Winners-Minus-adjusted-Losers: Optimizing Momentum Payoffs

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Presented to:

Professor Paulo M. M. Rodrigues

Presented by:

Jan Florens Keller

Student-ID: 31748

jkeller@novasbe.pt

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Jan Keller

Jan Florens Keller

Abstract

While being considered one of the most pervasive and return-promising anomalies across various asset classes Momentum has strained investors with extreme crashes in the past. A proposed ex-ante implementable strategy based on key-findings in the available literature about the characteristics, patterns and predictability of Momentum crashes more than doubles the Sharpe ratio of conventional Momentum. More importantly it significantly reduces the crash risk by adjusting the exposure to those stocks being mostly responsible for these crashes. The strategy yields positive results during a period from 1964 to 2018 and has been tested in various subsamples.

Keywords: Momentum, Crash Risk, Market Anomalies

1. Introduction

Since the emergence of Exchange Traded Funds (ETFs) in the early 1990s, such passively managed investment products have reached almost $4.5 trillion in global Assets under Management (AuM) by 2017, according to EY, a consulting firm (EY, 2017). This growth has been supported by persuasive features of these passively managed funds such as substantially lower management fees than actively managed products, easily-accessible diversification through exposure to a wide range of markets and high tradability. While conventional ETFs merely replicate an index, usually by weighting components based on their market capitalization, more sophisticated alternatives, so-called “Strategic-” or “Smart-Beta” ETFs have become increasingly popular. These products can be described as compound between active and passive asset management, following a passive strategy but optimizing asset allocation based on one or more factors. As such, they aim at capturing additional returns and outperforming a chosen benchmark, as opposed to index-replicating ETFs which merely track the benchmark, trying to minimize the tracking-error. Strategic-Beta ETFs can be attributed to “rules-based” or “attribute-based” investment, meaning that instead of chasing returns, e.g. through stock picking by a portfolio manager, asset allocation is conducted based on one or more factors that reflect a stock’s, bond’s or other asset’s attributes, indicating above-average expected returns (i.Shares.com, 2018).

One of the most pervasive factors in literature and practice is Momentum, which can be described as a “bet on past returns predicting the cross section of future returns, typically implemented by buying past winners and selling past losers” (Daniel, Moskowitz, 2016, p. 221). Positive abnormal returns of Momentum strategies in US stocks have first been shown by Jegadeesh and Titman (1993) from 1965 to 1989, and have since been proven to exist in many other asset classes and markets around the globe (e.g. Moskowitz and Grinblatt, 1999; Barroso and Santa Clara, 2015). However, while Momentum outperforms the benchmark in times of economic growth, crashes of the strategy can be disastrous for investors wiping out decades of growth, as in 2009 when the winners-minus-losers (WML) approach experienced losses of -73.24% within three months (Barroso and Santa Clara 2015). Various research has been conducted to investigate the causes for such severe Momentum crashes and ways to predict these to ultimately adjust the strategy to achieve more stable returns with less risk. Daniel and Moskowitz (2016) show that Momentum crashes tend to occur when the market rebounds after a longer period of negative returns, being accompanied by ex-ante measures of high volatility and high concurrent market returns. Moreover, they show that especially the losers are responsible for the severity of Momentum crashes as they cause the strategy to have a highly negative beta after a significant market decline. The latter is an intuitive finding since a WML strategy is long past winners, in a bear market usually low-beta stocks, and short past loser, in a bear market usually high-beta stocks. Given that during a crisis the winner portfolio is usually composed of counter-cyclical or defensive firms (low-beta) and the loser portfolio of highly-levered firms (high-beta) (Daniel and Moskowitz, 2016), in case of a quick market rebound, a Momentum strategy crashes. Barroso and Santa-Clara (2015) argue that the risk of Momentum strategies is highly variable and predictable by the realized variances of daily returns. Consistently, Stivers and Sun (2010) find that Momentum premium is low when market volatility is high and vice-versa. Thus, conditional Momentum strategies which reduce exposure to the WML approach during such times have been shown to exhibit superior performance to unconditional Momentum strategies (e.g. Daniel, Jagannathan and Kim, 2012; Barroso and Santa-Clara, 2015).

This paper aims at analyzing whether bringing together key insights in the literature about the characteristics, patterns and predictability of Momentum crashes enables investors to manage their investment in a way that allows them to benefit from the strategy's convincing upside potential, while minimizing exposure to crash-risk. It is structured as follows: Section 2 analyses existing research on the performance and risk of Momentum strategies and possible implications for investors. Section 3 introduces and analyses the proposed WMaL strategy based on insights of Section 2. Section 4 discusses the findings of the previous section, their robustness, potential weaknesses and applicability for real-life investors. Section 5 presents the conclusions to be drawn.

2. Advanced Momentum Strategies

In this section, existing research on Momentum and how the strategy's risk-return profile can be improved are introduced and analyzed. This serves as a preliminary step to understand the in-depth characteristics of Momentum to then investigate further return-optimization potential for investors in the next section.

2.1 Risk-managed Momentum

Various research has been conducted on the predictability of Momentum crashes linked to market volatility (e.g. Barroso and Santa-Clara, 2015; Moreira and Muir, 2016). Barroso and Santa-Clara (2015) propose a method to optimize Momentum strategies by measuring their risk, based on the realized variance of daily returns as a forecast of future volatility. Based on the insight that Momentum tends to perform poorly in high-risk episodes, Barroso and Santa-Clara (2015) suggest scaling the portfolio to constant volatility by adjusting the investor's exposure to the WML strategy, investing more in times of low predicted volatility and vice-versa. The aim of the proposed strategy is to reduce the crash-risk of an unadjusted Momentum strategy, being reflected by a fat left tail, i.e. a high excess kurtosis of 18.24 and a negative skewness of -2.47 (Daniel and Moskowitz, 2016). An explanation of this high crash risk is the strategy's time-varying exposure to market risk (Barroso and Santa Clara, 2015) measured by beta. This is intuitive since, as Grundy and Martin (2001) point out, after a downturn of the market a WML strategy naturally tends to be short high-beta stocks (recent losers) and long low-beta stocks (recent winners), resulting in poor performance when the market recovers after a crash. The potentially disastrous effect of naïve WML strategies during market recoveries could be observed from March to May of 2009, when the past-loser's decile rose by 163% and the past-winner's decile by only 8% Daniel and Moskowitz (2016). Such shocks can have a devastative effect on the long-run performance of the strategy, making it unattractive for long-term passive investors. Barroso and Santa-Clara (2015) further investigate the time-varying risk of Momentum based on ex-ante available data to show a potential reason for the above-mentioned unattractive characteristics. They show that an auto-regression of monthly realized variances of the daily returns of the portfolio's components yields an out-of-sample (OOS) R-squared of 57.82%, indicating strong predictability. This implies that more than half of the risk of the considered WML strategy is predictable, thus form a basis for managing this risk and optimizing returns. Barroso and Santa-Clara (2015) forecast the variance as follows:

(1) $$\hat{\sigma}^2_{WML,t} = 21 \sum_{j=0}^{125} r^2_{WML,d_{t-1}-j} / 126$$

where $\hat{\sigma}^2_{WML,t}$ is the WML variance forecast for month t, $\{r_{WML,d}\}_{d=1}^{D}$ are the daily Momentum returns and $\{d_t\}_{t=1}^{T}$ the time series of the dates of the last trading session of each month. Subsequently the strategy is scaled as follows to adjust for constant volatility:

(2) $$r_{WML^*,t} = \frac{\sigma_{target}}{\hat{\sigma}_t} r_{WML,t}$$

where $r_{WML,t}$ is the monthly return of unscaled Momentum, $r_{WML^*,t}$ is the monthly return of scaled Momentum and σ_{target} is the target level of volatility. Thus, instead of having a constant weight of one in the short and the long leg, the strategy invests more in times when the predicted volatility ($\hat{\sigma}_t$) is low and vice-versa. Since WML in a frictionless market is a self-financing strategy it can here be scaled without problem. The proposed strategy by Barroso and Santa-Clara (2015) with a target volatility of 12% p.a. has been shown to provide the investor with substantial economic gains, almost doubling the Sharpe Ratio from 0.53 to 0.97 and improving the higher-order moments by drastically reducing excess kurtosis (from

18.24 to 2.68) and left-skewness (from -2.47 to -0.42) as compared to unscaled Momentum, indicating a way to significantly reduce crash risk.

2.2 Dynamic Momentum Strategy

In a similar approach, based on the intuitive finding that the poor performance of Momentum strategies during rebounds after crises can be explained by their natural exposure to market risk (i.e. high-beta and low-beta stocks), Daniel and Moskowitz (2016) further investigate ways to predict Momentum crashes. They find that especially the behavior of the losers in the WML portfolio is responsible for the dimension of the observed crashes. To assess to what extent these crashes are predictable, Daniel and Moskowitz (2016) scrutinize the effect of time-varying conditional betas and the implied option-like payoffs of the loser portfolio. Particularly the beta of the Momentum portfolio's loser decile occasionally shoots up in volatile periods. While during the market rebounds after the Great Depression in the 1930's and the crisis of 2008-2009 the beta of the winner-decile peaks at around 2, the loser decile's beta reaches levels of up to 5 (Appendix 1), indicating that the latter are much more sensitive to market recovery and are drivers of the poor Momentum performance after bear markets. Given that crash periods usually exhibit sudden and substantial market upswings, this finding appears to be a logical explanation for the poor performance of Momentum strategies in such situations, which are short losers and long winners (Daniel and Moskowitz, 2016). By investigating the effect of time-varying betas on the WML strategy's mean return, Daniel and Moskowitz (2016) argue that the strategy's payoffs in bear markets effectively resemble those of a written Call option on the market, meaning the strategy gains a little when the market falls but loses a lot when the market rises. This is shown by Daniel and Moskowitz (2016) through the fact that the up-market beta of the WML loser-portfolio in bear markets is more than double the down-market beta (-1.796 vs. -0.742). Thus, a portfolio which is short these stocks gains little when the market drops, but loses heavily if the market jumps up. These facts imply that a Momentum strategy will have a significant negative market exposure after bear markets, just at the time when the market rebounds, leading to low expected returns of the WML portfolio (Daniel and Moskowitz, 2016). Based on these insights about the forecastability of Momentum payoffs and the fact that the strategy's volatility is predictable itself (e.g. Barroso and Santa-Clara, 2015; Moreira and Muir, 2016), Daniel and Moskowitz (2016) propose what they call a "Dynamic" Momentum strategy which adjusts the weight on the Momentum strategy based on its forecasted mean return and variance, maximizing its Sharpe Ratio. Following this approach, the optimal weight invested in the risky asset (i.e. the WML portfolio) at time t-1 is:

(3) $$w^*_{t-1} = \frac{1}{2\lambda}\frac{\mu_{t-1}}{\sigma^2_{t-1}}$$

where μ_{t-1} is the conditional expected return on the zero-investment WML portfolio over the next month, σ^2_{t-1} is the conditional variance of the WML portfolio over the next month and λ is a constant scalar which controls the unconditional risk and return of the dynamic portfolio, i.e. to scale annualized volatility to a target level. To forecast the expected return, Daniel and Moskowitz (2016) use a fitted regression over the previous six months on the interaction between a bear market indicator and the market variance. The volatility is forecasted by a linear combination of the standard deviation of the previous 126 daily returns and a volatility-forecast based on a GARCH model. The strategy's return in period t-1 is then simply given by

(4) $$r_{WML^*,t-1} = w^*_{t-1}\, r_{WML,t-1}$$

where $r_{WML^*,t-1}$ is the return of the scaled Momentum in t-1, w^*_{t-1} is the derived optimal weight invested in Momentum and $r_{WML,t-1}$ is the return of the unscaled Momentum in t-1.

The proposed Dynamic Momentum strategy by Daniel and Moskowitz (2016) is shown to significantly outperform both, a static WML approach and constant volatility approach as suggested by Barroso and Santa-Clara (2015). For a period from 1927:03 to 2013:03 and an annualized volatility scaled to 19%, the Dynamic strategy provides a Sharpe Ratio of 1.19 as compared to 1.02 of a constant volatility approach and 0.59 of a static WML strategy. This however comes at the expense of higher trading costs, as the Dynamic strategy's weights are 3.6 times more volatile than the constant-volatility weights for the considered time horizon (Daniel and Moskowitz, 2016). Thus, it is questionable whether after accounting for these additional costs the strategy still provides superior performance to an investor over the easily-implementable volatility-timing strategy. Nevertheless, it can be noted that in addition to the benefits provided through the forecastability of WML volatility, the predictability of Momentum premium as investigated by Daniel and Moskowitz (2016) provides further potential for optimizing Momentum strategies.

2.3 Factor Momentum

The above considered approaches move assets out of the WML strategy if crashes appear likely or expected returns are low. However recent studies have shown complements to Momentum strategies, which have provided investors with positive returns during times when Momentum crashed, superior to simply reducing overall invested assets from time to time.

Arnott at al. (2018) investigate potential benefits for investors from capturing so-called *factor* Momentum, which refers to WML strategies investing in the cross-section of different factor portfolios rather than of a portfolio consisting of stocks or other assets. While industries have been shown to exhibit Momentum-like stock returns (Moskowitz and Grinblatt, 1999), Arnott et al. (2018) show that this stems from differences in factor loadings of respective industries. They thus argue that industry returns are linear combinations of factor returns hence implying that if a combination of factors exhibits Momentum, the factors themselves exhibit Momentum. Their research shows that a strategy, which buys factor-portfolios with high recent returns and sells portfolios with low recent returns generates significant alpha. To show that industry Momentum stems from factor Momentum, Arnott et al. (2018) construct industry-neutral factor portfolios and show that a WML strategy based on these portfolios earns an average return of 7.5% with a t-value of 5.84. Moreover, past returns of unadjusted factors contain no predictability of future returns once controlled for Momentum in industry-adjusted factors, supporting the hypothesis that industry Momentum stems from factor Momentum. Arnott et al. (2018) argue that Momentum in industry-neutral factors fully subsumes industry Momentum by showing that after controlling for individual stock Momentum and the five Fama and French (2016) factors, an industry Momentum strategy still earns a statistically significant return but after controlling for factor Momentum the alpha becomes statistically indifferent from 0. The authors rank factors based on their contribution to the factor-Momentum strategy's Sharpe Ratio. The greater the reduction of the Sharpe Ratio after removing the factor from the strategy, the more important the factor is. While factors that relate to stock Momentum are shown to have a negative impact on the factor-Momentum strategy's profits, factors that are based on illiquidity and profitability are the most beneficial. Based on these insights, Arnott et al. (2018) show that, whereas stock Momentum tends to register heavy losses after financial crises (e.g. Barroso and Santa Clara 2015, Daniel and Moskowitz 2016) factor Momentum may even generate significant profits in such situations. It can thus be argued that instead of scaling a WML strategy up and down (like in the approaches of sections 2.1 and 2.2), a factor-based WML approach appears to be an attractive strategy to shift part of one's assets to, when Momentum's expected returns are low/negative. These insights will be used within this paper, to provide attractive investment alternatives during times when approaches as in sections 2.1 and 2.2 suggest that an investor should reduce his weight invested in a Momentum strategy.

3. Winners-minus-adjusted-Losers (WMaL)

Daniel and Moskowitz (2016) show that the loser decile is mostly responsible for the severe crashes of WML strategies after bear markets, due to its high up-market beta and the implied optionality in the strategy's return, promising low returns in case of a further downturn and heavy losses in case of a sudden market recovery. Therefore, a conventional WML strategy can be expected to perform well in ongoing bull-markets but with a higher likelihood of a bear-market state a static Momentum strategy becomes increasingly risky for an investor. Based on these findings I propose a strategy which lowers the portfolio's exposure to past losers if there is a strong signal for a prevalent bear market to mitigate the heavy repercussions during crises. By following this approach, the aim is to benefit from the pervasive positive performance of Momentum in times when the market expands but at the same time avoiding severe crashes as observed several times throughout the last decades. In a next step I show that a volatility-timing strategy for the adjusted WML strategy also works and provides a superior risk-return trade-off, however containing a different flaw for investors: A constant-volatility strategy as proposed by Barroso and Santa-Clara (2015) for a considered time horizon from 1964:07 to 2018:09 implies an average monthly weight in the standard Momentum strategy of 0.92, with a maximum monthly weight invested of 2.01 and a minimum of only 0.13, investment being <1 in 63% of all months. For the proposed WMaL strategy the invested amount is still <1 in 56% of all months, with an average weight invested of 0.97 and a minimum monthly weight of 0.2. As a WML strategy itself is self-financing it is no problem to scale the invested weight up and down in theory but it is arguable that a real-life investor forsakes potential investment opportunities by simply holding the non-invested assets in a risk-free alternative and not shifting them to an alternative strategy which promises positive returns in times when a volatility-timing strategy suggests a Momentum weight of <1. Arnott et al. (2018) show that Factor Momentum exists for a portfolio consisting of the Fama-French 5 Factor model (FF5F) yielding an average annualized return of 6.6% with a t-value of 3.10 and an annualized alpha of 9.0% with a t-value of 4.18 over the conventional FF5F strategy, by not being consistently long the factor with the highest premium but shifting towards the strategy which is about to earn high returns. Furthermore, they find that profitability and illiquidity based factors contribute the most to a Factor Momentum strategy's profits, even potentially generating positive crashes when stock momentum experiences negative crashes. Thus, I investigate the possibility to capture additional profits by shifting the dispensable assets into a Factor Momentum portfolio, while maintaining the advantages provided by an WMaL approach and through scaling the Momentum investment as proposed by Barroso and Santa-Clara (2015) or Daniel and Moskowitz (2016).

3.1 Data and Methodology

For the purpose of this paper I obtained daily and monthly returns from Kenneth R. French's data library for basic Momentum, the market-excess return and the factors included in the Factor Momentum strategy, which will be explained in detail later. To construct the basic Momentum portfolio all value weighted stock returns within NYSE, AMEX and NASDAQ from the Centre for Research in Security Prices (CRSP) have been sorted in deciles based on the realized returns in months t-2 to t-12. The most recent month is left out because individual stock returns exhibit reversals at the one month horizon (Jegadeesh, 1990) which may create microstructure distortions. The conventional WML strategy is then to short the decile with the lowest prior return and be long in the decile with the highest prior return. The monthly risk-free rate is the 1-month US T-Bill rate, retrieved from Ibbotson and Associates.

What I call a *Winners-minus-adjusted-Losers* (WMaL) strategy is also long the highest-return decile but is not to naïvely short the decile with the lowest previous returns. It instead utilizes different deciles for the short-leg of the WML portfolio, depending on the strength of an applied three-stage bull-market indicator. Related to the approach by Daniel and Moskowitz (2016) a strong bull-market indication is recognized if the cumulative past 24-months return of the market is positive. A semi-strong and weak bull-market indication is recognized if the respective cumulative past 12-months and 6-months return of the market are positive. The proposed strategy then uses the lowest-return decile (i.e. sticks with the conventional WML approach) if there is a strong bull-market indication, uses the third-lowest decile if there is only a semi-strong bull-market indication, uses the fifth-lowest decile if there is a weak bull-market indication and the seventh-lowest decile if there is no bull-market indication at all. The overall WMaL return $r^{*}_{WMaL,t}$ in month t is then given by:

(5) $r^{*}_{WMaL,t} = r_{W,t} - r_{L^{*},t}$

where $r_{W,t}$ is the return of the highest previous-return decile in month t and $r_{L^{*},t}$ is the return of the respective loser decile in month t. Appendix 3 shows the applied loser decile during the crisis period from 2008:01 to 2010:12 showing that as intended, the short-decile of the strategy is adjusted in times of market distress, reducing the exposure to recent Losers as the market rebounds.

For the application of the risk-managed Momentum, the optimal weight to be held in the WML strategy each month by the investor is derived following Barroso and Santa-Clara (2015)[1], using daily Momentum returns and a target volatility of 12% p.a.. The monthly weight is computed at the first trading session of each month, being assumed to be the date at which the investor rebalances his portfolio. To derive the optimal monthly weight of the WMaL approach, the appropriate daily returns of an analogous WMaL strategy have been computed in a preliminary step, using the cumulative 504 (24 months), 252 (12 months) and 126 (6 months) daily market returns to generate the strong, semi-strong and weak bull-market indicators, thus assuming 21 trading sessions per month, following Barroso and Santa-Clara (2015). These returns are then used for the monthly variance forecast and subsequent computation of optimal monthly weights.

If the optimal monthly weight w* is less than one, 1-w* is invested in a Factor Momentum portfolio, which is itself a zero-investment strategy. Thus, the overall strategy remains easily scalable. For the conventional WML strategy, the resulting average weight invested in the Factor Momentum strategy is 0.21 per month with a maximum monthly weight of 0.86. For

[1] See formulas (1) and (2)

the WMaL strategy the respective numbers are 0.17 and 0.8. The investment in the complementary strategy is lower for WMaL, since its volatility is already reduced compared to the conventional WML approach, resulting in a higher optimal Momentum weight.

For the Factor Momentum portfolio, instead of the FF5F factors, 5 factors which are related to profitability and illiquidity have been selected from the factor universe on Kenneth French's data library and subsequently used to construct the WML portfolio, since factors in those categories have been shown to have the most beneficial impact on a Factor Momentum strategy's profit, even experiencing positive crashes when stock-momentum crashes down (Daniel and Moskowitz, 2016). The included factor portfolios are based on Operating Profit, Investment, Net Share Issues, Earnings/Price and Cash-Flow/Price. Each factor return is equivalent to being long the highest-return decile and short the lowest-return decile of the respective month. The portfolios contain value weighted returns using the CRSP database. To compute the Factor Momentum strategy's returns, each factor's cumulative return over months t-2 to t-12 have been calculated and the factors ranked from one to five accordingly. The factor-WML strategy is then long an equal weight in the two strategies with the highest previous return and short an equal weight in the two strategies with the lowest previous return, and does not invest in the factor with the third lowest/highest past return.

3.2 Strategy Performance

In a 54-year period from 1964:07 to 2018:09 the proposed WMaL strategy provides considerable economic gains over a conventional WML strategy. The average annual return increases from 12.84% to 15.31% while the annual standard deviation decreases from 24.26% to 20.14%, resulting in an improvement of the Sharpe ratio (SR) by almost 60% from 0.33 of the conventional Momentum to 0.53 of the WMaL strategy (the applied annual risk-free rate for the SR-calculation equals 4.71% p.a. and is the geometric annual average over the considered period). Another substantial improvement can be recognized in the strategy's higher-order moments, namely a reduction of kurtosis from 7.6 to 6.04 and more than a bisection of skewness from -1.38 to -0.67, indicating a much lower crash risk (for an overview of strategy performances see Appendix 2). This effect of reduction in crash-risk could be observed during the financial crisis of 2008/2009 (see Figure 1; for strategy performance in the remaining sample periods see Appendix 4), when the minimum monthly return of the WMaL strategy was -16.57% while the conventional Momentum strategy crashed by as much as -45.58% in one month, reducing annual volatility in the period from 2008:01 to 2010:12 from 49.95% to 25.65%.

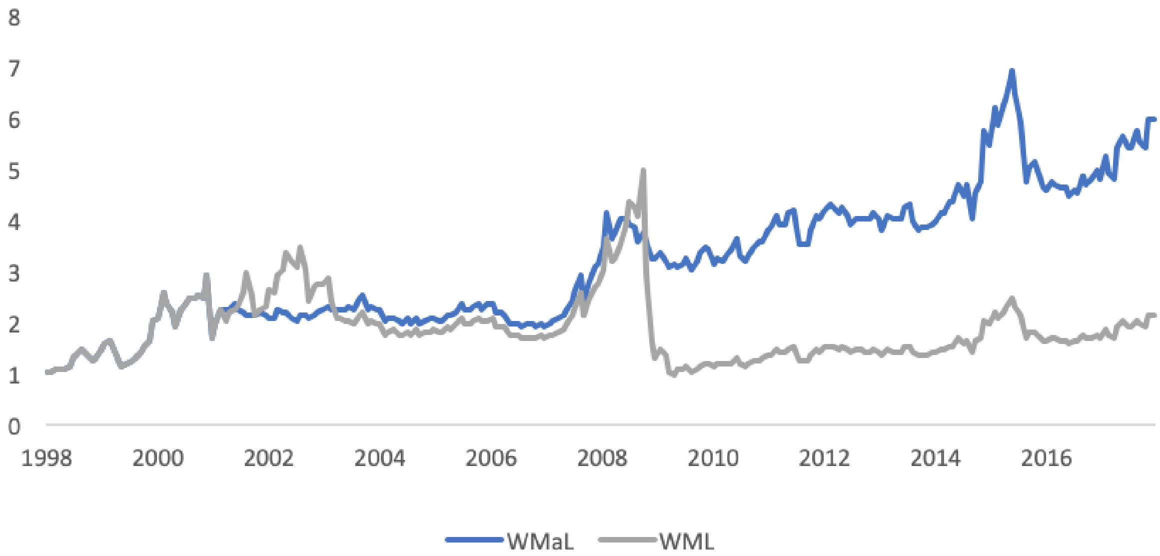


Figure 1: WMaL & WML cumulative strategy returns from 1998:01 to 2018:09. Source: Author's calculations

Over the entire sample period from 1964:07 to 2018:09 the WMaL strategy generates an annualized alpha of 4.37% over the conventional WML strategy with a t-value of 2.91, a p-value of 0.38% and is thus both, economically and statistically significant (see Table 1).

Applying a risk-management approach as proposed by Barroso and Santa-Clara (2015) also provides economic gains for the WMaL approach and results in a strategy that yields superior results to a risk-managed version (WML*) of a conventional WML approach. The risk-managed WMaL strategy (WMaL*) offers a Sharpe ratio of 0.80 and WML* of 0.78. Both nearly doubled compared to the approaches without risk-management (for performance overview see Appendix 2). Consistent with the results from Barroso and Santa-Clara (2015) the risk-managed strategies provide a drastic improvement of higher-order moments. The kurtosis of both strategies decreases to approximately 1.17. However, the WMaL* strategy provides an even stronger reduction in skewness to -0.04 compared to -0.11 of the WML* strategy. This indicates that the high crash risk of a conventional Momentum strategy is nearly eliminated in both cases (see Table 1). Yet, given that modifying a WML strategy to a WMaL strategy already provides the investor with a significant improvement of performance, one could have achieved a comparable result by only risk-managing a conventional WML strategy (see Figure 2).

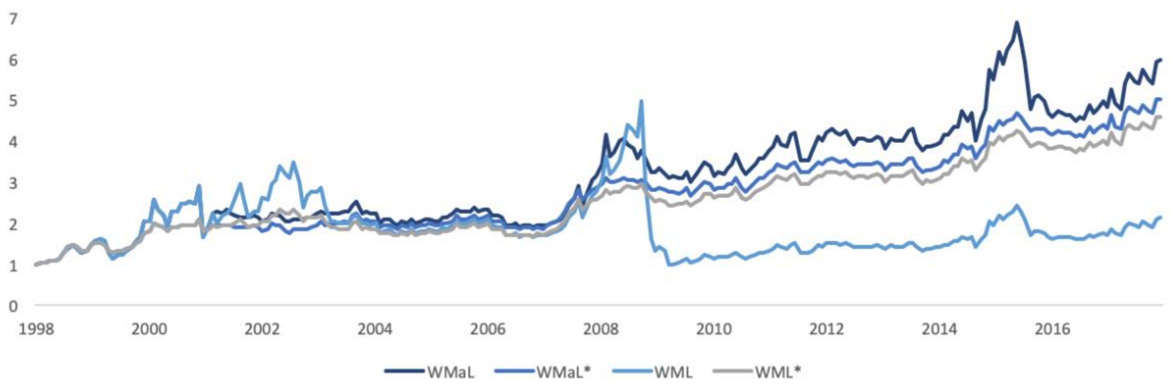


Figure 2: WMaL, WMaL, WML and WML* strategy cumulative returns from 1998:01 to 2018:09. Source: Author's calculations*

Period: 1964:07 - 2018:09	WML	WMaL	WML*	WMaL*	
Kurtosis	7,60	6,04	1,17	1,18	
Skewness	(1,38)	(0,67)	(0,11)	(0,04)	
Excess Returns Regressions	**Y:** WMaL **X:**WML	**Y:**WML* **X:**WML	**Y:**WMaL* **X:**WMaL	**Y:**WML* **X:**Mkt	**Y:**WMaL* **X:**Mkt
Annualized Alpha	4,37%	7,40%	4,89%	14,74%	14,24%
t-value	2,91	5,70	4,61	5,97	5,87
p-value	0,003765528	1,8349E-08	4,88163E-06	3,81528E-09	6,86957E-09

Table 1: Overview higher-order moments and regression alphas for WML, WMaL, WML and WMaL* strategies for a period from 1964:07 to 2018:09. Source: Author's calculations*

Table 1 provides an overview over the statistical properties and interrelation of the strategies portrayed in Figure 2, showing that both risk-managed strategies generate a statistically significant alpha over a non-risk-managed version of the strategy, each outperforming the market by >14%p.a..

Complementing the considered WMaL* and WML* strategies in a final step with a Factor Momentum strategy provides the investor with higher average returns but comes along with an increased volatility, making it questionable whether the outcome can be considered an improved strategy. This issue will be dealt with more detailed in the Discussion of Section 4. Compared to the WMaL* and WML* strategies without periodically added Factor Momentum, the annual return for the considered period (1964:07 to 2018:09) increases from 18.08% to 18.55% and from 17.97% to 19.35% respectively (for performance overview see Appendix 2). The larger increase for the WML* strategy can be explained by a lower average weight w* invested in the conventional Momentum strategy and thus a larger average weight in the complementary Factor Momentum strategy (21.27% for WML*, 17.06% for WMaL*). The volatility however increases from 16.72% to 23.59% for WMaL* and from 17.01% to 25.19% for WML*, yielding Sharpe ratios of 0.59 and 0.58 respectively. Thus, the risk-return trade-off is better compared to a conventional Momentum and even a WMaL strategy, yet worse than those of the simply risk-managed approaches. Simultaneously, the skewness improves significantly for both approaches (0.40 for the WMaL* + Factor Mom strategy, 0.26 for the WML* + Factor Mom strategy), now even having positive values. The reduction of kurtosis however compared to unadjusted WML and WMaL is much less than those of simply risk-managed approaches (see Table 2).

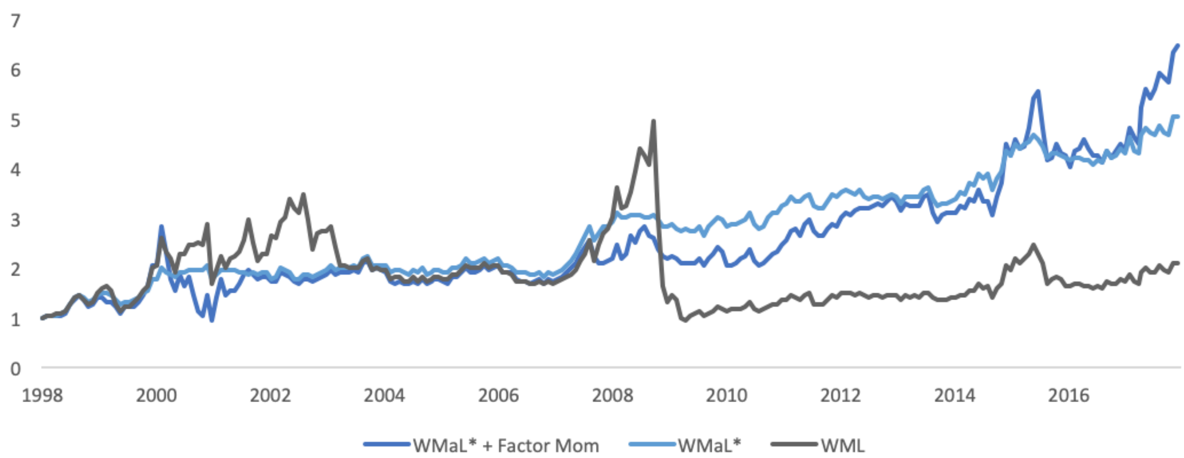


Figure 3: Cumulative return of WMaL + Factor Mom, WMaL* and WML from 1998:01 to 2018:09. Source: Author's calculations*

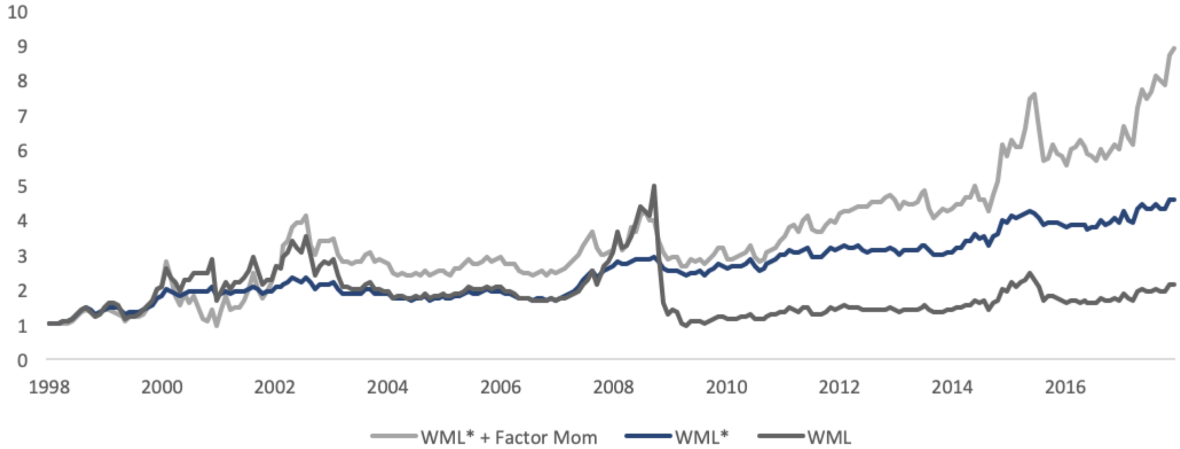


Figure 4: Cumulative return of WML + Factor Mom, WML* and WML from 1998:01 to 2018:09. Source: Author's calculations*

It can be argued that complementing the risk-managed Momentum strategies WMaL* and WML* with a Factor Momentum portfolio does allow an investor to capture additional profits through shifting assets to return-generating alternative rather than a risk-free asset (see Figures 3 and 4, Table 2). However, the second conjecture that Factor Momentum is an especially efficient complementary when Momentum crashes does not seem to prove true for the considered period.

Period: 1964:07 - 2018:09	WML*	WMaL*	WML* + FM	WMaL* + FM
Kurtosis	1,17	1,18	4,72	5,92
Skewness	(0,11)	(0,04)	0,26	0,40
Excess Returns Regressions	**Y:**WML*+FM **X:**WML*	**Y:**WMaL*+FM **X:**WMaL*	**Y:**WML*+Fm **X:**Mkt	**Y:**WMaL*+FM **X:**Mkt
Annualized Alpha	7,35%	3,42%	18,69%	16,46%
t-value	3,69	2,03	5,03	4,76
p-value	0,00024	0,04235	6,30428E-07	2,42889E-06

Table 2: Overview higher-order moments and regression alphas for WML, WMaL*, WML* + Factor Mom and WMaL* + Factor Mom strategies for a period from 1964:07 to 2018:09. Source: Author's calculations*

Nevertheless, the proposed strategy of complementing risk-managed Momentum portfolios with Factor Momentum provides statistically and economically significant alphas over the respective non-complemented strategies and the market (see Table 2). Considering the changes in Sharpe ratio and higher-order moments (see Appendix 2), the approach doubtlessly alters the strategies' risk-return profile which an investor must be willing to accept.

3.3 Robustness Test

The total sample period from 1964:07 to 2018:09 comprises one Momentum crash of an especially large magnitude in 2009 and a bull market of unprecedented length and extent from 2010 until 2018 during which period the market expanded by almost 320% equivalent to a 14.07% annual growth. Naturally the 54-year period contains a variety of market states throughout the included historical data. To test the robustness of the results in Section 3.2 and to ensure that the pervasive features of the proposed strategies are not due to one of these particularities several subsample tests have been conducted. To do so, the strategies' performance has been tested in two 30-year subsamples from 1988 to 2018 and from 1964 to 1994, a no-crash sample from 1964 to 2018 excluding the crash period of 2009 and from 1964 to 2007, excluding the financial crash period of 2009 and the above-mentioned bull market (for an overview of subsample testing see Appendix 5).

A consistent result throughout all subsamples is that a WMaL strategy provides a higher return at a lower risk compared to a conventional Momentum strategy, thus improving the Sharpe ratio and skewness in all sub-samples. The same is true for an optimization from WML* to WMaL*. These results are consistent with Barroso and Santa-Clara (2015), yet it appears that WMaL offers additional potential for improvement to a scaled Momentum risk-management. Sharpe ratio and skewness also improve from conventional WML and WMaL strategies when combining a Factor Momentum weight with the risk-managed Momentum strategies but less than through simple risk-managing. In some subsamples the return even decreases while the volatility increases, thus hardly providing an investor with any benefit. The approach does however provide the largest (positive) skewness except for the subsample from 1964 to 1994, where it still provides a significant improvement over the unadjusted WML and WMaL strategies. Hence, it might still be an interesting option for some investors, willing to accept additional volatility. Furthermore, there might be room for improvement regarding the added Factor Momentum portfolio with more beneficial return characteristics. This issue will be further discussed in Section 4. Generally, it can be concluded that the results, positive and negative, are robust across subsamples and did not depend on one of the above-mentioned events. The following section deals with outlooks and limitations and discusses the relevance of the presented findings from the perspective of a real-life investor.

4. Discussion

Even though the proposed reduction of the exposure to losers in a Momentum portfolio is shown to yield considerably economic gains for an investor, risk-managed approaches as suggested in existing literature (e.g. Barroso and Santa-Clara, 2015) provide even better results. Furthermore, the results of the proposed strategy to complement volatility-scaled WML strategies with a Factor Momentum portfolio are not very pervasive. These are some major limitation of the proposed (complemented) WMaL strategy and their reasons must be scrutinized carefully.

It can be argued that the basic WMaL approach introduced in this paper is simpler than other risk-management approaches for Momentum, since it only relies on previous market returns as input and no forecasts of volatility or expected returns. Furthermore, the underlying assumption that winners during a crisis are usually defensive and counter cyclical firms and losers their highly-leveraged opposites (Daniel and Moskowitz, 2016), thus resulting in the described option-like payoff during bear markets, seems to be solid and is supported by the strong performance of the proposed WMaL strategy. The relatively poor performance of the Factor Momentum addition could be linked to the used universe of factor. Arnott et al. (2018) use different data and a larger number of factor to construct their portfolios. As they show, some factors are more beneficial for the performance of the constructed portfolio than others, especially depending on their correlation with stock-momentum performance. Thus, it is likely that an optimization of the included factors can enhance the performance of the proposed strategy. Another issue is that of transaction costs which have not been included in calculations and whose effect should also be scrutinized more profoundly. As short-selling past losers is likely to incur higher transaction costs than recently better-performing stocks, WMaL may even allow an investor to reduce costs, since it is shifting the short-leg of the strategy away from past losers. However, especially when adding a Factor Momentum component, the turnover of stocks increases (as does the amount invested) also making the maintenance of the strategy more complicated due to the variety of contained factors and stocks. Nevertheless, the findings presented in this paper constitute a promising basis for further research, such as implications of the modified WML construction for the presented risk-management approaches, potential benefits of using other short-leg adjustment except the arbitrarily chosen 3rd, 5th and 7th deciles and further optimization potential through applying leverage and forsaking the zero-investment criteria of the WML approach, just to name a few.

From a real-life investor's perspective, the implementation of the proposed strategies is easily feasible as they are only built on ex-ante available information and assume monthly rebalancing, a usually acceptable frequency. Moreover, a WMaL strategy provides an attractive risk-return trade-off while keeping the invested weight constant, as opposed to managing risk by scaling the investment itself up and down, as proposed by Barroso and Santa-Clara (2015) or Daniel and Moskowitz (2016). This might be an especially interesting advantage for investors who are obliged to have a certain amount in other than risk-free assets and are restricted in applying leverage, as WMaL is a simple one-long, one-short strategy.

5. Conclusion

Conventional Momentum does not provide investors with attractive risk-return characteristics, especially due to the high crash-risk, sometimes annihilating decades of profits.

However, utilizing and combining insights about the predictability and characteristics of Momentum risk and the striking contribution of losers to the extent of the crashes allows investors to position themselves in way that allows them to capture most of the strategy's benefits while minimizing their exposure to crash-risk. As most of the approaches in the considered literature scale investment down during times when Momentum crash-risk is considered high, a portfolio complementation with the strategy that performs well in these times appeared promising. However, the recently introduced Factor Momentum has not been proven to be ideal for that purpose, as the resulting strategy rather has a different risk-return profile, than generally constituting an attractive strategy.

Bibliography

Arnott, Rob, Mark Clements, Vitali Kalesnik and Juhani Linnainmaa. 2018. “Factor Momentum”. Unpublished working paper. The Wharton School, University of Pennsylvania, Pennsylvania.

Barroso, Pedro, and Pedro Santa-Clara. 2015. "Momentum has its moments." *Journal of Financial Economics* 116 (1): 111-120.

Daniel, Kent, Ravi Jagannathan, and Soohun Kim. 2012. “Tail risk in momentum strategy returns*”*. No. w18169. National Bureau of Economic Research.

Daniel, Kent, and Tobias J. Moskowitz. 2016. "Momentum crashes." *Journal of Financial Economics* 122 (2): 221-247.

Ernst and Young. 2017. “Global ETF research”. Accessed October 12. https://www.ey.com/Publication/vwLUAssets/ey-global-etf-survey-2017/%24FILE/ey-global-etf-survey-2017.pdf

Fama, Eugene F., and Kenneth R. French. 2016. "Dissecting anomalies with a five-factor model." *The Review of Financial Studies* 29 (1): 69-103.

Grundy, Bruce D., and J. Spencer Martin Martin. 2001. "Understanding the nature of the risks and the source of the rewards to momentum investing." *The Review of Financial Studies* 14 (1): 29-78.

iShares. 2018. “What is Smart Beta”. Accessed October 18.

https://www.ishares.com/us/education/smart-beta

Jegadeesh, Narasimhan. 1990. "Evidence of predictable behavior of security returns." *The Journal of finance* 45 (3): 881-898.

Jegadeesh, Narasimhan, and Sheridan Titman. 1993. "Returns to buying winners and selling losers: Implications for stock market efficiency." *The Journal of finance* 48 (1): 65-91.

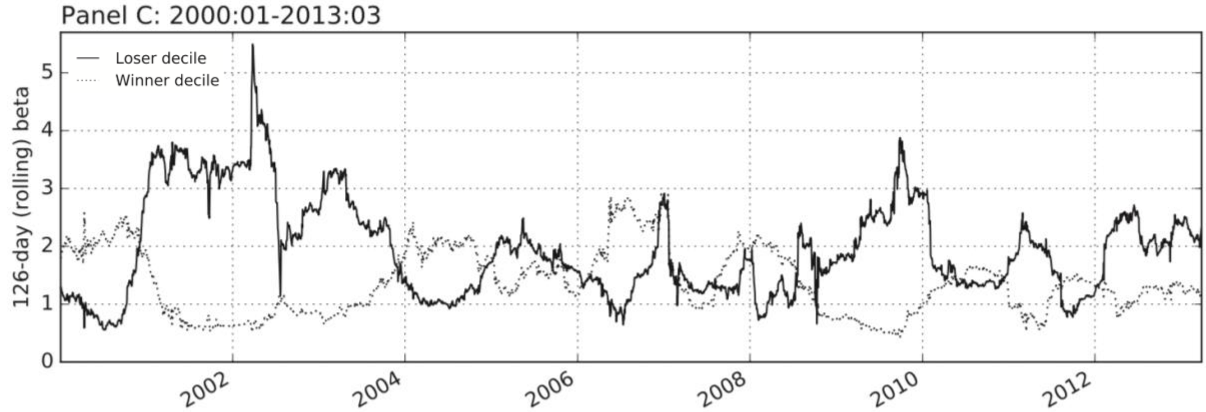
Moreira, Alan, and Tyler Muir. 2017. "Volatility-Managed Portfolios." *The Journal of Finance* 72 (4): 1611-1644.

Moskowitz, Tobias J., and Mark Grinblatt. 1999. "Do industries explain momentum?." *The Journal of Finance* 54 (4): 1249-1290.

Stivers, Chris, and Licheng Sun. 2010. "Cross-sectional return dispersion and time variation in value and momentum premiums." *Journal of Financial and Quantitative Analysis* 45 (4): 987-1014.

Appendix

Appendix 1: Market Betas of Winners and Losers



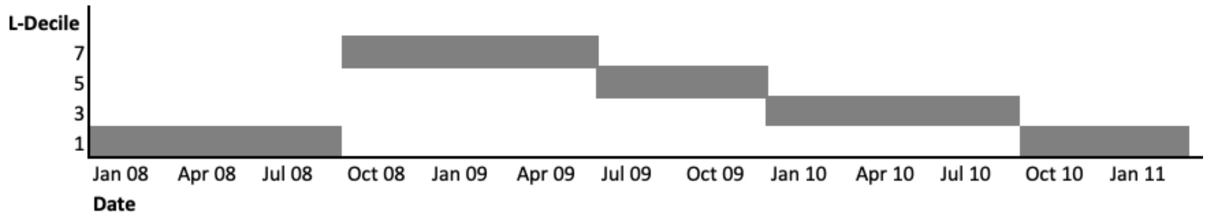
Market Betas of Winner and Loser deciles from 2000:01 to 2013:03. Source: Daniel and Moskowitz (2016)

Appendix 2: Strategy Performance Overview

Period: 1964:07 - 2018:09	WML	WMaL	WML*	WMaL*	WML* + FM	WMaL* + FM
Average annual return	12,84%	15,31%	17,97%	18,08%	19,35%	18,55%
Stdev	24,26%	20,14%	17,01%	16,72%	25,19%	23,59%
Sharpe Ratio	0,33	0,53	0,78	0,80	0,58	0,59
Kurtosis	7,60	6,04	1,17	1,18	4,72	5,92
Skewness	(1,38)	(0,67)	(0,11)	(0,04)	0,26	0,40

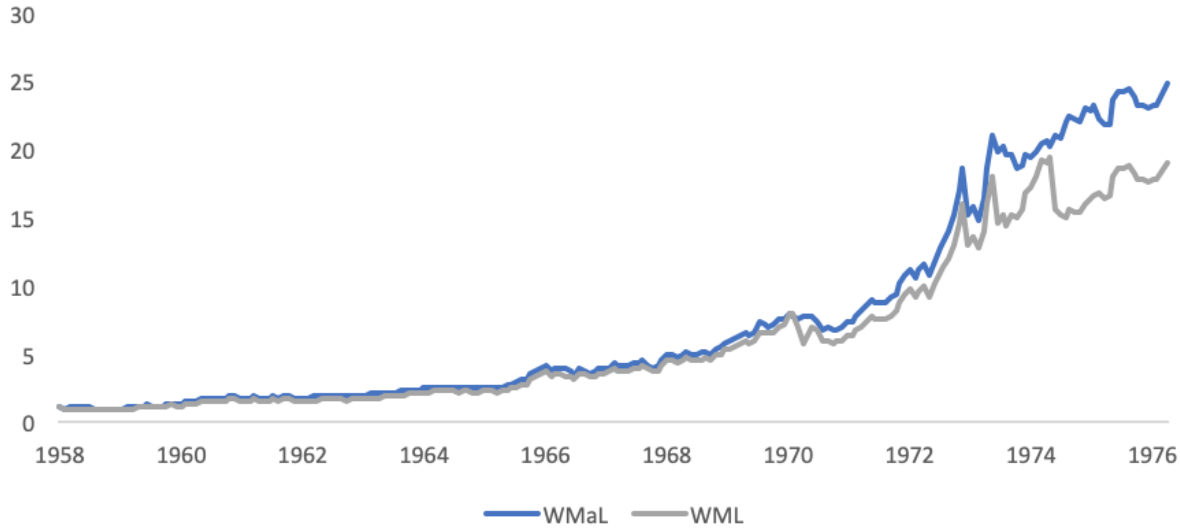
Overview strategy performance characteristics for a period from 1964:07 to 2018:09. Source: Author calculations

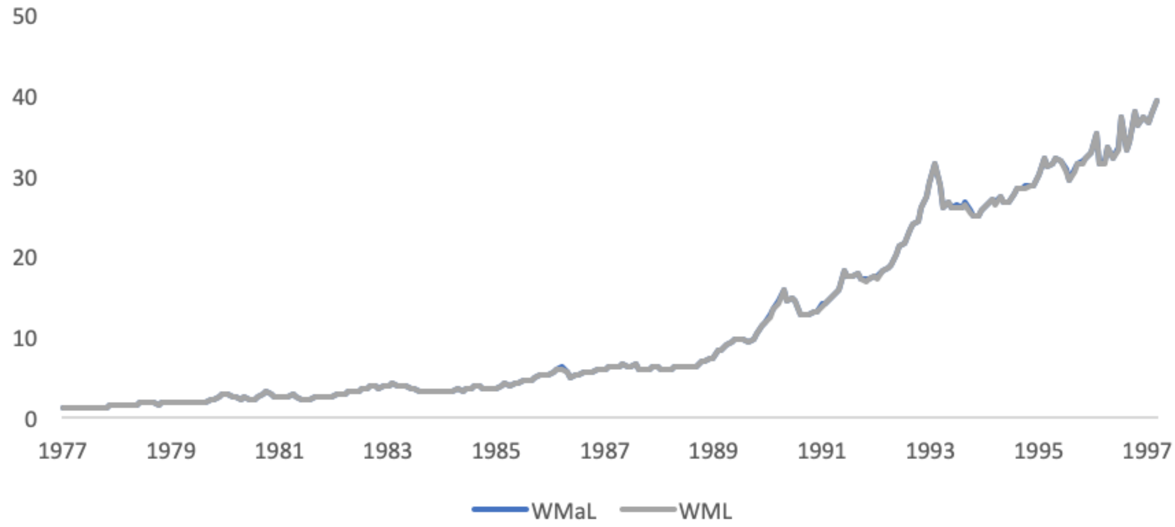
Appendix 3: WMaL Loser-Deciles



Graph showing the used loser-deciles for the construction of the WMaL portfolio for a period from 2008:01 to 2011:01. Exact dates rounded to full months for illustration purposes. Source: Author's calculations

Appendix 4: Cumulative Strategy Returns





Graphs showing cumulative returns of WML and WMaL strategies for the periods from 1958:01 to 1976:12 and fro 1977:01 to 1997:12. Source: Author calculations

Appendix 5: Performance Overview

Period: 1988:01 - 2018:09	WML	WMaL	WML* + Factor Mom	WMaL* + Factor Mom	WML*	WMaL*
Skewness	(1,42)	(0,69)	0,50	0,69	0,13	0,19
Kurtosis	7,48	7,06	4,90	6,83	1,03	1,14
Min monthly return	(45,58%)	(42,03%)	(33,10%)	(33,10%)	(13,68%)	(13,68%)
Max monthly return	26,16%	26,16%	44,47%	44,47%	16,12%	16,12%
Average annual return	8,50%	12,22%	15,62%	14,43%	13,05%	13,38%
Stdev	27,36%	21,89%	28,18%	25,95%	14,93%	14,79%
Sharpe Ratio	0,20	0,42	0,45	0,44	0,67	0,70

Period: 1964:07 - 2018:09 (ex. 2009)	WML	WMaL	WML* + Factor Mom	WMaL* + Factor Mom	WML*	WMaL*
Skewness	(0,78)	(0,68)	0,26	0,38	(0,13)	(0,05)
Kurtosis	4,50	6,12	4,83	5,92	1,17	1,16
Min monthly return	(42,03%)	(42,03%)	(33,10%)	(33,10%)	(17,23%)	(17,23%)
Max monthly return	26,16%	26,16%	44,47%	44,47%	21,78%	21,78%
Average annual return	15,98%	16,00%	20,63%	19,51%	18,62%	18,59%
Stdev	22,20%	20,18%	25,16%	23,68%	17,07%	16,81%
Sharpe Ratio	0,50	0,55	0,63	0,62	0,81	0,82

Period: 1964:07 - 1994:07	WML	WMaL	WML* + Factor Mom	WMaL* + Factor Mom	WML*	WMaL*
Skewness	(0,81)	(0,47)	(0,35)	(0,27)	(0,27)	(0,18)
Kurtosis	2,13	1,31	1,11	0,95	1,03	0,97
Min monthly return	(19,70%)	(18,67%)	(19,67%)	(18,52%)	(17,23%)	(17,23%)
Max monthly return	16,23%	16,23%	21,78%	21,78%	21,78%	21,78%
Average annual return	19,48%	20,03%	25,80%	25,61%	26,11%	25,94%
Stdev	18,77%	17,27%	20,07%	19,62%	18,82%	18,46%
Sharpe Ratio	0,68	0,78	0,95	0,97	1,03	1,05

Period: 1964:07 - 2007:12	WML	WMaL	WML* + Factor Mom	WMaL* + Factor Mom	WML*	WMaL*
Skewness	(0,94)	(0,85)	0,26	0,42	(0,19)	(0,11)
Kurtosis	5,35	7,79	5,07	6,52	1,04	1,05
Min monthly return	(42,03%)	(42,03%)	(33,10%)	(33,10%)	(17,23%)	(17,23%)
Max monthly return	26,16%	26,16%	44,47%	44,47%	21,78%	21,78%
Average annual return	16,77%	17,49%	22,17%	21,05%	21,24%	21,40%
Stdev	22,07%	19,65%	25,98%	24,19%	17,94%	17,59%
Sharpe Ratio	0,50	0,59	0,63	0,63	0,86	0,89

Table providing an overview over performance statistics and higher-order moments of indicated subsample periods. Source: Author calculations