-1.09
COM_{KF}	12.71	-14.98	6.37	7.93	0.80	6.21	-0.88

Fig 2: **Density of momentum (WML) and Combo**

The figure shows the density distribution of the returns of momentum. Panel A plots the density for Kenneth French's momentum (KF WML) and its combination with the value (KF COM). Panel B shows the plot for Kent Daniel's momentum (KD WML) and its combination with value (KD COM). The sample period is from 1927:01 to 2011:12

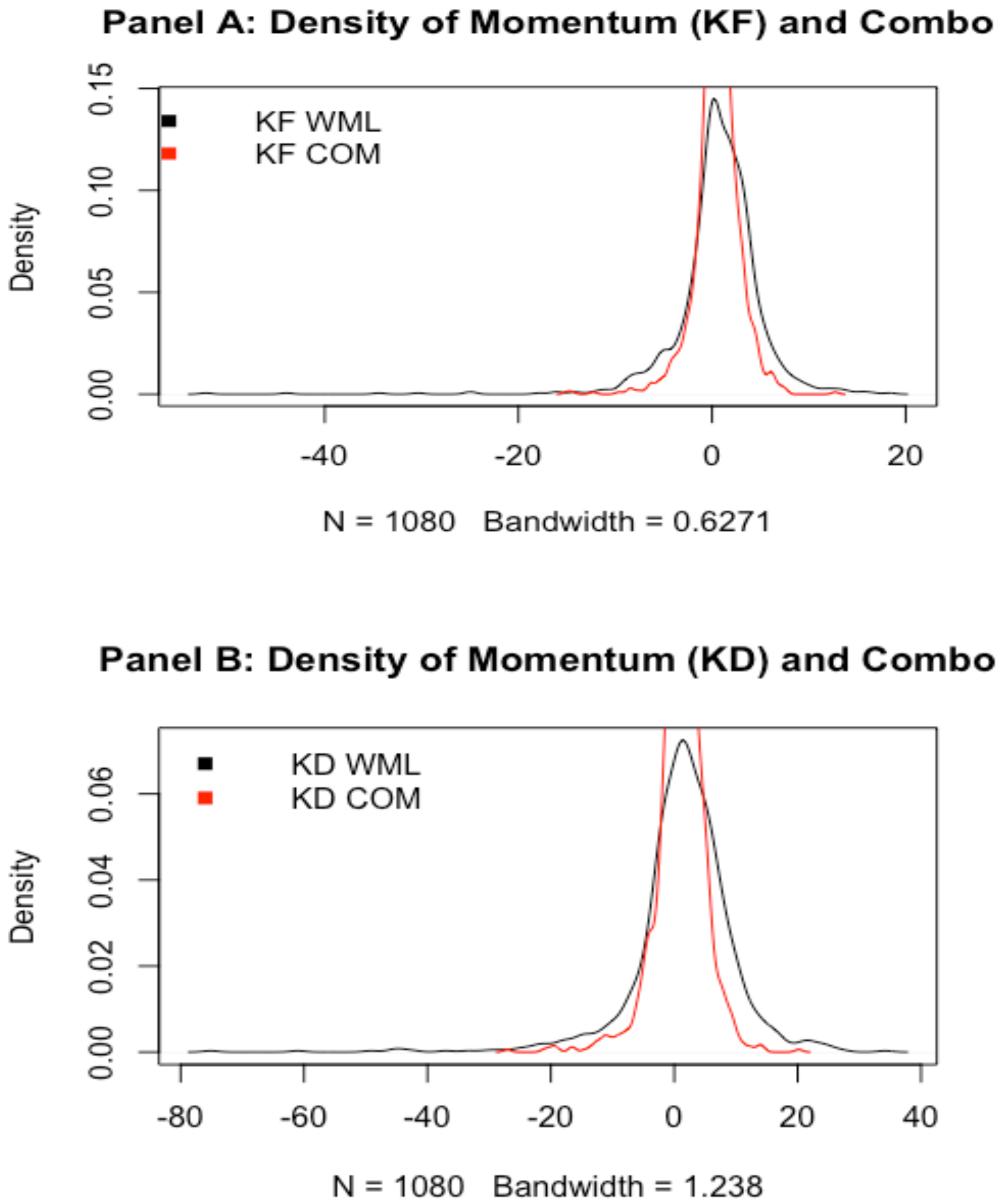
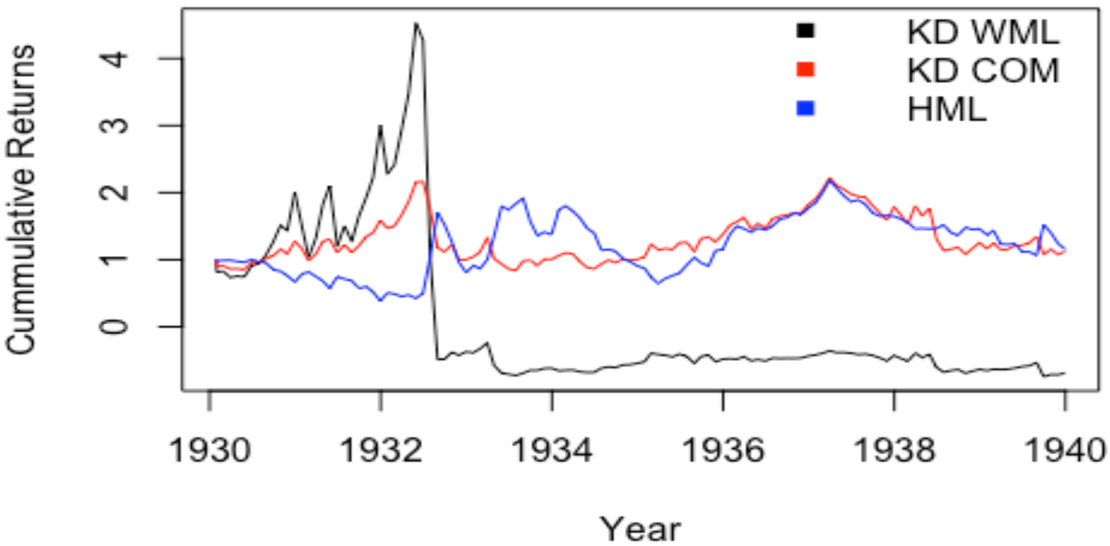


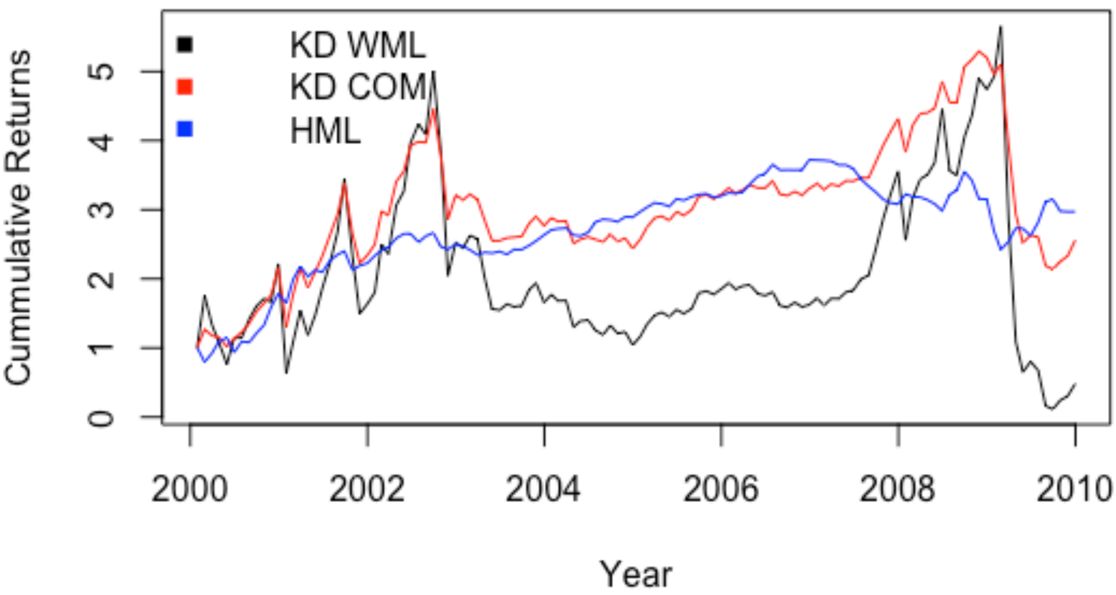
Fig 3: **The performance of combo and momentum portfolios in the crash decades**.

The figure shows a comparison of the cumulative returns of momentum (KD WML), combo (KD COM) and value (HML) returns for the two most turbulent momentum decades: 1930s and 2000s

Panel A: Cummulative Retruns - 1930:01 to 1939:12



Panel B: Cummulative Retruns - 2000:01 to 2009:12



3.6 Modified volatility managed combo portfolio

In earlier literature, volatility management has been applied to the strategies – Momentum, value, size, etc. – in isolation. We apply volatility management to the combo portfolio to see its effects. Specifically, we apply the modifications of volatility management we introduced in section 3.4 to the combo portfolio to see if it performs better than the modified volatility managed momentum portfolio.

We check for two main things. First, does volatility managed combo strategy further improve the risk characteristics such as standard deviation, skewness and kurtosis? Secondly, we check if the benefits of volatility managed combo portfolio (prior managed) are better that the average benefits of the volatility managed value and momentum strategies (post managed). The results are show in table 6 below.

Table 6: **Performance of modified volatility managed combo portfolio.**

This table shows the descriptive statistics of the modified volatility managed portfolio. The combo portfolio is a 50-50 combination of the returns of value and momentum strategies. Subscripts KD and KF represents the combo portfolio created with momentum strategies as created by Kent Daniel and Kenneth French respectively. Panel A shows the results for the modification which uses information for all months prior to the current month. Panel B shows the results for the modification which uses information from the previous decade to manage the returns of the next decade.

Portfolio	Maximum	Minimum	Mean	Standard deviation	Sharpe ratio	Kurtosis	Skewness
			Panel A: Managed with monthly varying "C"				
COM_{KD}^{σ}	29.75	-25.78	19.92	17.64	1.13	5.50	0.92
COM_{KF}^{σ}	21.88	-15.30	12.31	11.39	1.08	5.76	1.03
			Panel B: Managed with decade varying "C"				
COM_{KD}^{σ}	21.53	-24.00	15.72	13.88	1.13	6.05	0.50
COM_{KF}^{σ}	13.47	-13.14	10.39	8.85	1.17	5.03	0.66

We compare the results in table 6 to the results in table 4. We see that managing the risk of the combo portfolio improves the risk return trade-off and also improves the higher moments better than the managed momentum portfolio. Comparing the combo portfolio strategy created with the Kent Daniel's momentum portfolio and its corresponding momentum portfolio, the Sharpe ratio of the modified managed combo portfolio is 1.13 which is higher than that of the modified managed momentum of 0.93. Skewness and Kurtosis are also significantly improved. The managed momentum has excess kurtosis and skewness of 22.68 and -0.17 respectively compared to that of the managed combo of 5.50 and 0.92 respectively.

From table 4, the average of the Sharpe ratio of volatility managed value and momentum is 0.64 which is lower than the Sharpe ratio of the managed combo portfolio. This indicates that the benefits of the combo portfolio are not derived from the average benefit of value and momentum.

The main point of our findings is that the using only past information to volatility manage the momentum strategy is not effective because it does not improve the kurtosis. However, the managing the combo portfolio achieves the goal of improving the kurtosis and skewness and also increases the Sharpe ratio significantly. In the next section, we address the question of why volatility management works.

4 Risk Return Dynamics

It is obvious why the combination of value and momentum has better Sharpe ratio, skewness and kurtosis that the momentum factor alone. The negative correlation of the two provides a way to avoid part of the large plummets in returns characterised by crashes. Therefore, the value portfolio serves as a hedge to momentum which increases the benefits of the risk-return trade-off.

The more fundamental question is why does volatility management work. We showed informally that a comparison of Fig 4 and Fig 5 indicated that the volatility managed portfolios decrease risk exposure when the volatility is high as evident in the periods that experience crash. This is contradictory to the return predictability literature that suggest high risk predicts high return.

Moreira and Muir (2016) reconcile this contradiction by showing that the frequency of return and volatility behave differently. They show that volatility reverses quickly after a hike whereas expected returns are more persistent. First, we show that the improvements in the Sharpe ratio and higher moments of the combo portfolio are backed by significant positive alphas even after controlling for the Fama-French three risk factors, the momentum factor and the unmanaged combo portfolio. Table 6 gives the results.

The managed combo portfolio is therefore not loading on any of the known risk factors. The risk – return dynamics should therefore help explain why volatility managing works. One major insight is that the relationship between variance and return, though direct, is not proportional. An increase or decrease in volatility does not lead to the same proportional change in returns. Therefore, volatility does not predict returns. To show this, we run a regression of the unmanaged combo portfolio on both its one month lagged volatility and the one month lagged volatility of the market. The results are shown in table 7.

Table 6
Volatility Managed Combo portfolio alpha
We run time-series regression of the managed combo portfolio on the Fama-French three risk factors, momentum factor and the unmanaged combo portfolio $COMKD^{\sigma}{}_{t} = \alpha + \beta MKT_t + \gamma SMB_t + \lambda HML_t + \delta WML_t + \phi COMKD_t + \varepsilon_t$. The data is monthly and the sample is 1927 – 2016. Reported in brackets are the T statistics of the coefficients which are calculated with standard errors that are adjusted for heteroscedasticity.

alpha COMKD	MKT	SMB	HML	WML	
1.41 (11.45)	-0.05 (-2.03)				
1.42 (11.52)		-0.18 (-4.12)			
1.43 (11.57)	-0.01 (-0.58)	-0.17 (-3.86)			
1.34 (11.04)			0.10 (2.47)		
1.39 (11.41)	-0.03 (-1.30)	-0.18 (-3.94)	0.13 (3.37)		
0.23 (9.94)				1.04 (9.37)	
0.78 (7.42)	0.09 (4.05)	-0.11 (-3.19)	0.34 (8.09)	0.29 (13.03)	
0.85 (8.26)					0.57 (12.88)
0.78 (7.42)	0.09 (4.05)	-0.11 (-3.19)	– –	-0.05 (-1.34)	0.68 (8.09)

Table 7
Risk return trade-off
We regress returns at time t + 1 for each factor on the volatily at time t. The regression gives us a sense of the risk return relation. The data is monthly and the sample is from 1927 to 2016. T statistics are in parenthesis and are calculated using standard errors that are adjusted for heteroscedasticity.

	COMKD
σ_{COMKD}	-0.593
	(0.75)
σ_{MKT}	-0.004
	(1.07)
_cons	0.017
	(5.34)***
R^2	0.01
N	1,079

We see that the coefficients are negative but not significant which indicates that there is no clear relationship between the volatility and its future expected return[8]. This explains why the strategy works. Since the volatility does not predict an increase in returns, the increase volatility implies bad risk return trade-off which makes reducing the exposure optimal.

[8] We run regressions of the returns and more lags of the volatility the combo returns and we find that it takes up to the sixth lag to show significant coefficients. However, the coefficients become insignificant again after ninth lag.

5 Robustness checks

As we saw in fig 4 and 5, the main benefit of volatility management is achieved in turbulent times when volatility is high. This raises the question whether it is better to only managed the portfolio when volatility is high and hold when volatility is low. We have two major such periods in our sample: the first in 1932 and the second in 2009. Therefore, we check if the benefits of volatility management are entirely driven by these two events.

To evaluate this, we analyse the performance of the combo portfolio and volatility-managed combo portfolio in different subsamples. First, we split the sample into two equal parts. This is to check of the results are entirely driven by one of the crash periods. Since, both halves include a major crash, we use the entire sample without the years in which the two major crashes occur. Finally, we look at a period that has no crashes and is continuous. This is the period from 1945:01 to 1999:12. This is the period after the 1932 crash and before the dot com bubble of the 2000 and the financial crisis of 2008 to 2009.

In all samples, risk management reduces left skewness. In all but the benign sample, risk management reduces excess kurtosis. Excess kurtosis reduces from 4.85 to 4.54 in the first half and from 6.13 to 391 in the second half. However, it increases from 2.50 to 5.20 in the benign sample. Skewness increases from negative to positive in all samples. It is therefore not clear that volatility management has the same effect of reducing high moment risk since kurtosis increases in the benign sample that has no known crash but reduces in the other sample.

Sharpe ratio on the other hand increases in all samples though the increases in the benign sample is quite small. The Sharpe ratio increases by 0.26 in the first half, 0.45 in the second half and 0.22 in the no crash sample. In the benign sample the sharpen ratio increased by only 0.04.

Table 8

Performance of plain combo portfolio(COM) and scaled combo portfolio ($COMKD^{\sigma}$) in different subsamples

The first half of the sample is from 1927:01 to 1971:12. The second is from 1972:01 to 2016:12. The no-crash is from 1927:01 to 2016:12, excluding the years of 1932 and 2009. The benign sample is from 1945:01 to 1999:12. The Sharpe ratio, standard deviation and the mean returns are annualized.

Statistic	First half		Second half		No-crash		Benign	
	COM	$COMKD^{\sigma}$	COM	$COMKD^{\sigma}$	COM	$COMKD^{\sigma}$	COM	$COMKD^{\sigma}$
Maximum	10.78	29.75	20.16	20.57	20.17	29.75	9.60	29.75
Minimum	-21.05	-25.76	-27.04	-14.67	-27.04	-25.78	-14.39	-25.78
Mean	9.86	21.19	12.51	17.63	12.23	20.39	13.60	25.38
Standard deviation	12.25	20.65	15.47	13.99	13.17	17.76	10.42	18.76
Shape ratio	0.81	1.07	0.81	1.26	0.93	1.15	1.31	1.35
Skewness	-0.97	0.72	-1.14	1.21	-0.79	0.90	-0.63	0.92
Kurtosis	4.85	4.54	6.13	3.91	5.72	5.41	2.50	5.20

It is clear the improvements are not entirely driven by the rare events in 1932 and 2009. However, it is not certain that volatility management offers benefits in all subsample.

One question to address is the length of time volatility management works. Moreira and Muir (2016) propose that volatility management is for long term investors. We look if the short-term investors can also benefit from volatility management. We compare the Sharpe ratios of the plain combo and managed combo for ten years periods. We use the modification to the volatility management that uses the information of the previous ten years to manage the returns of the next ten years.

In all but one of the periods, risk management improves Sharpe ratio. The periods that have the highest improvements are those period in which there were major crashes. From 2007 to 2016, the Sharpe ratio increased by 1824% and from 1937 to 1946, it increased by 110%. It is clear that volatility management is most beneficial when the market is in bad times. We also see less benefits in some periods and even a reduction in the Sharpe ratio in 1957 to 1966 of -0.53%.

It is however important to have other issues such as transaction cost – which is not addressed in the paper – in mind. In the periods where the benefits of volatility management are not large can be worse if transaction costs are taken into consideration.

In general, volatility management is beneficial to both long term and short-term investors[9]. However, since the benefits are not consistent in all periods it would be most appropriate if short-term investors can predict if managing the volatility in the period is worthwhile.

[9] We also check for a shorter period of 5 years and we find similar results as in ten years.

Table 9

Comparison of Shape ratios of plain and volatility managed combo portfolios

The sample is divided into sub periods of ten years. Reported are the Sharpe ratio of unmanaged combo portfolio (COMKD) and volatility managed combo portfolio ($COMKD^{\sigma}$). Change is the percentage change of the Sharpe ratios. The Sharpe ratio is annualised in percentage terms.

PERIOD	COMKD	$COMKD^{\sigma}$	CHANGE
1937 – 1946	0.44	0.92	110%
1947 – 1956	1.24	1.27	2.71%
1957 – 1966	1.52	1.51	-0.53%
1967 – 1976	1.19	1.90	59.69%
1977 – 1986	1.45	1.60	9.77%
1987 – 1996	1.34	1.79	33.34%
1997 – 2006	0.73	1.18	61.59%
2007 – 2016	0.04	0.74	1824%

6 Conclusion

In this thesis, we first replicate the volatility management methodologies of Barroso & Santa-Clara (2015) and Moreira and Muir (2016). We point out that some of the details of the methodologies are a potential source of bias. One main problem with those methodologies is that they use ex-post information in their calculations. We implemented two proposed modifications to volatility management to make it implementable such that it uses only past information and find that volatility management methodologies do not provide the benefits as promise. We find that though, there are improvements in the Sharpe ratio and skewness, the kurtosis of the modified managed momentum which is 22.68 is greater than that of the unmanaged momentum of 12.77. Therefore, volatility management in real time does not eliminate the long tails of momentum returns.

We also introduce the combo portfolio by Asness, Pedersen and Moskowitz (2013) which is a 50-50 combination of the returns of momentum and value strategies. We show the combo portfolio in itself improves all the risk factors and hence can serve a hedge against momentum crashes. This is a result of the negative correlation between value and momentum.

Furthermore, we apply our modifications of volatility management to the combo portfolio and find that the it performs better than the unmanaged combo portfolio and the modified managed value and momentum portfolio. Kurtosis and skewness are reduced as well as a significant reduction in standard deviation leading to a higher Sharpe ratio. One fascinating findings in our results is that the Sharpe ratio of the modified managed combo portfolio is larger than the average Sharpe ratios of the modified managed momentum and value portfolios.

This indicates that the benefits of volatility managing the combo portfolio is not entirely derived from the average benefits of managed value and momentum portfolios. Therefore, we propose a combination of the volatility management approach and the combo portfolio is more effective in dealing with momentum crashes.

We also find the method can also be used by investors with a shorter horizon such as ten or five years but should be used with caution. The benefits are not consistent in all the time periods. In some periods, the method performs worse or indifferent compared to the unmanaged portfolio. There is a dilemma for short term investors since they do not know if they should manage or buy and hold.

We know that managing works best when volatility is high and we therefore surmise that we can predict if managing would be beneficial or not. We, therefore, recommend for further studies, a way for investors to predict the performance of the managing the portfolio since we know that the approach works best when volatility is high. Also, having a static 50-50 proportion of value and momentum may not be optimal. We recommend further studies that develops a method that dynamically adjusts the proportion according to some market conditions to improve the results.

As an aside, we find that the differences in the momentum portfolios as created by Kenneth French or Kent Daniel do not affect our conclusions.

7 Appendix

A. Portfolio names and their meanings

This table shows that meaning of all the portfolio names used in this paper.

Portfolio names	Meaning
MKT/RMRF	Market portfolio: A value weighted portfolio of all stocks in the USA market (NYSE, AMEX and NASDAQ).
HML	Value portfolio: A strategy that buy firms with the highest book to market ratio and sells firms with the lowest book to market ratio.
WML_{KD}	Kent Daniel's momentum. A strategy that buys winners and sells losers as formed by Kent Daniel.
WML_{KD}	Kenneth French's momentum. A strategy that buys winners and sells losers as formed by Kenneth French.
COM_{KD}^{σ}	Kent Daniel's volatility managed combo portfolio: A volatility managed portfolio of the combination of value and momentum portfolio as created by Kent Daniel.
COM_{KF}^{σ}	Kenneth French's volatility managed combo portfolio: A volatility managed portfolio of the combination of value and momentum portfolio as created by Kenneth Daniel.

References

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006b. The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Asness, C., 2011. Momentum in Japan: the exception that proves the rule. *Journal of Portfolio Management,* 37, 67–75.

Asness, C., Liew, J., Stevens, R., 1997. Parallels between the cross-sectional predictability of stock and country returns. *Journal of Portfolio Management* 23, 79–87.

Asness, C., Moskowitz, T. J., & Pedersen, L. H., 2013. Value and Momentum Everywhere. *The Journal of Finance, 68*(3), pp. 929-985.

Asness, Cliff, Antti Ilmanen, Ronen Israel, and Tobias J Moskowitz, 2013, Investing with style: The case for style investing, Working paper, AQR Capital Management.

Asness, C., Frazzini, A., 2013. The devil in HML´s details. The Journal of Portfolio Management, 39(4), 49-68.

Asness, C. S., Frazzini, A., Isreal, R., & Moskowitz, T. J. (2014). Fact, Fiction and Momentum Investing. The Journal of Portfolio Management, 40(5), pp. 75-92.

Barroso, P., & Santa-Clara, P., 2015. Momentum has its moments. *Journal of Financial Economics, 116*(1), pp. 111-120.

Bollerslev, Tim, and Viktor Todorov, 2011, Tails, fears, and risk premia, *Journal of Finance* 66, 2165–2211.

Carhart, M. M., 1997. On Presistence in Mutual Fund Performance. *Journal of Finance, 52*(1), pp. 57-92.

Cooper, M., Gutierrez, R., Hameed, A., 2004. Market states and momentum. *Journal of Finance* 59, 1345–1366.

Daniel, K., & Moskowitz, T. J., 2013. Momentum Crashes. *Journal of Financial Economics, 122*(2), pp. 221-247.

Frazzini, A. and Pedersen, L.H., 2014, Trading costs of asset procing anomalies. *Working paper.*

Fama, E., French, K., 1992. The cross section of expected stock returns. *Journal of Finance* 47, 427–465.

Fama, E., French, K., 1996, Multifactor explanations of asset pricing anomalies, *Journal of Finance* 51, 55–84.

Fama, E., French, K., 2012. Size, value, and momentum in international stock returns. *Journal of Financial Economics* 105, 457–472.

Geczy, Christopher, and Mikhail Samonov, 2013, 212 years of price momentum (the world's longest backtest: 1801-2012), Octoquant working paper and SSRN # 2292544.

Glosten, Lawrence R., Ravi Jagannathan, and David Runkle, 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks, *Journal of Finance* 48, 1779–1801.

Grundy, B., Martin, J., 2001. Understanding the nature of the risks and the source of the rewards to momentum investing. *Review of Financial Studies* 14, 29–78.

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

Jegadeesh, N., & Titman, S. (2001). Profitability of Momentum Strategies: An Evaluation of Alternative Explanations. *The Journal of Finance, 56*(2), pp. 699-720.

Kothari, S.P., and Jay Shanken, 1992, Stock return variation and expected dividends, *Journal of Financial Economics* 31, 177–210.

Lesmond, D., Schill, M., Zhou, C., 2004. The illusory nature of momentum profits. *Journal of Financial Economics* 71, 349–380.

Moreira, Alan and Muir, Tyler, 2016. Volatility-Managed Portfolios. *Journal of Finance, Forthcoming*. Available at http://dx.doi.org/10.2139/ssrn.2659431

Ozoguz, Arzu, 2009. Good Times or Bad Times? Investors' Uncertainty and Stock Returns. *The Review of Financial Studies*, Vol. 22, Issue 11, pp. 4377-4422, 2009. Available at SSRN: https://ssrn.com/abstract=1519262 or http://dx.doi.org/hhn097

Rouwenhorst, K. G., 1998. International Momentum Strategies. *The Journal of Finance, 53*(1), pp. 267-284.