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Enhancing Momentum with Volatility and Risk Management

An Empirical Analysis of Momentum in US Equities

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Abstract

In this thesis, we examine two approaches to enhance the performance of a momentum strategy. First, we investigate if stocks with similar cumulative returns but different daily standard deviation during the formation period perform differently in the holding period. We find a large variation in the performance of portfolios within each decile formed on cumulative returns, where the most volatile portfolio clearly underperforms. We construct a volatility dependent momentum strategy, that excludes the most volatile winners and losers. We find that our volatility dependent momentum strategy outperforms a generic momentum strategy, with an annualized Sharpe ratio of 0.43 versus 0.35.

Similar to other momentum strategies, we find that our volatility dependent momentum strategy inherits the risk of large drawdowns in periods when the market rebounds after a major decline. In order to reduce the impact of momentum crashes, we introduce a new risk management approach. We exit our volatility dependent momentum strategy when the 12-month cumulative return of the market is negative. Risk management further enhances the Sharpe ratio from 0.43 to 0.81. We find that the combination of taking volatility and risk management into account generates a monthly alpha of 0.62% after controlling for Fama/French 5 Factors including momentum.

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1. Introduction

Since Jegadeesh & Titman (1993) provided the first evidence of momentum in US equities, the momentum anomaly has been a widely researched topic in finance. Jegadeesh & Titman (1993) document that stocks that have done well (poor) historically tend to do well (poor) in the near future. They show that an investment strategy that goes long winners and short losers[1] based on past cumulative returns generates significant returns. Based on these results, Carhart (1997) constructs a momentum factor and shows that the performance of the best performing mutual funds can be explained by being accidentally exposed to the one-year momentum factor. In more recent years, Asness et al. (2012) use the same method of portfolio construction as Jegadeesh & Titman (1993) and find that the momentum premium is persistent over time, in multiple markets, both across and within asset classes.

When Jegadeesh & Titman (1993) define winners and losers, they rank stocks solely based on their cumulative returns from the beginning to the end of a defined formation period. We argue that this way of measuring momentum ignores an important aspect; the price movements and the behavior of stocks that occur within the formation period. We argue that stocks that have achieved their cumulative returns through less volatile daily returns have a stronger momentum effect. By sorting each decile on realized volatility, we are able to identify differences in the behavior of stocks in the way they have achieved their cumulative returns. This gives a more holistic perspective when momentum is measured. We argue that it is possible to enhance the performance of a momentum strategy by addressing differences in volatility of winners and losers within the formation period. Given the choice between two winners (losers) with the exact same cumulative return, we argue that it is preferable to hold the stock that has achieved its cumulative return with lower volatility.

In this thesis, we examine a different approach to construct a momentum strategy by taking into account the volatility of winners and losers during the formation period. First, we sort stocks into deciles based on their cumulative return, consistent with the methodology of Jegadeesh & Titman (1993). Then, we split each decile into quintiles based on their realized daily standard deviation during the formation period. We end up with 50 portfolios that are double sorted on cumulative return and volatility. The summary statistics of the formation period show that there are significant differences in average daily standard deviation between the five portfolios within all deciles, even though the average cumulative returns are quite

[1] Winners (losers) are the top (bottom) 10% of stocks measured by cumulative return in a given formation period.

similar within most deciles. This shows that stocks within each decile achieve their cumulative returns from very different price behavior.

We find that the holding period performance of the five portfolios within each decile differs considerably. Within most deciles, stocks with a lower degree of volatility in the formation period outperform stocks with a higher degree of volatility. Within the winner decile, the least volatile portfolio achieves an annualized Sharpe ratio of 0.92, while the most volatile winner portfolio achieves a Sharpe ratio of 0.53. This clearly makes the most volatile winner portfolio a less attractive portfolio to buy compared with the least volatile winner-portfolio. Within the loser-decile, we find that the Sharpe ratios are quite similar. However, the most volatile portfolio has a remarkable high average return and standard deviation, which makes it an unattractive portfolio to short compared with the least volatile loser-portfolio. The differences in holding period performance within deciles indicate that volatility matters for momentum strategies.

Based on these results, we construct a volatility dependent momentum strategy, hereafter referred to as VOLMOM. We construct VOLMOM by excluding the most volatile portfolio from the winner and loser-decile and go long the remaining four winner portfolios and short the remaining four loser portfolios. The removal of the most volatile winners and losers enhances the Sharpe ratio of Jegadeesh & Titman's momentum strategy, hereafter referred to as WML[2], from 0.35 to 0.43. When we control for the Fama/French 5 factors (FF-5), the alpha increases from 0.81% to 0.94% per month. These results show that the enhanced performance from taking volatility into account cannot be explained by additional exposure to systematic risk.

Even though VOLMOM outperforms WML on all statistical performance measures, it occasionally experiences large drawdowns. Despite the removal of the most volatile winners and losers, VOLMOM is long winners and short losers and has similar characteristics as a generic momentum strategy[3]. Grundy & Martin (2001), Barroso & Santa-Clara (2015) and Daniel & Moskowitz (2016) show that momentum strategies inherit the risk of large drawdowns in certain periods. These drawdowns tend to occur during rebounds following a major market decline where losers rebound more sharply than winners (Daniel & Moskowitz, 2016). VOLMOM experiences large drawdowns in the same periods as WML, which means

[2] Winners Minus Losers (WML)

[3] We define a momentum strategy that is only formed on cumulative return as a generic momentum strategy.

that removing the most volatile portfolios does not make the strategy immune to crash risk. In the aftermath of The Great Depression and The Global Financial Crisis, VOLMOM lost 89.4% and 63% respectively. In comparison, WML lost 91.7% and 61%. In most periods, VOLMOM delivers a positive return premium, however, the risk of large drawdowns makes the strategy somewhat unappealing.

We find that the most volatile losers show the highest returns during market rebounds, and the removal of this portfolio might be a minor way to manage the crash risk of momentum. Therefore, we cannot be certain that our enhancement comes from taking volatility into account and not as a result of an indirect crash risk management.

Our second contribution is to introduce a new method that manages the crash risk of VOLMOM. We add this contribution for two reasons; 1) to verify that removing the most volatile portfolios is not an indirect way of managing the crash risk, and 2) to make VOLMOM a more appealing momentum strategy. In order to reduce the impact of sudden momentum crashes, we exit VOLMOM when the market is in a declining trend. More precisely, if the 12-month cumulative return of the market is negative, we withdraw the invested capital from VOLMOM and receive zero returns the following month. By being out of VOLMOM when the market declines, we avoid the risk of a large drawdown when the market suddenly rebounds. When we apply our risk management approach to VOLMOM, we find that the Sharpe ratio almost doubles, from 0.43 to 0.81. By managing the crash risk of VOLMOM, we are able to avoid the largest losses VOLMOM experiences throughout the sample period, which makes the strategy more appealing.

We find that both of our contributions enhance the performance of WML. Removing the most volatile portfolio from winners and loser enhances the Sharpe ratio from 0.35 to 0.43. Our method of crash risk management further enhances the performance of VOLMOM from 0.43 to 0.81. To verify that both contributions enhance the performance of WML individually, we examine our two contributions in reverse order. We find that risk managing WML enhances its performance from 0.35 to 0.67. If we compare the Sharpe ratio of the risk managed VOLMOM, 0.81, with the risk managed WML, 0.67, we see that taking volatility into account also enhances the performance of WML after our method of risk management is applied.

The risk managed version of VOLMOM, hereafter referred to as VOLMOM*[4], achieves a monthly alpha of 0.62% after controlling for FF-5 including WML. We find that taking volatility into account and our method of crash risk management achieves abnormal returns individually. We find that the largest enhancement comes from risk management. The monthly alpha that comes from crash risk management is 0.53%, whereas the monthly alpha from taking volatility into account is 0.24%.

The rest of the paper is organized as follows; Section II reviews literature related to our two contributions. Section III describes the data and portfolio construction procedure. Section IV presents the empirical results of our analysis. In section V we conduct various robustness tests to verify our results. Section VI concludes our results.

[4] We mark strategies that are risk managed with a * notation

2. Literature review

In this section, we present literature that is related to both our contributions and include our own results when appropriate. First, we present research linked to our first contribution; the price behavior of stocks in the formation period. Then, we present research related to our second contribution; managing the crash risk of momentum strategies.

2.1 Momentum in equities

The first paper to discover persistence in returns of securities was Jegadeesh & Titman (1993). In the paper, they show that stocks exhibit intermediate-term return continuation of up to 12 months. The authors find that buying winners and selling losers based on their recent cumulative returns generate significant positive abnormal returns in the near future. Jegadeesh & Titman (1993) examine 16 long/short strategies with different combinations of formation and holding period and find that the optimal momentum strategy uses 12-month formation and 3-month holding period, with monthly rebalancing. They further show that skipping the last week of the formation period enhances the performance of a momentum strategy since it helps to avoid short-term reversals. Based on the results from Jegadeesh & Titman (1993), Carhart (1997) constructs a momentum factor that is able to almost completely explain the one-year performance of the best performing mutual funds. Jegadeesh & Titman (2001) show that the momentum strategies explored by Jegadeesh & Titman (1993) are robust out of sample, as they are still profitable from 1990-1997. In a more recent study, Israel and Moskowitz (2013) extend the sample period examined by Jegadeesh & Titman (1993) and confirm that the results of the momentum effect are robust. Based on our results from the replication of Jegadeesh & Titman (1993) with an extended sample, we confirm that the momentum premium is persistent from 1927-2018.

The majority of momentum strategies are constructed using the principles outlined in Jegadeesh & Titman (1993). Formation and holding periods may vary, but the way momentum is measured is similar. A generic momentum strategy is constructed by ranking stocks based on their cumulative returns. However, there are research papers that have explored alternative ways of constructing momentum strategies, and some link momentum with past volatility; Arena, et. al (2008) find that the returns of momentum are higher among high volatility stocks. However, they find that these stocks also show the largest reversals.

Bornholt & Malin (2011) explore whether past volatility of international indices is able to improve upon a momentum strategy that buys winner indices and sell loser indices. They first sort indices based on their cumulative returns into quartiles. Then they split the winner and loser quartile in half based on their formation period volatility. They find that recent high-volatility winner indices outperform recent low-volatility loser indices. They further explain that such a strategy improves upon a regular momentum strategy, with most of the outperformance coming from high volatility winners.

Gharaibeh (2016) examines whether momentum is present in Arabic indices and if it is possible to improve momentum in these indices by considering their past volatility. His research uses a similar approach to Bornholt & Malin (2011). The 10 indices he examines is divided into 5 winner and 5 loser indices. He then constructs a strategy that buys the two winner indices with the lowest volatility and shorts the two loser indices with the highest volatility. He finds that momentum is present and that the strategy outperforms a generic momentum strategy in these indices. Bornholt & Malin (2011) and Gharaibeh (2016) conclude that it is possible to use past volatility to enhance the performance of a momentum strategy in indices.

Da, et al. (2012) link momentum to the behavior of stocks within the formation period by using another approach than past volatility. They distinguish between stocks that achieve their cumulative return from frequent small price movements versus returns from infrequent large price movements in the formation period. First, they rank stocks based on their cumulative returns. Then they perform a sequential sort based on the fraction of positive return days during the formation period[5]. They show that price momentum following infrequent large price movements lasts shorter than price momentum following frequent small price movements. In other words, they find that the type of price movements matters for return predictability in momentum.

When we construct our enhanced momentum strategy, we use the same methodology to sort stocks based on cumulative returns as described in Jegadeesh & Titman (1993). Then we perform a sequential sort of stocks based on their past volatility, similar to the double sort approach described in Bornholt & Malin (2011) and Gharaibeh (2016). While Bornholt & Malin (2011) and Gharaibeh (2016) examine if past volatility enhances a momentum strategy

[5] They construct a variable for information discreteness, defined as: ID = sgn(PRET) * [%neg - %pos], where sgn(PRET) is +1 if a firm´s cumulative return in the formation period is positive and -1 if a firm´s cumulative return in the formation period is negative. %neg and %pos is the percentage of days during the formation period with negative and positive returns. See Da, et al. (2012) for a more detailed description.

in international indices, we examine if past volatility enhances the performance of a momentum strategy in stocks. We find that winners with low volatility outperform winners with high volatility. The Sharpe ratio of low volatility winners is approximately double that of high volatility winners. In addition, we find that it is worse to short losers with high volatility than losers with low volatility.

Our research reaches the same conclusion as Bornholt & Malin (2011) and Gharaibeh (2016); it is possible to use past volatility to enhance the performance of a momentum strategy. We confirm that this can be applied to momentum strategies in US equities. When we compare our strategy with Bornholt & Malin (2011), we find different results on the long side of the strategy. While they find that high volatility winner indices outperform, we show that low volatility winner stocks outperform. On the short side, we find similar results as Bornholt & Malin (2011), as both our and their strategy find that it is best to short low volatility losers.

When we compare our results with Gharaibeh (2016), we find confirming evidence that low volatility winners outperform high volatility winners. However, on the short side of the strategy, we find that it is better to be short low volatility losers than high volatility losers, which contradicts his results.

2.2 Momentum crash risk

Despite the existence of a positive momentum premium, a momentum strategy inherits the risk of large drawdowns. Kothari & Shanken (1992) show that there are time-varying betas of return-sorted portfolios. Grundy & Martin (2001) use the insights from Kothari & Shanken (1992) and show that momentum strategies have time-varying market exposure. They further explain that momentum has significant negative beta following large market declines. They show that it is possible to hedge the time-varying market exposure of momentum and thus stabilize momentum returns. However, as the market exposure is unknown in real time, their results can be argued to have forward-looking bias. This method can therefore not be used in real time to avoid crashes.

Barroso & Santa-Clara (2015) use a different approach to avoid crashes, based on the realized volatility in the momentum strategy itself. They show that the volatility of a momentum strategy is highly predictable and that momentum crashes tend to occur when the volatility is high. They find that the Sharpe ratio of momentum almost doubles from 0.53 to 0.97 by varying the exposure to the strategy so that the expected volatility of the strategy is constant. In periods when the realized volatility of momentum is high, the exposure to the strategy is reduced in the following month, and vice versa.

Daniel & Moskowitz (2016) uses a similar approach as Barroso & Santa-Clara (2015) where they forecast the mean and variance of the momentum strategy so that the unconditional Sharpe ratio of the portfolio is maximized. Daniel & Moskowitz are able to more than double the Sharpe ratio of a generic momentum strategy by applying their method, and effectively avoid crashes.

We develop a new method of dealing with momentum crashes, which is quite different to the methods of Grundy & Martin (2001), Barroso & Santa Clara (2015) and Daniel & Moskowitz (2016). We use the concept of Time Series Momentum (Pedersen, et al., 2012), hereafter referred to as TSMOM. TSMOM looks at an asset´s own past returns in contrast to cross-sectional momentum which looks at assets' relative returns. A negative TSMOM means that an asset has experienced negative cumulative returns in the formation-period and predicts that the returns will continue to decline in the near future.

By considering the TSMOM of the market, we are able to identify periods when momentum crashes are more likely to occur. When the market has declined during the last 12 months, the likelihood of a major decline is higher, which is followed by a major rebound. Therefore, by taking precautionary actions and exiting our volatility dependent momentum strategy when the 12-month cumulative return is negative, we are able to avoid the most extreme losses and still capture most of the premium associated with our momentum strategy. The idea of exiting momentum when the probability of a momentum crash is higher than normal is similar to the principles of Barroso & Santa-Clara (2015) and Daniel & Moskowitz (2016). We chose to go completely out of the strategy, whereas Barroso & Santa-Clara and Daniel & Moskowitz only reduce the exposure to momentum in these periods.

The results from using our method for avoiding crashes are similar to the results obtained by Barroso & Santa-Clara (2015) and Daniel & Moskowitz (2016). We find that the Sharpe ratio of the momentum strategies we consider in this thesis is almost doubled when our method is applied.

3. Data and portfolio construction

In this section, we provide a detailed description of the data we use for our analysis. In subsection 3.1 we describe a three-step procedure of how we construct volatility dependent momentum portfolios. Then, in subsection 3.2, we describe how we create the variable we use to manage the crash risk of momentum strategies.

3.1 Constructing volatility dependent momentum portfolios

First, we replicate the results from Jegadeesh & Titman (1993) to sort stocks based on their cumulative returns. Then, we construct ten momentum deciles using the same approach as Jegadeesh & Titman (1993) with an extended sample in order to include as much data as possible. Lastly, we conduct a sequential sort based on the stocks´ realized daily volatility within the formation period.

3.1.1 Replication of Jegadeesh & Titman (1993)

We begin the portfolio construction by replicating Table 1, Panel A from Jegadeesh & Titman (1993). The authors examine four formation-periods (J) when they form momentum strategies, namely 3, 6, 9 and 12 months. The formation-periods are combined with four holding-periods, also 3, 6, 9 and 12 months (K). This results in 16 strategies of buying winners and selling losers with a unique combination of formation and holding period. Jegadeesh & Titman use the daily returns from CRSP and compound the returns into monthly returns. We find it more practical to use monthly returns directly from CRSP.

The analysis covers the returns of NYSE and AMEX listed stocks from January 1965 until December 1989[6]. In cases where a stock misses a return observation, we set the delisting return as the return for that particular month. If a stock both has a registered return and delisting return, we compound the registered return and the delisting return. Finally, we delete all observations with missing returns from the dataset.

Next, we calculate the past 3, 6, 9 and 12-month cumulative returns of all stocks in the sample for each month. If a stock misses a monthly observation within the formation period, we delete the observation. The stocks are then sorted into ten deciles according to each of the

[6] The longest formation-period requires 12 months of historical returns, meaning we require data from January 1964

four different formation periods. Then, we calculate the return series from buying winners and selling losers for each of the 16 combinations of formation and holding periods. We calculate the winner-returns and loser-returns separately and subtract the loser-returns from the winner-returns to find the returns of the zero-cost long/short-portfolios.

The strategies are rebalanced every month and held for K months. This results in what Jegadeesh & Titman (1993) refer to as overlapping portfolios. Each month, 1/K of the total portfolio is rebalanced. For example, for a strategy with a 3-month holding period, the total portfolio in month t consist of one portfolio bought in month t, one bought in $t-1$ and one bought in $t-2$[7]. The return in month t is the equal-weighted return of the total portfolio. Finally, we calculate the returns of all winners, losers and the zero-cost portfolios, and their respective t-statistics.

Table I presents the results of the replication. J is the formation period, K is the holding period, *Sell* corresponds to losers and *Buy* corresponds to winners. The *Buy-Sell*-returns are the zero cost portfolios of buying winners and selling losers for a given formation and holding period. We find that all 16 *Buy-Sell*-portfolios have positive average returns, and 14 are statistically significant at a 5% level[8]. The only two strategies that do not show significant returns are the strategies with 3- and 6-months holding period and 3-month formation period. Jegadeesh & Titman find that the only insignificant strategy is the strategy with 3-month formation period and 3-month holding period. The (J=3, K=6)-strategy of our replication has a t-statistic of 1.81, whereas Jegadeesh & Titman find a t-statistic of 2.29.

In general, our results show less significant average returns than Jegadeesh & Titman (1993). The average t-statistic of our replication are 0.0681 lower than documented by Jegadeesh & Titman. However, the average returns of the 16 strategies are extremely similar to the original results. The average returns of our replication is 3 basis points below the original results. (J=12, K=3), which is documented as the best strategy by Jegadeesh & Titman, is nearly identically replicated with an average return of 1.32% per month compared to 1.31% in the original study.

Our results show more deviation from the original paper on the buy-portfolios than the sell-portfolios. The buy-portfolios are 5 basis points below the original on average, whereas the sell-portfolios are 1 basis point above on average. However, the deviations are small and

[7] Jegadeesh & Titman (1993) argue that overlapping portfolios increase the power of their tests

[8] We consequently use 5% as the level of significance throughout the paper

do not have any practical meaning. If the reader wants to confirm the results, we refer to Jegadeesh & Titman (1993). The relevant table is listed in appendix A of this paper.

Table I – Replication of Jegadeesh & Titman (1993)

The CRSP monthly file is used to calculate the returns. The return series covers the period from January 1965 until December 1989. Average monthly returns of the portfolios are based on the stocks cumulative return for the past *J* month and held for *K* months with monthly rebalancing. *t*-statistics are in parentheses[9]. Portfolios marked with *Sell* are the loser-deciles. Portfolios marked with *Buy* are the winner-deciles. Portfolios marked with *Buy-Sell* are the zero-cost portfolios of buying winners and selling losers. All returns are equally weighted. The table we replicate is listed in appendix A.

J=		*K*=	3	6	9	12
3	Sell		0.0110	0.0096	0.0094	0.0087
			(2.21)	(1.98)	(1.97)	(1.87)
3	Buy		0.0133	0.0141	0.0147	0.0152
			(3.44)	(3.60)	(3.70)	(3.79)
3	Buy-Sell		0.0023	0.0045	0.0053	0.0066
			(0.81)	(1.81)	(2.46)	(3.57)
6	Sell		0.0087	0.0081	0.0084	0.0088
			(1.68)	(1.61)	(1.72)	(1.82)
6	Buy		0.0163	0.0167	0.0171	0.0163
			(4.13)	(4.20)	(4.24)	(4.06)
6	Buy-Sell		0.0075	0.0087	0.0087	0.0075
			(2.21)	(2.85)	(3.36)	(3.10)
9	Sell		0.0077	0.0067	0.0071	0.0080
			(1.46)	(1.32)	(1.42)	(1.61)
9	Buy		0.0179	0.0179	0.0170	0.0159
			(4.45)	(4.42)	(4.20)	(3.93)
9	Buy-Sell		0.0102	0.0112	0.0099	0.0079
			(2.88)	(3.53)	(3.36)	(2.82)
12	Sell		0.0057	0.0060	0.0069	0.0082
			(1.09)	(1.18)	(1.36)	(1.61)
12	Buy		0.0189	0.0178	0.0166	0.0154
			(4.60)	(4.35)	(4.08)	(3.78)
12	Buy-Sell		0.0132	0.0118	0.0097	0.0072
			(3.84)	(3.59)	(3.14)	(2.43)

Through the replication of Jegadeesh & Titman (1993), we have verified that we are able to construct momentum portfolios recognized in academic literature. In the next subsection, we apply the methodology of Jegadeesh & Titman (1993) to an extended sample and create ten deciles formed on cumulative returns.

[9] The T-statistic is calculated as $t = \frac{\bar{x}}{\sigma/\sqrt{n}}$ where $\bar{x}$ is the mean return of the strategy, σ is the standard deviation, and n are the number of observations.

3.1.2 Constructing momentum deciles with an extended sample

Since CRSP offers monthly stock returns from 1927-2018, we extend the sample to include all data available[10]. Whereas Jegadeesh & Titman only analyze stocks listed on NYSE and AMEX, we decide to include stocks listed on NASDAQ in our analysis. Stocks listed on NASDAQ make up the majority of the investable universe and tend to be smaller companies than companies listed on NYSE and AMEX. In order to avoid that these stocks decide the decile breakpoints, we calculate breakpoints based on stocks listed on NYSE[11]. The ten resulting deciles have an unequal number of total stocks, but an equal number of NYSE stocks each month. In addition, we skip the last month of returns in the formation period when assigning stocks into deciles as research has shown that this enhances the performance of momentum (E.g. Jegadeesh & Titman (1993), Grinblatt & Moskowitz (2004)).

Each month, we calculate the cumulative return of all NYSE stocks where we skip the last month of returns in the formation period. The NYSE stocks are sorted into ten deciles with an equal number of stocks based on their cumulative return. The NASDAQ and AMEX listed stocks are then assigned to one of the ten deciles based on their cumulative return in relation to the NYSE breakpoints. We require all stocks to have a valid monthly return in each month of the formation period to be included in the sample. In addition, we require all firms to have a valid share price and number of shares outstanding at the time of portfolio construction.

In Table II, we show the performance of the same 16 momentum strategies examined by Jegadeesh & Titman (1993) with the modifications explained above. We find that the strategy of buying winners and selling losers with 12-month formation period and 3-month holding period still has the strongest performance. The magnitude of the returns from the buy-sell-portfolios is lower in our sample than the original study of Jegadeesh & Titman. However, most of the zero cost-strategies deliver a significant return premium.

We find that a momentum strategy formed on past 12-month cumulative return and held for 3 months has the preferred combination of formation and holding period. Consequently, we use a 12-month formation period and a 3-month holding period when we sort stocks into deciles based on cumulative returns. To analyze whether volatility in the

[10] The first monthly return on CRSP is December 1925. We require twelve months of historical returns, meaning the first full year we can analyze is 1927. Thus, our final return series is from January 1927 - June 2018.

[11] Using NYSE breakpoints is the normal practice when dividing stocks into portfolios.

formation period matters in addition to cumulative return, we split each of the ten deciles into separate portfolios that take volatility into account.

Table II – Performance of momentum strategies with an extended sample

The sample covers the period from January 1927 until June 2018, including all common stocks on the NYSE, AMEX, and NASDAQ stock exchanges. Average monthly returns of the portfolios are based on the stocks cumulative return for the past *J* month where the last month of the formation period is ignored and held for *K* months. *Sell (Buy)* indicates the loser (winner)-decile in relation to NYSE breakpoints of the stock universe each month. *Buy-Sell* are the zero-cost portfolios of buying winners and selling losers. To be included in the sample in month *t*, we require all stocks to have a known market equity at the end of month *t-1.* T-statistics are in parentheses. Returns are equally weighted.

J		*K*=	3	6	9	12
3	Sell		0.0113	0.0112	0.0116	0.0117
			(3.58)	(3.59)	(3.78)	(3.87)
3	Buy		0.0138	0.0144	0.0146	0.0146
			(5.83)	(6.09)	(6.14)	(6.07)
3	Buy-Sell		0.0025	0.0033	0.0031	0.0029
			(1.59)	(2.36)	(2.49)	(2.70)
6	Sell		0.0102	0.0103	0.0110	0.0119
			(3.05)	(3.15)	(3.49)	(3.81)
6	Buy		0.0158	0.0160	0.0158	0.0146
			(7.03)	(7.03)	(6.85)	(6.34)
6	Buy-Sell		0.0055	0.0057	0.0048	0.0027
			(3.05)	(3.15)	(3.49)	(3.81)
9	Sell		0.0100	0.0100	0.0109	0.0123
			(2.91)	(2.95)	(3.28)	(3.72)
9	Buy		0.0169	0.0165	0.0152	0.0139
			(7.44)	(7.16)	(6.60)	(6.05)
9	Buy-Sell		0.0069	0.0064	0.0042	0.0016
			(2.92)	(2.97)	(2.14)	(0.84)
12	Sell		0.0094	0.0103	0.0117	0.0131
			(2.68)	(2.99)	(3.43)	(3.86)
12	Buy		0.0169	0.0158	0.0143	0.0129
			(7.48)	(6.94)	(6.31)	(5.75)
12	Buy-Sell		0.0075	0.0054	0.0026	-0.0002
			(3.11)	(2.39)	(1.21)	-(0.07)

3.1.3 Sequential sort on formation period volatility

As outlined in the introduction, we hypothesize that the price behavior of momentum stocks within the formation period matters for holding period performance. When we sort deciles formed on cumulative returns into separate portfolios based on volatility, we are able to distinguish between stocks that achieve similar cumulative returns from different price behavior. Barroso & Santa Clara (2015) find that realized volatility of a momentum strategy has predictability for its future volatility. Thus, we argue that there is a likelihood that the most volatile momentum stocks during the formation period continue to have the highest volatility in the holding period.

We calculate the daily standard deviation during the formation period for all stocks in the ten deciles. Stocks with less than 200 daily return observations in the formation period are excluded. Next, we divide each decile into five portfolios sorted on daily standard deviation by using NYSE breakpoints. The sequential sort results in 50 portfolios sorted on (1) cumulative returns and (2) daily standard deviation in the formation period.

In Table III, we present summary statistics of the formation period for the 50 portfolios. Panel A shows that there are large differences in average cumulative return of the five portfolios within the winner decile. The high volatility winner-portfolio have an average cumulative return of 130.8%, which is almost twice the magnitude of the low volatility winner-portfolio. The differences are smaller within the loser-decile, where the high volatility loser-portfolio achieves -43.9% in cumulative returns on average, compared to -30.4% for the low volatility loser-portfolio. Within the remaining eight deciles, the differences in formation period average cumulative return are almost zero.

In Panel B, we observe that the portfolios within each decile have a large variation in realized daily standard deviation. The most volatile portfolio in all deciles has more than three times the standard deviation of the least volatile portfolio. We see that the most volatile portfolio within all deciles has values of daily standard deviation that are higher than the average volatility of the decile. The four least volatile portfolios within each decile have average values of volatility that are lower than the average volatility of the decile. This indicates that the most volatile portfolios contribute with most of the volatility of the deciles.

Table III – Summary statistics of volatility dependent momentum portfolios within the formation period

Losers (*Winners*) is the decile with the lowest (highest) cumulative return in the formation period each month. *LowVol* (*HighVol*) is the quintile within each decile with the lowest (highest) standard deviation of daily returns in the formation period each month. *Decile* is the collection of all portfolios within a given decile. Panel A shows the average cumulative return in the formation period for the 50 portfolios sorted on cumulative returns and volatility. Panel B shows the average volatility of the portfolios in the formation period. Panel C shows the average number of stocks each month in the portfolios.

Panel A: Average cumulative return		Losers	2	3	4	5	6	7	8	9	Winners
	Decile	*-38.4%*	*-17.3%*	*-7.9%*	*-0.6%*	*6.1%*	*12.9%*	*20.4%*	*29.8%*	*44.0%*	*103.4%*
	LowVol	-30.4%	-16.6%	-7.6%	-0.5%	6.1%	12.8%	20.3%	29.5%	42.9%	71.7%
	2	-33.0%	-17.0%	-7.8%	-0.5%	6.1%	12.9%	20.4%	29.7%	43.7%	79.3%
	3	-35.2%	-17.3%	-7.9%	-0.6%	6.1%	12.9%	20.4%	29.8%	44.0%	88.0%
	4	-38.1%	-17.5%	-8.0%	-0.6%	6.1%	12.9%	20.4%	29.9%	44.2%	99.4%
	HighVol	-43.9%	-17.7%	-8.1%	-0.7%	6.1%	12.9%	20.4%	29.9%	44.5%	130.8%

Panel B: Average daily σ		Losers	2	3	4	5	6	7	8	9	Winners
	Decile	*4.4%*	*3.2%*	*2.9%*	*2.7%*	*2.6%*	*2.5%*	*2.5%*	*2.6%*	*2.8%*	*3.6%*
	LowVol	2.1%	1.6%	1.4%	1.3%	1.2%	1.2%	1.2%	1.3%	1.4%	1.7%
	2	2.7%	2.1%	1.9%	1.7%	1.7%	1.6%	1.6%	1.7%	1.8%	2.3%
	3	3.3%	2.5%	2.2%	2.1%	2.0%	2.0%	2.0%	2.0%	2.2%	2.7%
	4	4.1%	3.1%	2.8%	2.6%	2.5%	2.4%	2.4%	2.5%	2.7%	3.3%
	HighVol	6.7%	4.9%	4.5%	4.3%	4.1%	4.1%	4.0%	4.1%	4.3%	5.5%

Panel C: Average number of stocks		Losers	2	3	4	5	6	7	8	9	Winners
	Decile	*492*	*304*	*262*	*244*	*233*	*227*	*228*	*238*	*259*	*376*
	LowVol	49	41	39	38	36	36	36	37	39	43
	2	52	38	35	34	33	33	33	34	35	43
	3	68	42	38	37	36	36	35	36	39	50
	4	102	53	46	43	41	41	41	43	46	68
	HighVol	220	130	104	92	86	82	83	88	100	172

In Panel C, we find that there is considerable variation in the average number of stocks in each portfolio. The majority of stocks within a decile are assigned to the most volatile portfolio, which is a result of using NYSE breakpoints, as many volatile NASDAQ stocks are assigned to these portfolios.

We have now constructed 50 portfolios that consider both cumulative return and daily standard deviation in the formation period. The summary statistics show that stocks behave very differently in the way they achieve similar cumulative returns, shown by the large variability in volatility within deciles. In decile 9, which is considered a winner-decile in Carhart's momentum factor (MOM[12]), we see that differences in cumulative returns are practically zero, while the daily standard deviation is more than three times as large for the most volatile portfolio compared to the least volatile portfolio. Our first contribution is to

[12] The MOM factor goes long the top 30% and short the bottom 30% of stocks formed on cumulative return. The factor also takes size into account, and use value weighted returns. There are in other words some differences, but it is reasonable to assume that many of the stocks in decile 9 will be included in the factor.

examine how this affects the holding period performance of momentum. However, as our thesis also address the issue of crash risk in momentum strategies, we first explain how we construct our risk management variable to reduce the impact of momentum crashes.

3.2 Variable used for crash risk management

Momentum crashes typically occur when the market rebounds after a major decline[13]. In order to avoid exposure to the momentum strategy when the market rebounds, we use a precautionary method to exit the momentum strategy when the market is in a declining trend.

As a proxy for the market return, we use the value-weighted CRSP index. Each month, we calculate the 12-month cumulative return of the index. The 12-month return of the index corresponds to the same formation period as the portfolios constructed in section 3.1. If the 12-month cumulative return of the index is negative, we exit the strategy and receive 0% returns the following month. In cases where the 12-month cumulative return of the index is positive, we receive the returns associated with the momentum strategy. From 1927 to 2018, the 12-month cumulative return of the value-weighted CRSP index was negative in 282 out of 1098 months.

Having described how we construct volatility dependent portfolios and the variable that we use to manage the crash risk of momentum strategies, we proceed to present our empirical analysis.

[13] See Grundy & Martin (2001), Barroso Santa Clara, (2015), Daniel & Moskowitz (2016)

4. Empirical results

In this section, we present the results of our two enhancements of a generic momentum strategy. First, we show the performance statistics of the 50 volatility dependent momentum portfolios created in sub-section 3.1. Then, we construct a momentum strategy that takes both cumulative return and volatility into account. The performance of our strategy is then compared and contrasted with a generic momentum strategy. Next, we address the issue of momentum crash risk by applying our risk management method. Lastly, we examine if the enhancement from considering volatility and risk management is explained by systematic risk factors.

4.1 Performance of volatility dependent momentum portfolios

In order to evaluate the holding period performance of the 50 portfolios constructed in sub-section 3.1, we examine their monthly average excess returns[14], monthly standard deviations and annual Sharpe ratios. The returns are calculated using the methodology of Jegadeesh & Titman (1993), with 3-month holding period and monthly rebalancing. In Table IV, we present the performance statistics for each of the 50 portfolios.

Panel A shows that winners tend to achieve higher average returns than losers. The winner-decile achieves an average monthly return of 1.4%, whereas the loser-decile achieves an average monthly return of 0.7%. Thus, a strategy of buying winners and selling losers achieves a monthly return premium of approximately 0.7%, which is not surprising given the well-documented premium associated with a generic momentum strategy. When we examine the average returns of the portfolios, we find that the most volatile portfolio within a decile during the formation period tend to achieve the highest returns in the holding period. We see this trend for all deciles except the winner-decile, where the second most volatile portfolio achieves the highest return. The portfolios within the winner decile achieve quite similar returns, ranging from 1.4% to 1.6%. When we look at the portfolios within the loser-decile, we find that the average returns show more variation, ranging from 0.6% returns for the least volatile to 1.1% for the most volatile portfolio. The most volatile loser portfolio achieves almost double the returns of the least volatile loser portfolio and 50% higher returns compared

[14] Returns are excess returns calculated as raw returns minus the risk-free rate from Ken French Library

with the loser-decile as a whole.

Table IV – Performance of volatility dependent momentum portfolios

Losers (Winners) represent the stocks that each month of the period have the lowest (highest) 12-month cumulative return where we skip the last month of the formation period. Within each decile, stocks are sorted based on realized daily volatility in the same formation period. LowVol (HighVol) represents the stocks that had the lowest (highest) daily standard deviation in the formation period. Panel A shows the monthly average excess returns of the portfolios. Panel B shows their respective standard deviation. Panel C presents the annualized Sharpe ratios. All returns are equal-weighted. The tables are color coded. The scaling goes from red to green, where dark red indicate bad performance and dark green indicate good performance. In Panel A, dark green indicates higher returns. In Panel B, dark green indicates lower standard deviation. In Panel C, dark green indicates a higher Sharpe ratio.

Panel A: Monthly average excess returns	Losers	2	3	4	5	6	7	8	9	Winners
Decile	*0.7%*	*0.9%*	*0.9%*	*1.0%*	*1.0%*	*1.0%*	*1.1%*	*1.1%*	*1.2%*	*1.4%*
LowVol	0.6%	0.6%	0.7%	0.7%	0.8%	0.8%	0.8%	1.0%	1.1%	1.4%
2	0.6%	0.8%	0.8%	0.9%	0.9%	0.9%	1.0%	1.0%	1.2%	1.4%
3	0.5%	0.8%	0.9%	0.9%	0.9%	1.1%	1.1%	1.1%	1.2%	1.5%
4	0.8%	0.9%	1.0%	1.0%	1.1%	1.1%	1.2%	1.1%	1.2%	1.6%
HighVol	1.1%	1.1%	1.3%	1.2%	1.3%	1.3%	1.3%	1.4%	1.4%	1.5%

Panel B: Monthly standard deviation	Losers	2	3	4	5	6	7	8	9	Winners
Decile	*11.0%*	*8.8%*	*7.9%*	*7.2%*	*6.9%*	*6.6%*	*6.3%*	*6.2%*	*6.3%*	*7.3%*
LowVol	8.6%	6.8%	5.9%	5.4%	4.9%	4.6%	4.4%	4.4%	4.6%	5.1%
2	9.6%	8.1%	7.2%	6.4%	6.0%	5.6%	5.4%	5.2%	5.4%	6.1%
3	10.4%	8.6%	7.9%	7.2%	6.9%	6.4%	6.2%	6.0%	6.1%	7.1%
4	11.7%	9.8%	8.6%	8.2%	7.6%	7.4%	7.2%	6.9%	6.8%	8.1%
HighVol	15.2%	11.4%	10.8%	9.8%	9.6%	9.6%	8.8%	8.8%	8.9%	10.2%

Panel C: Annualized Sharpe ratio	Losers	2	3	4	5	6	7	8	9	Winners
Decile	*0.22*	*0.34*	*0.41*	*0.46*	*0.50*	*0.55*	*0.59*	*0.63*	*0.68*	*0.67*
LowVol	0.23	0.30	0.43	0.48	0.55	0.61	0.67	0.77	0.85	0.92
2	0.20	0.34	0.40	0.47	0.53	0.57	0.64	0.68	0.74	0.78
3	0.17	0.34	0.38	0.45	0.47	0.57	0.59	0.66	0.69	0.72
4	0.22	0.33	0.38	0.43	0.49	0.53	0.56	0.56	0.63	0.68
HighVol	0.25	0.35	0.41	0.42	0.46	0.46	0.50	0.53	0.54	0.53

In Panel B, we show the monthly standard deviation of the holding period returns for each of the 50 portfolios. We find the same trend in standard deviations as for average returns; the most volatile portfolio during the formation period experiences the highest volatility in the holding period. The most volatile portfolio within each decile has approximately twice the standard deviation of the least volatile portfolio. Our results in Panel B indicate that past volatility seems to predict future volatility. These results are consistent with the results of Barroso & Santa-Clara (2015). Whereas Barroso & Santa-Clara find that past volatility in a momentum strategy predicts future volatility, our results indicate that the same is the case for our volatility dependent momentum portfolios.

When we examine the standard deviations of the portfolios within both the winner and loser-decile, we find that the volatility varies quite significantly. Within the winner-decile, we find that the monthly standard deviation ranges from 5.1% for the least volatile portfolio to 10.2% for the most volatile portfolio. When we look at the loser-decile, the monthly standard deviation ranges from 8.6% for the least volatile portfolio to 15.2% for the most volatile portfolio. Except for the loser-decile and decile 2, we find that the differences in standard deviation within deciles are larger than the differences in average returns. This is especially the case in the winner decile, where the average returns of the least and the most volatile portfolio are quite similar, whereas the standard deviation is approximately twice as large for the most volatile portfolio. These results have implications for the portfolios´ performance in terms of their Sharpe ratios.

Panel C presents annualized Sharpe ratios[15] for the 50 portfolios. We find that the Sharpe ratios tend to increase as we move from the most volatile loser portfolio to the least volatile winner portfolio. In other words, the Sharpe ratios tend to increase as we move from losers to winners, and from the most volatile to the least volatile portfolio within each decile. We find that the Sharpe ratios of the least volatile portfolios are higher than the Sharpe ratios of the most volatile portfolios in all deciles, except for the loser-decile and decile 2. The difference in the Sharpe ratio of the most volatile and least volatile portfolio within a decile increases as we move closer to the winner decile.

The Sharpe ratios of the portfolios within the winner decile vary significantly. The most volatile winner portfolio has an annual Sharpe ratio of 0.53, whereas the least volatile winner portfolio has a Sharpe ratio of 0.92. The winner decile as a whole, which does not consider volatility, has an annual Sharpe ratio of 0.67. These results indicate that the most volatile winner portfolio underperforms compared with the least volatile winner portfolio. The volatility of stocks within the formation period seems to matter for holding period performance of momentum portfolios. Even though the most volatile winner portfolio achieves slightly higher returns than the least volatile winner portfolio, it experiences a significantly higher standard deviation, which results in worse performance.

We find that there are several portfolios outside the winner decile that outperform the most volatile winner-portfolio. For example, the least volatile portfolio within decile 9 has a Sharpe ratio of 0.85, which makes it the second-best performing portfolio in terms of Sharpe

[15] Annualized Sharpe ratio = $\frac{12 * r}{\sigma\sqrt{12}}$. We consistently present Sharpe ratios annualized throughout this paper

ratio. It is interesting that the least volatile portfolio in decile 9 beats all of the winner portfolios except the least volatile winner portfolio. If we look further outside the winner decile, we find that all of the least volatile portfolios in decile 5-9 outperform the most volatile winner portfolio. This shows that the generic way of measuring momentum is missing out important information on the behavior stocks within the formation period. In many cases, we find that stocks with lower cumulative returns achieved through less volatile price movements outperform stocks with higher cumulative returns achieved through more volatile price movements. The Sharpe ratios of the winner-portfolios indicate that formation period volatility of winners matters for the performance of a momentum strategy.

The Sharpe ratios within the loser-decile, however, are quite similar and do not give any clear evidence on whether formation period volatility matters for performance. Both the returns and the standard deviations of the portfolios seem to increase at the same rate. For example; the least volatile loser-portfolio achieves an average return of 0.6% with a standard deviation of 8.6%, which results in a Sharpe ratio of 0.23. In comparison, the most volatile loser-portfolio achieves an average return of 1.1% at a standard deviation of 15.2%, which results in an almost identical Sharpe ratio of 0.25. The Sharpe ratio of the loser-decile as a whole is 0.22. We find that the differences in Sharpe ratios among the loser portfolios are almost non-existent. However, there are some aspects of the loser-portfolios that are not captured if we only look at the Sharpe ratios. The most volatile loser-portfolio achieves both the highest average returns and the highest volatility. In addition, the most volatile loser-portfolio achieves a maximum return of 184.2%[16], twice the maximum return of the least volatile loser-portfolio. Therefore, we consider the most volatile loser-portfolio less attractive to short compared with the least volatile loser-portfolio.

The results from Table IV show that volatility matters for the performance of momentum portfolios. Low volatility momentum portfolios tend to outperform high volatility momentum portfolios. Therefore, it makes sense to concentrate a momentum strategy towards winners and losers that have achieved their cumulative returns with lower volatility. However, these results do not tell us exactly how we should proceed in order to construct a new strategy that takes volatility into account. Therefore, we examine five different long/short strategies that buy winner and sell loser portfolios with matching volatility. We name the strategies WML_x, where the subscript indicates the volatility quintile described in Table IV.

[16] See appendix B for additional summary statistics for the 50 portfolios

The performance statistics of the five strategies are shown in Table V, including their abnormal returns controlled for the Fama French 5-factor model[17]. We find that WML_{LowVol} - WML_4[18] deliver quite similar performance, while $WML_{HighVol}$ underperforms. $WML_{HighVol}$ achieves a lower return premium and has a higher standard deviation compared with the other four strategies. The Sharpe ratio of $WML_{HighVol}$ is significantly lower compared to the Sharpe ratios of WML_{LowVol} - WML_4. $WML_{HighVol}$ has a Sharpe ratio of 0.14, whereas the Sharpe ratio of WML_{LowVol} - WML_4 ranges from 0.37 to 0.46.

Table V – Performance of five long/short strategies with matching volatility

WML is the generic momentum strategy of buying winners and selling losers based on 12-month cumulative return and held for 3 months with monthly rebalancing. WML_{LowVol} goes long the quintile of low volatility winners and shorts the quintile of low volatility losers. $WML_{HighVol}$ goes long/short on the most volatile quintile of winners and losers. WML_2 – WML_4 are for the three quintiles in between LowVol and HighVol, where a lower number means lower volatility. The average returns and standard deviations are monthly. The Sharpe ratios are annualized. Maximum and minimum return is the highest and lowest registered one month-return through the sample. Maximum drawdown is the maximum loss from peak to trough when being invested in the strategy throughout the sample. Alpha and *t*-statistic come from regressing the strategy returns onto Mkt-RF, SMB, HML, RMW, and CMA for the period July 1963 – June 2018.

	WML	WML_{LowVol}	WML_2	WML_3	WML_4	$WML_{HighVol}$
Average return	0.7%	0.8%	0.8%	1.0%	0.8%	0.5%
Standard deviation	7.3%	6.9%	7.2%	7.2%	7.9%	10.9%
Annualized Sharpe ratio	0.35	0.39	0.40	0.46	0.37	0.14
Maximum return	18.9%	27.1%	25.8%	27.1%	24.4%	56.8%
Minimum return	-84.7%	-74.3%	-84.4%	-92.7%	-106.1%	-151.7%
Skewness	-4.30	-3.25	-3.46	-3.66	-3.89	-4.58
Kurtosis	39.34	27.83	30.50	36.02	37.66	52.20
Five factor alpha	0.81	0.89	0.94	1.01	1.05	0.53
Alpha *t*-statistic	3.63	4.53	4.55	4.68	4.36	1.91

The FF-5 alpha of $WML_{HighVol}$ is approximately half the magnitude of the other four strategies. We find that $WML_{HighVol}$ has the largest one-month loss of all strategies, more than double the magnitude of the largest one-month loss in WML_{LowVol}. Lastly, the kurtosis of $WML_{HighVol}$ shows that it has more extreme return observations compared with WML_{LowVol} - WML_4, particularly on the negative side of the return distribution, as it has the largest negative value of skewness. All performance statistics show that $WML_{HighVol}$ causes a negative impact on the performance of WML. On the other hand, the performance statistics of WML_{LowVol} - WML_4 show that they all achieve higher Sharpe ratios and alphas compared with WML, thus

[17] The regressions are from 1963-2018 as data on RMW and CMA are not available prior to 1963

[18] WML_{LowVol} – WML_4 means all five strategies except $WML_{HighVol}$

contributing positively to the performance of WML. We conclude that $WML_{HighVol}$ is an outlier of the strategies examined. Because $WML_{HighVol}$ reduces the performance of WML, it is logical to exclude the most volatile winner and loser portfolios as we proceed to construct a new momentum strategy that takes volatility into account.

The results in this subsection indicate that the volatility of winners and losers in the formation period matters for the performance of a momentum strategy. The results support our initial thoughts; by only looking at cumulative returns, a generic momentum strategy misses out on valuable information on the price behavior of stocks within the formation period. If a stock´s cumulative return was the only important factor to capture persistence in performance, we would not expect to find significant differences in holding period performance among the portfolios sorted on past volatility within the same decile. In addition, we would not expect to find that the least volatile portfolio in deciles 5-9 would outperform the most volatile winner portfolio. In contrast to the way a generic momentum strategy thinks about cumulative returns, “more is better”, our results show that a stock with less cumulative returns achieved in a less volatile way, actually outperforms a stock with higher cumulative returns achieved in a more volatile way. We argue that the volatility of stocks within the formation period should be considered when constructing a momentum strategy. The persistence in performance of the most volatile winner and loser portfolios seems to be lower than for the other four winner and loser portfolios. Therefore, we decide to exclude the most volatile winner and loser portfolio and construct a new momentum strategy with the remaining four winner and loser portfolios.

4.2 VOLMOM – A volatility dependent momentum strategy

The exclusion of the most volatile winner and loser portfolios results in an exclusion of just under half the stocks on average[19]. By excluding the most volatile winner and loser portfolio, we remove the worst performing momentum stocks. Even though these stocks are considered winners and losers in a generic momentum strategy, the results from the previous subsection clearly show that these stocks reduce the potential performance of WML. When we construct our enhanced momentum strategy, we go long the four least volatile winner portfolios and short the four least volatile loser portfolios. We name our enhanced momentum

[19] Refer to the summary statistics in Table III, Panel C.

strategy VOLMOM, as it is a volatility dependent momentum strategy. In this section, we compare and contrast the performance of VOLMOM with the performance of WML.

The empirical evidence from the first two columns of Table VI, shows that VOLMOM outperforms WML on all performance measures. We find that VOLMOM achieves a higher average return and a lower standard deviation compared with WML. This results in a Sharpe ratio of 0.43 for VOLMOM compared with 0.35 for WML. In addition, VOLMOM has higher maximum returns, lower minimum return, and values of skewness and kurtosis that are slightly closer to a normal distribution compared with WML. In Panel B we regress the return series of VOLMOM and WML on FF-5 and find that VOLMOM achieves a monthly alpha of 0.94% versus 0.81% for WML. The enhancement of WML can therefore not be explained by additional exposure to systematic risk factors.

Table VI – Summary statistics and performance measures for WML versus VOLMOM

WML is the generic strategy of buying winners and selling losers based on 12-month cumulative return and held for 3 months. VOLMOM is the enhanced momentum strategy that takes volatility into account by excluding the most volatile winners and losers from WML. Winners (Losers) is the long (short) side of WML. VOLWinners (VOLLosers) is the long (short)-side of VOLMOM. Panel A shows the summary statistics. Returns and standard deviations are monthly. Sharpe ratio is annualized. Maximum and minimum return is the highest and lowest registered one month-return in the sample. Maximum drawdown is the maximum loss from peak to trough when being invested in the strategy throughout the sample. Panel B shows the respective loading on the Fama French Five-Factor model from July 1963 – June 2018.

Panel A: Summary statistics	WML	VOLMOM	Winners	VOLWinners	Losers	VOLLosers
Average return	0.7%	0.8%	1.4%	1.5%	0.7%	0.6%
Standard deviation	7.3%	6.8%	7.3%	6.4%	11.0%	9.9%
Annualized sharpe ratio	0.35	0.43	0.67	0.78	0.22	0.21
Maximum return	18.9%	21.6%	55.9%	52.3%	113.9%	100.7%
Minimum return	-84.7%	-76.5%	-32.8%	-31.3%	-36.8%	-37.8%
Max drawdown	-99.1%	-97.3%	-74.8%	-73.4%	-94.7%	-94.9%
Skewness	-4.30	-3.70	0.19	-0.06	2.90	2.57
Kurtosis	39.34	31.47	6.11	6.75	23.27	21.56

Panel B: Exposure to risk factors	WML	VOLMOM	Winners	VOLWinners	Losers	VOLLosers
Beta	-0.03	-0.07	1.03	1.00	1.05	1.07
T-stat	*(0.48)*	*(1.35)*	*(47.55)*	*(47.96)*	*(21.65)*	*(28.58)*
SMB	-0.23	-0.27	0.93	0.69	1.15	0.96
T-stat	*(2.92)*	*(3.77)*	*(30.90)*	*(23.85)*	*(17.06)*	*(18.45)*
HML	-0.59	-0.45	-0.19	-0.02	0.39	0.44
T-stat	*(5.46)*	*(4.61)*	*(4.68)*	*(0.38)*	*(4.17)*	*(6.08)*
CMA	0.51	0.38	0.02	0.12	-0.48	-0.26
T-stat	*(3.21)*	*(2.63)*	*(0.40)*	*(2.07)*	*(3.49)*	*(2.44)*
RMW	0.52	0.58	-0.21	0.31	-0.73	-0.27
T-stat	*(4.82)*	*(5.83)*	*(5.00)*	*(7.58)*	*(7.73)*	*(3.74)*
Alpha	0.81	0.94	0.56	0.55	-0.26	-0.39
T-stat	*(3.63)*	*(4.57)*	*(6.40)*	*(6.49)*	*(1.31)*	*(2.62)*

Even though our results show that VOLMOM outperforms WML, it is interesting to examine whether the outperformance comes from the long side, the short side or both. Therefore, we compare and contrast the performance of the long side and short side of WML and VOLMOM. We find that the exclusion of the most volatile momentum portfolios has benefits for both the long and short side of a momentum strategy.

In column 3-4 of Table VI, we look at the long side of the strategy and find that VOLWinners achieves a higher average return as well as a lower standard deviation compared with Winners from WML. Most of the enhancement comes from reducing the volatility associated with the most volatile winners. The exclusion of the most volatile winners results in an improvement in Sharpe ratio of 0.12. However, we find that the alpha of VOLWinners and Winners are almost identical, so the increase in Sharpe ratio seems to be explained by additional exposure to systematic risk.

In column 5-6, we examine the short side of the strategy and find that the Sharpe ratios of VOLLosers and Losers are almost equal. However, VOLLosers has lower average returns and standard deviation compared with Losers. The fact that the return distribution of VOLLosers are more centered around a lower return, makes it more attractive to short. We further find that VOLLosers has a significant alpha of -0.39% per month compared to a non-significant alpha of -0.26% for Losers.

We find that both Winners and Losers become less exposed to the SMB factor as we exclude the most volatile winners and losers. This indicates that we mainly remove smaller stocks from the winner and loser deciles when we remove the most volatile winners and losers. VOLMOM consist of larger and less volatile stocks, and therefore we argue that the strategy has less limits to arbitrage[20] compared with WML.

From the regressions, we see that the exclusion of the most volatile winners and losers enhances both the short-side and the long-side performance of a momentum strategy. The alpha from WML is therefore both smaller and more difficult to achieve as a result of higher transaction costs involved with implementing the strategy, which makes VOLMOM a superior strategy both on paper and in reality.

This subsection shows that a generic momentum strategy is improved by excluding the most volatile winners and losers. However, the volatility dependent momentum strategy is still exposed to large drawdowns. The maximum drawdown of VOLMOM is 97.1% versus

[20] Both indirect and direct transaction costs and liquidity issues

99.1% for WML. We address this issue in the following section for two reasons; 1) Reducing the exposure to crash risk makes the strategy more appealing to investors, and 2) to verify that removing the most volatile portfolios is not an indirect way of managing the crash risk. The most volatile loser portfolio has the highest returns during market rebounds following a major market decline. The removal of this portfolio may cause the impact of momentum crashes to be lower in VOLMOM compared with WML. By applying our method of crash risk management, we are able to analyze whether VOLMOM outperforms WML because VOLMOM takes volatility into account or because it possesses less crash risk.

4.3 Managing momentum crash risk

In Figure I, we illustrate the performance of VOLMOM and WML during two of the worst periods for momentum strategies. In the months following The Great Depression, VOLMOM lost 89.4%, compared to a loss of 91.7% for WML. In the months following The Financial Crisis, VOLMOM lost 63%, versus a 61% loss for WML.

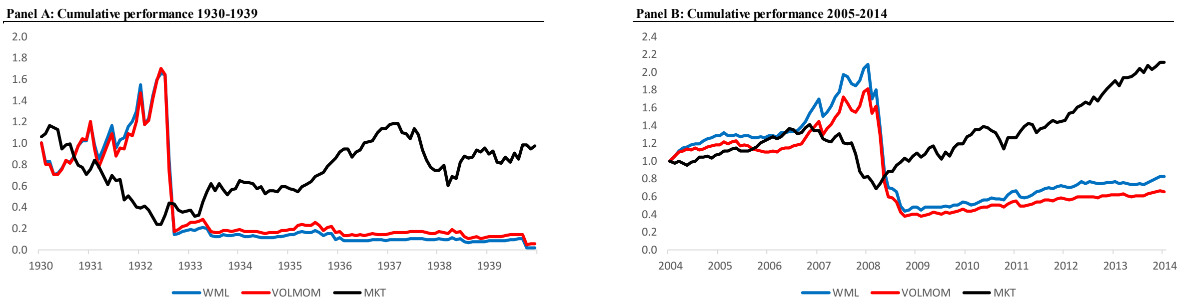
Grundy & Martin (2001) explain that when the market declines, the beta of the loser-portfolio tends to be substantially higher than the beta of the winner-portfolio, which results in a negative beta for the momentum strategy. When the market suddenly turns, high-beta stocks (losers) experiences the largest rebounds, which causes momentum strategies to crash. Even though we have excluded the most volatile winners and losers, VOLMOM it is still long winners and short losers based on past cumulative returns. Therefore, it is not surprising that our strategy is exposed to momentum crash risk.

During normal market environments, momentum offers a positive return premium and is considered an attractive investment strategy (Daniel & Moskowitz, 2016). However, as illustrated in Figure I, there are periods when years of positive return premium is wiped away in a short period. Barroso & Santa-Clara (2015) and Daniel & Moskowitz (2016) show that there are effective ways of dealing with momentum crashes.

We have shown that it is possible to use past volatility of momentum stocks in order to enhance the performance of WML. However, since research has shown that it is quite easy to manage the crash risk of momentum strategies, the enhancement has little value if it is not present after a method of risk management is applied. Since the enhancement we have made to WML come from excluding the most volatile winner and loser portfolios, it might be the case that our enhancement is only a minor crash risk management. Therefore, we examine if the enhancement is still present after our method of risk management is applied.

Figure I – Cumulative performance of WML and VOLMOM during crashes

The figures show the performance of WML and VOLMOM during the two worst periods for momentum strategies. Panel A shows the performance from 1930-1939. Panel B shows the performance from 2004-2014. The crashes occur in the market rebound following the Great Depression and the Global Financial Crisis. VOLMOM is the volatility dependent momentum strategy. WML is the strategy from Jegadeesh & Titman (1993) with a 12-month formation period and 3-month holding period. MKT is the value-weighted CRSP index.



We introduce a new approach that deals with momentum crashes, that decides when we should be exposed to VOLMOM based on the 12-month TSMOM of the market. Our approach takes inspiration from the explanation by Daniel & Moskowitz (2016) above. In normal market environments, we invest in VOLMOM and collect the premium associated with the strategy. However, when the 12-month cumulative return is negative, we consider the probability of a further decline followed by a sudden rebound to be higher. By being out of VOLMOM early, we avoid being exposed when the market rebounds. We invest in VOLMOM in time *t,* using information available at time *t.* More specifically, our crash risk management approach can be described as following; If the twelve-month cumulative return of the value-weighted CRSP index at the end of month t-1 is positive, we receive the returns in month t associated with a given momentum strategy. If the twelve-month cumulative return of the value-weighted CRSP index at the end of month t-1 is negative, we receive 0% in month t.

When we apply our crash risk management approach to VOLMOM, the performance is massively improved. The difference in performance of VOLMOM and VOLMOM* (the risk managed version of VOLMOM), is shown in the first two columns of Table VII. We find that VOLMOM* has the same average return as VOLMOM, but only half the standard deviation. The reduction in standard deviation is not surprising, since in 25% of the months examined, the returns of VOLMOM are replaced with 0%. The fact that the average returns are unaffected, indicate that when we are risk managing the strategy, we avoid large drawdowns, but at the same miss out on many months with positive returns. The largest one-month loss of VOLMOM* is -26.8% compared to -76.5% for VOLMOM and the maximum drawdown is massively reduced from -97.3% for VOLMOM to -60.9% for VOLMOM*. The maximum return is also somewhat lower for VOLMOM* at 17.2% compared to 21.6%. However, the advantage of avoiding large drawdowns by far outweigh the disadvantage of giving up many months with smaller positive returns. Risk managing VOLMOM increases the annualized Sharpe ratio from 0.43 to 0.81. We find that both the skewness and excess kurtosis is massively reduced from -3.70 to -1.27 and 31.47 to 9.74 respectively. The frequency distribution of returns moves closer to the mean with fewer extreme observations.

Table VII – Enhanced performance of risk managing VOLMOM and WML

WML is a generic momentum strategy of buying winners and selling losers based on 12-month cumulative return and held for 3 months. VOLMOM is the volatility dependent momentum strategy. VOLMOM* and WML* are the risk managed versions of VOLMOM and WML. Their returns are 0% if the 12-month cumulative return of the value weighted CRSP index is below 0%. Panel A shows the summary statistics of the strategies. Returns and standard deviations are monthly. Sharpe ratios are annualized. Maximum and minimum return is the highest and lowest registered one-month return. Maximum drawdown is the maximum loss from peak to trough. Panel B shows their exposure to the Fama French Five-Factor model from July 1963 – June 2018. *t*-statistics are in parentheses.

Panel A: Summary statistics	VOLMOM	VOLMOM*	WML	WML*
Average return	0.8%	0.9%	0.7%	0.8%
Standard deviation	6.8%	3.7%	7.3%	4.1%
Annualized sharpe ratio	0.43	0.81	0.35	0.67
Maximum return	21.6%	17.2%	18.9%	18.9%
Minimum return	-76.5%	-26.8%	-84.7%	-37.1%
Max drawdown	-97.3%	-60.9%	-99.1%	-71.9%
Skewness	-3.70	-1.27	-4.30	-1.87
Kurtosis	31.47	9.74	39.34	16.36
Panel B: Exposure to risk factors				
Beta	-0.07	0.12	-0.03	0.11
t-stat	*(1.35)*	*(3.73)*	*(0.48)*	*(3.28)*
SMB	-0.27	-0.06	-0.23	-0.03
t-stat	*(3.77)*	*(1.37)*	*(2.92)*	*(0.61)*
HML	-0.45	-0.16	-0.59	-0.28
t-stat	*(4.61)*	*(2.52)*	*(5.46)*	*(4.17)*
CMA	0.38	0.02	0.51	0.06
t-stat	*(2.63)*	*(0.24)*	*(3.21)*	*(0.65)*
RMW	0.58	0.19	0.52	0.07
t-stat	*(5.83)*	*(2.97)*	*(4.82)*	*(0.98)*
Alpha	0.94	0.88	0.81	0.85
t-stat	*(4.57)*	*(6.75)*	*(3.63)*	*(6.06)*

When we apply our risk management approach to WML, we find similar positive effects as for VOLMOM. Average returns are unaffected, the standard deviation is reduced, the Sharpe ratio almost doubles, the skewness and kurtosis are reduced, the minimum returns are slightly lower and the max drawdowns are significantly lower. We find that our risk management approach reduces the impact of momentum crashes in both VOLMOM and WML. Our approach almost doubles the Sharpe ratio, similar to the results of Barroso & Santa-Clara (2015) and Daniel & Moskowitz (2016).

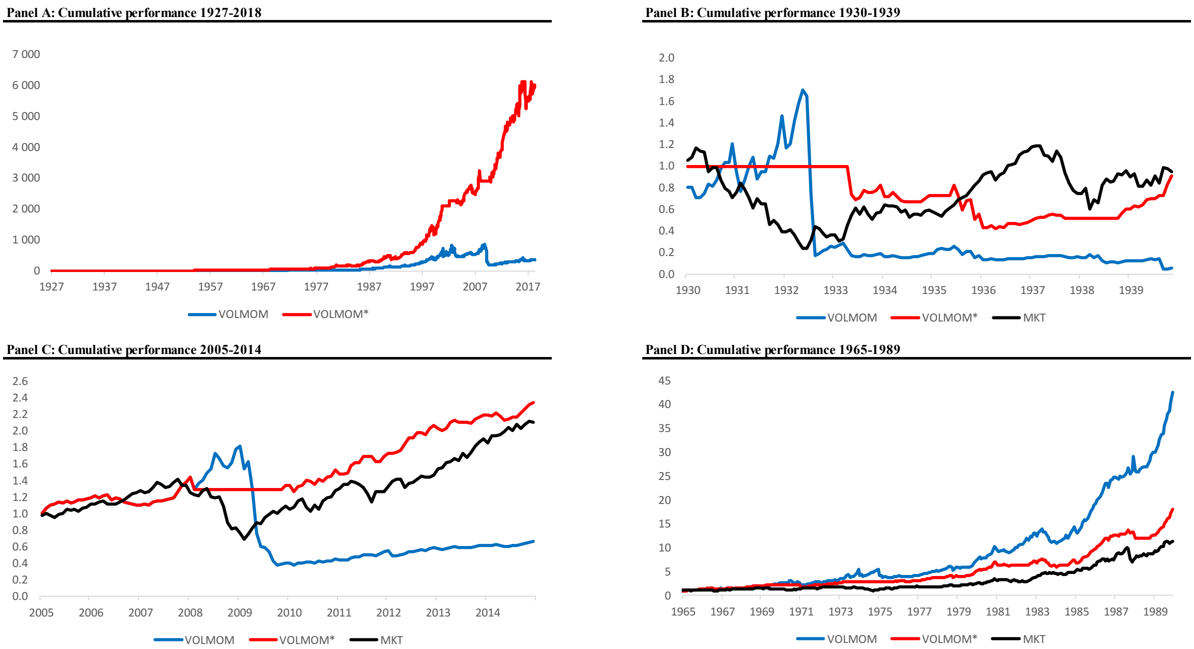
The summary statistics in Table VII, Panel A, show that VOLMOM* outperforms WML*. This means that the enhancement from taking volatility into account is still present after risk management is applied. The volatility dependent momentum strategy achieves higher average returns and lower volatility compared with the generic momentum strategy, both before and after the strategies are risk managed. Before crash risk management is taken into account, the difference in Sharpe ratio between VOLMOM and WML is 0.09. After we apply crash risk management, the difference in performance increases to 0.15. This shows that removing the most volatile stocks is, in fact, a true enhancement of WML and not only a minor way of dealing with crash risk. This indicates that our two contributions enhance the generic momentum strategy independently.

Panel B of Table VII shows the abnormal returns of WML, WML*, VOLMOM, and VOLMOM*. When we regress the return series of VOLMOM and VOLMOM* on FF-5, we find that the alpha is slightly lower when crash risk management is applied. However, they are not meaningfully different. When we consider WML and WML*, we find that the risk managed version achieves a slightly higher alpha. The results from Panel B are somewhat surprising, given that risk management almost doubles the Sharpe ratio of both VOLMOM and WML. On the other hand, the alphas of the two strategies do not consider that VOLMOM and WML are more exposed to momentum crash risk than their risk managed versions, something that is not captured by systematic risk factors. For this reason, it is difficult to draw any conclusions from the alphas. We find that the alpha of VOLMOM* is slightly higher than the alpha of WML*, 0.88 vs 0.85. However, the alphas are quite similar, which is a bit surprising given what we find in Panel A in terms of the two strategies´ summary statistics. The results from Panel B indicate that volatility does not seem to matter that much after risk management is taken into account. However, when we consider both summary statistics and abnormal returns, the overall performance of VOLMOM* is better than WML*.

We find that most of the enhancement to WML come from risk management. To better understand the dynamics of our crash risk management approach, we analyze the effect it has on VOLMOM in different market environments. Figure II illustrates how an investment of $1 evolves through different sub-periods. By looking at Panel A, we see that risk management has a large positive impact on the cumulative performance of VOLMOM over the full data sample we study. $1 invested in VOLMOM in January 1927 would have increased to $361, compared to $6,009 if invested in VOLMOM*.

Figure II – Cumulative performance of VOLMOM and VOLMOM*

The figures show the performance of a $1 investment at the start of a given sub-period and held throughout the given period. Panel A shows the 1927-2018 horizon to show the overall performance. Panel B shows the performance before, during and after the Great Depression, from 1930-1939. Panel C shows the performance before, during and after the Financial Crisis, from 2005-2014. Panel D is the sample period studied by Jegadeesh & Titman in the original momentum study where momentum was found to return a significant premium, from 1965-1989. The blue line is VOLMOM and the red line is VOLMOM*. MKT is the value-weighted CRSP index



Panel B and C show the effect risk management has in the worst performing periods for momentum strategies: The Great Depression and The Global Financial Crisis. In Panel B we see that $1 invested in VOLMOM in 1930 would have declined to $0.06 by the end of 1939. The loss would not have been recovered until June 1960. Even though VOLMOM* also experienced a decline during this period, it suffered less compared with VOLMOM, and the dollar invested would have been recovered in 1939. In Panel C, we observe that a dollar invested in VOLMOM in 2004 would be worth about $0.50 by the end of 2014. In fact, the huge loss in the aftermath of The Great Financial Crisis has not been recovered to this day. In the same period, the cumulative performance of VOLMOM* never went below the initial investment of $1.

Even though our risk management approach is not able to fully protect against momentum crashes, it is able to reduce the impact of momentum crashes by being precautionary. Our crash risk management approach signals that we should exit VOLMOM years before momentum crashes actually occur. When the market declines, VOLMOM outperforms VOLMOM* and looks like the superior strategy of the two. However, as the market sentiment suddenly turns, the precautionary actions taken in VOLMOM* avoid the large drawdowns and make the strategy superior to VOLMOM. Our risk management approach is not able to identify exactly when market rebounds occur, but it is able to identify periods when the likelihood of a large rebound is higher.

Panel D shows the effect of our risk management approach during a more normal market environment, where we use the sample period covered by Jegadeesh & Titman (1993). During this sample period, VOLMOM generates 5 times the return of VOLMOM*. The stock market is volatile, and the 12-month cumulative return of the market often drops below zero percent without a large crash and the occurrence of a major rebound. In these periods, VOLMOM* misses out on a lot of months with positive returns that VOLMOM achieves. In other words, risk management seems to only enhance a momentum strategy during extreme events. Taking a precautionary approach, like our crash risk management approach, avoids large drawdowns at the expense of giving up returns during normal market environments. However, the advantage from avoiding huge losses associated with momentum strategies, outweigh the disadvantage of missing out on months with positive returns.

We find that taking volatility into account enhances a generic momentum strategy, both with and without crash risk management. Momentum stocks with low volatility in the formation period deliver better performance than momentum stocks with high volatility in the formation period. The least volatile momentum stocks in the formation period have less volatile returns in the holding period and vice versa. The crash risk is not eliminated by excluding the most volatile momentum stocks from WML. By applying our method of crash risk management, we are able to almost double the Sharpe ratio of VOLMOM and WML. Even though we exclude the most volatile momentum stocks when we construct VOLMOM, which tend to experience the largest losses during market rebounds, the effect of crash risk management is equally effective for VOLMOM as for WML. Therefore, our enhancement is still present after risk management is considered, confirming that taking volatility into account enhances momentum.

4.4 Abnormal returns beyond a generic momentum factor

In this subsection, we examine the abnormal returns of our contributions beyond a generic momentum strategy. In Table VIII we show 3 regressions. In regression (1), we examine the abnormal returns from combining our two enhancements. In regression (2) and (3), we isolate the effect of taking volatility into account and managing crash risk respectively.

In regression (1), we regress VOLMOM* on FF-5 including WML to examine the combined effect of our contributions. VOLMOM* achieves a significant monthly alpha of 0.62%. In other words, the combination of our enhancements generates a monthly abnormal return of 0.62% beyond a generic momentum strategy, with less exposure to momentum crash risk. The combination of our enhancements can therefore not be explained by systematic risk factors, including WML. The results show that either volatility, crash risk management, or both, contribute to abnormal returns beyond WML. This shows that there are additional potential returns to be achieved from the momentum anomaly beyond what a generic momentum factor is able to capture.

In regression (2), we regress VOLMOM on FF-5 including WML, in order to isolate the effect from considering formation period volatility. We find that VOLMOM loads extremely positive on WML, with a monthly loading of 0.86%. However, the results show that VOLMOM achieves a monthly alpha of 0.24%. The abnormal returns show that excluding the most volatile momentum stocks in the formation period enhances the monthly abnormal returns of a generic momentum strategy. These results suggest that only considering cumulative returns when measuring momentum does not fully capture persistence in performance. We argue that volatility should be considered in addition to cumulative return when constructing a momentum factor. A momentum factor tilted towards low volatility winners and losers capture more persistence in returns compared with a generic momentum factor.

In regression (3), we regress WML* on FF-5 including WML to examine the effect from applying our risk management approach. We find that WML* achieves a positive alpha of 0.53% per month beyond FF-5 and WML. This shows that the abnormal returns from managing crash risk is more than twice as large as the abnormal returns from taking volatility into account.

Table VIII – Regression results of volatility dependency and crash risk management

Regression (1) regresses VOLMOM* on FF-5 plus WML to show the combined effect of volatility dependency and crash risk management. In regression (2) we show the enhancement from only taking volatility into account to enhance WML by regressing VOLMOM on FF-5 plus WML. In regression (3) we control for WML and FF-5 to find the individual enhancement due to crash risk management.

	(1) VOLMOM*	(2) VOLMOM	(3) WML*
Mkt-RF	0.13***	-0.05**	0.12***
	(4.76)	(-2.52)	(4.65)
SMB	0.01	-0.07***	0.06
	(0.27)	(-2.90)	(1.63)
HML	0.03	0.05	-0.05
	(0.53)	(1.38)	(-0.87)
RMW	0.02	0.13***	-0.14***
	(0.39)	(3.67)	(-2.68)
CMA	-0.14*	-0.05	-0.14*
	(-1.80)	(-1.03)	(-1.80)
WML	0.32***	0.86***	0.40***
	(16.66)	(67.58)	(21.18)
Constant	0.62***	0.24***	0.53***
	(5.64)	(3.28)	(4.82)
Observations	660	660	660
R^2	0.339	0.892	0.447

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

By considering the volatility of stocks in the formation period and a method of risk management in addition to cumulative returns, we have constructed an enhanced momentum strategy that beats a generic momentum strategy on all statistical measures. VOLMOM* is also easier to implement as we argue that it possesses less limits to arbitrage compared with a generic momentum strategy.

5. Robustness tests

In this section, we conduct various robustness tests to examine the reliability of our results. First, we verify that the abnormal returns in Table VIII do not occur as a result of how we construct our controlling momentum factor. Therefore, we replace WML with the MOM-factor from Kenneth French's data library and use this factor as an independent variable in the regressions from Table VIII. Then, we analyze the performance of the 50 portfolios sorted on cumulative return and volatility using value-weighted returns. We round off this section by examining other thresholds for risk management than 0% for the cumulative return of the market.

Replacing WML with the MOM-factor

We examine if our results are reliable by controlling for a momentum factor that is constructed differently than WML. In Table IX, we repeat the regressions from Table VIII, and replace WML with MOM from Kenneth French's data library. The MOM-factor is created using value-weighted returns and takes both size and cumulative returns into account.

In regression (1) we find that VOLMOM* achieves a significant monthly abnormal return of 0.56% when controlling for FF-5 including MOM. The main difference we find by comparing regression (1) from Table VIII with Table IX, is the significant loading on the SMB-factor. VOLMOM* seems to have a higher loading on the SMB-factor when controlling for MOM, which is logical, since MOM is created by taking size into account. Nevertheless, we find that the abnormal returns are of similar economic magnitude.

In regression (2), we find that VOLMOM does not yield significant abnormal returns beyond MOM. However, we argue that a magnitude of 0.15% per month are economically meaningful and that volatility still matters. It is important to remember that WML and MOM are constructed differently. WML only consider the top and bottom decile formed on cumulative returns while MOM considers the top and bottom 30 percent. If we were to remove the most volatile quintile of stocks from decile 2, 3, 8 and 9 as well, the results are likely to be different. We do not address this here but based on the results that the most volatile stocks within each decile underperform, we would expect the abnormal returns of VOLMOM to be higher if we removed these stocks.

Table IX – Regression results controlling for the MOM-factor

Regression (1) regresses the risk managed version of VOLMOM on the Fama/French 5 Factor model where we include the momentum factor (MOM) from Kenneth French's data library. Regression (2) regresses using VOLMOM as the dependent variable to isolate the effect of removing the volatile winners and losers. Regression (3) have a risk managed version of the MOM-factor as the dependent variable to isolate the effect of managing crash risk. Regression (4) regresses MOM on WML. *t*-statistics are in parentheses.

	(1) VOLMOM*	(2) VOLMOM	(3) MOM*	(4) MOM
Mkt-RF	0.18***	0.07***	0.13***	
	(6.48)	(2.79)	(6.82)	
SMB	-0.09**	-0.33***	0.10***	
	(-2.33)	(-9.22)	(3.82)	
HML	0.07	0.10**	-0.03	
	(1.21)	(1.99)	(-0.80)	
RMW	0.08	0.32***	-0.21***	
	(1.53)	(6.20)	(-5.73)	
CMA	-0.13*	-0.01	-0.15***	
	(-1.72)	(-0.08)	(-2.92)	
MOM	0.43***	1.08***	0.50***	
	(16.55)	(43.18)	(28.42)	
WML				0.58***
				(33.90)
Constant	0.56***	0.15	0.34***	0.19*
	(5.08)	(1.40)	(4.52)	(1.94)
Observations	660	660	660	660
R^2	0.336	0.775	0.613	0.636

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In regression (3), we find that our risk management approach shows significant abnormal returns when applied to the MOM-factor. The magnitude of the abnormal return is 0.34% per month. This concludes that risk management works on another momentum factor as well, not only on WML. The final regression (4) shows that there are small differences between MOM and WML since almost all of the returns from MOM are explained by the WML-strategy we construct.

These regressions show that the enhancement from crash risk management seems to be more robust than the enhancement from taking volatility into account. However, the results from section 4.1 indicate that if the most volatile stocks are removed from deciles 2, 3, 8 and 9 as well, the performance beyond MOM might have been improved more.

Value-weighted returns

Next, we calculate value-weighted returns for the 50 portfolios to minimize size effects within portfolios to see if volatility matters for the performance of momentum. We calculate the total market equity of each portfolio in each month and give the stocks within the portfolio a weight corresponding to that stock´s share of the total market equity of the portfolio.

We find a similar trend for the portfolios within deciles as when we use equal-weighted returns. The least volatile portfolio outperforms the most volatile portfolio for all deciles. We find that the returns of the most volatile portfolio are lower when we use value-weighted returns instead of equal-weighted returns. This indicates that the large average returns we see in these portfolios when we use equal weighted returns, might be driven by small stocks. In terms of standard deviation in the holding period, the most volatile portfolios continue to have high volatility. We find that the Sharpe ratio of the least volatile portfolio is higher than the Sharpe ratio of the most volatile portfolio within each decile.

If we look at the winner decile, we find that the least volatile winner portfolio achieves a Sharpe ratio that is approximately double the magnitude of the most volatile winner portfolio. Consistent with previous findings, we find that the most volatile winner portfolio underperforms and should be excluded from a momentum strategy.

We find that the most volatile loser portfolio has a monthly average value weighted return of -0.2%. The equal-weighted average return for the same portfolio is 1.1% per month. If we were to construct a volatility dependent momentum strategy using value-weighted returns instead of equal-weighted returns, the results from Table X does not suggest that we should remove the most volatile loser portfolio. If we only consider the Sharpe ratios of the loser portfolios, removing the least volatile losers seems to be a better option than to remove the most volatile losers. Nevertheless, the robustness test shows that volatility matters in addition to cumulative returns also when we use value-weighted returns.

Table X – Portfolio performances with value-weighted returns

The momentum deciles are constructed using the methodology from Jegadeesh & Titman (1993), including NYSE, AMEX, and NASDAQ stocks. Losers (Winners) represent the stocks that each month of the period have the lowest (highest) 12-month cumulative return. Within each decile, stocks are sorted on the realized daily volatility in the same period. LowVol (HighVol) represents the stocks that had the lowest (highest) daily standard deviation in the formation period. NYSE breakpoints ensure that there is an equal number of NYSE stocks within each portfolio. Panel A shows the monthly average value weighted returns of the portfolios. Panel B shows their respective standard deviation. Panel C presents the annualized Sharpe ratios. The tables are color-coded to make the trends easier to see for the reader. The scaling goes from red to green, where dark red indicate bad performance and dark green indicate good performance. For average returns, dark green indicates a higher return. For standard deviation, dark green indicates a lower standard deviation. For Sharpe ratio, dark green means a higher Sharpe ratio.

Panel A: Monthly average excess returns	Losers	2	3	4	5	6	7	8	9	Winners
Decile	*0.1%*	*0.5%*	*0.6%*	*0.6%*	*0.7%*	*0.6%*	*0.7%*	*0.8%*	*0.9%*	*1.1%*
LowVol	0.3%	0.5%	0.7%	0.6%	0.7%	0.7%	0.7%	0.8%	0.9%	1.2%
2	0.3%	0.6%	0.6%	0.7%	0.7%	0.7%	0.8%	0.8%	0.9%	1.1%
3	0.1%	0.5%	0.5%	0.7%	0.8%	0.7%	0.8%	0.9%	1.0%	1.3%
4	0.1%	0.7%	0.5%	0.7%	0.7%	0.8%	0.8%	0.8%	0.9%	1.4%
HighVol	-0.2%	0.4%	0.8%	0.6%	0.8%	0.9%	0.7%	0.8%	0.9%	1.1%
Panel B: Monthly standard deviation	**Losers**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Winners**
Decile	*9.4%*	*7.9%*	*6.9%*	*6.2%*	*5.8%*	*5.6%*	*5.3%*	*5.2%*	*5.5%*	*6.4%*
HighVol	8.8%	7.3%	6.4%	5.7%	5.2%	5.0%	4.9%	4.8%	5.1%	5.6%
2	10.1%	8.6%	7.5%	6.9%	6.5%	6.1%	5.8%	5.6%	5.9%	6.7%
3	10.8%	9.1%	8.2%	7.6%	7.2%	6.9%	6.5%	6.5%	6.3%	7.4%
4	11.8%	10.2%	8.4%	8.2%	7.7%	7.5%	7.2%	7.2%	7.0%	8.4%
HighVol	14.1%	10.8%	10.4%	9.3%	9.4%	8.6%	8.7%	8.5%	8.7%	10.3%
Panel C: Annualized Sharpe ratio	**Losers**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Winners**
Decile	*0.05*	*0.21*	*0.29*	*0.34*	*0.41*	*0.41*	*0.49*	*0.57*	*0.61*	*0.64*
LowVol	0.12	0.25	0.38	0.36	0.48	0.49	0.50	0.63	0.66	0.78
2	0.11	0.25	0.29	0.36	0.39	0.44	0.52	0.54	0.58	0.58
3	0.05	0.21	0.21	0.33	0.38	0.35	0.43	0.51	0.59	0.63
4	0.02	0.24	0.22	0.32	0.34	0.37	0.42	0.41	0.46	0.61
HighVol	-0.04	0.14	0.27	0.24	0.30	0.36	0.31	0.35	0.40	0.41

Higher threshold for crash risk management

Exiting a momentum strategy when the market has a 12-month cumulative return that is below 0% may seem too conservative. A 0% threshold might be too cautionary, since rebounds occur after larger market declines. Therefore, we examine the effect of using higher thresholds for when we exit our volatility dependent momentum strategy, namely -5%, -10% and -20%. The results are shown in Table XI.

We find that all four thresholds are effective ways to reduce the impact of momentum crashes, and show better performance statistics compared with the non-risk managed VOLMOM. Using a 0% threshold when risk managing VOLMOM seems to be the best option of the four thresholds. This yields the lowest minimum return and drawdown to the strategy and is thus the most effective threshold to reduce the impact of crashes. However, a low threshold means that one will go in and out of the momentum strategy more often, causing more transaction costs. Nevertheless, we conclude that using the 12-month cumulative return of the value-weighted CRSP index is an effective method of reducing the impact of momentum crashes.

Table XI – Risk managed VOLMOM with different thresholds

Panel A shows the performance of VOLMOM with different thresholds for crash risk management. The first column is the performance if we go out of VOLMOM when the cumulative return of the market is below 0%. The second columns exit VOLMOM when the cumulative return of the market is -5%. Column 3 and 4 uses -10% and -20% as the threshold respectively. Panel B shows the unmanaged version of VOLMOM for comparison.

	Threshold for risk management			
Panel A: Risk managed VOLMOM	0%	-5%	-10%	-20%
Average return	0.9%	1.0%	1.0%	0.9%
Standard deviation	3.7%	4.4%	4.7%	5.4%
Annualized Sharpe ratio	0.81	0.78	0.76	0.61
Maximum return	17.2%	17.2%	17.2%	18.9%
Minimum return	-26.8%	-68.3%	-68.3%	-68.3%
Max drawdown	-60.9%	-74.6%	-78.3%	-76.3%
Skewness	-1.27	-4.30	-3.68	-3.07
Kurtosis	9.74	59.64	47.66	30.20

Panel B: VOLMOM	
Average return	0.8%
Standard deviation	6.8%
Annualized Sharpe ratio	0.43
Maximum return	21.6%
Minimum return	-76.5%
Max drawdown	-97.3%
Skewness	-3.70
Kurtosis	31.47

6. Conclusion

In this thesis, we examine two ways that enhance a generic momentum strategy. First, we look into whether the volatility of stocks within the formation period can be used to enhance the performance of a generic momentum strategy. We use the methodology of Jegadeesh & Titman (1993) to construct deciles formed on cumulative returns and then split each of the deciles into quintiles based on the stocks' realized volatility. We find that the portfolios with the lowest volatility within the formation period tend to show better holding period performance than the portfolios with the highest volatility. The results imply that stocks that achieve their cumulative returns through less volatile price movements show more persistence in performance in the holding period. We conclude that volatility matters in addition to cumulative returns for momentum strategies.

We use these results to construct a volatility dependent momentum strategy by removing the most volatile stocks from a generic momentum strategy (WML), as these stocks reduce the potential performance of WML. The strategy, which we name VOLMOM, outperforms the generic momentum strategy on all statistical performance measures. The annualized Sharpe ratio of VOLMOM is 0.43 compared to 0.35 for WML. We find that the enhanced performance is not explained by additional exposure to systematic risk. VOLMOM has an alpha of 0.94% vs 0.81% for WML when we control for the Fama/French 5 factor model. We conclude that a volatility dependent momentum strategy is superior to a generic momentum strategy.

The enhancement from taking volatility into account achieves a monthly alpha of 0.24% beyond WML and the Fama/French 5 Factor model. The abnormal returns imply that the momentum factor is sub-optimally created. We find that momentum stocks with less volatile price movements in the formation period show more persistence in performance in the holding period. Stocks that have achieved their cumulative returns from more volatile price movements tend to show less persistence in performance during the holding period. The probability that these stocks will keep on winning (losing) is lower than for stocks that have achieved their cumulative return with low volatility. VOLMOM therefore owns momentum stocks with the highest probability of showing persistence in performance. We argue that a momentum factor that considers volatility in addition to cumulative returns captures more of the momentum effect.

Momentum strategies come with the risk of large drawdowns, and VOLMOM is no exception. We address the issue of momentum crash risk by introducing a new risk management approach based on the Time Series Momentum (TSMOM) of the market. The method is able to reduce the impact of momentum crashes. We chose to only invest in VOLMOM at time *t* if the 12-month cumulative return of the market is positive at time *t*. We find that the method further enhances the annualized Sharpe ratio of VOLMOM from 0.43 to 0.81, similar to the results from Barroso & Santa Clara (2015) and Daniel & Moskowitz (2016).

The most volatile losers show the largest rebounds after a market decline, causing the most negative impact to WML in these periods. Excluding these may therefore be an indirect way of minor crash risk management. To be certain that the enhancement from removing volatile winners and losers are not due to minor crash risk management, we apply our crash risk management approach to WML and compare its performance to the risk managed version of VOLMOM. We find that the annualized Sharpe ratio of WML is enhanced from 0.35 to 0.67 when risk managed. In comparison, the risk managed version of VOLMOM provides 0.81 in annualized Sharpe ratios. We conclude that volatility also matters when crash risk management is taken into account.

When we examine the crash risk management approach in isolation, we find a monthly alpha of 0.53% beyond WML and the Fama/French 5 Factors. The magnitude of the abnormal returns is twice as large as the abnormal return generated from taking volatility into account.

The risk managed volatility dependent momentum strategy, VOLMOM*, achieves 0.62% in abnormal returns beyond WML and the Fama/French 5 Factors. We conclude that volatility should be considered when constructing a momentum strategy, and our method of risk management should be applied to reduce the impact of momentum crashes.

Our results have implications for asset managers investing in momentum strategies. In addition to superior performance, a volatility dependent momentum strategy is easier to implement compared to generic momentum strategy. We show that our risk management approach can easily be applied to VOLMOM and increase its performance.

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Appendix A:

Original table from Jegadeesh & Titman (1993)

			Panel A			
J		*K*=	3	6	9	12
3	Sell		0.0108	0.0091	0.0092	0.0087
			(2.16)	(1.87)	(1.92)	(1.87)
3	Buy		0.0140	0.0149	0.0152	0.0156
			(3.57)	(3.78)	(3.83)	(3.89)
3	Buy-Sell		0.0032	0.0058	0.0061	0.0069
			(1.10)	(2.29)	(2.69)	(3.53)
6	Sell		0.0087	0.0079	0.0072	0.0080
			(1.67)	(1.56)	(1.48)	(1.66)
6	Buy		0.0171	0.0174	0.0174	0.0166
			(4.28)	(4.33)	(4.31)	(4.13)
6	Buy-Sell		0.0084	0.0095	0.0102	0.0086
			(2.44)	(3.07)	(3.76)	(3.36)
9	Sell		0.0077	0.0065	0.0071	0.0082
			(1.47)	(1.29)	(1.43)	(1.66)
9	Buy		0.0186	0.0186	0.0176	0.0164
			(4.56)	(4.53)	(4.30)	(4.03)
9	Buy-Sell		0.0109	0.0121	0.0105	0.0082
			(3.03)	(3.78)	(3.47)	(2.89)
12	Sell		0.0060	0.0065	0.0075	0.0087
			(1.17)	(1.29)	(1.48)	(1.74)
12	Buy		0.0192	0.0179	0.0168	0.0155
			(4.63)	(4.36)	(4.10)	(3.81)
12	Buy-Sell		0.0132	0.0114	0.0093	0.0068
			(3.74)	(3.40)	(2.95)	(2.25)

Appendix B:

Additional summary statistics on volatility dependent momentum portfolios

Panel A: Maximum return		Losers	2	3	4	5	6	7	8	9	Winners
	Decile	*113.9%*	*103.6%*	*82.9%*	*72.8%*	*67.7%*	*69.5%*	*50.6%*	*50.0%*	*47.6%*	*55.9%*
	LowVol	90.1%	73.8%	61.0%	50.8%	46.1%	37.8%	29.0%	27.7%	28.8%	29.3%
	2	101.7%	98.8%	65.9%	62.1%	61.9%	52.5%	46.8%	35.5%	40.6%	37.8%
	3	113.8%	103.1%	82.5%	62.1%	64.3%	62.8%	65.4%	53.1%	45.9%	73.7%
	4	126.6%	118.3%	79.5%	80.6%	69.8%	68.2%	70.8%	69.4%	50.2%	78.0%
	HighVol	184.2%	132.1%	128.4%	113.6%	121.7%	141.9%	100.3%	103.8%	72.8%	93.1%

Panel B: Minimum return		Losers	2	3	4	5	6	7	8	9	Winners
	Decile	*-36.8%*	*-38.1%*	*-36.1%*	*-31.8%*	*-32.3%*	*-30.2%*	*-31.4%*	*-29.1%*	*-30.3%*	*-32.8%*
	LowVol	-40.4%	-36.3%	-35.8%	-31.1%	-27.9%	-24.5%	-26.3%	-24.4%	-27.8%	-29.3%
	2	-40.1%	-40.7%	-37.7%	-32.6%	-35.3%	-33.0%	-30.5%	-27.0%	-29.1%	-29.9%
	3	-41.4%	-39.6%	-40.5%	-34.1%	-37.6%	-35.9%	-34.4%	-27.9%	-30.5%	-31.3%
	4	-32.5%	-38.3%	-37.9%	-33.0%	-35.2%	-32.8%	-36.3%	-33.4%	-28.9%	-32.7%
	HighVol	-36.4%	-35.4%	-31.0%	-36.1%	-33.5%	-31.8%	-33.9%	-35.7%	-33.2%	-39.5%

Panel C: Skewness		Losers	2	3	4	5	6	7	8	9	Winners
	Decile	*2.90*	*2.91*	*2.54*	*2.14*	*1.94*	*1.75*	*0.82*	*0.61*	*0.04*	*0.19*
	LowVol	2.54	2.17	2.05	1.63	1.44	0.66	-0.34	-0.18	-0.51	-0.57
	2	2.45	3.03	2.14	2.11	1.78	1.07	0.64	-0.03	-0.33	-0.53
	3	2.48	2.77	2.54	1.91	1.78	1.27	0.75	0.49	-0.17	0.72
	4	3.23	3.37	2.27	2.50	1.79	1.84	1.41	1.03	0.24	0.56
	HighVol	4.55	3.97	4.35	3.20	3.44	4.06	2.15	2.21	1.30	1.93

Panel D: Kurtosis		Losers	2	3	4	5	6	7	8	9	Winners
	Decile	*23.27*	*28.85*	*24.93*	*21.35*	*20.54*	*20.48*	*11.96*	*10.32*	*6.40*	*6.11*
	LowVol	24.85	27.15	27.41	23.75	21.08	14.64	9.41	6.75	5.92	4.34
	2	21.98	34.44	23.51	24.65	23.01	16.96	12.55	7.48	6.37	3.89
	3	21.79	28.51	27.26	19.14	20.97	16.99	16.28	10.87	6.81	13.63
	4	27.30	35.11	20.54	24.27	19.17	19.97	17.30	15.19	6.97	10.09
	HighVol	41.57	38.22	45.85	32.92	36.92	51.66	22.67	23.43	11.53	16.67