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Avoiding crashes: Exploring risk-managed Momentum strategies

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Abstract

The momentum effect is a persistent and stable phenomenon, achieving very high abnormal returns, which could not yet be explained by conventional pricing models. However, this very high returns are punctuated by extreme strategy crashes leading to high losses, for which investors need decades to recover from. This makes momentum less attractive for risk-averse investors and motivates an appropriate risk management. Previous literature introduced different approaches to manage the risk of this otherwise very profitable strategy. Therefore, this thesis studies and compares different risk-managed momentum strategies in terms of performance throughout all relevant crises of the past century.

1. Introduction

The Capital Asset Pricing Model (CAPM) of William Sharpe (1964) and John Lintner (1965) is widely used to estimate the cost of capital of companies or to evaluate the performance of portfolios. The model provides a testable prediction of the relationship between systemic market risk and expected return. It identifies the efficient pricing of assets when the market is in equilibrium.[1] An advanced empirical pricing model adding company size and book-to-market equity is introduced by Fama and French in 1992.[2] In 2015 Fama and French revolutionize their three-factor pricing model by adding two factors capturing profitability and investment patterns.[3]

Nevertheless, these pricing models are not all-inclusive: some anomalies exist that remain unexplained by their risk factors. One of the most popular anomalies is momentum, a short-term irregularity that can be exploited to generate high excess returns on average. The momentum strategy divides stocks into winners and losers, depending on their past performance. To profit from the anomaly, investments are made to benefit from ongoing losses by losers and consistent gains by winners. This strategy, also known as Winner-Minus-Loser (WML), is used in many variations. Momentum exists in most of all geographic markets, as well as in various asset classes.[4]

The unusually high abnormal returns of the strategy are, however, accompanied by rare collapses in returns, i.e., momentum crashes. These momentum crashes happen after a stock market crash, when stock prices stop falling and start to rebound. The two most severe crashes experienced by momentum so far happened after the Great Depression in 1932 and after the financial crisis in 2009 with drops in the cumulative return of 418% during the months of April to August in 1932 and by as much as 730% during the months of March to May in 2009.

A widely accepted assumption in the theory of financial economics is that investors have a concave utility function and can therefore be classified as risk averse. The relatively high volatility of returns (induced by momentum crashes) makes the momentum strategy less attractive for risk averse investors, especially if the long recovery from crashes is considered.[5] This investor preference motivates the practice of risk management.

[1] Fama and French (2004)
[2] Fama and French (1992)
[3] Fama and French (2014)
[4] Barroso and Santa-Clara (2014)
[5] Barroso and Santa-Clara (2014)

A key characteristic of momentum crashes mentioned in the literature is their presumed predictability. They appear at times when the market begins to recover after a market crash and the strategy volatility is very high. The predictability of these periods can be exploited by risk-managed strategies to reduce or even completely avoid the losses associated with crashes. Therefore, risk-managed strategies can add value by squeezing the left tailed distribution thereby reducing the negative skewness. This way severe losses of the left tail of the distribution can be avoided. Even though avoiding these losses would borne the cost of missing out on very extreme positive returns, risk-management would still add value.

The central contribution of this thesis is therefore the performance analysis of different risk-managed momentum strategies and their comparison with each other. Three prominent risk-managed momentum strategies as well as a strategy firstly introduced by the authors are being studied in this thesis.

One of the two volatility managed strategies discussed in this thesis is the constant volatility momentum strategy, which was firstly introduced by Barroso and Santa-Clara (2014). The authors aim to avoid losses by scaling their exposure to the long and short portfolio of momentum with the aim of achieving a constant volatility.

The second strategy discussed in this paper is the dynamic volatility momentum strategy by Moreira and Muir (2017), whose work is based on the constant volatility strategy. Instead of always assuming a constant volatility, the authors scaled their exposure to the long and short portfolio of momentum with a dynamically changing weight according to the standard deviation of the previous month. Thereby, a more realistic approach is presented which mirrors flexible preferences during changing market states.

The third strategy is the combined momentum strategy by Asness, Moskowitz and Pedersen (2013), who found that value and momentum are negatively correlated. To exploit this relation, the authors created a combined portfolio, that takes a 50% position in a value portfolio and a momentum portfolio, effectively creating a hedge for both.

Daniel and Moskowitz (2016) claim that most of the crash loss of momentum can be traced back to the short positions on the losers. Therefore, the strategy firstly presented by the authors of this thesis, is the Winner Investing strategy. This strategy exclusively holds a long position in the winner portfolio.

In order to compare the strategies an analysis of the key statistical features is conducted as well as a comparison of cumulative returns. This leads to very interesting results.

Since the raw momentum strategy is broadly known as one of the last anomalies which are not explained by the Fama French model, applying these models still leads to high excess returns.

The additional two factors of the five-factor model explain just slightly more of the return of the raw WML.

Given our objective to compare those risk-managed strategies with the raw momentum, an in-depth analysis of all strategies during all severe market crashes of the past century is conducted. This represents an additional contribution to the existing literature since most of it focusses exclusively on the two most severe strategy crashes in 1932 and 2009. One very surprising result of this analysis is that contrary to what is mentioned in the existing literature, momentum strategy crashes are not occurring consistently in rebounding market. Therefore, momentum crashes are not as predictable as presented by the literature.

Another observation is that, very often before the raw momentum strategy[6] as well as the risk-managed momentum strategies crash they experience an increase in cumulative returns, which could eventually be a superior predictor of a momentum crash.

Lastly, the authors of this paper introduce the Winner Investing strategy and find that this strategy achieves extremely high abnormal returns. Due to the removal of the short position a limit to losses is set since a long position cannot lose more than the initial invested amount. However, the strategy is not very efficient at avoiding strategy crashes. It experiences even larger crashes than raw momentum. Furthermore, these crashes are not like the regular momentum crashes, that happen during rebounding markets. Instead, they appear at the same time as the market crash itself. Furthermore, the Winner Investing strategy would not be self-financing, since it receives no gains from shorting the loser portfolio, therefore investors might need to keep their funds invested in the winner portfolio.

The thesis is structured as follows:

The next section provides an overview of the existing literature, which serves as basis for this thesis. Following, section 3 provides theoretical explanations for the momentum effect by discussing the properties of the momentum strategy using behavioral and rational explanations for the occurrence of the anomaly. Section 4 provides an overview of the key characteristics of momentum crashes and presents different approaches that could explain their occurrence as well as a short overview of the historical market crashes of the past century. In section 5, all risk-managed strategies that are empirically analyzed, are summarized. Lastly section 6 contains the empirical section including a robustness check. The last section concludes the findings of this thesis.

[6] The momentum strategy will be henceforth referred to as Winner-Minus-Losers (WML) or raw momentum, whereas the momentum anomaly itself will be referred to as momentum.

2. Related studies

Jegadeesh and Titman (1993) were one of the first ones to discover the momentum effect with significant positive returns over three to twelve month holding periods. The authors implemented a strategy that formed portfolios by ranking stocks into deciles according to their previous twelve-month cumulative returns. Their momentum strategy forms portfolios by buying the highest ranked (highest decile) and short-selling the lowest ranked stocks (lowest decile), whereby they create a self-financing investment strategy. Jegadeesh and Titman (1993) state that significant abnormal returns were observed between 1965-1989, meaning that past winners in the US stock market outperform past losers by roughly 1.50% per month.[7] Furthermore, momentum is not just a US stock market anomaly. This has been examined by Asness, Moskowitz and Pedersen (2013) who found a persistent momentum premium across eight different markets and asset classes. Asness, Liew and Stevens (1997) claimed that firm characteristics such as the book-to-market ratio, market equity and one-year past return might explain the differences in expected returns for various country stock indices. Moreover, Rouwenhorst (1998) supports these findings, as he observes that momentum is present in twelve different international equity markets and lasts for about one year on average. Therefore, it can be stated that momentum is a pervasive anomaly throughout different markets and asset classes.[8]

Even though momentum strategies had significant abnormal returns over the past decades, Daniel and Moskowitz (2016) claim that these excessive returns come at the expense of a very high excess kurtosis and a negative skewness. These two attributes of the distribution of momentum returns imply a very fat left tail, which indicates a significant crash risk. The authors found that momentum returns can turn into a free fall very quickly, eliminating decades of previously earned returns.[9] For instance, an investor who invested one US Dollar in the winner-minus-loser (WML) strategy during the Great Depression in 1932 would need approximately 31 years to recover from those losses. Therefore, the authors claim that the large abnormal returns of the momentum strategy do not fairly compensate for the reoccurring crashes. This requires a long-run perspective on the risk of momentum investing.[10]

Over the last decades, several researchers have tried to predict and mitigate momentum crashes. One of the first fundamental contributions was made by Kothari and Shanken (1992) who argue

[7] Jegadeesh and Titman (1993)
[8] Fama and French (1996)
[9] Daniel and Moskowitz (2016)
[10] Daniel and Moskowitz (2016)

that past-return sorted portfolios will have significant time-varying exposure to systematic factors. This means that the inherited beta will be positive after bull markets and negative after bear markets. They claim that following negative returns of the overall market, winners tend to be low beta stocks and losers high beta stocks, which makes the winners-minus-losers (WML) strategy obtain a negative beta in those periods. By showing this effect, the authors claim that the time-varying beta is partly responsible for causing the crashes. Their finding was one of the first evidence that momentum crashes are predictable and might be partially avoidable.[11]

Based on this work, Grundy and Martin (2001) further examined the time-varying nature of the momentum strategy's risk exposure. They showed in their published work from 2001, that the average momentum returns could not be explained as a compensation for bearing exposure to the three factors of the Fama French model (1996) or by cross-sectional variability of average stock returns or industry factors. In line with Kothari and Shanken (1992), the authors state that the momentum beta can be explained by the past market returns. They found that following up markets, the strategy will go long in stocks that outperform the market ($\beta > 1$) and short in stocks that underperform compared to the market ($\beta < 1$). This reverses in down markets, where stocks moving into opposite directions of the markets perform best.[12] By hedging out momentum's estimated factor exposure, the authors establish a risk-managed momentum strategy with higher payoffs due to avoidance of often very unprofitable bets against the January effect[13] and implicit bets on momentum in the factors.[14] The risk-managed strategy reduces the volatility of monthly returns by over 78% and leads to even more significant and larger returns than the unadjusted momentum strategy.[15] Nevertheless, their strategy is not really applicable in real life, as in order to assess the hedge it would be required to know the the future factor exposure to be realized over the subsequent six months at the beginning of each investment. An alternative would be to estimate factor exposure based on ex post data. [16]

Another study implementing a risk-managed momentum strategy is the work of Barroso and Santa-Clara (2014), who construct a constant volatility strategy that scales the long-short portfolio by its realized volatility over the previous six months. The authors found that the high volatility of momentum as well as the predictability of the strategy's crashes could be exploited to achieve higher profitability. Their results show that a risk-managed momentum approach

[11] Kothari and Shanken (1992)
[12] Grundy and Martin (2001)
[13] The January Effect is a seasonal increase in stock prices perceived during the month of January.
[14] Grundy and Martin (2001)
[15] Grundy and Martin (2001)
[16] Grundy and Martin (2001)

broadly avoids crashes.[17] Furthermore, the constant volatility strategy leads also in non-crash periods to an improved Sharpe Ratio[18], a reduced excess kurtosis as well as a less pronounced left skewness, thereby significantly decreasing its risk.[19] Since the authors use a very simple approach and ex ante information, their strategy is especially useful in real time due to its easy implementation. Barroso and Santa-Clara (2014) scale the momentum returns using an annualized target volatility of 12%.[20] However, this choice is not further explained in their paper and can therefore be assumed to be a subjective choice.[21] It may be more realistic to assume investor's risk preference to vary over time. For example, it might be appropriate to assume that an investor wants to take more risk in bull markets and relatively less risk in bear markets. Due to the strategy's broad approval in the momentum literature, this strategy is applied in the empirical analysis. Furthermore, we represent an extended dataset and include the recently experienced and still ongoing Covid-19 pandemic.

The authors Daniel and Moskowitz (2016) follow up on the results of Barroso and Santa-Clara (2012)[22] and present a dynamic volatility momentum strategy that exploits its properties.[23] They implement a strategy that dynamically changes its long and short positions, similar to that of Barroso and Santa-Clara (2014). Instead of trying to achieve constant volatility, the authors' target is to continuously maximize the Sharpe Ratio. They calculate the optimal weight by using a Lagrange optimization procedure to maximize the Sharpe Ratio. A GJR-GRACH model and a maximum likelihood model have been used to estimate the variance and return. As a result, the dynamic strategy leads to a smoothened volatility of the momentum portfolio, similar to the approach of Barroso and Santa-Clara (2014). The authors recognize that the additional improvement provided by dynamic weighting indicates that gains are even achieved in markets where the raw momentum strategy was unable to generate profits. A prominent example of this is the Japanese stock market.[24] The results of the dynamic strategy would be similar to those of the constant-volatility strategy if the Sharpe Ratio of the momentum strategy were time-invariant. This means that the predicted average return is always proportional to the predicted

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[17] Barroso and Santa-Clara (2014)
[18] The Sharpe Ratio is a financial metric used by investors to assess the performance of an investment. It will be further explained in section 3.1.
[19] Barroso and Santa-Clara (2014)
[20] Barroso and Santa-Clara (2014)
[21] Testing for different target volatilities leads to the result that a similar Sharpe ratio is obtained for a target volatility of 8% to 15%.
[22] Daniel and Moskowitz relate their work to a previously published 2012 working paper on the published 2014 article by Barroso and Santa-Clara.
[23] Daniel and Moskowitz (2016)
[24] Daniel and Moskowitz (2016)

volatility. In this case, an optimal dynamic strategy would be a constant volatility strategy.[25] Since in fact the momentum return is negatively correlated with the predicted volatility (option-like behavior), the dynamic volatility momentum strategy is not identical to that of Barroso and Santa-Clara (2014).[26]

Daniel and Moskowitz (2016) were the first to relate this behavior to that of a written call option on the market. A closer examination of this option-like behavior reveals that the crash performance is mostly attributable to the short side or the performance of the losers, meaning that when the market declines they gain a little, but when the market increases, they lose a lot.[27] Daniel and Moskowitz's (2016) results are consistent with the results of Cooper, Gutierrez, and Hameed (2004) and Stivers and Sun (2010), who find that momentum returns are reversed during bear markets and fail to generate positive returns when market volatility is high.

Another study establishing a dynamic momentum strategy, was presented by Moreira and Muir (2017). The authors established a more realistic strategy by constructing dynamic volatility-managed portfolios. They found that implementing this strategy realizes significant risk-adjusted returns for not only for momentum, but also for market, value, return on equity, investment, profitability, betting-against-beta factors in equities and currency carry trade.[28] Moreira and Muir (2017) construct momentum portfolios, by scaling monthly returns using the inverse of their previous month's realized variance. This decreases their risk exposure when a recently high variance can be observed and vice versa. Since variance is highly predictable in the short run and variance forecasts are only weakly related to future returns at these horizons, their volatility-managed portfolios earn significant risk-adjusted returns. The authors also found empirical patterns implying a high willingness to take stock market risk in periods of high volatility, which is in contrast to most theories. Volatility is the highest in times of recessions, financial crises and after a market crash, where investors should reduce their risk exposure.[29] However, Moreira and Muir's (2017) approach which is based on an ex-post volatility target calculated on the entire sample might lead to some potential biases. The authors assume that the standard deviation for the whole sample period is given at the start of the period. This might not seem realistic because in their model an investor would know the volatility for the entire sample regardless of the moment he invests. For instance, an investor who starts investing in

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[25] Daniel and Moskowitz (2016)
[26] Daniel and Moskowitz (2016)
[27] Daniel and Moskowitz (2016)
[28] Moreira and Muir (2017)
[29] Moreira and Muir (2017)

the middle of the sample period would know the volatility for the entire sample and would therefore scale the returns as such.[30]

This strategy is further examined in the empirical section of this paper as it represents an enhanced version of the strategy presented by Barroso and Santa-Clara (2014).

Asness, Moskowitz and Pedersen (2013), though not specifically searching for strategy avoiding momentum crashes, found that value and momentum strategies are negatively correlated with each other across various asset classes.[31] They specifically found significant evidence that liquidity risk is negatively correlated to value and positively related to momentum globally, implying that the negative correlation between the two strategies is driven by opposite exposures to liquidity risk.[32] In order to benefit from their negative correlation, the authors established a joint strategy combining momentum and value by constructing a portfolio that takes a 50% position in a value portfolio and a 50% position in a momentum portfolio.[33] The negative correlation between momentum and value implies that the strategies could be used as a hedge for each other's risks.[34] Therefore, the combined portfolio is much closer to the efficient frontier with a significantly increased Sharpe Ratio (1.45) than either strategy and experiences less variance across markets over time.[35]

Due to the significant performance improvement of momentum by combining it with the value portfolio, we include this strategy as further option to implement a risk-managed momentum strategy. Furthermore, we are also including this strategy to compare the volatility managed strategies with a different risk-management approach.

Daniel, Jagannathan and Kim (2012) tie in with the work of Asness et al. (2013) and established a conditional momentum strategy, that combines momentum and value only in times of crashes.[36] The authors developed a two-state hidden Markov model that assumes the economy to have two states: calm and turbulent. In their model they establish two different processes to generate momentum returns according to the current state. They estimate the probability of the economy currently being in a turbulent state by using maximum likelihood.[37] In times of a high probability of turbulent states, the authors suggest the usage of a conditional momentum strategy that hedges value and momentum.[38] The incorporation of this optionality in the model

[30] Moreira and Muir (2017)
[31] Asness, Moskowitz and Pedersen (2013)
[32] Asness, Moskowitz and Pedersen (2013)
[33] Asness, Moskowitz and Pedersen (2013)
[34] Asness, Moskowitz and Pedersen (2013)
[35] Asness, Moskowitz and Pedersen (2013)
[36] Daniel, Jagannathan and Kim (2012)
[37] Daniel, Jagannathan and Kim (2012)
[38] Daniel, Jagannathan and Kim (2012)

significantly improves the skewness and kurtosis of the original momentum strategy, leading to normally distributed hidden Markov model specifications.[39] As a result, the estimates of turbulent states and simultaneous large momentum crashes of the hidden Markov model are far more accurate than alternative explanatory variables like past momentum and market returns or forecasts from a GRACH model. The authors state that the incorporation of optionality is the key explanatory variable to forecast these tail events.[40]

Another momentum strategy that employs risk management to improve returns of the momentum anomaly is presented by Ruenzi and Weigert (2018). The authors particularly emphasize an incorporation of crash sensitivity in momentum stocks. They examine a proposed risk-managed strategy, that buys stocks with high crash sensitivity and sells stocks with low crash risk sensitivity.[41] By controlling for the exposure to systematic crash risk, the authors reduce the momentum effect from a significant 11.94% to an insignificant 1.84% per year. This means that a substantial part of the strategy’s profitability is a compensation for its systematic crash risk exposure.[42]

The authors Han et al. (2016) introduce in their paper “Taming momentum Crashes: A Simple Stop-Loss strategy”, a risk-managed momentum strategy that limits exposure to losses by implementing a simple 10% stop-loss rule. This means positions in both the winner portfolio and the loser portfolio are closed when a 10% drop occurs. Surprisingly, limiting the risk is not reducing the return. Instead, the risk-managed strategy achieves higher average returns, reduced standard deviation and an increased Sharpe Ratio. In practice, stop strategies are commonly used by professional traders as a risk management tool.[43] Furthermore, transaction costs are also not diminishing the increased profitability, since returns increase by 70% and transactions increase only by 40%, the stop-loss strategy remains clearly more profitable.[44] But these results pose questions as to whether the high momentum returns are not the fair compensation for crash risk exposure.[45]

A more recent risk-managed momentum strategy was introduced by Dobrynskaya in 2019. In line with Daniel and Moskowitz (2015), the author found, that the high returns are due to the

[39] Daniel, Jagannathan and Kim (2012)
[40] Daniel, Jagannathan and Kim (2012)
[41] Ruenzi and Weigert (2018)
[42] Ruenzi and Weigert (2018)
[43] Han et. al (2014)
[44] Han et. al (2014)
[45] Han et. al (2014)

long position, whereas the negative skewness, the high volatility and the negative market beta are mainly caused by the short position of a momentum portfolio.[46]

Another finding was that momentum strategies react to market plunges with a significant delay of one to three months. The reason for this lagged behavior is probably related to the best practices of momentum portfolio formation. The stocks are usually sorted by their previous performance, whereby the most recent month is skipped to avoid short-term reversal effects and due to the rebalance of portfolios on a quarterly basis.[47] Therefore, Dobrynskaya (2019) proposes a dynamic volatility momentum strategy that equals the raw momentum strategy in calm market states and switches to a contrarian strategy after a market crash, keeping this position for three months and reverting to the initial strategy thereafter. This means the strategy starts with the raw momentum that deducts losers from winners (WML) and switches in turbulent market states to a strategy that deducts winners from losers (LMW). Resulting, this strategy turns major momentum crashes into gains and generates an average return that is 1.5 times higher than that of the raw momentum strategy.[48]

Furthermore, the strategy is easier to implement than most of the other forecasting models with constant volatility scaling (Barroso and Santa-Clara, 2014) or dynamic volatility scaling (Daniel and Moskowitz 2016) due to no requirements of additional estimations and additional in- or outflows of funds. The strategy also achieves a lower risk and since the crashes occur very rarely and realized losses of raw momentum would be high, the additional transaction costs are assumed to not eliminate the additional gains of the risk-adjusted returns.[49]

The following section introduces theoretical explanations for the momentum effect and crashes.

[46] Dobrynskaya (2019)
[47] Dobrynskaya (2019)
[48] Dobrynskaya (2019)
[49] Dobrynskaya (2019)

3. Theoretical background of momentum

In the following section, theoretical foundations of the momentum strategy are presented, that provide a basis for the empirical analysis in this paper. Section 3.1 summarizes the main properties of the momentum strategy. The following sections 3.2 and 3.3 explain possible behavioral and rational explanations for the occurrence of the momentum anomaly itself.

3.1 The momentum strategy

The momentum anomaly describes the tendency of stocks to continue recent upward or downward price development of the recent past in the short-term future. Therefore, the momentum strategy uses this pattern to generate excess profits.[50] Investors implementing this strategy analyze realized returns of stocks and predict the expected future returns based on their observations.[51]

This pattern is used to generate high profits with supposedly low risk. The basis of the strategy is the classification of stocks. Profitable shares of the recent past form the winner portfolio, analogously unprofitable stocks form the loser portfolio. Most commonly, stocks are ranked according to their past performance and assigned to one of ten decile portfolios. To form the strategy, the most profitable decile is labeled the winner portfolio and the least profitable one is labeled the loser portfolio.

However, there are also less conventional approaches to form momentum portfolios. Asness et. Al (2013) for example, instead rank stocks in only three portfolios and takes a long position in the top third and a short position in the bottom third.[52]

In general, profits are expected to occur because investors speculate that this short-term trend will continue in the near future. In expectation that prices will continue to rise, winning stocks are bought. Accordingly, loser shares are sold short[53] to generate profits from the expected price losses.[54] As long as the loser portfolio continues to achieve a lower return than the winner portfolio in the near future, the strategy remains profitable.[55]

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[50] Daniel, Jagannathan and Kim (2012)

[51] Daniel and Moskowitz (2016)

[52] Asness, Moskowitz and Pedersen (2013)

[53] In a short sale of a stock, a party A borrows a stock from party C for a certain period. Shortly thereafter, the borrowed stock is sold by that party A to a party B. When the stock has to be returned to party C, party A has to buy the stock back on the public market in order to return the previously borrowed stock to party C. The best case in this transaction for Party A would be that the share price has fallen in the meantime. Then party A makes a profit, since it can buy back the share at a lower price than it originally sold the share to party B.

[54] Daniel, Jagannathan and Kim (2012)

[55] Barosso and Santa-Clara (2014)

In most cases, the momentum strategy is characterized by its extremely high Sharpe Ratio. The Sharpe Ratio is used to measure the profitability of a stock in relation to the risk taken. It is defined by the following formula:

$$(1) \qquad Sharpe\ Ratio = \frac{\mu_i - r_f}{\sigma_i}$$

Where μ_i is the expected return of the asset i, r_f displays the interest rate of a risk-free investment and σ_i is the standard deviation of the asset return i. The risk-free return is commonly assumed to be zero.[56]

The momentum strategy has a positive alpha, meaning it generates a higher return than factor models predict.[57] This qualifies the strategy as one of the last anomalies that cannot be fully explained by the generally used pricing models.[58]

In their paper, Barroso and Santa-Clara (2014) use the three factors of the Fama and French model (SMB, HML and Market) and compare their statistical characteristics with WML. Their results are displayed in *Table 1*.

Table 1 was created based on historical data from March 1927 to December 2011. The WML-strategy compared in the long-term leads to the highest average yearly return of 14.46%. The Sharpe Ratio of 0.53 is high and exceeds the market's Sharpe Ratio by 0.14.

The above-average returns are accompanied by a high kurtosis of 18.24. This implies that extremely negative or positive returns occur more frequently. The negative skewness of -2.47 means that more than half of all returns are below the mean.[59] A high kurtosis and a negative skewness are characterizing momentum crashes and will be more closely discussed in the empirical analysis.

Most literature tries to explain the abnormal momentum returns with factor models. Most commonly, they use the three-factor Fama French model and the in 2014 presented adapted five-factor asset pricing model. The three-factor model uses the excess market return, high-minus-low factor (HML) and the small-minus-big (SMB) factor as risk factors. The five-factor model adds the two risk factors conservative-minus-aggressive and robust-minus-weak.[60] By adding additional explanatory variables to the model, the authors found that most capital market

[56] Lo (2002)
[57] Daniel and Moskowitz (2016)
[58] Daniel, Jagannathan and Kim (2012)
[59] Von Hippel (2014)
[60] Fama and French (2014)

anomalies can be explained. However, the momentum anomaly remains not fully explained by the model, but its previously unexplained excess returns are reduced.[61]

Due to the timeliness of the five-factor model and the subsequent rareness of studies applying this model, we will apply both factor models in our work to seek an explanation for the momentum effect in our dataset.

Despite the high average returns for investors there is, as mentioned before, a significant downside risk in the form of momentum crashes. This phenomenon is considered in more detail in chapter 4.

3.2 Rational explanation for momentum effect and profits

In the following section, several possible explanations for the momentum effect that refer to the market efficiency hypothesis are presented. The market efficiency hypothesis states that, in efficient markets, all available information is immediately reflected in asset prices. Accordingly, no rational market participant can generate above-average profits on a sustained basis at no cost.[62]

Conrad and Kaul (1998) present one of the first studies, attempting to determine the source of momentum, by decomposing profits into time-series predictability in stock returns and cross-sectional variation in the mean returns of stock included in the portfolio. They found that momentum profits can be largely explained by their cross-sectional variation in mean returns.[63]

Lesmond, Schill, and Zouh (2001) offer another perspective on excess returns. They consider the abnormal returns of the strategy to be an illusion due to previously underestimated transaction costs. They recognize that momentum stocks require very high transaction costs and thus reduce profits to the extent that no excess returns remain for the investor.[64]

Johnson (2002) examines the relationship of episodically changing growth rates on momentum stocks. The author finds that firms with large recent positive price movements are more likely to have a positive growth rate shock and are therefore assigned to a winner portfolio in momentum portfolio formation.[65] Therefore, the momentum effect is based on continued growth expectations, where companies with high growth prospects constitute the winner portfolio and those with low growth constitute the loser portfolio.

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[61] Fama and French (2015)
[62] Shefrin und Statman (1985)
[63] Conrad and Kaul (1998)
[64] Lesmond, Schill and Zouh (2001)
[65] Johnson (2002)

Li, Miffre, Brooks, and O'Sullivan (2008) consider the news impact on unsystematic risk of winner and loser portfolios of momentum returns. The authors found that winner stocks react significantly faster to recent news than loser stocks. Since loser stocks are more likely to receive bad news, they may be more likely to not disclose the negative information immediately. By withholding the bad news loser stocks would reduce price pressure and incur therefore a higher volatility. On the other hand, winning stocks are more likely to receive positive news and thus have a stronger incentive to disclose positive information directly. The result is a stronger reaction to recent news from winners and a stronger reaction to older news from losers, which could cause the momentum effect.[66]

Barroso and Santa-Clara (2014) find a very high kurtosis and negative skewness in their analysis of momentum returns and explain these attributes, which are indicative of a risky investment, by the time-varying risk of the strategy. Through a regression, it was also determined that the majority, i.e., 77% of the total momentum risk, is strategy-specific and cannot be explained with the help of the market. Only the remaining 23% of the momentum risk can be explained by systematic risk. Conducting an autoregression of the risk factors, they find that past data of the market specific factor does not provide a good estimator for the future expected risk. In contrast, an autoregression of the momentum-specific factor yields the result that historical data offers significantly higher predictability.[67] These properties are used by Barroso and Santa-Clara for their constant volatility momentum strategy, which is discussed in more detail in Section 5.1.1.

Novy-Marx (2015) analyzed the influence of past historical earnings on momentum and found that the momentum effect in stock prices is reflecting the momentum in earnings. Therefore, stocks of companies that recently announced strong earnings outperform stocks of companies with weak earnings. This implies that momentum could result from a higher likelihood of companies with higher historical earnings to maintain a high performance compared to low historical earnings.[68]

Lastly, momentum crashes, which play a central role in this paper, constitute the main source of risk for the strategy. Daniel and Moskowitz (2016) describe momentum returns as a fair compensation for the high crash risk.[69]

[66] Li et. al (2008)
[67] Barroso and Santa-Clara (2015)
[68] Novy-Marx (2015)
[69] Daniel and Moskowitz (2016)

In conclusion many different factors could play a significant role in explaining the momentum effect, but all together are somewhat related to higher risks, for which an investor needs to be compensated.

3.3 Behavioral explanation for momentum effect and profits

As the existence of momentum contradicts asset pricing theory and the theory of rational expectations, previous studies explored behavioral theories to explain the strategy's excess return. Behavioral financial market theories use psychological and sociological concepts to explain how human behavior can influence an investor's decision-making and thus the market.[70] All concepts presented assume psychologically as well as sociologically influenced investors who do not rationally incorporate available information into their decision making.

The conservatism bias represents a behavioral tendency that may account for an underreaction to new information. This tendency causes individuals to update their beliefs slowly in the presence of new information. One reason for this could be that investors may believe that there is a large temporary component to the new information.

The representativeness heuristic offers another possible explanation for the phenomenon. It describes the perception that investors are too quick to recognize certain stocks as the "ideal type" and end up making an erroneous judgment. Consequently, investors update their beliefs too slowly when confronted with contradictory findings.[71]

These biases initially lead to momentum as stock prices react with a delay to company-specific information. This indicates that investors' irrationality causes deviations from fundamental values and can thus lead to mispricing.[72]

Daniel, Hirshleifer, and Subrahmanyam (1998) argue that overconfidence and a biased self-assessment of investors create momentum. Overconfidence refers to the overestimation of an investor's private information signal and the consequent underestimation of all publicly received information. The overweighting of the private signal over the public one causes stock prices to overreact to private information signals and underreact to public ones.[73]

The authors Hong and Stein (1999) constructed a unified behavioral model, that includes two types of boundedly rational agents: ”newswatcher” and ”momentum traders”. In their model each type of agent is only able to “process” some subset of all available public information.

[70] Ackert and Deaves (2010)
[71] Li et. al (2008)
[72] Barberis et. Al (1998)
[73] Daniel, Hirshleifer and Subrahmanyam (1998)

Newswatchers are only able to use private information and momentum traders are using historic price changes to forecast future fundamentals. Furthermore, they assume private information to diffuse gradually, resulting in an initial underreaction of newswatcher to news and therefore a lower market price. This underreaction offers the possibility for momentum traders to make excess profits. However, since momentum traders are assumed to be limited to simple strategies, an initial convergence of prices towards the fundamental value is accelerated, but often also causes an overreaction to news. Therefore, the first momentum buyers exert a negative effect on later momentum buyers, which cause further increases in stock prices.[74]

The authors Grinblatt and Han (2002) see the disposition effect as the main driver of momentum. This refers to the behavioral economic effect that individuals perceive and evaluate gains and losses differently.[75] Accordingly, investors have a preference to hold falling stocks (losers) for too long and to sell rising stocks (winners) too early.[76] The authors show empirically that the disposition effect explains the tendency for past winners to perform better later compared to losers. These irrational actions of investors result in stock prices not reflecting complete information and therefore deviating from the fundamental value. Since a sole deviation from the fundamental value does not yet offer a profit opportunity for momentum to exploit, market prices must converge to the fundamental value over time. By trading the stock, market prices converge towards the underlying intrinsic value. Profits can be made by investing in undervalued stocks and short-selling overvalued stocks.[77]

The behavioral economic models try to explain why, based on past returns, forecasts about future returns can be made. Overall, an underreaction by the market to new information is assumed to be the main cause of the momentum anomaly.

[74] Hong and Stein (1999)
[75] Grinblatt and Han (2002)
[76] Shefrin and Statman (1985)
[77] Grinblatt and Han (2002)

4. Momentum crashes

The following chapter provides an overview of the key characteristics of momentum crashes. Subsequently, different approaches are presented that could explain their occurrence. This section serves as a theoretical foundation for our empirical analysis.

4.1 Key characteristics of momentum crashes

In certain market situations, the positive average returns of the momentum strategy are replaced by losses that occur rarely and can persist for several months, so-called crashes. These momentum crashes can be observed in the negative skewness and high kurtosis of the strategy, which characterize a considerable risk. Accordingly, a momentum crash in the cross-section leads to the occurred losses being significantly higher in magnitude than the average gains of the momentum strategy. This makes the entire strategy less attractive to risk-averse investors. According to Barroso and Santa-Clara (2014) such crashes reserve significance in terms of their length of recovery. The authors argue that an investor would need decades to recover from such losses.[78]

In the existing literature, Daniel and Moskowitz (2016) define a momentum crash as a moment in which the short portfolio (losers) crashes up rather than down.[79] A more quantifiable definition was made by Daniel, Jagannathan and Kim (2012) who characterize a crash when the momentum loss exceeds 20%.[80] A similar approach was established by Lou, Dong and Polk (2013) who define “bad” weeks as having a momentum return below -5%. Moreover, the author found similar results when defining momentum crashes by -10%, -15%, and -20%. By applying these different cut-offs, they ensure that the previous skewness results are not due to a small number of extremely negative returns of the momentum strategy.[81]

In this paper, a momentum crash will be defined as experiencing a change in cumulative returns of the previous month of -20% or less. This definition is in line with most literature and includes only severe and persistent crashes.

Barroso and Santa-Clara (2014) and Daniel and Moskowitz (2016) have discovered that a momentum crash is most likely to occur during periods when the market is beginning to recover,

[78] Barroso and Santa-Clara (2014)
[79] Daniel and Moskowitz (2016)
[80] Daniel, Jagannathan and Kim (2012)
[81] Lou, Dong and Polk (2013)

after preceding market declines. These so called “panic states” are characterized by high returns and a high ex ante volatility following bear markets.

This led the authors to argue that momentum shortfalls can be circumvented and mitigated early through an appropriate risk-management. The risk factor of momentum crashes could thus be minimized or perhaps even be eliminated, and the risk-managed strategy could become profitable in otherwise loss-making periods. The expected gains from anticipating impending crashes using risk-managed momentum strategies are discussed in more detail in the next chapter. Empirical evidence of this phenomenon can be found in historical data. One of the biggest losses of the WML strategy was realized in July and August 1932, when the market started to recover from the consequences of the Great Depression. The second major and more severe collapse of the strategy occurred in 2009, when the economy began to recover from the financial crisis.[82] The most recent crisis, the Covid-19 pandemic, occurred in 2020. The highest loss was realized in March and April, shortly after the pandemic had majorly influenced the global economy.

Furthermore, it can be observed that in crash periods the volatility of the strategy is unusually high. *Figure 1* plots the volatility of the WML strategy over time. The 1932, 2009 and 2020 crashes can be noticed by the relatively high spikes of the graph. It can be observed that the crashes occur in situations where the WML volatility is highest.

The three major crash periods can also be identified by their past returns. *Figure 2* plots the cumulative returns of the momentum strategy in 1932, 2009 and 2020. The three most severe crashes can be seen in the sloping curves of the graph. In 1932, the cumulative return drops by 418% during the months of April to August and by as much as 730% during the months of March to May 2009. During the recent Covid-19 crisis, the cumulative return of WML drops by over 230% from April to June.

Daniel and Moskowitz (2014) consider the performance of winners and losers separately. For each formation of the momentum portfolio, they use the returns of the common stocks of all companies listed on the NYSE, AMEX or NASDAQ at the time of formation. The criterion of the selected companies is that they have a valid share price and a valid number of shares at the date of formation. In addition, at least eight monthly returns must have been documented.[83]

Appendix 1 compares the cumulative returns of four different investments over a period from January 1927 to March 2013: (1) risk-free investment; (2) CRSP-value-weighted index; (3) loser portfolio (past losers); and (4) winner portfolio (past winners). On the right side of the

[82] Daniel and Moskowitz (2016)
[83]Daniel and Moskowitz (2016)

chart the final dollar values for each of the four portfolios are noted, at a $1 investment in January 1927. Overall, it can be observed that the performance of the winning portfolio outperforms that of the losing portfolio. However, this is not the case in periods of momentum crashes. In these situations, a reversal of the expected performance of the losers can be perceived. Instead of continuing to generate falling returns as expected, the supposed loser portfolio shows gains based on rising prices. These returns even exceed those of the winning portfolio. The result of this event is high losses for the momentum strategy, as it holds a short position in the loser portfolio. A possible reason for this reversal can be the time-varying beta[84] of the WML strategy.[85]

The variation of the beta factor of winners and losers can lead to the momentum crashes. Since a momentum strategy is constructed based on past performance, sudden changes in the stock market, as often experienced in rebounding markets after a crisis, can change the beta of both the winner and loser portfolio. For example, a portfolio formed during bear markets includes low beta stocks in the winner portfolio. On the other hand, during a portfolio formation in bull markets, the winner portfolio includes high beta stock. The sudden change between bear and bull markets cannot be anticipated by the momentum strategy and therefore leads to momentum crashes.

According to Daniel and Moskowitz, in July and August 1932 the loser portfolio generated a 232% increase in returns in two months, whereas the winner portfolio only achieved a 32% increase. In March to May 2009, when the second crash occurred, the loser portfolio increased by 163%, while the past winners' portfolio did not increase by more than 8%. Therefore, the crash risk is mainly driven by short positions.

4.2 Potential reasons for momentum crashes

To define a possible source for the performance of raw momentum during a crash, it makes sense to first take a closer look at the formation factors of a momentum portfolio. As already explained in the previous sections, portfolios are formed based on past returns of stocks. Accordingly, stocks are divided into winners and losers based on past performance. The momentum effect is then exploited by investors by taking a short position in loser stocks and a

[84] Beta is commonly defined as the quotient of the covariance of the return on an asset with the return on the market portfolio and the market variance. A beta greater than one means a greater variation of a stock compared to the market. A beta smaller than one, on the other hand, means that a stock has a lower fluctuation than the market. A beta of exactly one indicates an identical fluctuation with the market.

[85] Daniel and Moskowitz (2016)

long position in winner stocks. Here, the beta factor, defined as the sensitivity of a stock to systemic market risk, plays an important role.

Cooper, Gutierrez, and Hameed (2004) consider the impact of market state on momentum strategy in their work. They define an "up-state" and "down-state" momentum and recognize that the WML return depends on the economic market condition.[86] Their finding was attributed by Daniel and Moskowitz (2016) to the time-varying betas of the winner and loser portfolios. They examine the beta factor in different market conditions of the portfolios. As a result, they recognize that the betas show a higher variation in more volatile market periods. Furthermore, a comparison of the winner and loser portfolios shows that the fluctuation of the loser beta is significantly higher than that of the winner beta.[87] To better understand this pattern, the change in the beta factor for winners and losers in rising and falling markets is explained as follow.

In the case of portfolio formation during rising markets (bull markets), winning stocks characteristically have a high beta i.e., a beta factor greater than one. While loser stocks have a low beta factor i.e., a beta smaller than one. As a result, the momentum portfolio has a long position in high beta stocks and a short position in low beta stocks. Accordingly, the beta factors reverse when the momentum portfolio is constructed during falling markets (bear markets). In these periods past winners are most likely to be low beta companies and past losers will have a high beta.[88] A breakdown of the momentum strategy occurs at times when the market starts to recover, especially when market volatility is high. It can be assumed that the momentum portfolio was constructed based on the price information that is still available during the recession. In this case, since the winners have low sensitivity and the losers have high sensitivity to the market, the expected effect is reversed and results in high losses. If the market recovers too quickly, the strategy collapses because the momentum portfolio cannot adjust its positions fast enough.[89]

However, a momentum crash cannot be observed after bull markets, defined as market periods of an extensive economy. It results in an asymmetry of the risks of winners and losers compared to market returns in extreme periods. These findings are illustrated in *Appendix 2*, which plots the betas of the winner and loser portfolios and compares them during crashes as well as during crash-free periods. The asymmetry of the beta factors of the loser and winner portfolios indicates that the losses are mainly due to the short position in the loser portfolio. *Appendix 3*

[86] Cooper, Gutierrez and Hameed (2004)
[87] Daniel and Moskowitz (2016)
[88] Grundy and Martin (2001)
[89] Daniel and Moskowitz (2016)

shows the beta values of the momentum portfolios. In times of a crash, the loser portfolio has a beta factor that is higher than that of the market, while the winner portfolio has a negligible lower beta compared to the market. [90]

Another factor that can influence crashes is the market imbalance that occurs during rapid changes. During an incipient market recovery, there may still be an uneven distribution of information. As a result, mispricing of stocks occurs. The payoff profile of momentum can be compared to a short position in a call option during recessionary markets, so-called bear markets. The strategy makes only relatively small profits during falling markets. On the other hand, losses can be high during rising markets. This is also due to the asymmetric market sensitivities of losers and winners in times of market recovery.[91]

4.3 Types of crashes

In previous research many different definitions of market disruptions can be found. This paper will emphasize in particular the approach of Jorda, Schularick, and Taylor (2010) and Muir (2017) who defined two main types of market disruptions: a financial crisis and a recession. Jorda, Schularick, and Taylor (2010) characterized a financial crisis as an event in which a country's banking sector collapses i.e., a sharp rise in default rates accompanied by large capital losses that lead to public intervention and bankruptcies.[92] On the other hand, Muir (2017) distinguished between financial crises, recessions and "deep recessions". The author also defines a financial crisis as a failure of a country's banking system. He defined a recession as a nonfinancial event that does not coincide with a financial crisis. Furthermore, Muir (2017) used the term "deep recession" as a nonfinancial recession for which the initial drop in consumption exceeded more than 2%. Similarly, Shiller (2005) defined a recession as an "economic crisis" where unexpected shocks in supply or demand with large effects throughout the economy happen.

Muir (2017) finds that asset prices decline during both types of events, but the decline during financial crises is much higher than the decline in recessions. Therefore, the author claims that risk premia might increase and expected returns might decrease much more in a financial crisis, compared to an only a slightly increase in recessions. Moreover, the author shows that asset prices recover much faster after a recession compared to financial crises. Muir (2017) finds that

[90] Daniel and Moskowitz (2016)
[91] Daniel and Moskowitz (2016)
[92] Jorda, Schularick, and Taylor (2010)

asset prices could recover within months after a recession whereas it could take years after a financial crisis.

There are several potential challenges posed by the findings that financial crises have much higher risk premia and take longer to recover than a recession.

The first challenge is a possible inaccuracy of the conclusions. It is a rational consequence that prices decline and risk premia rise during financial crises if a "crisis" is defined ex post as a sharp decrease in asset values. Accordingly, the data for financial crises are defined as systemic events - a major bank failure - and not according to what happens to stock prices. Secondly, dividend yields and credit spreads are not the most appropriate measures of risk premia. An increase in dividend yields during crises, might reflect expected dividend growth during these events, however, the predictive power in under these conditions is limited. The standard results in the literature show that dividend yields are mainly related to expected returns rather than dividend growth during crises and recessions. However, Muir (2017) states that dividend yields are strong measures of expected returns because they solidly predict returns under both types of episodes.

These results confirm that the main feature of financial crises, compared to typical recessions, is the discount rate effect or the increase in risk premia. In contrast, subsequent realized returns are not unusually high for the other events. As a result, the additional decline in returns during financial crises compared to recessions completely reverses several years later, so there is a very small difference in long-term prices or cash flows, but a significant difference in discount rates during these episodes.[93]

In our empirical analysis we will apply the conclusions of Muir (2017) to explain differences in magnitudes and the performance of a momentum crash between different crises.

4.4 Stock market crashes

Most of the empirical research regarding momentum crashes is related to the two largest crashes in global history, the Great Depression in 1932 and the Financial Crisis in 2007/08. As previously mentioned, one explanation for momentum crashes is presented by Daniel and Moskowitz (2016), who found the reversed betas of winner and loser portfolios to cause major losses.[94] The authors argue that a significant increase in the loser portfolio’s beta is mainly observable in these two crashes. This might also explain why most authors do not further

[93] Muir (2017)
[94] Daniel and Moskowitz (2016)

discuss any other historic crashes. The different implemented risk-managed momentum strategies in this paper will be analyzed during the following discussed periods of market disruptions.

The Great Depression is referred to as the worst economic crisis in the history of the industrialized world, lasted from 1929 to 1939. The crisis started with the stock market crash in October 1929 known as Black Thursday, which wiped out millions of investors and heralded the Great Depression. Thereafter, between 1929 and 1933 the US economy shrank by more than 36% measured by Gross Domestic Product (GDP). Several US banks were closed, leading to billions of losses in savings and the unemployment rate increased to 25%. The Great Depression had disastrous effects on countries around the world and on the entire global economy, making it the longest, deepest, and most widespread crisis of the 20th century.[95] According to the crash definitions in the previous section introduced by Muir (2017), this crisis can be classified as deep recession.

The next major crisis after the Great Depression was the OPEC oil embargo in 1973. During the Arab Israeli war in 1973, the Arab members of the Organization of Petroleum Exporting Countries (OPEC) established an embargo on the United States. The embargo prohibited both oil exports to the affected countries and cuts in oil production. Global growth suffered a severe blow during this first oil price shock. While the world economy still grew by 6.9% in 1973, the growth rate decreased to 2.1% in 1974 and to 1.4% in 1975. After three years in 1976 the global economy reversed back to its normal growth rate.[96] According to the crash definitions introduced by Muir (2017) this crisis can be classified as a recession.

The financial crisis in 1987, also referred as the Black Monday Crash was a rapid and sharp decline in U.S. stock prices that lasted for several days in late October 1987. After the crash originally started in the U.S., it quickly spread across several major stock markets around the world. The shock marked the beginning of a worldwide stock market crash. At the end of October 1987, most of the largest stock exchanges had plunged by more than 20%.[97] As stated in Jorda, Schularick, and Taylor (2010) such an event can be classified as a financial crisis.

The Dot-com bubble in 2000, also known as the internet bubble resulted from a combination of speculative investing. Presented by the overflow of venture capital funding for startups and the failure of dotcoms to turn a profit. Firstly, the value of equity markets increased exponentially, between 1995 and 2000 and ended up experiencing a bear market in 2001. The NASDAQ stock

[95] Romer (1990)
[96] Georgopoulou and Wang (2017)
[97] Amihud et al. (1990)

exchange experienced a drop of 77%, many other major stock markets around the world experienced similar drops.[98] Such an episode is categorized as financial crisis according to Muir's (2017).

The most recent crisis which has not been studied yet is the Covid-19 pandemic in 2020. This pandemic has been a severe global economic crisis that triggered a global recession. It has been considered as the worst global economic crisis since the Great Depression in 1932. The start of the recession coincided with the 2020 stock market crash, which happened in February and lasted until April 2020. The stock market crash led to a 20%-30% drop in the value of stock market indices around the world. Since it was of short duration, many market indices around the world recovered by the end of 2020. The Covid-19 pandemic and the oil price war between Russia and Saudi Arabia in 2020 resulted in a collapse of oil prices; the crash of tourism, hospitality, and energy; and a significant decline in consumption. The investigation of momentum strategies during this period is a major contribution to the existing literature since it has not been examined yet.[99]

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[98] Ljungqvist and William (2003)

[99] Mazur et al. (2021)

5. Risk-managed momentum strategies

The by the previous literature widely advertised predictability of momentum crashes can be exploited to construct risk-managed strategies. These strategies can limit or, ideally, eliminate losses.

In this section we present alternative approaches to risk-managed momentum strategies, which are empirically tested in chapter 6. As Barroso and Santa-Clara (2014) mention in their study, most of the crash risk is attributable to the momentum specific risk, which is determined by its volatility. Therefore, this thesis has a special focus on the most established volatility-managed strategies of Barroso and Santa-Clara (2014) and Moreira and Muir (2017). In order to enhance the quality of a broad overview on risk-managed strategies and to provide a benchmark for volatility managed strategies we additionally analyze the combined momentum strategy of Asness, Moskowitz and Pedersen (2013).

5.1 Volatility managed momentum portfolios

Several studies on risk-managed momentum strategies found that the strategy's volatility is highly variable and predictable over time. Grundy and Martin (2001) for example show the time-varying strategy beta following different markets states.[100] Daniel and Moskowitz (2016) find that the Sharpe Ratio of momentum also varies with changing volatility, it appears to be the lowest when the strategy volatility is forecasted to be high.[101] These findings are encouraging volatility-adjusted strategies. Specifically, we will present two approaches. The constant volatility strategy presented by Barroso and Santa Clara (2014) and the dynamic volatility strategy by Moreira and Muir (2017).

5.1.1 Constant volatility momentum

The risk-managed constant volatility strategy by Barroso and Santa-Clara (2014) will be explained in more detail in this section. To construct the momentum portfolios, all stocks are sorted by their past returns from month t_2 to t_{12} and then divided into deciles according to the NYSE limits. The lowest decile forms the loser portfolio, which corresponds to the worst performing 10% of stocks. The highest consists of the best 10%, thus forming the winning

[100] Grundy and Martin (2001)
[101] Daniel and Moskowitz (2016)

portfolio. The individual companies are weighted by value in each decile and the authors use historical data from March 1927 until December 2011 for their analysis.[102]

The authors tie in with the finding that estimating risk based on the time-varying betas is not successful. It implies a focus on the smaller and less predictable part of the risk. This assessment is consistent with the derivation of momentum risk in Section 4.2 since estimations using the betas only accounts for the market-specific risk of the strategy. However, since this only justifies the much smaller proportion of total risk, the authors instead use the realized variance of daily returns to estimate the risk of the strategy, which represents the momentum-specific risk.

They also recognize that the future variance can be predicted very well using this variable. The risk-managed strategy uses the realized variance of the past six months to scale the long-short momentum portfolio. The goal is to implement a strategy with constant volatility.

Specifically, an estimate of the future variance is calculated using past daily returns for each month, as this is shown in equation (2):

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

The variance estimate is calculated using the average daily return of the momentum portfolio over the last six months. The trading days of the last six months are approximated to 126 days. Multiplication by 21 is done to obtain a forecast of the monthly return.[103] Contrary to the traditional variance formula, the average return is not subtracted from the realized return, since it can be assumed to be zero on average.[104] Using the variance estimation, momentum returns can be rescaled to achieve constant volatility. Here, the returns of the risk-managed momentum strategy (WML^{const}) are calculated using the weighted returns of the unscaled momentum. The weight is the quotient of the target standard deviation divided by the previously estimated expected volatility of the WML. The return of the scaled risk-managed portfolio is calculated as follows:

$$(3) \qquad r_{WML^{Const},t} = \frac{\sigma_{target}}{\sigma_t} \, r_{WML,t}$$

[102] Barroso and Santa-Clara (2014)
[103] Barroso and Santa-Clara (2014)
[104] In order to check this hypothesis, variance was additionally calculated including the deduction of the mean. No significant difference between both approaches was found.

$r_{WML^{const},t}$ represents the return of the constant volatility portfolio, $r_{WML,t}$ denotes the return of the raw WML, σ_{target} is the constant target volatility, and σ_t denotes the previously determined estimate of future volatility. The authors use an annual target volatility of 12% in their paper, which is not further argued for.[105] This implies a subjective choice of target volatility. The weight of the scaled momentum can be interpreted as the dollar amount in the long or short leg. Therefore, the presented strategy changes its asset allocation by reducing or increasing the amount invested in in the long or short portfolio depending on their variance.

The authors applied this strategy using data provided by the Kenneth French data library.

In their results, they found that by using this risk-managed strategy the Sharpe Ratio and skewness could be increased while the excess kurtosis could be largely reduced. Therefore, their results indicate a reduction of crash risk. Furthermore, they found an increase in Sharpe Ratio also in the months without crashes.

Since a strategy adjusting the volatility to be constant at the same level disregarding changing risk preferences is not realistic, different approaches encouraging a variation in risk strategies may be more appropriate. Nevertheless, this constant volatility strategy achieves significant results and will be further analyzed in the empirical section of this thesis.

5.1.2 Dynamic volatility momentum

Moreira and Muir (2017) built on the constant volatility strategy of Barroso and Santa-Clara (2014) and introduced a dynamic volatility managed strategy. They apply a very similar weight as Barroso and Santa-Clara, but instead of using the previous six-month realized variance they adjusted their strategy by using the previous month's realized variance. This makes the strategy faster at adapting to changes in risk exposure. Furthermore, the authors scale the variance not by a fixed target volatility, instead they use a constant that controls for the average risk exposure. It represents the same unconditional standard deviation as the unmanaged strategy. Therefore, the risk exposure they are taking is depending on the previous month' volatility and decreases or increases based on the recent volatility.[106]

Daniel and Moskowitz (2016) also support a dynamic strategy that changes its volatility. They found that the return of WML is negatively related to the WML return volatility forecast, which implies that the Sharpe Ratio of an optimal dynamic portfolio varies over time.[107]

[105] Barroso und Santa-Clara (2014)
[106] Moreira and Muir (2017)
[107] Daniel and Moskowitz (2016)

By reducing the risk taking in times of “bad” market states where the volatility is high, the authors manage to introduce a strategy implying more realistic risk preferences of investors rather than a constant volatility throughout different market states. The volatility timing increased the Sharpe Ratio and consequently the return since usually changes in volatility are not compensated by proportional changes in expected returns.[108]

Similar to the constant volatility strategy, daily momentum returns data from the Kenneth French database were obtained.

Portfolios are constructed by changing the asset allocation to the long or short side of the momentum portfolio using the inverse of its monthly conditional variance. Therefore, the strategy’s risk exposure adjusts according to the conditional variance measure. The scaled portfolio returns can be calculated as followed:

$$(4) \qquad r_{t+1}^{dynamic} = \frac{c}{\hat{\sigma}_t^2(r)} r_{t+1}$$

where r_{t+1} represents the unadjusted return and $\hat{\sigma}_t^2(r)$ approximates the portfolios conditional variance and c is a constant that controls the average exposure of the strategy. Since the strategy should have the same unconditional standard deviation for the scaled portfolio as for the unadjusted portfolio, the constant c is chosen in a way to have an equal standard deviation for both.

The conditional variance is approximated by the previous month’s realized variance, using the past 22 values of daily returns[109]:

$$(5) \qquad \hat{\sigma}_t^2(r) = RV_t^2(r) = \sum_{d=\frac{1}{22}}^{1} (r_{t+d} - \frac{\sum_{d=\frac{1}{22}}^{1} r_{t+d}}{22})^2$$

The results of the authors indicate that great losses can be avoided by the volatility-managed portfolios. As predicted, large market losses can be observed in times of a high volatility, these can be avoided by risk-adjustments.[110]

Nevertheless, a flaw of the strategy is that the model assumes an investor to know the standard deviation of the whole sample at any time. One workaround for this could be to use cumulative statistics up to the formation month. This improvement will be implemented in the empirical section of this paper.

[108] Moreira and Muir (2017)
[109] This is the authors choice in the remaining analysis, we use 21 days to approximate monthly returns.
[110] Moreira and Muir (2017)

5.2 Combined momentum

The authors Asness, Moskowitz and Pedersen (2013), introduced a risk-managed momentum strategy that is; contrary to the previously presented strategies, not based on volatility management. Instead, they use the negative correlation of momentum and value to construct a risk-managed strategy. Furthermore, they found evidence that liquidity risk is causing this negative relationship between the two strategies, as liquidity risk is negatively related to value and positively related to momentum.

By constructing an equal-weighted combined portfolio of momentum and value, a reduction in momentum risk and an elimination of liquidity risk can be achieved.

Data from the equity stock markets of the United States, the United Kingdom, continental Europe, and Japan is used to form value and momentum portfolios. A simple combination of value and momentum implies a much closer position to the efficient frontier than it would be the case for each strategy individually.

The portfolio is structured in the following way:

$$(6) \qquad r_t^{COMBO} = 0{,}5r_t^{VALUE} + 0{,}5r_t^{MOMENTUM}$$

The authors results show that the average values of the combined portfolio are higher than for the individual portfolio. Furthermore, the combination portfolio features a lower standard deviation as well as a higher Sharpe Ratio and excess return (alpha). Even though momentum and value are not perfectly correlated, the average correlation of about -0,5 is high enough to gain significant returns from the diversification effects. Momentum crashes are not specifically observed by the authors in their paper: this will be another contribution to the existing literature by this thesis.

5.3 Winner Investing Strategy

Motivated by Daniel and Moskowitz (2016), who found that most of the losses during a crash stem from the short side of the portfolio, we are introducing a new risk-managed strategy.

Our hypothesis states that losses during periods of rebounding markets after a recession could be avoided by exclusively investing in the winner portfolio. The intuition behind this is that at this time the winner portfolio has a relatively low beta. This is due to the fact that the companies that were less correlated to the market had higher gains during a recession than companies that were highly correlated to the market, which correspond to the loser portfolio with a high beta. The losses result from the short position of the supposed loser portfolio. Instead of losing value, the loser portfolio increases more in value than the winner portfolio on which the strategy holds a long position. Therefore, during periods of market recovery, a Winner Investing Strategy could avoid such losses.

To implement this risk-managed strategy, we suggest ranking stocks according to their past performance and sort them into 10 portfolios. To form the Winner Investing Strategy, the only relevant portfolio is the one including the highest decile. Other than the traditional momentum strategy, there will be no gains from shorting the loser portfolio, the single source of return will be generated by the long position of the winner portfolio.

One big difference of the Winner Investing Strategy to the raw momentum is that due the missing proceeds from shorting the loser portfolio, the long position in the winner portfolio requires an outflow of own funds. The strategy is therefore not self-financed. As a result, investors applying this strategy have to consider the opportunity cost related to alternative investments.

Furthermore, the Winner Investing Strategy is expected to reduce or avoid losses, whereby the average long-term profitability of the strategy will be higher than the one for the raw WML. However, the profitability in non-crash periods might be lower since the gains from shorting the loser portfolio will not be realized.

Nevertheless, the Winner Investing Strategy comes with many benefits for risk-averse investors. First of all, since the majority of losses during crashes can be attributed to the loser portfolio, this risk-managed strategy is expected to significantly reduce losses from crashes.

Secondly, by eliminating the short position of the raw WML, generally losses are limited. To clarify, losses of a short sale can be infinite in theory since there is no limit in the rise of stock prices. If the shorted stock rises opposed to expectations, the stock must be purchased on the market at a higher price than anticipated when the position is closed, leading to losses.

On the other hand, holding a long position leads to loss limitation, as a stock price cannot be negative, therefore only the original investment can be lost. Furthermore, since the strategy requires the same portfolio construction steps as the raw momentum strategy and merely takes a long position in the decile with the highest return, no additional complicating adjustment would be required for investors. It is therefore easily applied by investors already investing in momentum. Another benefit would be the reduced transaction costs by eliminating the short position.

This new proposed risk-managed strategy will be empirically analyzed in the following chapter.

6. Empirical Analysis

In this section, we analyze and compare four different risk-managed momentum strategies. As previously mentioned, a prominent feature of momentum strategies is crash risk, therefore we provide a comparison of different risk-managed strategies and their performance throughout different market crises.

We analyze several crises of the past century to characterize momentum crash risk. Specifically, we study whether all crises are followed by a momentum crash and whether momentum performance is of similar magnitude and performance across crises. Differences in crises are analyzed according to the definition of Muir (2017), mentioned in section 4.4.

It will be assessed whether expected returns might decrease, and risk premia might increase much more in a financial crisis compared to a recession and whether a recovery appears to be faster after a recession compared to a financial crisis, as stated by the author.

Firstly, it will be examined whether momentum crashes are experienced following every market crash or if there are differences in performance throughout different crises. As mentioned in section 4.1 we define momentum crashes as an experienced change in cumulative returns of the previous 21 days of -20% or less. Lastly, different tests for robustness are conducted to stress the resilience of the results.

6.1 Data and Methodology

All underlying data for the analysis is retrieved from Kenneth R. French's data library.[111] For raw WML, daily returns of a predesigned momentum factor constructed from six value-weighted portfolios is provided by the library. These portfolios are compiled from independent sorts of NYSE, AMEX, and NASDAQ stocks by size and return. Furthermore, the daily returns of ten momentum sorted portfolios are used to analyze the winning and losing portfolios. In order to explain the abnormal return of momentum with the commonly known three-factor Fama French model, monthly returns for the market portfolio, the high-minus-low, the small-minus-big, and the risk-free rate (one-month Treasury-bill return) are obtained. Likewise, monthly returns of the market portfolio, the high-minus-low, the small-minus-big, the risk-free rate, robust-minus-weak and conservative-aggressive are also obtained to apply the five-factor

[111] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Fama French model. The market data used in section 6.2.2, was also obtained from three-factor Fama French data. To receive the market return before adjustment of the risk-free rate, the risk-free rate was added back. The data from the Kenneth R. French's data library was created using the CRSP database.

Constant volatility momentum

The previously presented risk-managed constant volatility strategy of Barroso and Santa-Clara (2014) is implemented and compared to the raw WML strategy. The construction of the risk-managed strategy is carried out according to the scheme described in Section 5.1.1:

1. To determine the constant volatility return, a variance forecast is computed by using the returns of the previous six months, as displayed in the following formula:

$$(7) \qquad \hat{\sigma}^2_{WML,t} = 21 \sum_{j=0}^{125} r^2_{WML,d_{t-1}-j} / 126$$

   Since the average return can be assumed to be zero, it can be neglected in the variance formula and will therefore not be deducted from the return.

2. Due to the self-financing feature of the strategy, no further constraints need to be considered to scale the strategy. The same annual target variance of 12% as used by Barroso and Santa-Clara (2014) is applied and the target daily standard deviation is calculated, assuming 252 trading days per year. The WML returns of the scaled portfolio are calculated as follows:

$$(8) \qquad r_{WML^{const},t} = \frac{\sigma_{target}}{\sigma_t} \, r_{WML,t}$$

The weight displayed as the quotient of the target volatility and the realized volatility represents the dollar amount in the long or short side. The allocation of funds is made according to the weight, therefore the amount invested in the long or short portfolio is scaled up or down depending on their variance.

Dynamic volatility momentum

The second strategy assessed is the dynamic volatility momentum strategy, that was firstly introduced by Moreira and Muir in 2017. The construction of the dynamic volatility momentum is carried out according to the scheme described in section 5.1.2:

1. To construct the risk-managed portfolio, the exposure to the long and short portfolio will be scaled by the inverted conditional variance. The first step is to calculate the previous month's realized variance:

$$(9) \qquad \hat{\sigma}_t^2(r) = RV_t^2(r) = \sum_{d=\frac{1}{21}}^{1}(r_{t+d} - \frac{\sum_{d=\frac{1}{21}}^{1} r_{t+d}}{21})^2$$

where r_{t+d} represents the daily stock return. Different to Moreira and Muir (2017) in this thesis a month is assumed to have approximately 21 trading days instead of 22 to remain consistent.

2. In contrast to Moreira and Muir (2017), it is not assumed that an investor knows the standard deviation of the whole sample. Instead, the cumulative statistics up to the formation date are used, which makes the term c_t change over time. The term c_t is computed by averaging the previously computed volatility forecast for the previous 21 days:

$$(10) \qquad c_t = \frac{\sum_{d=1}^{21} RV_t^2(r)}{21}$$

3. Lastly, the return of the volatility managed portfolios is approximated by multiplying the raw momentum return with the ratio of the constant divided by the realized variance:

$$(11) \qquad \mathrm{r}_{\mathrm{t+1}}^{\mathrm{dynamic}} = \frac{c_t}{\hat{\sigma}_{\mathrm{t}}^2(\mathrm{r})} \mathrm{r}_{\mathrm{t+1}}$$

Combined momentum

The third strategy in this analysis is the in section 5.2 presented combined momentum strategy of Asness, Moskowitz and Pedersen (2013). This strategy is in contrast to the previous ones, not using volatility management to limit exposure to crashes by momentum. According to their paper, a negative correlation between the raw WML and the value strategy can be observed. This can be used to hedge the risk of momentum crashes by combining value and momentum. The risk-managed strategy is simply constructed by investing half into the raw momentum and the other half into value[112]. The returns of the combined portfolio are therefore computed, as follows:

$$(12) \qquad r_t^{COMBINED} = 0{,}5 r_t^{VALUE} + 0{,}5 r_t^{MOMENTUM}$$

Winner Investing

Lastly, we examine the performance of a strategy firstly presented by the authors of this thesis, that proposes to exclusively invest into the momentum winner portfolio. As mentioned by Daniel and Moskowitz (2016), most of the strategy's losses are attributable to the short side of

[112] Asness, Moskowitz and Pedersen (2013) use a common value signal of the book value of equity in relation to the market value of equity to construct the value portfolio. Since the HML represents the average of the two high book/market portfolios and the two low book/market portfolios it forms the value portfolio.

the portfolio. It can be expected that the performance of a portfolio only investing in the long position of raw WML to be on average higher and to avoid crashes in the best case. To construct this only winner strategy, data of 10 momentum portfolios is used and only the best performing decile is invested in. The resulting strategy is expected to have much higher returns than raw WML but might still have a similar volatility as the raw momentum. Another downside would be that an exclusive investment in the winner portfolio is not resulting in a self-financing strategy. Investors therefore must consider both the direct costs and opportunity costs of their investment.

In order to compare key features of the strategies, the maximum, minimum, mean, standard deviation, kurtosis, skewness and Sharpe Ratio will be shown. The mean of the strategies denotes the geometric mean of the returns of 252 consecutive days, which roughly equals the returns of one year. Accordingly, the maximum and minimum of the returns denote the observed maximum and minimum average returns of 252 consecutive days, respectively. The standard deviation, the median and the Sharpe Ratio are also annualized. Skewness and kurtosis of the strategies are based on daily returns, to achieve a higher accuracy of the results due to the higher number of observations. These assumptions are similarly implemented for all strategies. To calculate the Sharpe Ratio, the annualized mean return is divided by the annualized standard deviation. The risk-free rate is not deducted from average return since we apply the commonly used definition of the risk-free rate to be zero.
The empirical analysis starts by introducing a linear regression model, that uses the three- and five-factor Fama French model to explain the abnormal returns of momentum. For this purpose, monthly data of the model factors and the momentum factor is used, to be able to compare the obtained results to those of Barroso and Santa-Clara (2014). The analysis of the three-factor Fama French model includes data from January 1927 to March 2021, the analysis using the five-factor Fama French model, includes data from July 1963 until March 2021 as it is not possible to obtain data for the five-factor model from before 1963 from the Kenneth French data library. Following this, the raw momentum performance during different market crises mentioned in Chapter 4 is analyzed. Finally, the previously in Chapter 5 presented risk-managed strategies are applied to the data set. For all risk-managed strategies, data of daily returns from November 1926 until March 2021 is used.

6.2 Results

6.2.1 Using Fama French models to explain WML returns

To attempt to explain the momentum returns using an advanced empirical pricing model, the first part of the empirical analysis uses the three-factor and the five-factor Fama French model. A simple linear regression is conducted to determine, whether the high raw WML returns can be explained by the excess market-return, the high-minus-low factor, and the small-minus-big factor for the three-factor model and additionally the robust-minus-weak and conservative-minus-aggressive factors for the five-factor model.

Since momentum is a widely known asset pricing anomaly, our hypothesis states that both models will still show a large excess return (alpha). This was already largely researched in the past literature and has led to similar results. Even though the Fama French five-factor model was only recently introduced in 2013, several authors like Moreira and Muir (2017) and Ehsani and Linnainmaa (2019) applied the model to explain to abnormal returns of raw WML. Resulting, the authors were not able to explain significantly more of the excess return by using the five-factor model instead of the three-factor model. Ehsani and Linnainmaa (2019) state: "Because the unconditional correlations between momentum and the other factors are close to zero, most factor models, such as the five-factor model, explain none of momentum profits. This result, however, does not imply that momentum is "unrelated" to the other factors."[113]

Table 2 compares the performance of momentum (WML) with the Fama and French risk factors for the period November 1926 until March 2021 for the three factors and from July 1963 to March 2021 for the additional factors included in the five-factor model. WML generated the highest yearly average return of 7.95 percent points, with a Sharpe Ratio of 0.51 representing a higher value than the market. Nevertheless, these abnormal returns come at the cost of a very high kurtosis of 29.77, which is the highest among all other factors. This means that extremely negative or positive returns occur more frequently. Moreover, a skewness of -2.96 implies that more than half of all returns are below the mean. These statistical characteristics of the distribution of momentum returns imply a very fat left tail which determines a significant crash risk.

An ordinary least squares (OLS) regression is conducted to determine whether the high abnormal momentum returns can be explained by using the three-factor Fama French model. The results of the regression are displayed in the following equation:

[113] Ehsani and Linnainmaa (2019)

$$(13) \qquad r_{WML,t} = 0.956 - 0.220 r_{RMRF,t} - 0.044 r_{SMB,t} - 0.472 r_{HML,t}$$

$$(7.73) \quad (-8.92) \qquad (-1.08) \qquad (-13.13)$$

The t-statistic of every value is displayed in parentheses below the equation. As the equation and *Table 3* show, momentum generated significant abnormal returns at a 1% level of 0.956 per month. Such a high alpha implies that a significant amount of momentum returns can still not be explained by the three-factor Fama French model. Still, some portion of WML can be explained by the model. The market factor has a negative magnitude with a value of -0.220 and is highly significant at a 1% level with a p-value of 0.000. The small-minus-big factor represents the only non-significant explanatory variable of the model. It has the weakest negative value of all three factors of -0.044 and an insignificant p-value of 0.280. Also, its t-statistic is the least negative of all factors which supports the insignificance. The high-minus-low factor has the highest absolute value of all three factors with -0.472 and is also highly significant at a 1% level with a p-value of 0.000 and the highest negative t-statistic of -13.13. All three factors of the Fama French model have a negative correlation with momentum, which implies that momentum provides some diversification in this sample period. Furthermore, by analyzing the R-squared it can be observed that the three Fama and French factors explain about 23.7% of the variation in momentum returns.

When comparing our results with Barroso and Santa-Clara (2014), we achieve results that are very much in line with theirs. Our regression leads to similar negative signs of the factors. Furthermore, we achieve very similar magnitudes. Just like Barroso and Santa-Clara the high-minus-low factor has the highest negative value, followed by the market factor, and lastly the lowest negative value for the small-minus-big factor. Similar patterns are also observable in the t-statistics. Differences arise predominately due to the fact that we use a larger sample, which includes approximately 10 more years of data.

Secondly, we also conducted an OLS regression of the five-factor Fama French model. The results of the regression are also displayed in *Table 3* and in the following equation:

(14)

$$r_{WML,t} = 0.702 - 0{,}155 r_{RMRF,t} + 0.037 r_{SMB,t} - 0.536 r_{HML,t} + 0.206 r_{RMW,t} + 0.356 r_{CMA,t}$$

$$(4.42) \quad (-4.00) \qquad (0.67) \qquad (-7.39) \qquad (2.70) \qquad (3.21)$$

The t-statistic of every value is displayed in parentheses below the equation. Including the two additional factors robust-minus-weak and conservative-minus-aggressive, changes the magnitude of the previously analyzed three factors and even the sign of one factor. Using this model, momentum still generates an abnormal monthly return of 0.702, which is lower compared to the three-factor model, at a highly statistical significance level of 1% with a p-value of 0.000 and a t-statistic of 4.42. The market factor keeps the negative sign and has a highly significant magnitude of 0.155 at a 1% significance level and p-value of 0.000 and the second most negative t-statistic of all factors. The small-minus-big factor changes signs using this model and exhibits a positive relationship to the WML. Similar to the first model, this factor is not significant at any level with a p-value of 0.502 and keeps also the lowest positive t-statistic of all factors. Also similar to the previous model, the high-minus-low factor has the highest value with a negative sign of -0.536. This value is also significant at a 1% level with a p-value of 0.000 and the most negative t-statistic of -7.39. Both additional factors have a positive sign and are statistically significant at a 1% level. The robust-minus-weak factor has a slightly higher p-value than the conservative-minus-aggressive factor with 0.007 and 0.001 respectively. In line with that the CMA has the highest positive t-statistic with 3.21 and RMW the second highest positive t-statistic with 2.70.

Concluding, the five-factor Fama French model explains more of the abnormal returns of momentum but is still not able to explain it fully. This can be observed by the slightly lower alpha in the five-factor model compared to the three-factor model. These results are in line with Moreira and Muir (2017) and Ehsani and Linnainmaa (2019) who were not able to explain significantly more of momentum's abnormal returns by using the five-factor model compared to the three-factor model.

6.2.2 Raw momentum across crises

In this section of our empirical analysis, we analyze the performance of raw momentum throughout the most relevant market crises in history, as introduced in section 4.4. This analysis serves as a benchmark for the comparison of different risk-managed strategies throughout different crises.

Previous literature mostly focused its analysis of momentum crashes and their performance on the two biggest crashes of raw momentum: The Great Depression 1932 and the financial crisis 2007/08. Therefore, a contribution of this thesis to the existing literature is the analysis of the momentum performance throughout the oil crisis in 1973, the Black Monday crash in 1987, the Dot-com bubble in 2000 and the recently experienced Covid-19 pandemic in 2020.

Appendix 4 displays a list of all occurrences meeting our definition of momentum crashes.[114] The highest negative change of the cumulative returns in a 21-day period was experienced on the 11th of August 1932 with a decrease of 38,37%.

Appendix 4 shows that WML crashes per our definition occurred during the Great Depression, the second world war[115], the Dot-com bubble, the financial crisis 2007/08 and the Covid-19 pandemic. The first major result of our analysis is, in contrast to most of the existing literature, that a momentum crash is not consistently occurring after market crashes. This is an interesting insight since it contradicts the hypothesis of momentum crashes to be predictable.

Key features of raw WML during all crises are presented in *Table 4*. The most relevant characteristic to determine the strategy's profitability is the Sharpe Ratio. Comparing the Sharpe Ratio during all crises with the one of the whole data sample, it is observable that raw WML has a higher Sharpe Ratio during the oil crisis, the Black Monday crash and the Dot-com bubble. During all analyzed crises, raw WML has a lower standard deviation than it has for the whole sample. Furthermore, the mean return is lower during all analyzed crises than for the overall sample, therefore the increase in Sharpe Ratio is mainly driven by the lower standard deviation. Analyzing the higher moments, it can be concluded, that mixed results can be observed throughout the crises, for the skewness and kurtosis. However, the absolute value of the skewness is lower for all crises compared to the whole sample.

Figure 3 displays the performance of raw momentum compared to the market portfolio throughout all the market crises mentioned in Chapter 4.

During the Great Depression 1932, it is observable, that raw momentum is overall mostly outperforming the market portfolio. In line with the widely spread hypothesis of momentum crashes to occur after a market crash, momentum increases its returns during the crisis and crashes down in rebounding markets. The strategy's crash is distinctly visible by the big drop of the graph.

A very similar pattern can be observed during the oil crisis in 1973, but with a lower magnitude of momentum crashes. Similarly, momentum returns increase during the crisis.

The Black Monday crash 1987 on the other hand contradicts the key characteristic of WML to gain high returns during the crisis itself. It can be observed that the market return is actually outperforming raw WML from 1983 onwards. Since the market crash is not extreme, the WML

[114] As mentioned in section 4.1: A momentum crash is defined as experiencing a change in cumulative returns of the previous month of -20% or less.

[115] Due to a high risk of uncomplete data, we decided not to analyze WML during the WWII to avoid biased results.

crash is even lower and therefore not classified as a crash according to our previously defined definition.

The crash of the Dot-com bubble is clearly visible in the graph, and the performance of WML is in line with the other crashes observed. The raw momentum returns increase during the market crash and crash down in rebounding markets. Surprisingly, the market portfolio outperforms the raw WML in times before and after the market crash.

A very similar pattern to the Dot-com bubble can be observed during the financial crisis 2007/08. The crash is very visible and even represents the worst crash in WML history. In contrast to the market portfolio, the raw WML seems to recover from the losses very slowly.

During the Covid-19 pandemic, an untypical performance can be observed. During this recently experienced crisis, the market portfolio consistently outperforms the raw momentum. But consistent with previous crises, momentum returns spike up during the market crash and crash down shortly afterwards in the rebounding market phase.

We define in section 4.4, the Black Monday crash 1987, the Dot-com bubble 2000 and the financial crisis 2007/08 as financial crises according to the definition of Muir (2017). On the other hand, we define the Great Depression 1932, the oil crisis 1973 and the Covid-19 pandemic as recessions.

Muir (2017) claims that asset prices decline during both types of events, but with a higher magnitude during a financial crisis compared to a recession. Therefore, risk premia might increase, and expected returns might decrease much more in a financial crisis and only slightly in a recession. Furthermore, the author spots a difference in the velocity of recovery after a recession and a financial crisis. He claims a recovery happens faster after a recession compared to a financial crisis.

The first hypothesis about differences in risk premia between a financial crisis and a recession cannot be confirmed. It cannot be observed that the highest magnitude of crashes and therefore the highest decrease in returns is experienced in financial crisis. Even though the lowest returns and one of the most severe crashes of raw WML happened after the financial crisis in 2007/08, the highest reduction in past month cumulative returns was experienced during the Great Depression, which is classified as recession. Furthermore, only a small decrease in returns was experienced during the Black Monday crash 1987, which is defined as a financial crisis.

The second hypothesis regarding the recovery pace, can also not be confirmed. In general, it can be said, that the higher the magnitude of the crash, the longer the recovery takes. No relation to the type of market crisis can be assumed.

After having analyzed raw momentum during different crisis we can draw three major conclusions:

1. Contrary to the existing literature, momentum crashes do not always occur shortly after a market crash due to a lack of adjustment of the strategy to rebounding markets.
2. Contrary to Muir’s (2017) hypothesis, the magnitude of crashes is not influenced by the type of crisis, but rather by the magnitude of the corresponding market crash.
3. The recovery rate is contrary to the expectations of Muir (2017) not influenced by the type of crisis but also rather by the magnitude of the crash.

6.2.3 Constant volatility momentum

In this section the previously presented constant volatility strategy was implemented. The main results are presented in *Table 5,* which compares the economic performance of the raw WML with the constant volatility momentum strategy between November 1926 and March 2021.

It is observable that the risk-managed strategy generates an average yearly return of 9.74 % which is 2.63 % per year higher than the raw momentum strategy. Furthermore, the risk-managed strategy is slightly less volatile with a standard deviation of 13.02 which is 1.46 lower than the raw momentum. The fact that the constant volatility momentum experiences a significantly lower minimum return, but just a slightly different maximum return than the raw momentum indicates that the reduced standard deviation of the risk-managed strategy is caused by reduced losses. As a result, the Sharpe Ratio is significantly higher and amounts to 0.75 compared to 0.49 of raw momentum. In total, the analysis conducted in this thesis achieved similar results as Barroso and Santa-Clara (2014). However, differences arise predominantly from the larger sample that includes approximately 10 more years of data. The most significant benefits of risk management are noticeable in the improvements of higher-order events. By using risk management, the excess kurtosis is lowered from 31.58 to 12.93 and the skewness improves from -1.72 to -0.93 which is in line with Barroso and Santa-Clara’s (2014) findings. Such a reduction in the left tail of the return distribution indicates a tremendous mitigation of the crash risk. Therefore, one might argue that the risk-managed strategy makes momentum far less variable and more persistent.

This outperformance of the constant volatility strategy for the whole data sample can be observed in *Figure 4.* Before the 1950s, no extreme outperformance by the risk-managed strategy compared to raw momentum is observable. Starting from the 1950s the risk-managed strategy begins to outperform the raw momentum by between one and three percentage points in cumulative returns until today.

The gains of risk management are specifically important in panic market states. *Figure 5* compares the performance of the constant volatility momentum strategy with raw momentum in decades where the most severe crises took place.

During the Great Depression, the cumulative returns of the raw momentum strategy drop by 418% in just two months whereas the risk-managed strategy can almost preserve the returns until that point. Nevertheless, it must also be considered that, as displayed in the first graph of *Figure 5*, the raw WML generated much higher returns than the constant volatility strategy, which leads to the fact that both strategies earn approximately the same return. Before this momentum crash, the risk-managed strategy does not experience returns as high as raw momentum.

A similar pattern of returns as in the first graph of *Figure 5* can be seen for the oil crisis in 1973. Just a relatively small crash can be observed in 1974 for the raw momentum, this drop is even lower for the risk-managed strategy. The constant volatility strategy performs slightly better than the raw WML up until and during the crisis. After the crisis, when markets start to rebound in 1974, the benefit of managing risk by holding the volatility constant increases significantly as the risk-managed strategy substantially outperforms the raw momentum.

Also, a very similar pattern as the overall cumulative returns applies to the Black Monday crash. In this market crash, no distinct crash in the raw WML can be observed. Just before the crisis, the constant volatility momentum starts outperforming the raw WML slightly. This difference between the strategies increases much more in the after-crisis period.

Comparing both strategies during the Dot-com bubble in 2000, a mixed performance of both can be observed. Like in the previous two crises, no tremendous strategy crash of the raw WML can be observed. Before the 2000s Dot-com market crash, the risk-managed strategy outperforms raw momentum slightly. After the crisis, it can be observed that the constant volatility generates lower returns. Like in the Great Depression, no significant benefit of applying the strategy can be noticed.

During the momentum crash after the financial crisis 2007/2008, the raw WML experiences a plunge in cumulative returns of roughly 730%, representing the biggest crash in WML so far. As observable in *Figure 5*, both raw WML and constant volatility momentum perform very similar before and during the crisis. When the markets start to rebound at the end of 2009, risk-managed momentum does not experience a similar crash and therefore significantly outperforms the raw momentum.

The most recent and never analysed crisis is the Covid-19 pandemic in 2020. As displayed in the graph, the constant volatility momentum generates on average higher returns than the raw

WML. It experiences similar high positive returns as the raw WML but avoids the high return drops of the raw WML in the rebounding markets after the market crash. More specifically, the cumulative returns of raw momentum decrease by 230% while the risk-managed strategy can mitigate the losses and earn stable returns.

Interestingly, the investigation of the Covid-19 pandemic is in line with Muir's (2017) finding that financial crises have much higher risk premia and take longer to recover than recessions. Since the Covid-19 pandemic can be classified as a recession according to the definition in section 4.4, it is noticeable in *Figure 5* that the returns recover much faster in the Covid-19 pandemic compared to the Financial Crisis in 2007/08. However, such a finding cannot be observed across other crashes like the oil crisis in 1973, Black Monday crash 1987 and the Dot-com bubble in 2000. This might be explained by the relatively moderate magnitude of the drops in returns since these crises were not as severe for WML.

It is clearly visible that in most crash periods for momentum, the risk-managed strategy outperforms the raw momentum in terms of higher cumulative returns. Moreover, one might notice that by risk managing momentum with a constant volatility strategy, the cumulative returns do not fluctuate as much, which was the goal of applying a constant variance. As a result, it can be argued that such type of risk management is stabilizing the returns to a certain extent and making momentum more resilient to crashes. This means that the constant volatility strategy is able to significantly reduce the losses occurred by crashes. Nevertheless, this does not apply for all market crashes, since WML appears to conserve high returns during the oil crisis, the Black Monday crash, and the Dot-com bubble.

6.2.4 Dynamic volatility momentum

In this section the main empirical findings of the previously presented dynamic volatility strategy will be analyzed. The key results are shown in *Table 5* which displays a comparison of the economic performance between the raw WML and the dynamic volatility momentum strategy.

It can be observed that the dynamic volatility momentum strategy generates an average yearly return of 13.70 % which is 6.59 % per year higher than the raw momentum strategy. However, the on average higher returns gained by the dynamic volatility momentum are related to a larger standard deviation of 18.18 which is 3.7 percentage points higher than the raw momentum. Nevertheless, the dynamic volatility momentum leads to a Sharpe Ratio of 0.75 compared to 0.49 for raw momentum. Similar to Moreira and Muir (2017), the results show a substantial increase of the annualized mean return and the Sharpe Ratio accompanied by an increased standard deviation. Slightly different results compared to Moreira and Muir (2017) can be explained by the usage of a larger sample, which includes approximately 10 more years of data. By using dynamic volatility momentum, the excess kurtosis is lowered from 31.58 to 14.56 and the skewness is improved from -1.72 to -0.30.

The outperformance of the dynamic volatility momentum compared to raw momentum over the whole period is displayed in *Figure 6.* The dynamic volatility momentum does not substantially outperform the raw momentum before 1940. However, from 1940 onwards the dynamic volatility momentum starts outperforming the raw momentum between two and five percentage points in cumulative returns.

Managing the risk of momentum pays off especially in turbulent market states or more specifically when the market starts to rebound. This can be observed in *Figure 7* which compares the performance of the dynamic volatility momentum with the raw momentum in the decades with the most severe market crashes.

The first graph in *Figure 7* compares both strategies during the Great Depression. The dynamic volatility momentum strategy generates similar cumulative returns like the raw momentum strategy between 1928 and 1931. Thereafter, the dynamic volatility momentum starts to slightly outperform raw momentum. However, once the market starts to recover after the Great Depression in 1932, both strategies experience a substantial drop in cumulative returns. Furthermore, it is crucial to note that when the market is moving back to a steady state, the dynamic volatility momentum starts to substantially outperform the raw momentum. This is exactly the period when risk management pays off and significant excess returns are generated. This finding is in line with the statement of Moreira and Muir (2017) that in market rebounds, risk-managed momentum does not experience an extreme crash and therefore significantly outperforms the raw momentum.

A similar pattern of cumulative returns is displayed in the second graph of *Figure 7* but to a smaller degree. Between 1968 and 1971 the dynamic volatility momentum strategy and the raw momentum strategy gain similar returns. Afterwards, the risk-managed strategy begins to marginally outperform the raw momentum. After the oil crisis, just a relatively small crash can be observed in 1974 for the raw momentum, whereas the drop is even worse for the risk-managed strategy. Therefore, with an initiating market rebound, a benefit of managing risk by dynamically adjusting volatility can be observed.

A slightly different performance can be observed during the Black Monday crash in 1987. The dynamic volatility strategy outperforms raw momentum before, during and after the crisis. A small but sharp increase in the return of the dynamic volatility strategy after the crisis in 1988 can be observed, while the raw momentum strategy crashes slightly. Therefore, the dynamic volatility strategy not only avoids the crash, but earns even higher returns.

Similar to the Great Depression and the oil crisis, the dynamic volatility momentum strategy is not substantially outperforming the raw momentum before the Dot-com bubble in 2000. However, after the crisis when the market starts to recover, a significant outperformance of the dynamic volatility strategy can be observed.

Comparing both strategies during the financial crisis, one can observe a similar pattern as for the Great Depression. Both strategies generate the same returns until the crisis happened in 2007/08. This event affects both strategies tremendously, representing the greatest crash in history for both raw WML and the dynamic volatility strategy. Thereafter, it is noticeable that during the market rebound period, the risk-managed strategy begins to substantially outperform the raw momentum.

The latest crisis that has not been examined before in the literature, is the Covid-19 pandemic in 2020. Interestingly, it can be observed that the raw momentum slightly outperforms the risk-managed strategy until 2018. Some months before the pandemic starts, the dynamic volatility strategy starts to gain slightly higher returns but both strategies experience return drops during the rebounding markets after the market crash. However, also after this crisis, the risk-managed strategy can recover faster from the crash and starts to generate higher returns soon after.

Concluding, it can be stated that in most momentum crash periods the risk-managed strategy outperforms the raw momentum, but this comes at the cost of a higher standard deviation. Even though the returns of the dynamic volatility momentum strategy fluctuate significantly, it can be observed that dynamic risk management generates significant abnormal returns during market rebounds.

6.2.5 Combined momentum

The following section analyses the previously implemented combined momentum strategy. The main findings are shown in *Table 5*, which compares the performance of the raw WML with the combined momentum strategy between November 1926 and March 2021. Other than Asness, Moskowitz and Pedersen (2013), we are not using data from the United States, the United Kingdom, continental Europe, and Japan. Instead, we are solely focusing on the US market. The reason for this is to keep consistency between the strategies and ensure comparability.

The combined momentum gains an average yearly return of 5.29 %, which is 1.82 percentage points per year lower than the raw momentum strategy. This means that on average the combined momentum generates a slightly lower abnormal returns than raw momentum over the sample period. However, by combining value and momentum, the standard deviation is reduced by 5.29 to 9.19. The fact that the combined momentum experiences a significantly lower minimum return value, but just a slightly different maximum return value than the raw momentum might indicate that the reduced standard deviation of the risk-managed strategy is caused by the reduced losses.

As a result, the Sharpe Ratio is moderately higher and amounts to 0.58 compared to 0.49 for raw momentum. Furthermore, the most crucial benefit of using combined momentum is observable in the left tail improvements of the distribution. Combining value and momentum lowers the excess kurtosis from 31.58 to 17.15 and improves the skewness from -1.72 to -0.46. This improvement of the higher-order moments might be an indicator of mitigated crash risk. The correlation of raw WML and value for our data is -0.22, which is lower than the -0.50 that Asness, Moskowitz and Pedersen (2013) found in their sample.

The difference could be explained by the different data sample used in this thesis compared to the authors. Nevertheless, the negative correlation between value and momentum strategies implies that a simple combination could lead to results that are much closer to the efficient frontier than either strategy alone.

A comparison of the performance of the two strategies throughout the entire sample can be observed in *Figure 8*. It can be observed that the combined momentum generates lower returns until 1940. Thereafter, combining value and momentum gains similar or slightly higher returns than the raw momentum until approximately 1960. After that, it can be observed that the raw momentum strategy outperforms the combined momentum until the end of the sample period.

In order to analyze the performance of the two strategies during market crashes, *Figure 9* compares both strategies in the decades with the most severe crashes reported in history.

The first graph of *Figure 9* displays their performance during the Great Depression. The raw momentum constantly outperforms the combined momentum. However, it can be observed that the cumulative returns of the raw momentum experience a significant drop after the crisis in 1933 when the market starts to rebound, whereas the combined momentum is able to mitigate the decrease in cumulative returns to a certain extent.

In this rebound period, combining value and momentum slightly increases the returns, but no outperformance of the risk-managed strategy can be observed. This might be explained by the negative correlation between value and momentum which leads to a lower variation in returns during turbulent market times. Once the market reaches a steady state, raw momentum is again outperforming the combined portfolio.

A different pattern is displayed in the second graph of *Figure 9* during the oil crisis in 1973. While both strategies generate similar returns from 1968 until 1972, raw momentum slightly outperforms the combined momentum during the crisis. However, it is visible that after the crisis when the market starts to recover in 1974, the raw WML strategy experiences a slightly greater crash than the combined momentum strategy. Hence, combining value and momentum generates higher returns and starts to slightly outperform raw momentum until 1978.

A similar pattern can be observed for the Black Monday crash in 1987. Before the crash, both strategies earn similar cumulative returns. During the market rebound period in 1988 it is beneficial to combine value and momentum. Once the market recovers and starts to enter a bull market, the raw momentum begins to outperform the combined momentum strategy.

During the Dot-com bubble in 2000 a slightly different pattern can be observed. Before the crash both strategies perform similarly. In 1999 the raw momentum starts to gain higher returns which continues over the displayed period, even though the combined portfolio is able to mitigate the losses during the market rebound after the crisis.

Comparing both strategies over the financial crisis in 2007/08, leads to interesting findings. In the period before the financial crisis, both strategies are able to achieve similar cumulative returns. However, during the market recovery phase in 2009/10 the raw momentum strategy drops tremendously and generates high losses. The combined portfolio on the other hand, reduces its losses and is able to generate slightly positive cumulative returns during the rebound state. This trend continues over the next couple of years after the crisis and can also be observed in the years before the Covid-19 pandemic.

The las graph of *Figure 9* displays the performance during the Covid-19 pandemic. Contrary to the other market crashes, the combined momentum strategy outperforms the raw momentum strategy before 2019. Thereafter, raw momentum initiates to outperform the combined momentum until the end of the sample period. However, during the market rebound period in mid 2020, the raw momentum strategy experiences a substantial drop in cumulative returns whereas no sudden crash of the combined portfolio strategy can be observed.

Overall, it can be concluded that the raw momentum strategy outperforms the combined momentum strategy on average. However, it is visible in most of the momentum crashes that the combined portfolio manages to reduce the losses and stabilizes its returns during market rebounds, hence showing more resilience against crashes.

As a result, our findings are in line with Asness, Moskowitz and Pedersen (2013) results that the negative correlation between value and leads to less variation across markets and over time.

6.2.6 Risk-managed strategies – compared

The following section compares the three previously presented risk-managed momentum strategies with raw WML. A comparison of the economic performance of the risk-managed strategies and raw WML is provided in *Table 5*.

The dynamic volatility strategy generates the highest mean return amounting to 13.70 % followed by the constant volatility strategy with 9.74 %, the raw WML with 7.11 % and lastly the combined momentum strategy with 5.29 %. However, high abnormal returns come at the expense of a large standard deviation. Thus, the dynamic volatility strategy shows the highest standard deviation whereas the combined momentum strategy has the lowest.

Interestingly, this relation of standard deviation and mean return does not apply to the constant volatility strategy, which has a lower standard deviation than the raw momentum even though it generates a higher abnormal return on average. This might be explained by the fact that the constant volatility strategy experiences a significantly lower minimum return value, but just a slightly different maximum return value than the raw momentum. This indicates that the reduced standard deviation is caused by a reduction of largely negative returns.

Similarly, the combined momentum has the second lowest minimum value and the lowest maximum value which leads to the smallest standard deviation among all strategies. As a result, the dynamic volatility strategy achieves the highest Sharpe Ratio of 0.75 which is just 0.01 higher than that of the constant volatility strategy. Interestingly, the raw WML strategy has by far the lowest Sharpe Ratio which means that the risk-adjusted profitability of the strategy is the lowest.

The performance of the analyzed strategies between 1926 and 2021 is presented in *Figure 10*. It is clearly visible that the dynamic volatility momentum strategy outperforms the other risk-managed strategies from 1930 onwards. Furthermore, it can be observed that the other three strategies perform quite similar until 1950. Thereafter, the constant volatility strategy starts to achieve higher returns than the raw momentum which gains larger returns than the combined momentum.

Furthermore, the most significant benefits of risk-management can be observed in the improvements of high-order events. Compared to the raw momentum, all risk-managed strategies are able to substantially lower the excess kurtosis and the skewness. Hereby, it is difficult to argue which of the three risk-managed strategies performs best and achieves the lowest crash risk. By comparing the excess kurtosis, the constant volatility strategy is able to reduce it to 12.93 which is lower than the other two risk-managed strategies. However, the constant volatility strategy has the highest skewness among the risk-managed strategies whereas the dynamic volatility strategy has the lowest skewness with -0.30. The combined momentum on the other hand, has the largest kurtosis among the risk-managed strategies and the second lowest skewness.

This relatively weak performance of the combined momentum strategy could lead to the conclusion, that a focus on negative correlation does not guarantee that volatility and therefore the crash risk is reduced. The correlation can change over time and does therefore not necessarily lead to a hedge.

In conclusion, solely analyzing excess kurtosis and skewness, the constant volatility or the dynamic volatility strategy perform the best. In order to find out which of the two strategies is more resilient against crashes, a closer analysis throughout different crises has been performed. *Figure 11* displays a comparison of cumulative returns of the risk-managed strategies and raw WML in decades with the most severe market crises reported in history.

In the first graph of *Figure 11* it is observable that until the Great Depression hit in 1932 the dynamic volatility momentum generates the highest cumulative returns followed by the raw momentum strategy, the constant volatility momentum and the combined momentum. However, all four momentum strategies start to crash after the Great Depression in 1933 when the market starts to recover. One might notice that the dynamic volatility momentum and the raw momentum strategy experience the largest drop in cumulative returns which might also be explained by their higher standard deviation and kurtosis compared to the constant volatility momentum and the combined momentum. As a result, it is crucial to note that the constant volatility and the combined momentum strategy achieve the highest reduction of crash losses and hence also manage to stabilize the returns to a certain extent. In the years after the crisis, the different momentum strategies perform in a similar manner as prior to the crisis. In terms of mitigating crash losses, it can be argued that the constant volatility strategy performs best during the Great Depression even though it is outperformed by the dynamic volatility WML with respect to cumulative returns.

A slightly different pattern is shown in the second graph of *Figure 11* during the oil crisis in 1973. It can be observed that the dynamic volatility strategy outperforms the other momentum strategies over the whole observation period, followed by the constant volatility momentum. The raw momentum generates the third highest returns over the period; however the combined momentum starts to outperform the raw momentum after the crisis from 1975 onwards. Due to the small effect of the oil crisis on momentum strategies, no clear winner in terms of risk mitigation can be defined.

A similar outperformance of the dynamic and constant volatility strategies can be observed during the Black Monday crash in 1987. In contrast to the oil crisis, the combined momentum achieves slightly higher returns than the raw WML, however after 1990 the raw momentum strategy outperforms the combined momentum. Again, the minor effect of the Black Monday crash on momentum strategies makes it difficult to declare a strategy that is the most resilient against the crash.

During the Dot-com bubble in 2000, the dynamic volatility strategy outperforms the other strategies. Interestingly, this time the raw momentum generates higher returns than the constant volatility strategy. The worst performance can be attributed to the combined momentum. Regarding the crash risk mitigation, it is crucial to note that the constant volatility strategy experienced the smallest drop in returns and hence preserved the most gains after the crisis.

The comparison of all four strategies during the financial crisis in 2007/08 is displayed in the fifth graph in *Figure 11*. It is visible that all strategies perform quite similar up to the crash with a moderate outperformance of the dynamic volatility strategy. Thereafter, it is observable that all momentum strategies crash right when the market begins to recover. Similar to the Great Depression, the largest drop in returns is experienced by the dynamic and the raw momentum strategy. The combined momentum reacts more resilient to the crash than the latter two. Interestingly, the constant volatility strategy experiences the smallest momentum crash and preserves the most returns during the market rebound. After the crisis, the constant volatility momentum is able to generate similar returns as the dynamic volatility strategy, whereas the raw WML generates negative returns.

During the Covid-19 pandemic the momentum strategies show completely different patterns compared to the other crises. Surprisingly, the combined and the constant volatility momentum are outperforming the other two strategies until mid 2018. Thereafter, the combined momentum starts to decline continuously. The other three momentum strategies perform quite similar around the Covid-19 pandemic in 2020. The raw and dynamic WML strategy crash with the highest magnitude in the beginning of the market rebound whereas the constant volatility strategy is able to significantly mitigate these crash losses.

Referring back to the initial conclusion that either the constant or the dynamic volatility strategy are reducing most of the crash risk, a clearer conclusion can be drawn now.

Since both volatility approaches have almost the same Sharpe Ratio, other characteristics need to be considered to define the best risk-managed strategy.

First, it is visible throughout all crises that the dynamic volatility strategy is generating the largest average returns and outperforms all other strategies in that sense. However, due to the relatively high standard deviation and kurtosis, the strategy is exposed to a larger crash risk. Therefore, it can be concluded that such a strategy might not be ideal for a risk-averse investor.

Second, throughout all crises that the constant volatility strategy is most of the times performing as the second best or sometimes as the third best strategy with regard to returns. This limitation in abnormal returns comes at the benefit of more stable returns. These risk-managed returns are displayed throughout almost all crises. It is clearly noticeable that the cumulative returns of the constant volatility strategy fluctuate substantially less compared to the dynamic volatility strategy, indicated by the lower standard deviation. Moreover, the low kurtosis and a relatively small skewness further support the maintenance of returns in crash periods. Resulting, such a strategy might be more appropriate for risk-averse investors who desire a lower crash risk without reducing WML returns dramatically.

Since the constant volatility strategy is also better performing in non-crash market periods, it can be concluded that managing the volatility of momentum is highly beneficial and successfully mitigates crash losses.

6.2.7 Winners only?

In addition to the previously presented strategies, we are proposing a new risk-managed strategy in section 5.3. This constitutes an early-stage experimentation, which might be further examined in the future.

Similar to the other presented strategies, we compare key features of the Winner Investing strategy with raw WML and further analyze their performance throughout the whole sample and several market crashes in detail.

Winner Investing, as previously mentioned, is a strategy that is exclusively holding a long position in the winner portfolio of WML. This means, that the short position of the raw WML is not considered. The incentive to waive possible returns of a short position comes from a claim of Daniel and Moskowitz (2016), who say that the losses experienced in raw WML are mostly attributable to the short side of the WML portfolio.

A comparison of the economic performance of the raw WML with the Winner Investing strategy between November 1926 and March 2021 is displayed in *Table 5*. The most striking attribute in the results is the tremendously high maximum return value of the Winner Investing strategy compared to raw momentum, whereas the minimum value is just slightly less negative. These extreme values are also mirrored in the standard deviation, it does not improve using the Winner Investing, instead it increases significantly from 14.48 for raw WML to 46.85 for Winner Investing. Despite the increased standard deviation, an improvement of the higher moments can be observed. The kurtosis for Winner Investing is with 22.10 lower than the one for raw WML (31.58) and the skewness increases from -1.72 to -0.53. Lastly, the Winner Investing strategy has a significantly higher mean, which is 23.03 % higher than raw momentum, and a higher Sharpe Ratio of 0.64 (compared to 0.49 for raw WML).

The cumulative return over the whole sample is shown in *Figure 12* for both strategies. It can be observed that raw WML and Winner Investing generate similar returns in the first years of the sample. From the mid-1930s on, the cumulative returns of the Winner Investing strategy is significantly higher than for raw WML. It accumulates to an outperformance by the Winner Investing strategy of raw WML by nearly 20%.

In *Figure 13* the cumulative performance of Winner Investing and raw WML is compared throughout all historical big market crashes.

Analyzing their performance during and around the Great Depression in 1932, it is observable that there is no distinct pattern in the performance of Winner Investing and raw WML before and during the crisis. At the time of the market rebound, raw WML experiences severe losses, whereas the Winner Investing strategy performs in a contrarian direction and even performs significantly and increasingly better than the raw WML. Furthermore, the Winner Investing strategy does not experience severe crashes and therefore successfully avoids losses during this period.

Similar indistinctive performance patterns can be observed for WML and Winner Investing at the time of the oil crisis 1973, specifically in the observed period until 1976. Interestingly, the Winner Investing strategy experiences a much higher volatility in returns compared to the raw WML and crashes several times in the analyzed period. Nevertheless, the Winner Investing strategy significantly outperforms the raw WML from 1976 onwards.

During the Black Monday crash, it can be observed that for nearly the whole sample the Winner Investing strategy outperforms the raw WML. However, the Winner Investing strategy also experiences higher drops in returns than the raw WML at the end of 1987 and in 1991. This is in line with the very high standard deviation of the strategy.

In the period of the Dot-com bubble, the Winner Investing strategy achieves at all times significantly higher returns than the raw WML. A small crash shortly after 2000 is observable in both strategies but at a higher magnitude for the Winner Investing strategy.
Comparing both strategies throughout the financial crisis 2007/08 shows a pattern that indicates opposing movements for both strategies. During this time, the Winner Investing strategy could be interpreted as being somewhat of a hedge for the raw momentum. The Winner Investing strategy performs better than the raw WML until the market crisis and crashes significantly during the crisis. Whereas raw WML increases returns during the crisis and crashes down after it, Winner Investing starts increasing its returns again. After this, Winner Investing generates exponentially growing returns whereas raw WML stabilizes and increases slightly.
Throughout the whole sample of the Covid-19 pandemic, the Winner Investing strategy outperforms the raw WML strategy. As also observed in some other crises, the Winner Investing crashes with the market crash in 2020, whereas raw WML crashes when markets are rebounding. At the same time when raw WML crashes, the Winner Investing strategy experiences increased returns. This pattern again signals somewhat opposing movement in both strategies.
In conclusion, after having analyzed and compared the Winner Investing strategy with raw momentum, it is very clear that the initial goal of avoiding crashes cannot be achieved, even though much less of its performance remains unexplained using the Fama French models. As displayed in the graphs in *Figure 13* as well as through the high standard deviation of the strategy, it becomes clear that crashes cannot be avoided and have often even a higher magnitude than the ones experienced in raw momentum. However, this implication is not true all the time and changes throughout the different market crises, leading to no consistent pattern. Another striking finding is that, on average, the Winner Investing strategy generates significantly higher returns than the raw WML. This poses the question: at what cost are these high returns earned?
The Winner Investing strategy is certainly not simply comparable to the previously mentioned strategies. As mentioned in section 5.3 the Winner Investing strategy is, other than raw WML, not self-financed and therefore requires an outflow of own funds which results in higher opportunity costs for investors whose money is tied up in the winner portfolio. One way to account for the opportunity costs of this investment is to adjust the returns of the Winner Investing strategy by deducting the market return. We therefore account for the return realized on the market, which must be renounced.

This adjusted Winner Investing strategy is included in the results displayed in *Table 5* and in *Figure 12* to *Figure 13*. The results still show a very strong performance compared to the raw WML and other risk-managed strategies. Even though the standard deviation is still high for the adjusted version, it earns an even higher Sharpe ratio than the unadjusted Winner Investing strategy. This improved performance can also be observed by the much more stable returns especially throughout the largest momentum crashes in 1932 and 2009. But an in depth-analysis of adjustments on a Winner Investing strategy goes beyond the scope of this thesis and will therefore be left open for further research.
The hypothesis that the Winner Investing strategy earns lower returns compared to raw WML in non-crash periods, due to the elimination of the short position, can be rejected since we observe on average higher returns for Winner Investing. Furthermore, the fact that the Winner Investing strategy often also tends to crash with the market, makes an avoidance of its crashes nearly impossible, since we are not able to forecast these crashes. Overall, using the Winner Investing strategy instead of the raw WML leads to much higher average returns. But these come at an even higher crash risk than the raw WML and a high standard deviation.

6.3 Robustness check

As previously analyzed, most risk-managed momentum strategies appear to be beneficial to avoid strategy crashes. Our data sample includes several momentum crashes, the most severe crashes are the Great Depression in 1932 and the Financial Crisis in 2007/08. We are therefore analyzing raw momentum as well as the previously presented risk-managed strategies throughout different subsamples.
First, we split the data set in half to ensure that our obtained results are not driven by one singular event. A further split to isolate the other crises is not necessary since the financial crisis and the Great Depression are the two most extreme momentum crashes.
Furthermore, the benefits of risk management in less turbulent times are examined. Therefore, we are analyzing the performance of all risk-managed strategies in periods without major momentum crashes or excluding data of momentum crashes.[116] This means, that we are constructing a non-crash sample of the entire period from November 1926 to March 2021 but excluding the years of the most severe momentum crashes in 1932 and 2009.

[116] Similar to Barroso and Santa-Clara (2014) we are not focusing on temporal dependent data rather we are comparing the descriptive statistics of the different subsamples which allows us to exclude the crash years.

Lastly, we are analyzing the performance of all strategies for a subsample including the span from January 1945 to December 2005. This time frame refers to a period after the second world war[117], where no major momentum crash occurred. This serves perfectly to analyze the performance of less turbulent times.

The first robustness check is displayed in *Table 6*, where the performances of all strategies between the first half of the sample and the second half of the sample are displayed. Analyzing the key features in both subsamples, it can be observed that all mean return values except for the combined momentum are higher for the risk-managed strategies compared to raw momentum. Also, for all risk-managed strategies in both the first and the second half, a reduction of the kurtosis as well as an increase of the skewness can be observed. For the constant volatility momentum and raw momentum, a rather big difference in the kurtosis between the first and the second half can be observed. Both display a lower kurtosis of 23.28 for raw WML and 6.61 for constant volatility momentum in the second half compared to the first half of the sample (41.24 & 18.54 respectively). The Sharpe Ratio for all risk-managed strategies is higher than for raw momentum. This assessment confirms that the previously presented results are not driven by the extreme momentum crashes in the 1930s and the 2000s.

Table 7 displays all strategies in samples which serve to check the strategy performance in less turbulent times. In the no-crash sample excluding the years 1932 and 2009, we can see that the results are very much in line with the ones of the whole sample set displayed in *Table 5*. Again, mean return values for all risk-managed strategies except combined momentum are higher compared to raw momentum. Also, the kurtosis of all risk-managed strategies is lower, and the skewness is higher compared to raw WML.

Differences can be observed in the subsample set of the data including data of the period after the second world war. Compared to the whole sample (*Table 5*), all strategies have a much lower minimum return value. The Winner Investing strategy shows a much lower maximum return value of 200.73% compared to 535.49% in the whole sample (*Table 5*).

Regarding the kurtosis, a lower value can be observed for the constant volatility momentum and the dynamic momentum, but it does not improve for the combined momentum and the Winner Investing strategy. The skewness is higher for constant volatility momentum with -0.68 and slightly higher for combined momentum with -0.63 and positive for dynamic momentum with 0.32, but more negative for Winner Investing with -1.07 compared to the raw WML skewness of -0.90. Lastly the Sharpe Ratio is higher for all risk-managed strategies compared

[117] Due to a high risk of uncomplete data, we refused to analyze WML during the second world war to avoid biased results.

to raw momentum, but since the Sharpe Ratio of raw WML in this subsample also increased from 0.49 for the whole sample to 0.85 for the post-war period, the differences between the Sharpe Ratio of risk-managed strategies and raw WML is a lot lower.

Overall, examining the performance of risk-managed momentum in less turbulent periods leads to mixed results. While the non-crash sample is confirming the robustness of our results, just focusing on the post-war periods shows less distinct benefits of using risk management. But since this period only focusses on a rather small part of the sample, we can overall conclude that the results of the robustness checks are confirming that the performance of the risk-managed strategies are not driven by either one of the two major crashes. Furthermore, the results of the robustness check show a similar performance compared to the assessment of the overall sample in less turbulent times.

7. Conclusion

Investing in momentum becomes more and more popular for investors but challenges them at the same time with severe return crashes that can take decades to recover from. In this thesis, we have provided an overview of theoretical frameworks explaining the momentum anomaly as well as its repeatedly occurring strategy crashes. In response to these crashes, we have analyzed different risk-managed strategies proposed in the literature which aim to provide a less risky approach to momentum investing. The result of this analysis is a broad comparison of all risk-managed strategies in relation to raw momentum throughout all relevant crises of the past century.

Firstly, we contributed to the existing literature by analyzing momentum performance throughout all severe market crashes of the past century, including the recently experienced Covid-19 pandemic. We found that, in contrast to the widely advertised hypothesis of the existing literature, momentum crashes are not fully predictable and do not consistently occur after a big market crash. We instead found very different performance patterns throughout the different crises. Furthermore, these differences could not be explained by the theory of Muir (2017), that markets and returns behave differently throughout financial crises and recessions. Generally, we could not find any reliable relation between market performance and raw WML performance, which might be exploited by risk-managed strategies. Instead, we found that raw WML as well as the risk-managed momentum strategies often seem to experience a sharp increase in returns before a strategy crash. Further research could pick up on this finding to investigate a way to potentially avoid momentum crashes. One conclusion we can come to is that, if a momentum crash occurs after a market crisis, its magnitude is higher and the recovery takes longer if the market crash is more severe.

Furthermore, another major contribution to the existing literature is the comparison of different risk-managed strategies. As result, we found that the dynamic volatility momentum strategy, which was firstly introduced by Moreira and Muir (2017), leads to the highest average returns, but rarely avoids crashes on its own and only slightly decreases the magnitude of these crashes. The constant volatility strategy of Barroso and Santa-Clara (2014) on the other hand, manages to significantly reduce crashes and fluctuation in returns but produces lower average returns than the dynamic volatility strategy, while still outperforming the raw WML strategy. The presented combined momentum strategy appears to not be a very attractive risk-management option since it earns on average a lower return as well as a just moderately higher Sharpe Ratio than the raw WML, even though it achieves a significant reduction in crash risk.

Concluding, whether the constant volatility strategy or the dynamic volatility strategy is to be preferred is highly dependent on the investor's individual preferences. While the dynamic volatility strategy generates significantly higher returns compared to the raw WML, the constant volatility strategy generates stable and moderately higher returns than the raw WML. However, it should be emphasized that the crashes of the dynamic volatility still result in very high returns compared to the raw WML.

In the last section we referred to the claim of Daniel and Moskowitz (2016), that losses of momentum are mostly attributed to the short side of the portfolio. We therefore present our own Winner Investing strategy, that exclusively invests into the winner portfolio and does not consider the loser portfolio. The analysis of this proposed strategy convinces by very high average returns at cost of a high standard deviation. However, we found that such a strategy results in an even higher crash magnitude and less predictability of crashes than raw WML. Nevertheless, the very high returns motivate further adjustments on the strategy to reduce risk and to account for the opportunity costs of such an investment. Further research on this could reveal instructive findings.

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Tables

Table 1: Performance comparison: Momentum, SMB, HML, Market Portfolio.
The table refers to the section 3.1.
Source: Barroso and Santa-Clara (2014)

Portfolio	Maximum	Minimum	Mean	Standard-deviation	Kurtosis	Skewness	Sharpe Ratio
RMRF	38.27	- 29.04	7.33	18.96	7.35	0.17	0.39
SMB	39.04	-16.62	2.99	11.52	21.99	2.17	0.26
HML	35.48	-13.45	4.50	12.38	15.63	1.84	0.36
WML	26.18	-78.96	14.46	27.53	18.24	-2.47	0.53

Table 2: Descriptive statistics.
The long-run performance of momentum (WML) is compared with the Fama and French risk factors: market (RMRF), size (SMB), value (HML), robust-minus-weak (RMW) and conservative-minus-aggressive (CMA). All statistics are computed with monthly returns. Reported are the following: maximum and minimum one-month returns observed in the sample, the mean average excess return (annualized), the standard deviation (annualized), excess kurtosis, skewness, and (annualized) Sharpe Ratio. The sample returns are from 1926:11 to 2021:03 for the Fama and French three factors and the momentum factor (WML). The additional Fama and French five factors (RMW and CMA) are computed from 1963:07 to 2021:03. The table refers to section 6.2.1.
Source: own calculation

Portfolio	Min	Max	Mean	Standard-deviation	Kurtosis	Skewness	Sharpe Ratio
RMRF	-29.13	38,85	7.22	21.82	10.55	0.17	0.42
SMB	-16.82	36.70	2.55	12.01	21.72	1.87	0.21
HML	-13.96	35.46	4.17	14.53	21.31	2.07	0.29
RMW	-18.48	13.38	3.23	9.35	14.98	-0.29	0.35
CMA	-6.86	9.56	3.27	8.77	4.56	0.32	0.37
WML	-52.27	18.36	7.95	15.72	29.77	-2.96	0.51

Table 3:Linear Regression Model of raw momentum on the Fama and French three- and five-factor models.
The sample used for the regression using the three-factor Fama French model includes monthly data from 1927:01 to 2021:03. The sample used for the five-factor model includes monthly data from 1963:07 to 2021:03.
The table refers to section 6.2.1.
Source: own calculation.

	Raw WML	
	3 FF model	5 FF model
Mkt-RF	-0.220***	-0.155***
	(0.025)	(0.039)
SMB	-0.044	0.037
	(0.041)	(0.055)
HML	-0.472***	-0.536***
	(0.036)	(0.073)
RMW		0.206***
		(0.076)
CMA		0.356***
		(0.111)
Constant	0.956***	0.702***
	(0.124)	(0.159)
Observations	1,131	693
R-squared	0.237	0.108

Standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

Table 4:Analysis of momentum throughout different crisis of the past century.
The max, min, mean, the standard deviation, the Sharpe Ratio are annualized whereas the kurtosis and skewness are based on daily returns.
The table is related to the section 6.2.2.
Source: own calculation.

Crisis **year**	**Great Depression** **1932**	**Oil crisis** **1973**	**Black Monday crash** **1987**	**Dot-com bubble** **2000**	**Financial crisis** **2007/08**	**Covid-19 pandemic** **2020**
Min	-52.96	-20.74	-14.40	-26.19	-62.13	-35.83
Max	51.18	49.89	41.39	58.88	57.53	32.92
Mean	6.96	9.02	9.62	11.97	1.21	1.82
Standard deviation	19.47	11.45	12.35	14.84	18.55	12.14
Kurtosis*	8.09	8.23	14.84	11.02	15.14	21.85
Skewness*	-0.88	0.11	-1.16	-0.89	-0.89	-1.65
Median	8.46	10.10	9.64	10.75	4.42	2.89
Sharpe Ratio	0.36	0.79	0.78	0.81	0.07	0.15

**Based on daily returns (not annualized)*

Table 5:Comparison descriptive statistics of risk-managed strategies and raw momentum.
Comparison of the six momentum strategies: raw WML, constant volatility momentum strategy, dynamic volatility momentum strategy, combined momentum, Winner Investing and adjusted Winner Investing (based on daily annualized returns). The max, min, mean, the standard deviation, the Sharpe Ratio are annualized whereas the kurtosis and skewness are based on daily returns. The table is related to section 6.2.3 – 6.2.7 and 6.3.
Source: own calculation

	Min	**Max**	**Mean**	**Standard deviation**	**Kurtosis***	**Skewness***	**Median**	**Sharpe Ratio**
WML	-62.13	58.88	7.11	14.48	31.58	-1.72	7.90	0.49
Constant volatility WML	-19.52	61.42	9.74	13.02	12.93	-0.93	8.17	0.75
Dynamic WML	-59.10	95.59	13.70	18.18	14.56	-0.30	11.90	0.75
Combined	-34.07	53.82	5.29	9.19	17.15	-0.46	4.89	0.58
Winner Investing	-49.79	535.49	30.14	46.85	22.10	-0.53	24.63	0.64
Adjusted Winner Investing	-24.27	246.13	19.37	26.57	17.52	0.21	12.49	0.73

**Based on daily returns (not annualized)*

Table 6:Robustness test splitting the data sample in half.
Performance of raw momentum, constant volatility momentum, dynamic volatility momentum, combined momentum and the Winner Investing in different subsamples. The first half of the sample is from 1926:11 to 1974:04. The second half is from 1974:04 to 2021:03. The max, min, mean, standard deviation and Sharpe Ratio are all annualized whereas the kurtosis and skewness are based on daily returns. The table is related to section 6.3.

	First Half (1926:11 – 1974:04)					**Second Half (1974:04 – 2021:03)**				
Strategy	Raw WML	Const. WML	Dyn. WML	Combined	Winner Investing	Raw WML	Const. WML	Dyn. WML	Combined	Winner Investing
Min	-52.96	-19.52	-59.10	-21.87	-49.26	-62.12	-17.58	-56.93	-34.07	-49.79
Max	51.18	59.13	85.11	37.21	535.50	58.88	61.42	95.59	53.82	204.95
Mean	6.84	8.96	13.14	5.35	32.37	7.39	10.59	14.28	5.21	27.75
Std. Dev.	13.79	11.97	15.72	8.68	57.27	15.18	14.00	20.48	9.71	31.82
Kurtosis*	41.24	18.54	12.98	16.68	23.45	23.28	6.61	15.74	16.39	17.58
Skewness*	-2.15	-1.23	-0.28	-0.26	-0.28	-1.33	-0.59	-0.31	-0.84	-0.97
Sharpe Ratio	0.50	0.75	0.84	0.62	0.57	0.49	0.76	0.70	0.54	0.87

** Based on daily returns (not annualized)*

Table 7:Robustness test including no crash sample and post second world war sample.
Performance of raw momentum, constant volatility momentum, dynamic volatility momentum, combined momentum and the Winner Investing in different subsamples. The no-crash sample is from 1926:11 to 2021:03, excluding the years of two major momentum crashes in 1932 and 2009. The after WWII sample is from 1945:01 to 2005:12. The max, min, mean, standard deviation and Sharpe Ratio are all annualized whereas the kurtosis and skewness are based on daily returns. The table refers to section 6.3.

	No crash sample (excluding 1932 and 2009)					**After the second world war (WWII) (1945:01 – 2005:12)**				
Strategy	Raw WML	Const. WML	Dyn. WML	Combined	Winner Investing	Raw WML	Const. WML	Dyn. WML	Combined	Winner Investing
Min	-54.95	-19.52	-59.10	-25.71	-49.26	-26.19	-17.58	-28.61	-16.55	-45.63
Max	58.88	61.42	95.59	53.82	535.50	58.88	61.42	95.59	53.82	200.73
Mean	7.60	10.01	13.98	5.57	30.86	9.62	12.86	15.56	7.45	29.62
Std. Dev.	13.50	12.99	17.31	8.84	46.61	11.30	13.62	15.21	7.73	30.63
Kurtosis*	35.18	13.02	13.33	17.83	23.00	14.51	8.29	14.38	18.43	17.50
Skewness*	-1.79	-0.93	-0.09	-0.46	-0.63	-0.90	-0.68	0.32	-0.86	-1.07
Sharpe Ratio	0.56	0.77	0.80	0.63	0.66	0.85	0.94	1.02	0.96	0.97

** Based on daily returns (not annualized)*

Figures

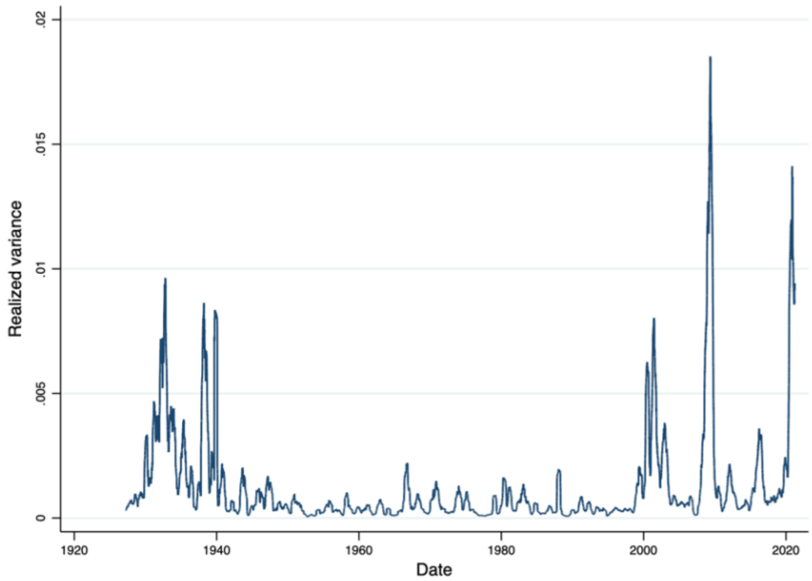


Figure 1: Volatility of momentum strategy.
Results from daily returns in each month from 1926:11 to 2021:03. The variance of raw WML was calculated using the classic variance formula. Specifically, the difference of daily return and 6 months average to the power of two is multiplied by 21 and divided by 126. Where 21 days approximate one month and accordingly 126 days approximate 6 months. This figure refers to section 4.1.
Source: Own calculations.

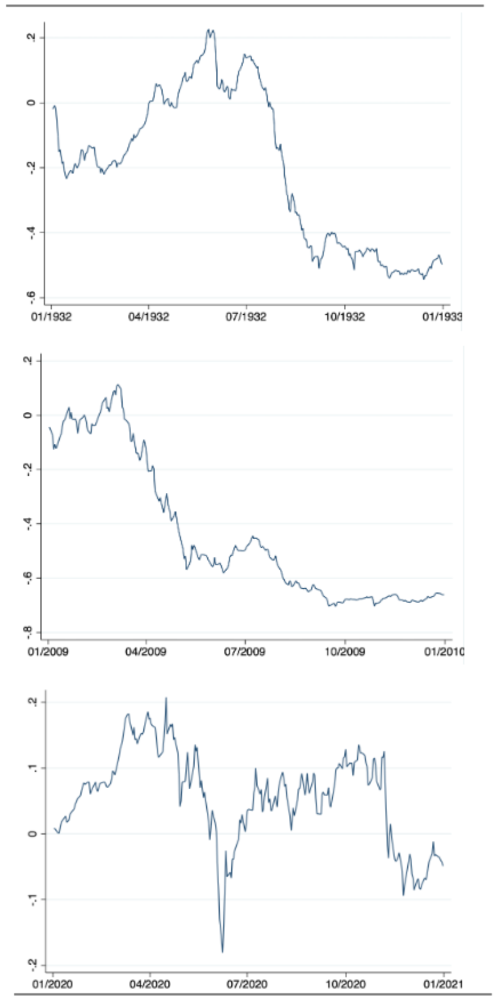


Figure 2: Cumulative momentum returns during the three most severe crashes.
This includes the Great Depression 1932, Financial Crisis 2007/08 and the latest Covid-19 pandemic in 2020. The cumulative returns have been computed by aggregating the daily returns over the observation period. This figure is related to section 4.1.
Source: Own calculation.

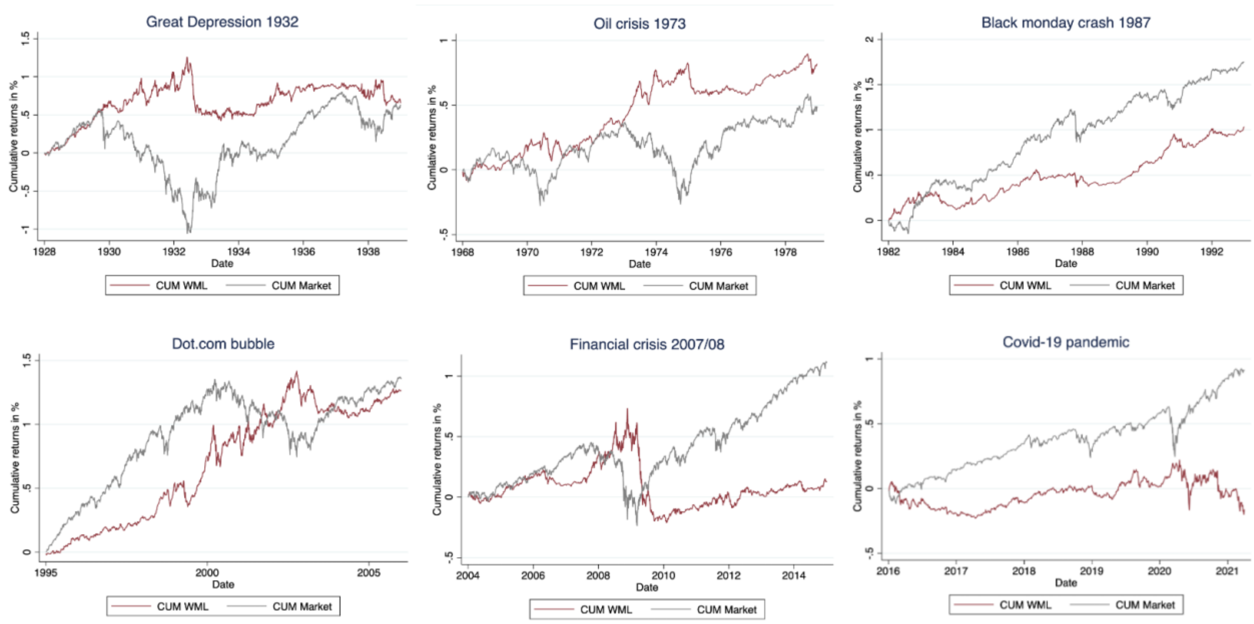


Figure 3: Comparison of the cumulative returns between the raw momentum strategy (WML) and the market over the different crises.
The return on the market is the value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares, and price data at the beginning of t, and good return data for t minus the one-month Treasury bill rate. The cumulative returns have been computed by aggregating the daily returns over the observation period. This figure refers to section 6.2.2.
Source: own calculation.

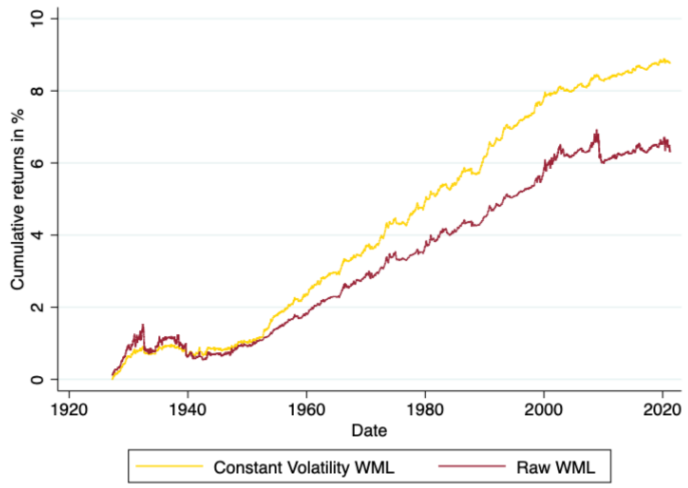


Figure 4: Comparison of the cumulative returns between the raw momentum strategy (WML) and the constant volatility risk-managed strategy.
A period from 1926:11 to 2021:03 is displayed. The cumulative returns have been computed by aggregating the daily returns over the observation period. The daily returns are calculated by the daily returns times the strategy specific weight explained in section 5.1.1. This Figure is related to section 6.2.3.
Source: own calculation.

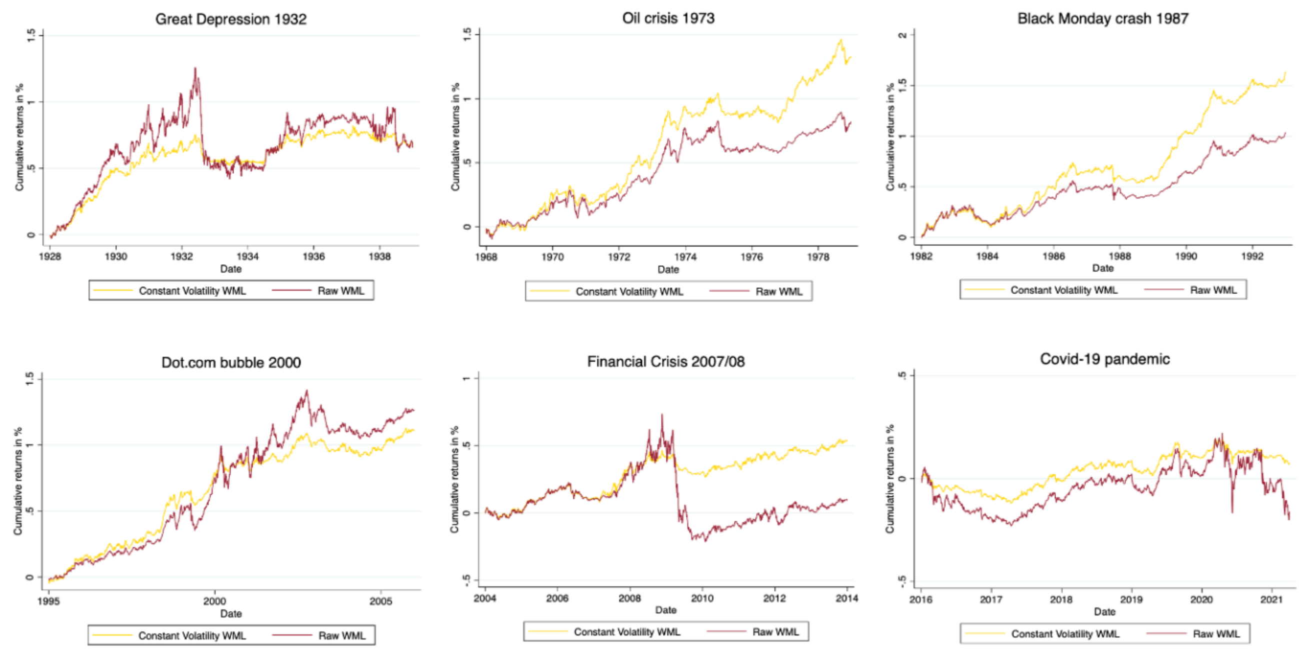


Figure 5: Comparison of the cumulative returns between the raw momentum strategy (WML) and the constant volatility risk-managed momentum strategy over the different crises.
The cumulative returns have been computed by aggregating the daily returns over the observation period. The daily returns are calculated by the daily returns times the strategy specific weight explained in section 5.1.1. This Figure is related to section 6.2.3.
Source: own calculation.

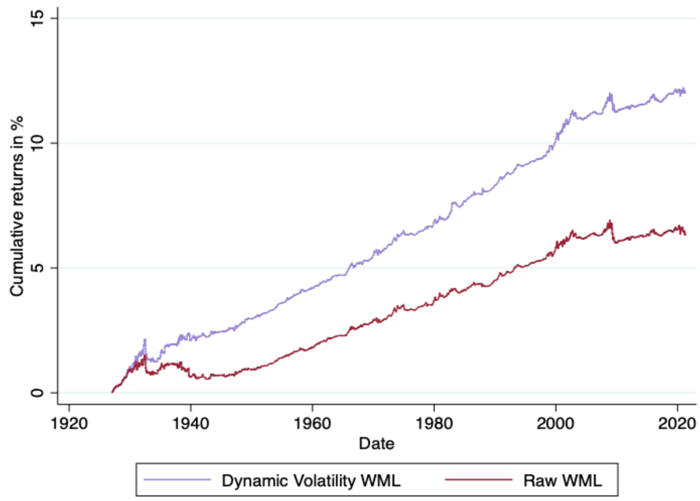


Figure 6: Comparison of the cumulative returns between the raw momentum strategy (WML) and the dynamic volatility risk-managed strategy.
A period from 1926:11 to 2021:03 is displayed. The cumulative returns have been computed by aggregating the daily returns over the observation period. The daily returns are calculated by the daily returns times the strategy specific weight explained in section 5.1.2. This Figure is related to section 6.2.4.
Source: own calculations.

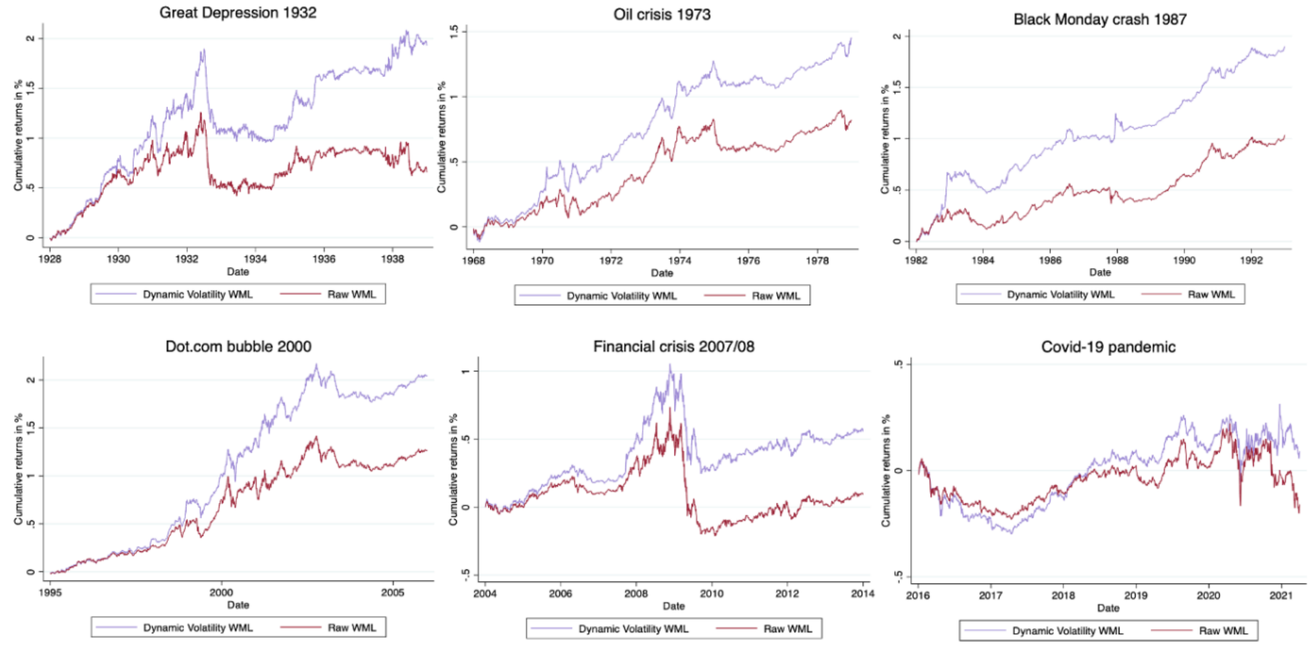


Figure 7: Comparison of the cumulative returns between the raw momentum strategy (WML) and the dynamic volatility risk-managed momentum strategy over the different crises.
The cumulative returns have been computed by aggregating the daily returns over the observation period. The daily returns are calculated by the daily returns times the strategy specific weight explained in section 5.1.2. This Figure is related to section 6.2.4.
Source: own calculation.

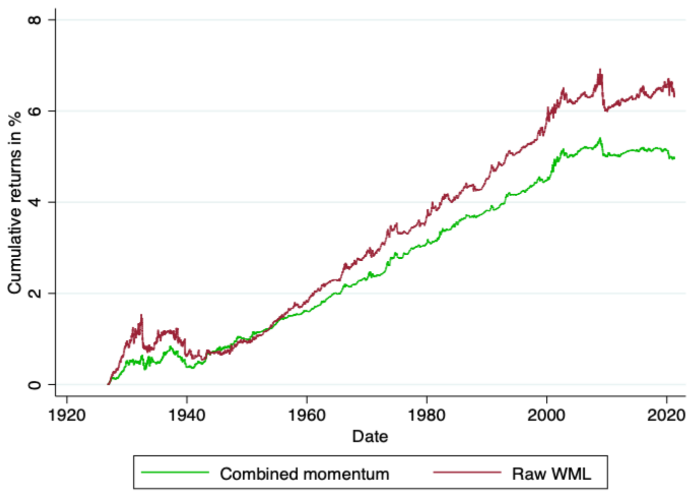


Figure 8: Comparison of the cumulative returns between the raw momentum strategy (WML) and the combined momentum. A period from 1926:11 to 2021:03 is displayed. The cumulative returns have been computed by aggregating the daily returns over the observation period. The daily returns are calculated by combining value (HML) and momentum as explained in section 5.2. This Figure is related to section 6.2.5.
Source: own calculations.

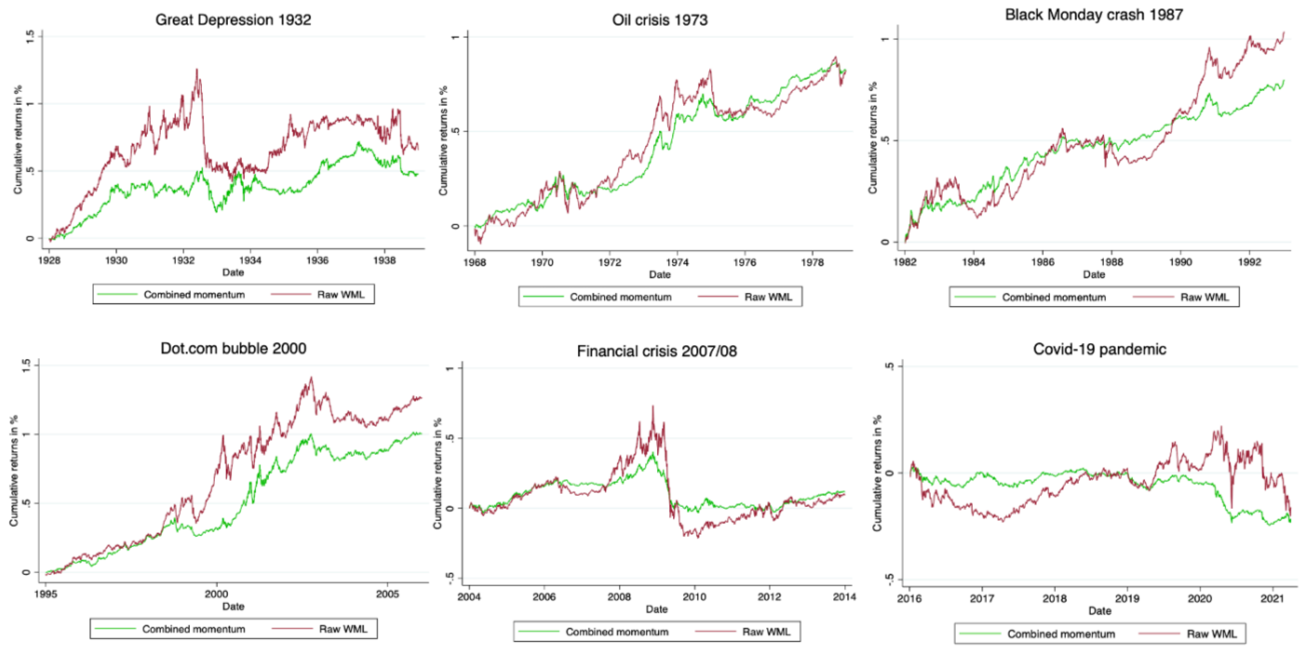


Figure 9: Comparison of the cumulative returns between the raw momentum strategy (WML) and the combined momentum strategy over the different crises.
The cumulative returns have been computed by aggregating the daily returns over the observation period. The daily returns are calculated by combining value (HML) and momentum as explained in section 5.2. This Figure is related to section 6.2.5.
Source: own calculation.

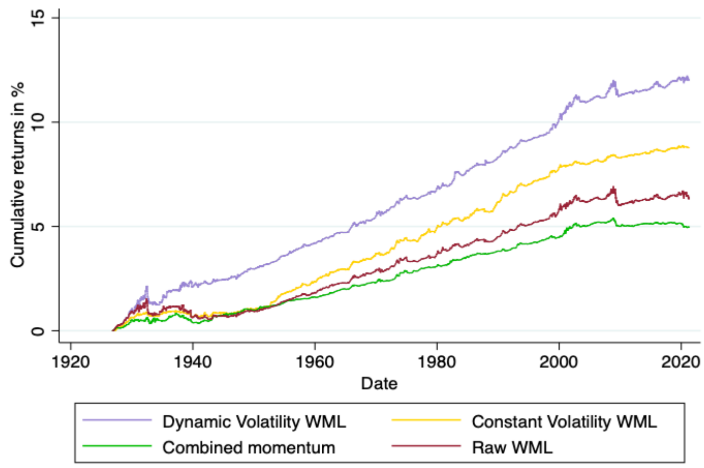


Figure 10:Comparison of three risk-managed strategies and raw momentum.
Displayed are raw WML, constant volatility momentum strategy, dynamic volatility momentum strategy and combined momentum from 1926:11 to 2021:03. The cumulative returns have been computed by aggregating the daily returns over the observation period. This Figure is related to section 6.2.6.
Source: own calculations.

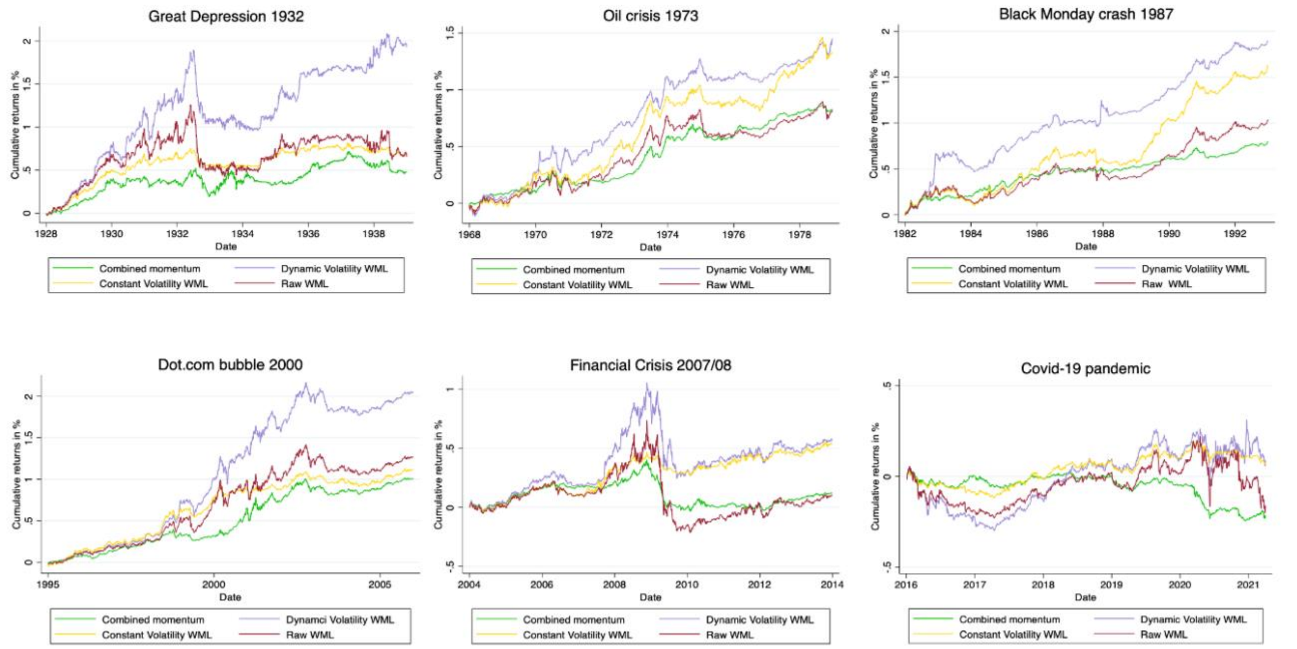


Figure 11: Comparison of three risk-managed strategies and raw momentum over the different crises.
Displayed are raw WML, constant volatility momentum strategy, dynamic volatility momentum strategy and combined momentum from 1926:11 to 2021:03. The cumulative returns have been computed by aggregating the daily returns over the observation period. This Figure is related to section 6.2.6.
Source: own calculation.

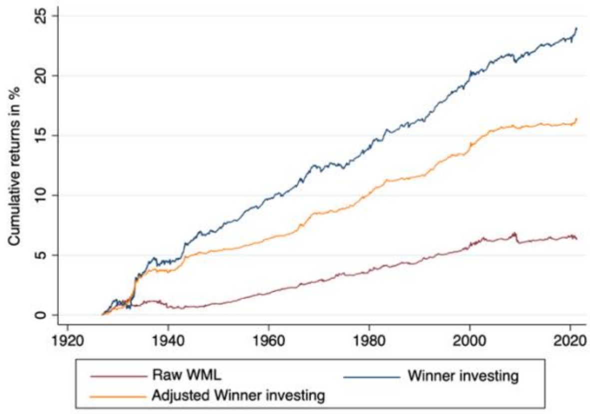


Figure 12: Comparison of the cumulative returns between the raw momentum strategy (WML), the Winner Investing and the adjusted Winner Investing managed strategy.
A period from 1926:11 to 2021:03 is displayed. The cumulative returns have been computed by aggregating the daily returns over the observation period. The daily returns are calculated by taking the highest decile portfolio as explained in section 5.3. This Figure is related to section 6.2.7.
Source: own calculations.

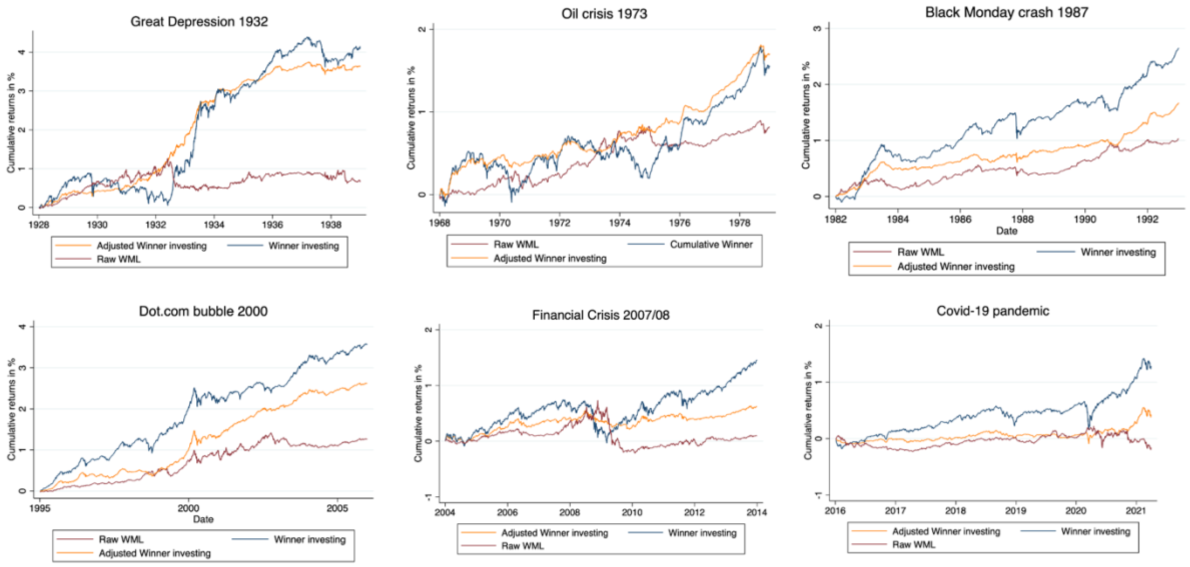
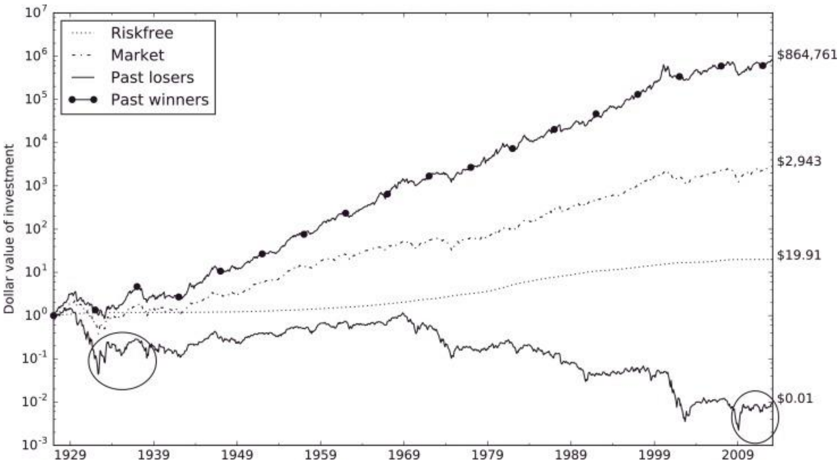


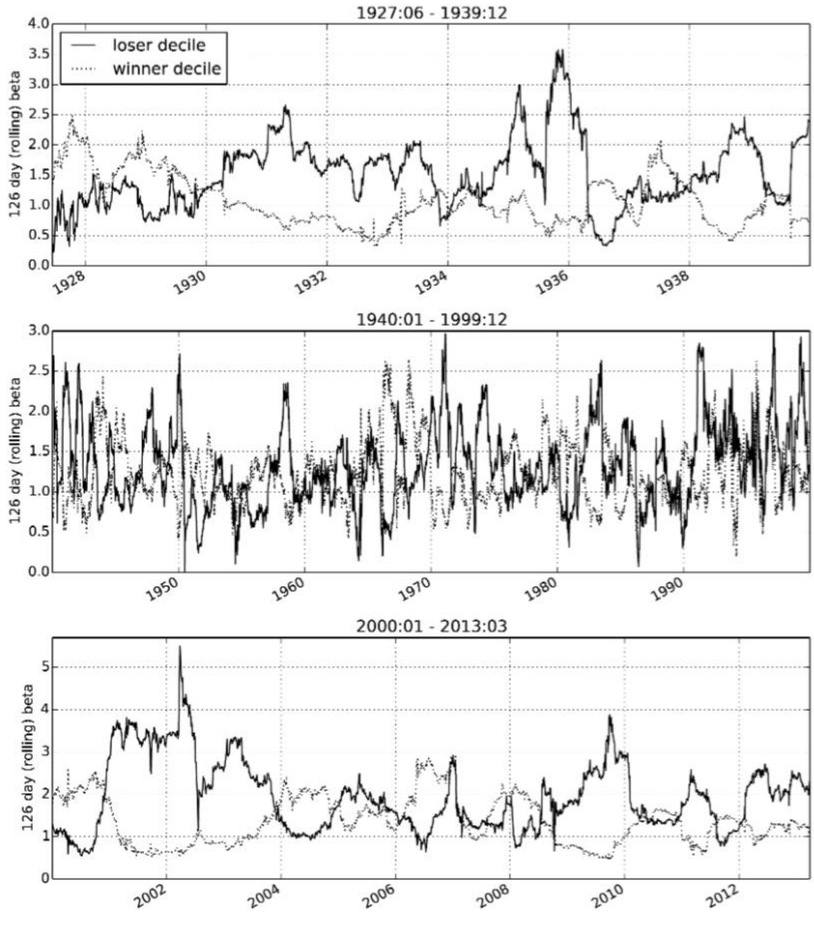
Figure 13:Comparison of the cumulative returns between the raw momentum strategy (WML), the Winner Investing and the adjusted Winner Investing strategy over the different crises.
The cumulative returns have been computed by aggregating the daily returns over the observation period. The daily returns are calculated by taking the highest decile portfolio as explained in section 5.3. This Figure is related to section 6.2.7.
Source: own calculation.

Appendix

Appendix 1: Cumulative returns of four investment positions.
This figure is related to section 4.1.
Source: Daniel and Moskowitz (2016).



Appendix 2: Beta factors of the winner portfolio (Winner decile) and loser portfolio (Loser decile) over different observation periods.
This figure refers to section 4.2.
Source: Daniel and Moskowitz (2016) p. 228.



Appendix 3: Regression results of the excess returns of the momentum decile portfolios and the winner-minus-loser (WML) long-short portfolio based on CRSP value weighting of excess returns, and some indicator variables.
Panel A shows the optionality results of winning and losing portfolios in falling markets (bear markets). Panel B reports the results in rising markets (bull markets). Decile 10 denotes the winner portfolio; correspondingly, decile 1 denotes the loser portfolio. The last row of Panel A (the coefficient β ̂_(B,U)) shows the higher betas for the loser and the winner portfolios in falling markets. The last row of panel B(the coefficient β ̂_(L,U)) shows the significantly lower difference between the beta factors of the loser(1) and the winner(10) portfolios in rising markets. The table refers to section 4.2.
Source: Daniel and Moskowitz (2016) p. 230

Coefficient	Momentum decile portfolio										
	1	2	3	4	5	6	7	8	9	10	WML
Panel A: Optionality in bear markets											
$\hat{\alpha}_0$	−1.406	−0.804	−0.509	−0.200	−0.054	−0.050	0.159	0.260	0.294	0.570	1.976
	(−7.3)	(−5.7)	(−4.9)	(−2.4)	(−0.7)	(−0.9)	(2.7)	(4.1)	(3.8)	(4.6)	(7.8)
$\hat{\alpha}_B$	−0.261	0.370	−0.192	−0.583	−0.317	−0.231	−0.001	−0.039	0.420	0.321	0.583
	(−0.4)	(0.8)	(−0.6)	(−2.1)	(−1.3)	(−1.2)	(−0.0)	(−0.2)	(1.7)	(0.8)	(0.7)
$\hat{\beta}_0$	1.338	1.152	1.014	0.955	0.922	0.952	0.974	1.018	1.114	1.306	−0.032
	(30.4)	(35.7)	(42.6)	(49.5)	(55.6)	(72.1)	(72.3)	(69.9)	(62.7)	(46.1)	(−0.6)
$\hat{\beta}_B$	0.222	0.326	0.354	0.156	0.180	0.081	0.028	−0.126	−0.158	−0.439	−0.661
	(2.2)	(4.4)	(6.5)	(3.5)	(4.7)	(2.7)	(0.9)	(−3.8)	(−3.9)	(−6.8)	(−5.0)
$\hat{\beta}_{B,U}$	0.600	0.349	0.180	0.351	0.163	0.121	−0.013	−0.031	−0.183	−0.215	−0.815
	(4.4)	(3.5)	(2.4)	(5.9)	(3.2)	(3.0)	(−0.3)	(−0.7)	(−3.3)	(−2.5)	(−4.5)
Panel B: Optionality in bull markets											
$\hat{\alpha}_0$	0.041	0.392	−0.249	0.222	0.089	0.048	0.097	0.079	0.188	0.388	0.347
	(0.1)	(1.4)	(−1.2)	(1.3)	(0.6)	(0.4)	(0.8)	(0.6)	(1.2)	(1.5)	(0.7)
$\hat{\alpha}_L$	−1.436	−1.135	−0.286	−0.653	−0.303	−0.084	−0.164	0.164	0.239	0.593	2.029
	(−2.9)	(−3.1)	(−1.1)	(−2.9)	(−1.6)	(−0.6)	(−1.1)	(1.0)	(1.2)	(1.9)	(3.1)
$\hat{\beta}_0$	1.890	1.664	1.459	1.304	1.188	1.097	0.992	0.877	0.860	0.754	−1.136
	(41.3)	(49.6)	(59.2)	(64.5)	(69.3)	(80.5)	(72.2)	(58.7)	(46.7)	(25.9)	(−18.7)
$\hat{\beta}_L$	−0.545	−0.498	−0.451	−0.411	−0.308	−0.141	−0.078	0.133	0.285	0.670	1.215
	(−6.0)	(−7.4)	(−9.2)	(−10.2)	(−9.0)	(−5.2)	(−2.9)	(4.5)	(7.8)	(11.5)	(10.0)
$\hat{\beta}_{L,U}$	−0.010	−0.025	0.017	0.138	0.094	−0.006	0.136	0.021	−0.077	−0.251	−0.242
	(−0.1)	(−0.2)	(0.2)	(2.2)	(1.8)	(−0.1)	(3.2)	(0.4)	(−1.4)	(−2.8)	(−1.3)

Appendix 4: List of all as crash defined occurrences in the raw WML.
We define crash as a change over 21 days that is -20% or less. *The table refers to section 6.2.2.*
Source: own calculations

Date	Return WML	Change over 21 days
11.08.32	-0,0087	-0,3837
10.08.32	-0,0405	-0,3649
06.05.09	-0,0367	-0,3434
16.08.32	-0,0296	-0,3405
08.08.32	-0,0532	-0,3384
09.08.32	-0,0048	-0,3347
14.09.39	-0,007	-0,3341
12.08.32	0,035	-0,3323
25.09.39	-0,0063	-0,3296
15.09.39	0,0055	-0,3294
18.08.32	-0,0106	-0,3286
21.09.39	-0,0151	-0,3249
12.09.39	-0,0125	-0,3244
07.05.09	0,0111	-0,3219
03.04.09	-0,0316	-0,3197

13.09.39	-0,0027	-0,318
22.09.39	0,0016	-0,317
17.08.32	0,0021	-0,3164
23.09.39	0,0025	-0,3152
16.09.39	0,0232	-0,3137
19.09.39	-0,045	-0,3124
26.09.39	-0,0122	-0,3089
20.09.39	-0,0048	-0,3053
13.04.09	-0,0392	-0,3014
11.09.39	-0,0431	-0,301
06.04.09	0,0027	-0,3004
06.08.32	-0,0446	-0,2978
15.08.32	-0,0298	-0,2956
25.08.32	-0,008	-0,2934
08.05.09	-0,0513	-0,2913
05.05.09	-0,0134	-0,2882
19.08.32	0,0031	-0,2878
04.08.32	-0,0171	-0,285
13.08.32	0,0218	-0,2838
02.04.09	-0,0429	-0,2824
07.07.38	-0,0032	-0,2779
15.04.09	-0,02	-0,2778
12.07.38	-0,0268	-0,2756
29.04.09	-0,0274	-0,2753
30.04.09	-0,0254	-0,2746
18.09.39	0,0382	-0,2745
27.09.39	0,0014	-0,2723
04.05.09	-0,0527	-0,2721
14.04.09	0,0145	-0,2721
01.08.32	-0,0099	-0,272
29.07.32	-0,034	-0,2713
30.07.32	0,0045	-0,2709
27.08.32	-0,0242	-0,2695
13.07.38	0,009	-0,2657
24.08.32	-0,0265	-0,2657
17.04.09	-0,0195	-0,2645
28.04.09	0,0127	-0,2639
03.08.32	-0,0296	-0,2638
05.08.32	-0,0099	-0,2635
09.04.09	-0,0819	-0,2633
29.08.32	-0,0032	-0,2628
26.08.32	0,0014	-0,2624
06.07.38	-0,0182	-0,2601

08.07.38	0,018	-0,2563
09.07.38	0	-0,2554
09.09.39	-0,0051	-0,2552
28.07.32	-0,0517	-0,2522
01.05.09	-0,0193	-0,251
22.08.32	-0,0397	-0,2507
08.06.20	-0,0508	-0,2494
23.08.32	0,0061	-0,2491
21.01.32	-0,0066	-0,2472
02.08.32	0,0197	-0,2458
19.12.08	-0,0121	-0,2453
20.08.32	-0,0089	-0,245
16.04.09	-0,0166	-0,2428
05.07.38	0,0085	-0,2416
08.09.39	-0,0187	-0,2415
13.01.32	-0,0274	-0,241
02.07.38	-0,0281	-0,2406
05.09.39	-0,1833	-0,2406
30.01.01	-0,0106	-0,2391
11.07.38	0,0155	-0,235
05.06.20	-0,0505	-0,2325
07.09.32	-0,0375	-0,2309
09.06.20	0,0436	-0,2305
11.08.08	-0,019	-0,2301
11.05.09	0,0225	-0,2296
06.09.39	0,0077	-0,2295
29.01.01	-0,0157	-0,2284
12.05.09	0,0178	-0,2263
01.07.38	-0,0229	-0,2258
20.01.32	-0,0046	-0,2255
07.09.39	0,0034	-0,2252
18.05.09	-0,0342	-0,224
20.04.09	0,0701	-0,2229
24.04.09	-0,0344	-0,2226
23.01.01	-0,0034	-0,2225
31.01.01	0,0055	-0,2211
14.04.00	-0,0301	-0,2199
08.04.09	-0,0104	-0,2169
24.01.01	-0,0107	-0,2165
07.04.09	0,0185	-0,2163
22.01.32	0,022	-0,2159
22.01.01	0,0114	-0,2155
26.01.01	0,0012	-0,2122

25.01.01	0,0241	-0,2121
19.01.01	-0,0117	-0,2113
30.08.32	0,0071	-0,2111
12.08.08	0,0207	-0,2111
23.04.09	-0,0103	-0,2104
27.04.09	0,0224	-0,2099
24.11.20	-0,0382	-0,2076
14.07.38	0,007	-0,2073
23.01.32	0,0099	-0,207
23.03.09	-0,0752	-0,2068
22.12.08	0,0342	-0,2064
01.04.09	-0,0261	-0,206
22.04.09	-0,0172	-0,2058
04.06.20	-0,0344	-0,2034
01.09.32	-0,0471	-0,2026
04.04.00	-0,0202	-0,2014
25.01.32	-0,0149	-0,2013
04.12.20	-0,0183	-0,2012
30.06.38	0,0071	-0,2002
19.01.32	0,0049	-0,2001