LUND UNIVERSITY

Risk-Managed Momentum in Europe

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Abstract

This thesis sets out to evaluate a risk-managed momentum strategy in the European stock market. The recent performance of momentum in Europe is first evaluated. A momentum premium still exists in Europe but the strategy suffered large losses in 2009. A risk-managed momentum portfolio is created by dynamically scaling the exposure to momentum based on a monthly volatility forecast. The risk-managed strategy is evaluated by comparing its performance to the original momentum portfolio. Risk management doubles the Sharpe ratio of the momentum portfolio and reduces tail risk. The greatest benefit of risk management comes from avoiding momentum crashes. The strategy increases the Sharpe ratio in all subsamples and the results are robust in international markets.

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1 Introduction

Momentum has received considerable attention in the literature ever since first documented in Jegadeesh & Titman (1993). Momentum is the general tendency for rising asset prices to continue rising and falling prices to continue falling. Buying stocks that have performed well in the past and selling stocks that have performed poorly has historically provided large returns. The sources of momentum profits are still not fully understood. Controlling for risk with traditional asset pricing models such as the capital asset pricing model (CAPM) or the three-factor model of Fama and French (1992) give significantly positive abnormal returns. Momentum might therefore seem like an attractive strategy for investors.

Although momentum has historically been a profitable strategy, more recent studies have highlighted the negative aspects of momentum. A left-skewed return distribution and high excess kurtosis makes the strategy vulnerable to crashes. The performance of momentum in the last decade is not particularly impressive. The strategy suffered large losses in 2009 - persistent losses that have never been regained. Because of these findings, the latest research has focused on the phenomenon of momentum crashes. Just like the name suggests, a momentum crash is an event where the momentum strategy fails and loses a large part of its value in a matter of months.

To address the issue of tail risk in momentum, Barroso & Santa-Clara (2015) and Daniel & Moskowitz (2016) have proposed modified versions of momentum, where the exposure to momentum is dynamically scaled every month. By dynamically scaling the exposure to momentum, they manage to take advantage of the profitability of momentum while minimizing the tail risk. The Sharpe ratio is doubled and momentum crashes are avoided.

The aim of this essay is to test the risk-managed momentum strategy of Barroso & Santa-Clara (2015) using a European stock portfolio between 1991:03 and 2017:06. Their study focuses on a US equity portfolio between 1926 and 2013. The main contribution of this essay is therefore to test if the risk-managed strategy works well in international markets (specifically, Europe). Furthermore, since my essay uses a shorter sample period, the analysis will be more focused on the recent performance of the strategy. While Barroso & Santa-Clara (2015) have the advantage of a longer sample period, their analysis is more general and less focused on the recent performance of the strategy. Naturally, this essay will also contribute to the discussion on momentum crashes in Europe and the recent performance of momentum.

The remainder of this essay is organized as follows. Section 2 reviews the literature on momentum and momentum crashes. Section 3 presents the data and describes the methodology used in the essay. Section 4 presents the results together with an analysis of the results. Finally, Section 5 ends the essay with a conclusion.

2 Literature review

2.1 Momentum

De Bondt & Thaler (1985) find empirical evidence for overreaction in stock markets. According to the overreaction hypothesis, if investors systematically overreact to new information, then stock prices should increase (decrease) dramatically following good (bad) news, causing the price to differ from its fundamental value. A dramatic movement of price in either direction will in the long run be corrected, which leads to a return reversal in the opposite direction. De Bondt & Thaler form portfolios by sorting stocks based on returns in the past 36 months (the formation period) and construct portfolios of "past winners" and "past losers" by selecting the stocks with the highest prior returns and lowest prior returns in the formation period. Portfolios of past losers outperform the market, while portfolios of past winners earn returns below the market returns, 36 months after portfolio formation. In other words, they find evidence for long-term reversal of stock prices. The difference is biggest in the second and third year after formation. Jegadeesh (1990) and Lehmann (1990) find similar return-reversals at the short (1-week to 1-month) horizon. Contrarian strategies where stocks are selected based on returns in the past week or month outperform the market. The strategy however is transaction intensive, and the abnormal returns are likely due to other factors than overreaction (Jegadeesh & Titman, 1993).

Jegadeesh & Titman (1993) find a momentum effect at the medium (3- to 12-month) horizon. They construct portfolios by sorting stocks based on their returns in the past 3- to 12-months and ranking them in deciles. A "winner minus loser" portfolio is then constructed by buying the stocks in the top ("past winners") decile and selling stocks in the bottom ("past losers") decile. The winner minus loser portfolio generates significant returns over 3- to 12-month holding periods. The returns of the portfolio partly dissipate in the following 2 years after the holding period, i.e. there is a return reversal in the long run. The returns of the momentum portfolio cannot be explained by its systematic risk.

Carhart (1997) finds that common factors in stock returns and transaction costs almost completely explain the short-term performance of mutual funds. The hot hands effect in mutual funds, the notion that mutual funds that have performed well in the past are more likely to perform well in the future, is likely due to the one-year momentum effect, according to him. The reason for this is not because fund managers deliberately follow momentum strategies, but because some mutual funds just happen to hold large positions in last year's winning stocks, he argues. Carhart introduces a four-factor model to explain returns, which is based on the three Fama and French (1992) factors plus a new momentum factor.

The profitability of momentum strategies is not exclusive to the US. Rouwenhorst (1998) finds that an internationally diversified portfolio of European stocks that follows a momentum strategy earns approximately 1 percent per month. The momentum effect is present in all 12 markets of the sample. Momentum is not unique to developed markets - emerging stock markets exhibit momentum as well (Rouwenhorst, 1999). In a sample of 41 countries from around the world, Chui et al (2010) found momentum to be profitable in all but four of the countries. Fama & French (2012) show that there is a momentum premium in international portfolios of the regions North America, Europe and Asia Pacific. Neither is momentum exclusive to equity markets. Evidence for the momentum effect has been found in currency markets (Okunev & White, 2003) and commodities (Erb & Harvey, 2006).

3.2 Explanations for momentum

The profitability of momentum strategies across a diverse range of markets, time samples and asset classes is well established. However, there has been some debate on the source of profits and the interpretation of the results. Momentum has on one hand been considered as evidence for market inefficiency, while others have argued that the returns may be due to a compensation for risk. To investigate whether exposure to market risk can explain momentum profits, Jegadeesh & Titman (1993) adjust for risk using the CAPM. Fama & French (1996) adjust for risk using the Fama and French (1992) three-factor model. Both cases give significantly positive alpha-values, meaning that traditional risk factors cannot explain the profits of momentum strategies. Conrad & Kaul (1998) find that cross-sectional variability in stock returns can explain the returns of momentum strategies. Jegadeesh & Titman (2002), however argue that these conclusions are wrongly made due to a small sample bias. An unbiased test shows that cross-sectional variability in stock returns explain little to none of momentum returns. Grundy & Martin (2001) argue that the positive mean return of momentum cannot be explained by the exposure to a conditional Fama and French three-factor model, nor by unconditional cross-sectional variability in stock returns or exposure to industry factors.

Traditional asset pricing models are not able to explain momentum profits. Instead, the empirical evidence on momentum seem to provide support in favor of behavioral theories (Jegadeesh & Titman, 2001). Daniel et al (1998) propose a behavioral theory based on investor overconfidence and biased self-attribution. The authors assume that overconfidence in investors causes them to overvalue their own private information, which leads to medium-run momentum effects and long-run return reversal effects in the stock market. To explain the causes of underreaction and overreaction, Barberis et al (1998) propose a behavioral model of how investors form beliefs. Hong & Stein (1999) offer a theory of underreaction and overreaction based on the way traders interact with each other on the market. Gervais & Odeon (2001) investigate the various aspects of investor overconfidence and the causes for it. According to their model, investors assess their ability from failures and successes. Investors with previous successes give too much credit for their successes when assessing their ability. As a result, they become overconfident.

The behavioral theory can be extended to predict differences in momentum profits across different market states. According to the theory, investor overconfidence increases when market returns are high, resulting in stronger momentum returns during bull markets. Cooper et al (2004) show that the profitability of the momentum strategy depends on the market state. Two market states are defined based on the lagged three-year market return. The average monthly momentum return is 0.93% when the lagged three-year market return is positive and -0.37% when the lagged three-year market return is negative. Chordia & Shivakumar (2002) show that momentum returns are explained by common macroeconomic variables that are related to the business cycle. They find that momentum returns are positive during economic expansions and negative during recessions. Griffin, Ji & Martin (2003), however find that conditional macroeconomic risks cannot explain momentum returns in international markets. Stivers & Sun (2010) find a negative relation between the return dispersion of the market and future momentum returns. When studying the effect of market cycles on momentum and contrarian strategies, Stivers & Sun (2013) find that the profits of these strategies are higher in up- and down-market states, but much lower in transitions between the two market states.

3.3 Momentum crashes

Jegadeesh & Titman (2011) follow up their studies from 1993 and 2001 by testing the performance of a momentum portfolio from 1990 to 2009. They find that although the momentum effect has continued after the 1990's, the effect has diminished over time. The most recent period saw low returns for the momentum portfolio, especially in 2009 when the portfolio suffered a loss of 36.5%. The beta value of the momentum portfolio was -.79 in 2009, while the beta was usually close to zero on average the rest of the years. The losses for the momentum portfolio in 2009 can partly be explained by the negative beta of the portfolio in

2009. Jegadeesh & Titman find that together with the portfolio beta, the lagged three-year market return and the market return dispersion can explain a large part of the negative momentum returns in 2009.

Daniel & Moskowitz (2016) provide an in-depth discussion of momentum crashes, events where momentum strategies suffer persistent strings of large negative returns. They argue that momentum crashes are partly forecastable. These happen in panic states, following market declines and in volatile periods. They also discuss the time-varying beta of the momentum portfolio and how it relates to momentum crashes. In bear markets, the beta of the loser portfolio increases, which makes the beta of the momentum portfolio negative. This is because past winners tend to be lower beta stocks during market recessions, and past losers tend to be higher beta stocks during market recessions. They show that momentum crashes do not occur because the winner portfolio crashes, but rather because the loser portfolio dramatically increases in value during market rebounds. Since the momentum strategy involves buying winners and selling losers, the strategy crashes when the loser portfolio jumps in value. A dynamic momentum strategy based on forecasts of the portfolio's mean and variance is tested. The strategy doubles the Sharpe ratio of the static momentum strategy and virtually eliminates the risk for momentum crashes.

Barroso & Santa-Clara (2015) explain that momentum strategies give rise to negative skewness and higher kurtosis compared to the market portfolio. They show that the risk of momentum fluctuates over time and that it is partly forecastable. A risk-managed momentum strategy is tested where the weight invested in the winner minus loser portfolio is dynamically changed every month depending on the forecasted variance of the portfolio. The objective of the strategy is to keep portfolio volatility relatively constant over time and greatly reduce the probability of large unexpected losses. The strategy doubles the Sharpe ratio of the static momentum strategy and reduces the kurtosis and the skewness of the return distribution.

The research that is closest to my paper are the studies of Barroso & Santa-Clara (2015) and Daniel & Moskowitz (2016).

3 Methodology

3.1 Data description

All data used in this paper is obtained from Kenneth French's data library. The dataset contains the monthly and daily returns for portfolios of stocks from 16 developed European stock markets from January 1991 to June 2017. The stocks are sorted into five size groups based on market equity value. Each size group is then subdivided into five (momentum) quintiles based on prior returns, with an equal number of stocks in each quintile. The first size group consists of the largest stocks in the sample that together make up 90% of the market's total equity value. The stocks in the first (biggest) size group are therefore the most representative of the market. In this paper, I have only looked at the largest stocks, i.e. only the first size group. For the momentum portfolios, all stocks in each respective size group are ranked in ascending order according to their returns from month t-12 to t-2. It is customary to skip the month between the formation period and the holding period, t-1, because of the short-term reversal effect showed by Jegadeesh (1990). The highest (winner) quintile is then the portfolio with the top 20 percent of stocks, and the lowest (loser) quintile is the group with the bottom 20 percent of stocks. The momentum portfolios are readjusted every month using the same procedure. The individual stocks are value-weighted in each portfolio. All returns are in US dollars.

3.2 Method

In this paper, I have followed the same procedure as Barroso & Santa-Clara (2015). First the winner minus loser portfolio is created, and then the risk-managed momentum portfolio is created by scaling the weight of the winner minus loser portfolio. Momentum is a zero-cost strategy which involves buying stocks with the highest prior returns and selling stocks with the lowest prior returns. The returns for the momentum portfolio are therefore calculated by taking the portfolio returns of the stocks in the highest quintile (past winners) and subtracting them with the portfolio returns of the stocks in the lowest quintile (past losers):

$$r_{WML,t} = r_{W,t} - r_{L,t}, \tag{1}$$

where $r_{WML,t}$ is the return of the winner minus loser portfolio (WML) at time t, $r_{W,t}$ is the return of the winner portfolio at time t, and $r_{L,t}$ is the return of the loser portfolio at time t. This is done with both monthly and daily returns.

To test if the Fama and French (1992) risk factors can explain the positive average returns of the WML portfolio, I run the following ordinary least squares (OLS) regression:

$$r_{WML,t} = \alpha + \beta_{RMRF} r_{RMRF,t} + \beta_{SMB} r_{SMB,t} + \beta_{HML} r_{HML,t} + \varepsilon_t, \tag{2}$$

where $r_{WML,t}$ is the return for the WML-portfolio at time t, $r_{RMRF,t}$ is the return for the market risk factor at time t, $r_{SMB,t}$ is the return for the size factor at time t and $r_{HML,t}$ is the return for the value factor at time t.

For each month, I compute the realized variance of the WML portfolio, RV_t , from daily returns in the previous 21 daily sessions. The realized variance for month t is the sum of squared returns for the daily returns of month t:

$$RV_t = \sum_{j=0}^{20} r_{d_t - j}^2, \tag{3}$$

where $r_{d_{t-j}}$ are the daily returns of the WML portfolio in month t.

An Autoregressive model of order 1 (AR(1)) is estimated, where RV_t is regressed by the lagged realized variance, RV_{t-1}, and a constant:

$$RV_t = \alpha + \rho RV_{t-1} + \varepsilon_t \tag{4}$$

The AR(1) model is estimated to measure the degree of persistence in the volatility of the momentum portfolio, and how well the realized variance is explained by its lag.

The forecasted variance of month t, $\hat{\sigma}_t^2$ is equal to the previous months' realized variance, $RV_{t.-1}$:

$$\hat{\sigma}_t^2 = \mathrm{RV}_{t-1} = \sum_{j=0}^{20} r_{d_{t-1} - j}^2 \tag{5}$$

Barroso & Santa-Clara (2016) use the 6-month realized variances as their variance forecast, but they also tested using one-month realized variances and three-month realized variances, and an exponentially moving average model with different half-lives. All of them worked well with almost identical results. Therefore, I chose the simplest variance forecast model of one-month realized variances. A more sophisticated variance model could potentially improve the variance forecast very slightly, but the results would most likely be the same.

The annualized volatility forecast, $\hat{\sigma}_t$, is calculated by taking the square root of the monthly variance forecast, $\widehat{\sigma}_t^2$, and multiplying by $\sqrt{12}$:

$$\hat{\sigma}_t = \sqrt{\widehat{\sigma}_t^2} * \sqrt{12} \tag{6}$$

The risk managed momentum returns are obtained by scaling the returns of the WML portfolio. The momentum returns are scaled by the ratio between a fixed target volatility and the forecasted volatility for month t:

$$r_{WML_t^*} = \frac{\sigma_{target}}{\hat{\sigma}_t} r_{WML_t}, \tag{7}$$

where $r_{WML_t^*}$ is the return for the risk managed momentum portfolio (WML*) at time t, σ_{target} is the annualized volatility target and $\hat{\sigma}_t$ is the annualized volatility forecast of month t. $\frac{\sigma_{target}}{\hat{\sigma}_t}$ is the weight invested in the WML portfolio. Conceptually, if a weight of 1 represents a 1$ long/1$ short investment in the WML portfolio, then a weight of 2 represents a 2$ long/2$ short investment in the WML portfolio, and so on. Since momentum is a zero-cost strategy where the long position is offset by the short position, there are no weight constraints.

12% per year is chosen as the annual volatility target, because this is the same as the average yearly market volatility. The target volatility can of course be increased or decreased depending on the investor's risk preference. A higher volatility target leads to higher expected returns at the cost of higher volatility, and a lower volatility target leads to lower volatility at the cost of lower expected returns.

4 Empirical analysis

4.1 European equity momentum

The results show that there is a momentum premium in the European equity market over the last quarter century. When stocks are sorted into quintile portfolios based on prior returns, the past winners (quintile 5) earn considerably higher average excess returns than past losers (quintile 1). Table 1 presents the summary statistics of returns for the five momentum quintile portfolios over this period. The winner portfolio earns an average excess return of 8.51% per year while the loser portfolio earns an average excess return of only 2.03% per year. The difference between past winners' and past losers' average returns is slightly higher than the average excess market return, which is 6.29% per year. Figure 1 plots the cumulative returns of the highest and the lowest quintile portfolios in the full sample period.

Table 1
Summary statistics of monthly returns for the momentum quintile portfolios sorted on prior returns from 1991:03 to 2017:06. The average excess return, the standard deviation and the alpha are annualized and in percent. The beta- and alpha values are estimated by running an OLS regression using the full sample data.

Portfolio	1 (lowest)	2	3	4	5 (highest)	WML	Market
Excess average return	2.03	5.45	7.08	7.61	8.51	6.48	6.29
Standard deviation	25.4	19.0	16.5	16.3	18.5	21.3	16.9
Alpha (t-statistic)	-6.32 (-2.73)	-1.18 (-0.92)	1.18 (1.36)	1.98 (1.68)	2.74 (1.38)	9.07 (2.29)	0
Beta	1.33	1.05	0.94	0.89	0.92	-0.41	1
Sharpe ratio	0.172	0.410	0.572	0.613	0.588	0.304	0.372

The momentum premium is not as strong as in Barroso & Santa-Clara (2015) or Daniel & Moskowitz (2016), but this suggests that the momentum premium has weakened in recent decades which is consistent with Jegadeesh & Titman (2011). Alternatively, it suggests that the momentum premium is smaller for large cap stocks which is consistent with Fama and French (2012). Finally, it could also suggest that the momentum premium is slightly smaller in Europe than in the US. The average loser portfolio beta is 1.33, much higher than the average winner portfolio beta, which is 0.92. The average beta-value of the winner-minus-loser portfolio is therefore negative, -0.41. This is consistent with the findings of Daniel & Moskowitz (2016). The average abnormal yearly return of the winner minus loser portfolio is 9.07% when controlled for market risk using the CAPM. Exposure to market risk can therefore not explain the positive average returns of momentum.

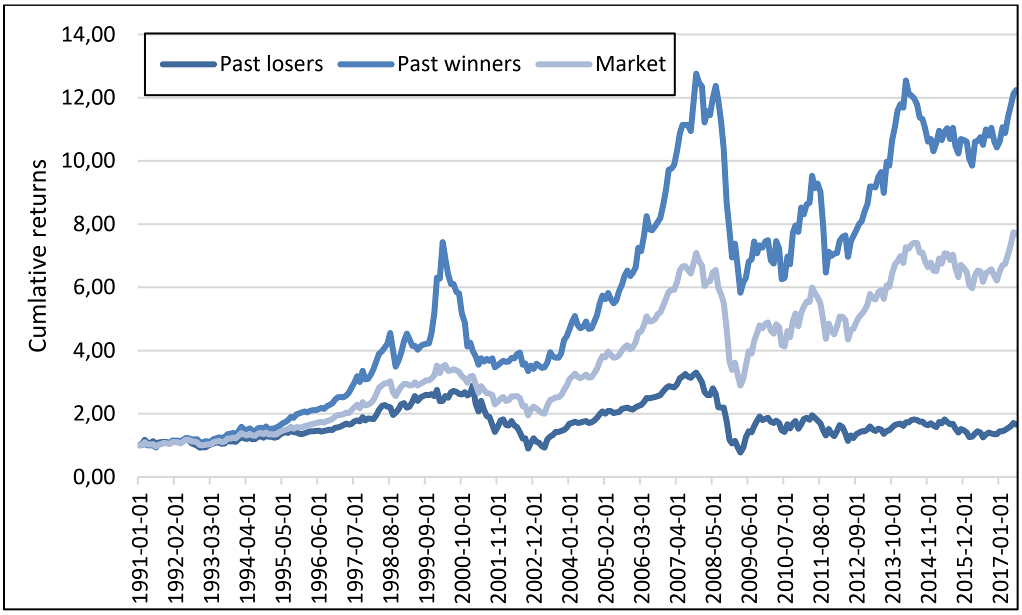

Fig. 1. Past winners and past losers, 1991-2017. Plotted are the cumulative returns for the top quintile "past winner" portfolio and the bottom quintile "past loser" portfolio, together with the market portfolio from 1991:01 to 2017:06.

Running an OLS regression of the WML on the three Fama and French factors (see Eq.2) gives the following estimates (t-statistics in parenthesis):

$$r_{WML,t} = 0.936 - 0.340 r_{RMRF,t} + 0.127 r_{SMB,t} - 0.634 r_{HML,t}$$

$$(2.91) \quad (-5.07) \qquad (0.880) \qquad (-4.78), \tag{8}$$

where the returns are in percent. Controlling for the Fama and French factors, the abnormal return of the WML is 0.936% per month, or 11.2% per annum. The WML is negatively correlated with both the market and the value factor. The exposures are very similar to the ones of the American momentum portfolio in Barroso and Santa-Clara (2015). The WML has a small positive exposure to the size factor (but the estimated coefficient is not statistically significant). The profitability of the momentum portfolio is left unexplained by the three-factor model. In fact, since the momentum portfolio has a negative loading on both the market risk factor and the value factor, the abnormal return given by the three-factor model is even greater than the raw momentum return.

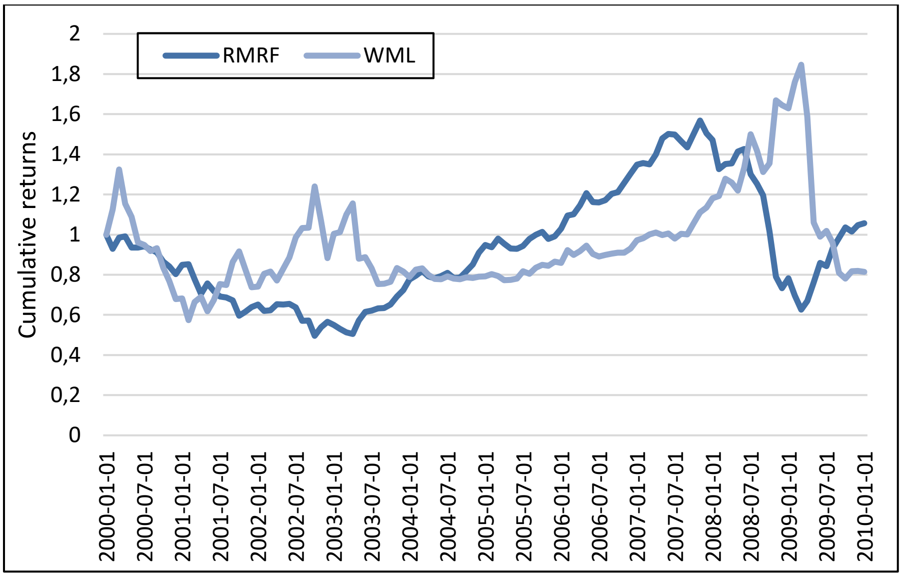

Fig. 2. Momentum in the 2000's. Plotted are the cumulative returns for the winner minus loser portfolio (WML) and the market portfolio minus the risk free rate (RMRF), from 2000:01 to 2009:12.

Figure 2 shows the cumulative returns for the WML and the market in the most turbulent subsample period 2000-2009. The drawbacks of the momentum strategy are clear when examining the performance of the WML in the 2000's. The WML suffers from severe momentum crashes in the 2000's. The year 2000 saw such an episode, but the most serious crash came in 2009. This is the momentum crash I will focus my discussion on. An invested dollar in the WML in the beginning of 2000 is worth less than a dollar a decade later because of the crash. The losses from the crash are persistent, in the sense that the losses are never fully regained during the full sample period (see Fig. 6.). A wrong timed investment in the WML can become a costly affair.

The existing literature on momentum crashes suggests that these occur in times following market declines, market rebounds and in times of high market volatility. When analyzing the momentum crash of 2009 in the US equity market, Daniel and Moskowitz (2016) show that the momentum portfolio's downfall was due to the short-side of the strategy. Similarly, Jegadeesh and Titman (2011) show that the momentum portfolio had a negative beta in 2009. During the market rebound of 2009, the past losers quickly gained in value, much more than the past winners. Since the winner minus loser portfolio sells the past losers, the portfolio suffers a loss when the past losers outperform the past winners. Similarly, if the beta of the winner minus loser portfolio is negative, then the portfolio suffers a loss when the market rebounds. Not surprisingly, this is what happened in the European winner minus loser portfolio in 2009. The portfolio made large gains up until 2009, even a year after the market started to crash. However, coinciding with the market rebound of 2009, the portfolio crashed. The winner minus loser portfolio lost 46% of its value in just three months. Figure 3 shows that the past losers completely outperformed the past winners in 2009. Therefore, the crash of the WML was due to the short-side of the portfolio. The WML had a beta-value of -1.11 in 2009, which is much lower than its full-sample average. Consistent with Jegadeesh & Titman (2011) and Daniel & Moskowitz (2016), the WML had a strongly negative beta in 2009 due to an increased loser portfolio beta and a decreased winner portfolio beta.

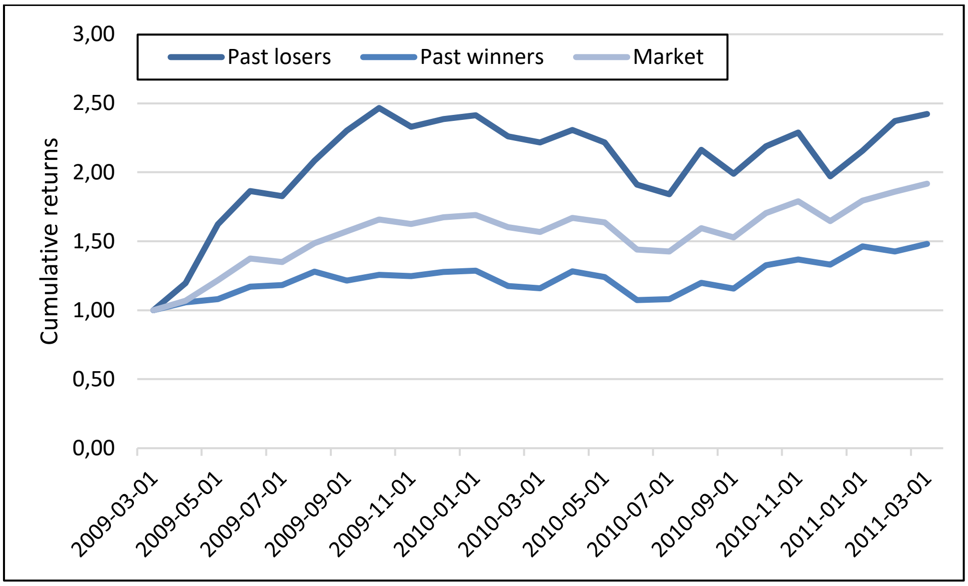

Fig. 3. Past winners and past losers, 2009-2011. Plotted are the cumulative returns for the top quintile "past winners" portfolio and the bottom quintile "past losers" portfolio along with the market portfolio from 2009:03 to 2011:03.

The evident riskiness of the momentum strategy in the 2000s raises the question if momentum is still a sound investment strategy. The empirical findings suggest that it was a poor strategy in the 2000's. Investors looking for less risky strategies can therefore either leave momentum altogether, or utilize modified momentum strategies in the spirit of Barrosso & Santa-Clara (2015) and Daniel & Moskowitz (2016). Barrosso & Santa-Clara employ a simple modification, with strong results. Since research on momentum has shown that the momentum portfolio performs worse after times of high market volatility, it seems obvious to take volatility into consideration. Their modification involves scaling the weight of the winner minus loser portfolio up or down depending on the trailing volatility of the portfolio. They show that the volatility of momentum is forecastable, and scaling the portfolio based on trailing volatility improves the portfolio's mean return, standard deviation, skewness and kurtosis. The risk for momentum crashes is virtually eliminated.

I employed the same strategy as Barroso & Santa-Clara (2015) because of the simplicity and intuitiveness of the strategy. Figure 4 shows the time-varying nature of volatility for the WML portfolio. There seems to be a relation between volatility and performance for the WML. For example, the calm 1990s seem to have yielded stable returns for the WML portfolio. Whereas, the volatility peaks in 2000 and 2009 were followed by large downturns.

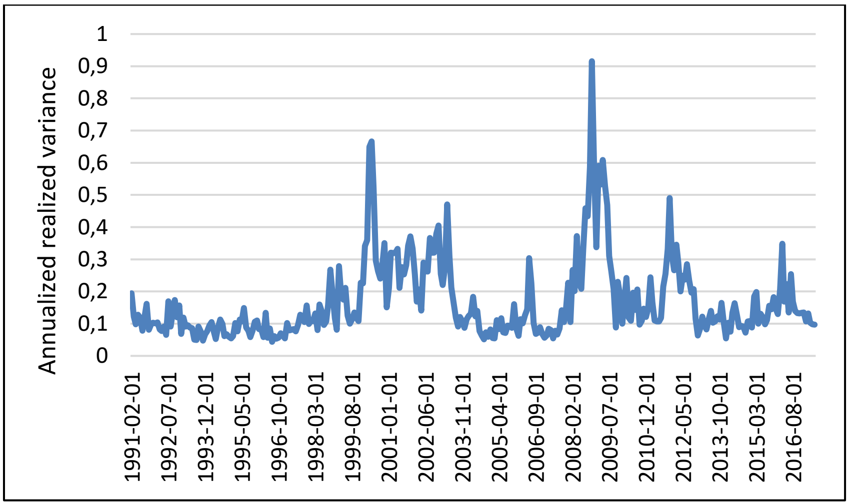

Fig. 4. Monthly realized variances of the WML portfolio, 1991-2017. Plotted are the annualized monthly realized variances of the winner minus loser portfolio from 1991:03 to 2017:06.

The estimates (and t-statistics) from running an AR(1) regression of the realized variance on its lag and a constant (see Eq.4) are:

$$RV_t = 0.0289 + 0.826 RV_{t-1}$$

$$(4.36) \qquad (25.9), \tag{9}$$

with $R^2 = 0.682$. The relatively high AR(1) coefficient of 0.826 means that there is a high degree of persistence in the risk of momentum. Months of increased volatility are clustered. Barroso and Santa-Clara (2015) show that the risk of momentum is more persistent than the risk of the market. They find that forecasting momentum volatility with lagged realized variance yields reliable results in an out-of-sample test. Finally, they show that there is a negative relation between the realized variance of momentum and returns. These factors suggest that the strategy employed by Barroso and Santa-Clara (2015) is reasonable to employ.

Because of the fluctuating nature of the portfolio's volatility, along with the fact that momentum volatility is forecastable, it is natural to scale the weight of the momentum portfolio based on a trailing volatility factor. As target volatility, I use an annualized volatility of 12% because this is the average market volatility for the entire sample. The weight of the portfolio increases above 1 if the trailing volatility is lower than the target volatility, and decreases below 1 if the trailing volatility is above the target volatility. Since the momentum portfolio is a zero-investment portfolio, the weight in the portfolio can increase above 1. The intuition is simple: during volatile periods, we take a smaller position in the momentum portfolio. During calmer periods, we take a larger position in the momentum portfolio. Figure 5 shows the weight of the momentum portfolio as it changes over time. The weight on the WML takes on values ranging between 0.13 and 2.74. Note how large the weight is in most of the 90s and mid-2000's, and how small it is in the early 2000s and in 2008-2009.

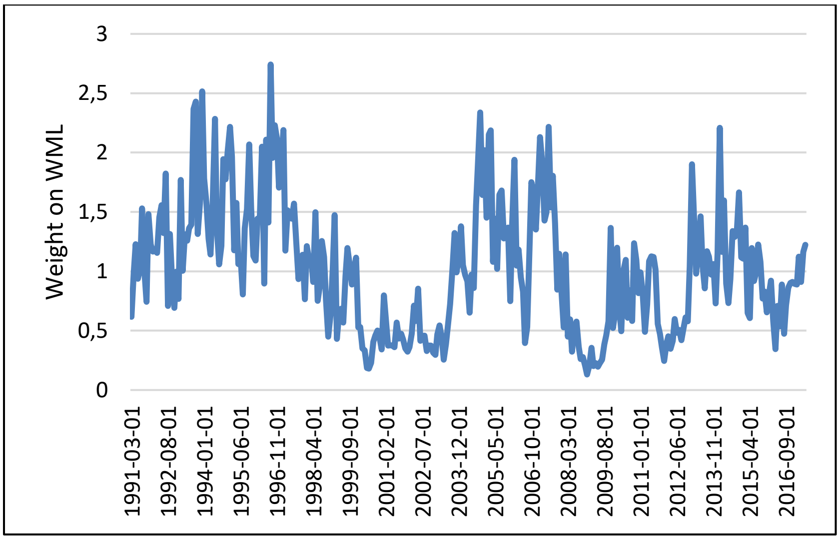

Fig. 5. Weight invested in the WML portfolio, 1991-2017. Plotted are the weights invested in the static winner minus loser portfolio to form the scaled winner minus loser portfolio from 1991:03 to 2017:03.

4.2 Risk-managed momentum

Table 2 presents the summary statistics of returns for the static momentum portfolio, the risk managed momentum portfolio and the market risk factor in the full sample period. The WML is a risky strategy: the standard deviation is higher than for the market and the kurtosis is much higher. Extreme values are therefore more likely in the WML. The risk-managed momentum portfolio performs considerably better than the static momentum portfolio. The average return of the risk managed momentum portfolio is 9.49% with a standard deviation of 15.3%. The static momentum portfolio averages only 6.48% per year, with a standard deviation of 21.3%. Risk management doubles the Sharpe ratio, from the static momentum portfolio's 0.304 to the risk-managed momentum portfolio's 0.620. The higher moments of returns: skewness and kurtosis, are greatly improved. Both the market's and the static momentum portfolio's return distributions are heavily skewed to the left, while the risk-managed momentum portfolio's return distribution is very symmetric. The risks associated with momentum crashes are drastically reduced with the risk-managed strategy. The maximum loss in a single month for the static momentum portfolio is 33.2%. For the risk-managed momentum portfolio, the maximum single month loss is 18.6%. These results are very similar to the results of Barroso & Santa Clara (2015), whose risk-managed momentum portfolio in the US doubled the Sharpe ratio when compared to the static momentum portfolio.

Table 2. Summary statistics of monthly returns for the winner minus loser portfolio (WML), the scaled winner minus loser portfolio (WML*) and the market portfolio minus risk free rate (RMRF), from 1991:03 to 2017:06. The maximum, the minimum, the mean and the standard deviation are in percent. The mean, the standard deviation and the Sharpe ratio are annualized.

Portfolio	WML	WML*	RMRF
Mean	6.48	9.49	6.29
Standard deviation	21.3	15.3	16.9
Maximum	23.3	16.9	13.8
Minimum	-33.2	-18.6	-22.1
Skewness	-0.590	0.0470	-0.576
Excess Kurtosis	4.32	1.61	1.71
Sharpe ratio	0.304	0.620	0.372

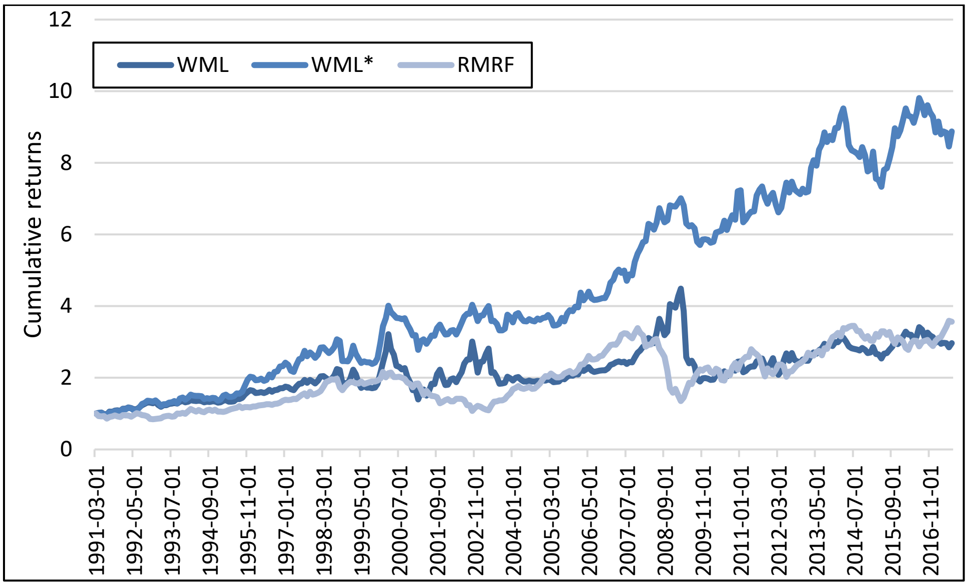

Fig. 6. WML and WML*, 1991-2017. Plotted are the cumulative returns of the static winner minus loser portfolio, (WML), scaled winner minus loser portfolio (WML*) and the market minus risk free rate portfolio (RMRF) from 1991:03 to 2017:06.

Figure 6 shows the cumulative returns of the WML, the WML* and the market risk factor during the full sample period. A dollar invested in the WML* at the start of the sample period is worth 8.88 dollars at the end of the sample period, compared to 2.97 dollars for the WML and 3.57 dollars for the market portfolio. It is interesting to compare the static momentum portfolio to the risk-managed momentum portfolio around the momentum crash of 2009. The value of the regular momentum portfolio peaks in 2009 just before the crash, then plummets and never returns to its peak value. The risk-managed momentum portfolio also loses some of its value in the same months of 2009, but the losses are not nearly as big as for the static momentum portfolio. Moreover, the losses are regained relatively quickly, and new highs are reached just a few years after the losses. The downside risk of the momentum strategy is greatly reduced with risk management. The modification also manages to catch some upside in the mid-to-late 1990s by increasing the weight in the momentum portfolio during calmer periods, resulting in larger gains.

To test how the risk-managed momentum strategy performs in different market conditions, I have divided the full sample into three smaller subsamples. The first subsample (1991-1999) represents a calm period without any market crashes, the second subsample (2000-2009) represents the most volatile period with two major market crashes and the third subsample (2010-2007) represents a post-crash period. The WML performed well in the first subsample with a Sharpe ratio of 0.739, extremely poorly in the second subsample (2000-2009) and average in the third subsample (2010-2017). Table 3 shows the summary statistics for the WML and the WML* in the three subsamples.

Table 3. Summary statistics of monthly returns for the static winner-minus-loser portfolio (WML) and the scaled winner-minus-loser portfolio (WML*) over the three subsamples: 1991-1999, 2000-2009 and 2010-2017. The mean, the standard deviation and the Sharpe ratio are annualized. The maximum, the minimum, the mean and the standard deviation are in percent.

Subsample	1991:03-1999:12		2000:01-2009:12		2010:01-2017:06	
Portfolio	WML	WML*	WML	WML*	WML	WML*
Mean	11.3	15.6	2.05	6.34	6.77	6.45
Standard deviation	15.3	17.8	28.1	14.3	16.6	13.4
Maximum	16.8	16.9	23.3	11.7	13.6	12.4
Minimum	-16.6	-18.6	-33.2	-12.7	-12.5	-12.3
Skewness	0.0118	0.0472	-0.565	-0.0349	-0.167	-0.152
Excess Kurtosis	3.50	1.76	2.56	0.58	0.22	1.00
Sharpe ratio	0.739	0.876	0.0730	0.443	0.408	0.481

Not surprisingly, the biggest gain from the risk-managed momentum portfolio comes in the second subsample. The mean return is tripled and the standard deviation is halved. The skewness and kurtosis of the return distribution is improved. The maximum loss decreased from 33.2% to 12.7%. The results show that the risk-managed momentum portfolio provides the biggest benefit in times of high volatility, especially when momentum crashes occur. Figure 7 shows the cumulative returns of the static momentum portfolio and the risk-managed momentum portfolio in the turbulent 2000s. The static momentum portfolio ends the decade down 19% because of the crash in 2009. The risk-managed momentum portfolio ends the decade 70% up as it manages to avoid the largest losses in the crash and preserve some of the positive returns in 2007-2008. The risk-managed portfolio performed well in the first subsample as well. The mean return is increased from 11.3% to 15.6%, although the standard deviation also increases, from 15.3% to 17.8%. Excess kurtosis is reduced from 3.50 to 1.76. The risk-managed portfolio therefore also offers an improvement in calm periods by increasing the mean return. The situation is less clear in the most recent subsample. The Sharpe ratio does improve, but not by much, from 0.408 to 0.481. The risk-managed portfolio has more excess kurtosis however, 1.00 compared to 0.22 for the static momentum portfolio. The return distribution of the risk-managed momentum portfolio is more skewed in the third subsample compared to the first and the second subsample, which suggests that risk management was unsuccessful in the third subsample.

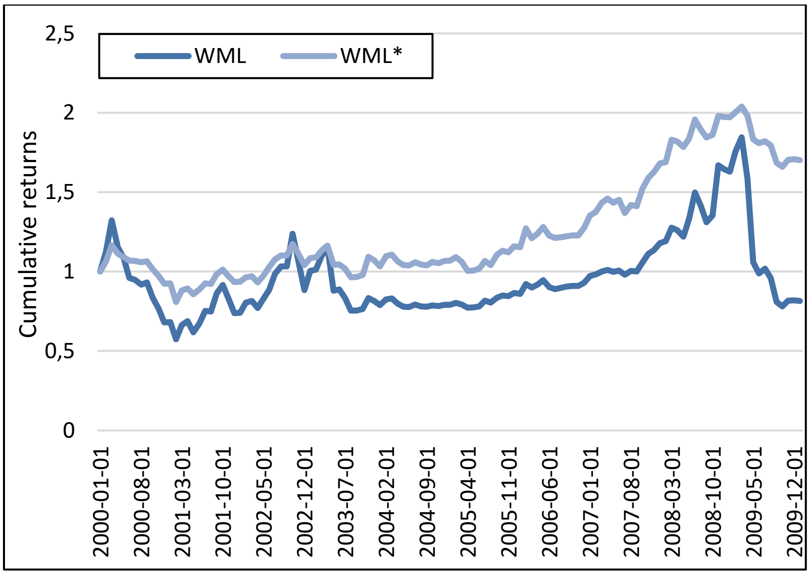

Fig. 7. WML and WML* in the 2000's. Plotted are the cumulative returns of the static momentum portfolio (WML) and the risk-managed momentum portfolio from 2000:01 to 2009:12.

To test if the risk-managed strategy offers benefits in international equity markets, I have tested the strategy in the regions North America (USA and Canada) and Asia Pacific (Australia, New Zealand, Singapore and Hong Kong). The data was obtained from Kenneth French's data library. The risk-managed momentum portfolios in these regions were created using the exact same procedure as the European risk-managed momentum portfolio. An annualized target volatility of 14% was used for North America and 20% for Asia Pacific, since these correspond to the respective region's average market volatility over the full sample period. Table 4 and 5 show the summary statistics of the WML and the WML* in North America and Asia Pacific.

Table 4. Summary statistics of monthly returns for the static winner minus loser portfolio (WML), the scaled winner minus loser portfolio (WML*) and the market portfolio minus risk free rate (RMRF), in North America from 1991:03 to 2017:06. The mean, the standard deviation and the Sharpe ratio are annualized. The maximum, the minimum, the mean and the standard deviation are in percent.

Portfolio	WML	WML*	RMRF
Mean	7.05	8.70	8.00
Standard deviation	22.9	17.7	14.5
Maximum	35.8	18.1	11.5
Minimum	-30.1	-16.0	-18.4
Skewness	-0.0172	0.135	-0.734
Excess Kurtosis	5.34	0.79	1.75
Sharpe ratio	0.308	0.492	0.552

The performance of the winner minus loser portfolio is similar in the North American and the European market. Just like in Europe, the WML is a risky portfolio with higher levels of volatility and kurtosis than the market. The main difference is that the return distribution of the WML is less skewed in North America than in Europe. The benefits from the risk-managed strategy are large. The strategy increases the yearly average return from 7.05% to 8.70%, and decreases the standard deviation from 22.9% to 17.7% when compared to the static momentum strategy. The Sharpe ratio improves from 0.308 to 0.492. Excess kurtosis is greatly reduced, from 5.34 to 0.79. The maximum single month loss decreases from 30.1% for the static momentum portfolio to 16.0% for the risk-managed momentum portfolio. The strategy does not outperform the market risk factor based on the Sharpe ratio, due to a higher standard deviation. But the strategy does give a return distribution that is less skewed than the market, and with less kurtosis.

Table 5. Summary statistics of monthly returns for the static winner minus loser portfolio (WML), the scaled winner minus loser portfolio (WML*) and the market portfolio minus risk free rate (RMRF) in Asia Pacific from 1991:03 to 2017:06. The mean, the standard deviation and the Sharpe ratio are annualized. The maximum, the minimum, the mean and the standard deviation are in percent.

Portfolio	WML	WML*	RMRF
Mean	1.75	10.1	8.94
Standard deviation	25.6	25.5	20.5
Maximum	26.1	25.0	20.5
Minimum	-57.3	-32.9	-26.1
Skewness	-1.78	-0.214	-0.378
Excess Kurtosis	12.6	2.58	2.45
Sharpe ratio	0.0684	0.396	0.436

The momentum effect is weak in Asia Pacific: the WML portfolio earns an average yearly return of only 1.75%. The risks of the static momentum strategy are high in this market. The return distribution is heavily skewed to the left, and the excess kurtosis, 12.6 is much higher than the market excess kurtosis, 2.45. Furthermore, the strategy lost a whopping 57% of its value during a single month in 1998. It is perhaps not surprising that the WML performed poorly in the region, due to higher market volatility in general, and the Asian financial crisis of 1997, which caused a major momentum crash. The risk-managed momentum portfolio earned an average yearly return of 10.1% - almost six times higher than the static momentum portfolio. The Sharpe ratio improves from 0.0684 to 0.396. The return distribution is much less skewed and the kurtosis is much lower compared to the static momentum portfolio. The largest monthly loss is reduced to 32.9%. The risk-managed momentum strategy does not outperform the market portfolio based on the Sharpe ratio, due to a higher standard deviation. But the return distribution is less skewed, while the kurtosis is the same as that of the market. The fact that the risk-managed momentum strategy worked well in Asia Pacific, where the momentum effect is weak, is interesting since it means that the risk-managed strategy also works in markets where momentum is less successful.

5 Conclusion

With this essay, I have analyzed momentum in the European stock market over the last quarter century. A momentum effect was found in Europe - the winner minus loser portfolio earns significantly positive abnormal returns. The strategy performed poorly in the second subsample period, 2000:01-2009:12. A momentum crash was observed in 2009, which wiped out the previous decade's earnings. The European momentum crash of 2009 had many similar features with the American momentum crash which was discussed in Daniel & Moskowitz (2016). The momentum portfolio crashed when the market rebounded because the loser portfolio, which the strategy short-sells, rose dramatically in value.

I have tested the risk-managed momentum strategy of Barroso & Santa-Clara (2015), which targets a constant volatility by dynamically scaling the exposure to momentum. Risk management greatly improves the performance of momentum in Europe – the Sharpe ratio is doubled. The main problems of momentum: time-varying volatility, high excess kurtosis and left-skewed return distribution, are solved with a risk-managed strategy. The risk-managed strategy improves performance in turbulent periods as well as calmer periods. The Sharpe ratio is improved in all the subsamples tested. The largest economic gain from the risk-managed strategy comes from avoiding momentum crashes in times of increased volatility. Risk management works internationally as well: the Sharpe ratio is improved in both the North American equity market and the Asian Pacific equity market. The strategy is implementable in real time as it only relies on information available at the turn of every month. For the investor, following a strategy where the volatility is held constant by dynamically changing weights should be more attractive than following a strategy with a fixed weight, which allows the volatility to vary with time. The risk-managed momentum strategy is therefore an interesting choice for investors looking to profit from momentum, while avoiding the crash risk of traditional momentum strategies.

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