

Volatility Managed Momentum Portfolios in Commodity Markets

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Abstract

The momentum strategies perform well across asset classes however, the stellar performance of momentum trading comes with periodic crashes that wipe out the accumulated returns. Based on previous works on the topic, I compare three volatility-scaled strategies in the US commodity futures market, namely the constant volatility scaled, the dynamic volatility scaled, and my enhanced dynamic volatility scaled momentum strategies. The implementation of the scalings enhances the returns of the portfolios and also reduces the skewness of the return distribution. A deeper examination reveals that the characteristics of the crashes are different from the ones usually experienced in equity markets. In commodity markets, the crashes tend to happen more frequently but they are smaller in absolute terms hence implementing risk management into portfolios achieves better results on a longer time horizon.

1 Introduction

One of the most puzzling and researched topics in the financial markets is the momentum strategy which buys past winners and sells past losers generating significant positive returns for investors. To this very day mutual funds incorporate aspects of the momentum into their investment strategies which signals the importance of the phenomenon. Since the discovery of the acute crash risk, different methodologies have been presented to eradicate the negative skewness and kurtosis of returns. One of them is volatility scaling which aims to reduce the tail risk by scaling the long and short leg of the momentum strategy avoiding huge negative returns and improving the Sharpe ratios.

The commodity markets in the early years existed in a bubble, there were no comovements with the stocks and the commodities seemed to be segmented also from each other. When the big crash occurred in the early 2000s, the negative correlation was discovered and the assets started to be used as hedges, and also index trading was picked up by institutions. As a result, billions of dollars flooded the market which marked the starting point of the financialization process. As a side effect thanks to the higher trading activity the commodity market became relatively more efficient as more watchful eyes were following the commodity markets, although the distance from an efficient market situation differs within commodity subcategories ([Ortiz-Cruz et al., 2012](#); [Kristoufek and Vosvrda, 2014](#)). The correlations between assets and other markets increased which indicated that the market integrated with the outside financial world. Consequently, the market exhibited heightened volatility, as the potential for a volatility spillover effect from an external market increased significantly ([Tang and Xiong, 2012](#)). The prices were no longer solely determined by supply and demand but the financial factors' influence also became more prominent.

Based on these characteristics of the commodity market, the volatility scaling methodology fits perfectly as my choice of research topic. The momentum strategy's existence has already been proved before however in the literature, a comprehensive comparison between different volatility scaled momentum strategies in the US commodity market does not exist. My research adds proof to the already existing momentum crash literature ([Barroso and Santa-Clara, 2015](#); [Daniel and Moskowitz, 2016](#); [Hanauer and Windmüller, 2023](#)) and challenges the findings of previous plain momentum returns in commodity markets ([Miffre and Rallis, 2007](#); [Kang and Kwon, 2021](#)). The results also reveal similarities and differences in momentum crash characteristics compared to equity markets.

The layout of the paper is as follows: [Section 2](#) explains the well-established momentum literature and reviews previous studies in commodity markets. [Section 3](#) gives an overview of the data used in the calculations and documents different factor constructions and momentum portfolio formations. [Section 4](#) introduces the foundation of volatility scaling and highlights the differences between the methodologies. In [Section 5](#), I assess the performance of the momentum strategies and link key findings to related articles. Finally, [Section 6](#) presents my conclusion about the results.

2 Literature review

Momentum is one of the long-standing asset pricing anomalies that researchers are still trying to figure out. The phenomenon was first introduced by Jagadeesh and Titman in 1993 when they examined different relative strength strategies and found that previous winners in the US stock market outperform past losers and realize significant abnormal returns over the period of 1965 to 1989 ([Jegadeesh and Titman, 1993](#)).

The strategy sorts the available assets into groups based on their cumulative returns in their past J months, also known as the formation period, then buys the "winner" assets that had the highest cumulative returns over the formation period and sells the "loser" assets that performed the worst. The long and short leg of the portfolio is pieced together to form a zero-cost strategy which can be done by equally weighing all assets or having a market-cap weighting within each leg. This portfolio is then held for K months either with or without overlapping periods which means multiple portfolios might be held at the same time. The most common J value is 12 months, while the K value is usually 1 month based on the empirical evidence that this strategy outperforms every other holding and formation period combination.

In the original paper, [Jegadeesh and Titman \(1993\)](#) find that the "winner-minus-loser" portfolio also referred to as the momentum strategy realizes a compound excess return of 12.01% per year on average. The research concluded that the excess returns cannot be attributed to systematic risk or lead-lag effects. The momentum directly contradicts the notion of fairly weak form of capital market efficiency introduced by [Fama \(1991\)](#) in his study. The weak form of the Efficient Market Hypothesis assumes that prices of securities already reflect all available market information, and the prices and returns are independent of future prices hence prediction based on historical time-series is not possible. However, it seems that identifying relatively better and worse-performing assets does yield additional information about the future relative performance of securities.

Although the original paper only analyzed the US markets, since then the momentum phenomenon has been found in other markets and asset classes as well. [Rouwenhorst \(1998\)](#) found evidence that abnormal returns are also pervasive in a lot of European countries. In another study, [Asness et al. \(2013\)](#) proved that the momentum strategy can be applied successfully also to other assets such as government bonds, commodity futures, and foreign currencies. What is even more puzzling, applying the sorting to other factors also yield significant abnormal returns and a rally of searching for factors began among researches to try to exploit the anomaly. More complex factors were built by combining different priorly known factors and tested in a wide range of datasets including US and non-US securities. The results show that most of the factor portfolios yield significant returns in most asset classes ([Asness et al., 2013](#)). The evidence was so overwhelming that a new fourth factor was introduced to the Fama-French 3-factor model by Carhart ([Carhart, 1997](#)). New studies also observed that focusing on purely a security's own returns can also give information about its relative performance in the future. This was

first identified by [Moskowitz et al. \(2012\)](#) and it is usually referenced as "time-series momentum". Findings indicate that the two types of momentum are closely connected.

During the past 30 years, several explanations have been researched but there wasn't any conclusive evidence that can be entirely attributable to this abnormal performance of the momentum strategy. The findings are best summarized by [Subrahmanyam \(2018\)](#) who separates the explanations into two different groups, the behavioral models and the empirical evidence.

In the world of behavioral models, one of the most accepted explanations is the over- and underreaction of investors. [Daniel et al. \(1998\)](#) argues that overconfidence in private information signals and an underreaction to public information signals can cause the prices to deviate from their fair value which reverses over a longer horizon. Another explanation centers around the limited attention bias that assumes the existence of an upper threshold for processing information about firms in a short horizon hence leaving the investors "uninformed". [Da et al. \(2014\)](#) reports that information arriving continuously in small portions is more likely to be ignored by investors unlike a huge infrequent change hence underreacting to them which accumulates momentum in those securities.

On the other hand, from an empirical side [Grinblatt and Moskowitz \(2004\)](#) argues that the patterns of the returns are just as important as the magnitude of the formation period returns. The consistency of the formation period return accumulation has a substantial impact on the momentum profits which also connects directly to [Da et al. \(2014\)](#). Other works tried to figure out the optimal composition of different momentum factor portfolios to achieve the best returns ([Asness et al., 2013](#)).

From the perspective of my research, the most important finding is the existence of momentum crashes. The stellar performance of the momentum trading strategy comes with periodic crashes that wipe out the accumulated returns. This property is displayed also by the highly negative skewness and kurtosis of the momentum returns. In the US equity market, the WML strategy experienced a -91.59% loss during a 2 months period in 1932 while in 2009 it delivered a -73.42% in just 3 months ([Barroso and Santa-Clara, 2015](#)). The reason behind this is that after a market crash, the momentum strategy has a large negative beta resulting in negative returns ([Daniel and Moskowitz, 2016](#)). Avoiding these periods in the trading strategy can substantially improve the performance. Different methodologies have been presented to eradicate the negative skewness and kurtosis of returns. One of them is volatility scaling which aims to reduce the tail risk by scaling the long and short leg of the momentum strategy avoiding huge negative returns and improving the Sharpe ratio.

The commodity market has been becoming more and more popular among researchers since the financial crisis as it's getting more integrated with outside financial markets. Several papers covered the momentum strategy in commodity markets. In their article, [Miffre and Rallis \(2007\)](#) test different momentum strategies across 31 US commodity futures contracts finding several to yield significant abnormal returns. They also find that

the momentum returns have a low correlation to other asset classes making this relative-strength portfolio suitable for including into a well-diversified portfolio. Another article examines a variant of the momentum strategy that is sorted based on the nearness of the previous 52-week high and low price. According to their results, the 52-week nearness ratio generates superior returns than traditional momentum even after controlling for well-known commodity factors. They attribute the returns to the anchoring behavior of the investors around highs and lows (Bianchi et al., 2016). Bianchi et al. (2015) also enhances the strategy and proves that a double-sorted portfolio achieves better results compared to the plain momentum. Controlling for a reversal signal can boost the profitability in the commodity futures space. Xu and Wang (2021) explored the strategy’s profitability in the Chinese commodity market while empirically investigating whether volatility management proves to be beneficial for managing risk within the momentum strategy. Their results show that the returns cannot be interpreted as risk premiums for any conventional risk factors, in accordance with previous papers. Volatility scaling also improves the momentum returns for US commodity futures however it argues that it is only true for an in-sample perspective (Kang and Kwon, 2021).

My research is different from the previously mentioned papers. I also examine the US commodity futures market however, I test different volatility scaling methodologies and try to assess which one spans all the other. The research highly builds on the findings of Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) while I introduce the momentum gap (Huang, 2022) as an additional variable that can help predict crashes which might strengthen the performance of the volatility scaled portfolios.

3 Data and methodology

3.1 Commodity futures data

I obtained daily settlement prices and volumes for 36 commodity futures contracts, following Sakkas and Tessaromatis (2020); Miffre and Rallis (2007), from Bloomberg which was my principal data source. The data starts from January 1979 to April 2024 from different commodities exchanges, namely the London Metal Exchange (LME), the Osaka Stock Exchange (OSE), the Intercontinental Exchange Group (ICE), including ICE-EU and ICE-US, and the Chicago Mercantile Exchange Group which consist of four exchanges, the Chicago Mercantile Exchange (CME), Chicago Board of Trade (CBoT), New York Mercantile Exchange (NYMEX), and The Commodity Exchange (COMEX). The data includes a variety of commodity futures, in particular, contracts on WTI crude oil, BRENT crude oil, heating oil, RBOB gasoline, gasoil, natural gas, aluminum, copper, nickel, lead, zinc, tin, gold, silver, platinum, palladium, Chicago wheat, Kansas (red) wheat, corn, soybeans, soymeal, soyoil, oats, rough rice, coffee, sugar, cocoa, cotton, lumber, orange juice, milk, rubber, lean hogs, live cattle, feeder cattle. During my sample period, the

gasoline contract changed its ticker in 2005, and for a short period, two different contracts were available for trading from October 2005 to December 2006. As they were separate contracts, I didn't merge the time series allowing the momentum strategy to take positions separately. In the sample period, the minimum number of available assets for which I have data is 16 commodity futures that mainly appeared in the early years. In later dates, the number of assets available increased to 36 commodity futures.

Summary of the commodity futures data

Category	Commodity futures	Exchange	Ticker	Start date	Delivery month
Energy	WTI Crude Oil	NYMEX	CL	1983:03	1:12
	Heating oil	NYMEX	HO	1986:07	1:12
	Gasoline	NYMEX	HU	1986:04	1:12
	RBOB Gasoline	NYMEX	XB	2005:10	1:12
	Brent Crude oil	ICE-Europe	CO	1988:06	1:12
	Gasoil	ICE-Europe	QS	1989:07	1:12
	Natural gas	NYMEX	NG	1990:04	1:12
Grains & Oilseeds	Chicago wheat	CBoT	W-	1979:01	3, 5, 7, 9, 12
	Kansas (red) wheat	CBoT	KW	1979:01	3, 5, 7, 9, 12
	Corn	CBoT	C-	1979:01	3, 5, 7, 9, 12
	Soybeans	CBoT	S-	1979:01	1, 3, 5, 7, 8, 9, 11
	Soymeal	CBoT	SM	1979:01	1, 3, 5, 7, 8, 9, 10, 12
	Soyoil	CBoT	BO	1979:01	1, 3, 5, 7, 8, 9, 10, 12
	Oats	CBoT	O-	1979:01	3, 5, 7, 9, 12
	Rough Rice	CBoT	RR	1988:12	1, 3, 5, 7, 9, 11
Livestock	Feeder Cattle				
	Lean hogs	CME	LH	1986:04	2, 4, 5, 6, 7, 8, 10, 12
	Live Cattle	CME	LC	1979:01	2, 4, 6, 8, 10, 12
	Feeder cattle	CME	FC	1979:01	1, 3, 4, 5, 8, 9, 10, 11
Precious metals	Gold	Comex	GC	1979:01	2, 4, 6, 8, 10, 12
	Silver	Comex	SI	1979:01	3, 5, 7, 9, 12
	Platinum	NYMEX	PL	1986:04	1, 4, 7, 10
	Palladium	NYMEX	PA	1986:04	1, 3, 6, 9, 12
Soft metals	Aluminium	LME	LA	1997:07	1:12
	Copper	Comex	HG	1988:12	3, 5, 7, 9, 12
	Nickel	LME	LN	1997:07	1:12
	Lead	LME	LL	1997:07	1:12
	Zinc	LME	LX	1997:07	1:12
	Tin	LME	LT	1997:07	1:12
Softs	Coffee	ICE-US	KC	1979:01	3, 5, 7, 9, 12
	Sugar	ICE-US	SB	1979:01	3, 5, 7, 10
	Cocoa	ICE-US	CC	1979:01	3, 5, 7, 9, 12
	Cotton	ICE-US	CT	1979:01	3, 5, 7, 10, 12
	Lumber	CME	LB	1986:04	1, 3, 5, 7, 9, 11
	Orange Juice	ICE	JO	1979:01	1, 3, 5, 7, 9, 11
	Rubber	OSE	OR	1997:07	1:12
	Milk	CME	DA	1996:01	1:12

Table 1: This table reports summary information of the 36 commodity futures and tabulates the categories they belong, the exchange on which they are traded, the Bloomberg/CRB ticker symbol, the year of the first recorded observation and the delivery months for the period 1979:01 to 2024:04. The commodity futures contracts are traded on the London Metal Exchange (LME), the Osaka Stock Exchange (OSE), the Intercontinental Exchange Group (ICE), the Chicago Mercantile Exchange (CME), the Chicago Board of Trade (CBoT), the New York Mercantile Exchange (NYMEX), and The Commodity Exchange (COMEX).

3.2 Negative prices of commodities

The prices of commodities, just like in other markets, are defined by the balance of sellers and buyers, or in other words the supply and demand. In equity markets, the price cannot go below zero as the investors would not owe anyone money upon bankruptcy. Hitting the zero price typically means that the shareholders lost all their investments and the earnings are worthless. However, in extreme scenarios, commodity prices can go negative because there are other factors to consider, the main being the costs of carry which include the physical transportation of the goods, the storage costs, and also the potential losses of obsolescence as some of the goods can have expiry dates or the procession of good has to happen before a certain date otherwise it can lose its quality. In 2020, during the COVID pandemic, the oil prices experienced a huge shock as the borders of the countries closed down and traveling was minimized throughout the world. The oil giants didn't cut their production in time resulting in running out of storage capacity. As the delivery day was approaching, investors started to sell off their contracts to get rid of the oil but as the buyers didn't have free storage capacity they didn't want to buy any more oil. Investors, however, didn't even have storage so upon receiving the oil they had to pay for storing the oil which would have been costly. Instead, the investors were willing to pay to sell their contracts just to avoid paying huge amounts of money for storing oil that they did not even need. On April 20th, the WTI Crude Oil price went below zero, closing at \$-37.63 per barrel that day. The next day the price recovered to around \$10 per barrel. As I calculate log returns, using [Equation \(1\)](#), in my research, dealing with negative prices is essential. I decided to exclude this day's price as it was an extreme case and changed the price to the previous day's value as it was just a result of a brief panic fueled by the investors.

$$r_{log,t} = \log \left(\frac{P_t}{P_{t-1}} \right) \quad (1)$$

3.3 Market portfolio and the risk-free rate

In choosing the market portfolio, I follow [Miffre and Rallis \(2007\)](#) and [Bianchi et al. \(2015\)](#) and use the S&P GSCI (GSCI hereafter), which serves as a benchmark for investments in the commodity market. I collect this data from Bloomberg as it is available from 1969. The index was developed in 1991 by Goldman Sachs and it includes 24 commodities from all sectors. The constituents are weighted by the average quantity of production over the last five years, making it a world-production-weighted index.

As for the risk-free rate, I use the one-month Treasury Bill rate from Kenneth French's data library and convert it according to [Daniel and Moskowitz \(2016\)](#). At the start of every month, I convert the monthly returns into daily ones and assume that they stay constant throughout that period.

3.4 Additional factors

Based on the data, I replicate factors that I use in the signal generating and in the volatility scaling calculations. As a market state indicator, I calculate for each date the past 2-years' cumulative return of the market portfolio, which in my case is the GSCI.

$$MKT_{-2y} = \sum_{j=1}^{504} r_{GSCI,t-j} \quad (2)$$

In the paper, I will refer to this factor as the MKT_{-2y} . Following [Daniel and Moskowitz \(2016\)](#), I compute an ex-ante bear market indicator, $(I_{B,t-1})$ based on the MKT_{-2y} . The indicator equals one if the cumulative GSCI return is negative and zero otherwise.

$$I_{B,t-1} = \begin{cases} MKT_{-2y} < 0 & = 1 \\ MKT_{-2y} \geq 0 & = 0 \end{cases} \quad (3)$$

I also calculate the volatility of the market portfolio based on the preceding 126 days' daily returns, also referenced as MKT_{VOL} . The calculation uses the following formula:

$$MKT_{VOL} = \hat{\sigma}_{m,t-1}^2 = 21 \sum_{j=0}^{125} r_{d_{t-1-j}}^2 / 126 \quad (4)$$

I also introduce the momentum gap into my examination based on [Huang \(2022\)](#). The momentum gap is the difference between either the 25th and 75th percentiles or the 90th and 10th percentiles of the distribution of the cumulative commodity returns in the formation period. This is a crash indicator that proved to be efficient in equity markets. Based on research, it can indicate underreaction and overreaction in the markets that can potentially help in forecasting reversal patterns ([Huang, 2022](#)).

3.5 Momentum portfolio construction

To form the momentum portfolios, I rank the commodity futures based on their past 12 months' returns and sort them into 3 groups. I chose to have 3 groups as only 36 commodity futures are available and in the early years, it's even less. I implement the strategy by allocating 30%-40%-30% of the assets within the groups, in accordance with previous articles. I do not skip the last month in the formation period because although [Jegadeesh \(1990\)](#) and [Lehmann \(1990\)](#) showed that in equity markets short-term reversals do have a significant impact, in commodity markets this effect is negligible hence the performance gain is inferior ([Miffre and Rallis, 2007](#); [Fuertes et al., 2010](#); [Bianchi et al., 2015, 2016](#)). The momentum portfolio takes long positions in the winner futures that have the best cumulative returns in the formation period and it shorts the worst-performing futures. The long and short positions are held for 1 month and then the portfolio is

rebalanced based on the monthly repeated past performance signals. The length of the formation and holding period was based on previous articles which all found that the most profitable and hence most frequently used strategy is the 12-1 strategy ([Asness et al., 2013](#); [Moskowitz et al., 2012](#)). This translates into 12 months long formation period following a 1-month-long holding period. Within each leg, the constituents are equally weighted based on the number of securities in the groups resulting in a zero-investment strategy. Implementing these strategies is not a concern from a liquidity perspective as commodity markets are increasingly liquid and short selling is not limited. Although the portfolio is only rebalanced monthly, I also track the daily returns to measure the daily volatility of the momentum strategy. In the remainder of the research, the terms "winner-minus-loser" (WML) and "plain momentum" (MOM) will be used interchangeably.

4 Volatility scaling

4.1 Momentum crashes

One of the biggest drawbacks of the momentum strategy is that it seemingly delivers a steady flow of abnormal returns, however, it experiences major drawdowns periodically which wipes out the previously accumulated returns. Wrong timing of the momentum strategy can lead to substantial losses from which it could take years to recover. In equity markets, [Barroso and Santa-Clara \(2015\)](#) showed that investing \$1 in July 1932 would recover only in April 1963, 31 years later, effectively leaving the whole investment worthless. Using the strategy imposes a risk, especially in a long-run perspective which is why a risk-managed momentum strategy can potentially realize higher returns by avoiding these periods or mitigating their impact over a longer horizon.

There is suggestive evidence that the time variation in betas is driving the crashes ([Daniel and Moskowitz, 2016](#)). Mostly, the crashes occur in equity markets when the market rebounds quickly and as the past prices do not reflect this information about the trend change, the momentum performs poorly. The reason behind this is that by buying past winners and selling past losers by definition the strategy takes a long position in high beta stocks while shorting the low beta stocks, however after a market crash as it is rebounding, the strategy takes a long position in the low beta stocks and shorts the high beta stocks that fell simultaneously with the market in the past months. It results in a large negative beta position leading to huge losses. The two main examples often brought up by researchers in equity markets are (1) the rebound in 1932 after the Great Depression that started with Black Tuesday in 1929 and (2) the rebound in 2009 after the Great Recession that started just after the housing bubble burst in the United States. However, we can see examples of smaller crashes that also have a big impact on the overall performance over time.

4.2 Forecasting momentum crashes

4.2.1 The market state

As we know which periods are more prone to possible crashes, the main question is whether we can actually forecast them. When the markets rebound, we can observe that the longer, past 2 or 3-year cumulative return of the market is usually negative as it experienced negative shocks however, the contemporaneous market return is positive. This is exactly what is reflected in the short and long legs of the WML portfolio. The divergence between long-term and short-term returns proved to be an efficient tool in equity markets to forecast the expected returns of the momentum strategy ([Daniel and Moskowitz, 2016](#)).

4.2.2 Momentum Gap

Another forward-looking indicator of a momentum crash is the momentum gap introduced by Huang in his paper. The momentum gap is calculated by measuring the difference between either the 25th and 75th percentiles or the 90th and 10th percentiles of the distribution of cumulative stock returns of the formation period ([Huang, 2022](#)). In my research, I used the latter approach as I calculated the momentum gap as the difference between the 90th and 10th percentiles. Its correlation to the momentum returns is negative indicating that when the momentum gap gets too wide it might experience a reversal effect resulting in lower returns. [Huang \(2022\)](#) didn't find an exact explanation for the momentum gap, although he found that it's not related to limits-to-arbitrage but rather associated with stock-level mispricing. Based on the findings the author suggests an explanation that's based on the deviation from real value due to underreaction and overreaction in the formation period which might revert in the holding period hence the strategy depends on the relative value of the indicator. [Huang \(2022\)](#) used it to decide whether to invest in the momentum portfolio or not, earning a better yield than the plain winner-minus-loser strategy. In my research, I used the momentum gap to help me forecast the expected return of the momentum portfolio and I used that insight in the volatility scaling process.

4.3 Negative volatility-return relationship

The Capital Asset Pricing Model (CAPM) established that the expected return has a linear positive relationship with risk. The beta of an investment describes its relative riskiness to the market portfolio. If an asset is riskier than the market then it will have a larger beta which translates into a higher expected return as compensation. Generally, we can assume that having a more volatile investment means also taking on higher risk as price fluctuations can be more dramatic in a shorter period so in theory, the risk-return relation should be positive. Although it might be true on paper, the empirical evidence shows differently. In the case of the momentum strategy, a negative relationship can

be observed (Barroso and Santa-Clara, 2015). Conditional on the previous six months realized volatility of the momentum returns, the next one year's return is substantially higher in a low volatility environment while the returns diminish in case of high volatility. It seems that a negative relationship is present which indicates that the winner-minus-loser portfolio generates significantly better when the volatility is low.

4.4 Methodology of momentum scaling

Based on this empirical evidence, volatility scaling was devised and applied to momentum trading strategies. The main idea behind it is that by scaling the long and short legs of the portfolio with the realized variance, the returns will experience fewer crash events. Barroso and Santa-Clara (2015) showed that the WML strategy is usually more volatile than the market portfolio however, its one-month realized variance is more predictable for both in-sample and out-of-sample hence the past realized volatility can be used as a proxy for future volatility. In my paper, I used 3 different volatility scaling strategies:

1. *Constant volatility-scaling*
2. *Dynamic volatility-scaling*
3. *Enhanced dynamic volatility-scaling*

In the case of the first one, the momentum is simply scaled to a constant volatility level which implies a constant risk level over time. The weight is defined by the following formula:

$$w_{cMOM,t} = \frac{\sigma_{target}}{\hat{\sigma}_t} \quad (5)$$

The $\hat{\sigma}_t$ is the expected volatility which is proxied by the previous six months realized volatility following Barroso and Santa-Clara (2015).

$$\hat{\sigma}_{MOM,t}^2 = 21 \sum_{j=1}^{126} R_{MOM,d-j,t}^2 / 126 \quad (6)$$

This equation is exactly identical to the Equation (4) that I used to calculate the market volatility. The σ_{target} was chosen as the annualized volatility of the plain momentum strategy as it gives a base for better comparison between scaled strategies. This weight by composition can only take up positive numbers or 0 as values. This method only mitigates the negative returns' impact.

The dynamic volatility scaling eliminates the problem that the weight cannot take up negative values by incorporating also the expected return of the momentum strategy hence it's able to gain even when the plain winner-minus-loser portfolio loses money. Following Daniel and Moskowitz (2016), I define the dynamic scaling in month t as

$$w_{dMOM,t} = \left(\frac{1}{2\lambda} \right) * \frac{\hat{\mu}_t}{\hat{\sigma}_t^2} \quad (7)$$

The λ is a time-invariant scalar introduced by [Daniel and Moskowitz \(2016\)](#) however the $(\frac{1}{2\lambda})$ essentially equals to the σ_{target}^2 . In this weighting scheme, the w can turn into negative by having a negative forecast for the expected momentum return. By having this attribution, the weights for the dynamic scaling might vary more. The $\hat{\mu}_t$ is calculated for every t by running a regression on the WML returns and forecasting it into the future. The regression looks like this:

$$R_{MOM,t} = \gamma_0 + \gamma_1 * I_{Bear,t-1} + \gamma_2 * \sigma_{GSCI,t-1}^2 + \gamma_3 * I_{Bear,t-1} * \sigma_{GSCI,t-1}^2 + \epsilon_t \quad (8)$$

The enhanced dynamic volatility scaling also includes the previously introduced momentum gap as a predictor variable and it also contains the past 2-years market returns resulting in the following regression:

$$R_{MOM,t} = \gamma_0 + \gamma_1 * I_{Bear,t-1} + \gamma_2 * \sigma_{GSCI,t-1}^2 + \gamma_3 * I_{Bear,t-1} * \sigma_{GSCI,t-1}^2 + \gamma_4 * MG_{10th,90th} + \gamma_5 * MKT R_{-2y} + \epsilon_t \quad (9)$$

In both cases, the variance in the denominator is calculated by exactly the same formula shown in [Equation \(6\)](#). After calculating the weights for all the different scaling methodologies, the momentum returns are calculated by simply multiplying the plain momentum returns by the w :

$$R_{cMOM/dMOM/dMOM_{ZS},t} = R_{MOM,t} * w_{cMOM/dMOM/dMOM_{ZS},t} \quad (10)$$

5 Results

In this section, I present the result of my analysis of the momentum in US commodity futures over the 1979-2024 time period.

5.1 Unscaled momentum portfolio performance

5.1.1 Negative momentum returns

[Figure 1](#) shows the cumulative performance of the strategy over the sample period. The results go against the previously established literature as the plain momentum strategy loses money over time. During the 1990s which is considered to be a well-performing period for momentum strategies across asset classes, we can see good results that are consistent with other researchers' findings. However, especially after the financial crisis, the momentum strategy underperforms in the subsequent periods leaving an unremarkable performance. Looking at [Table 2](#), the annualized performance of the winner-minus-loser portfolio is -6.3% . It means that investing \$1 in this strategy at the start of 1979 would result in \$0.07 which is an overall 93% loss of investment. The table also highlights summary statistics of the market portfolio. It seems that the market outperforms significantly

Summary statistics for the momentum strategy and the market portfolio

Strategy	Maximum	Minimum	Mean	Standard deviation	Kurtosis	Skewness
GSCI	26.6%	-43.4%	2.0%	22.9%	6.23	-3.38
WML	24.3%	-22.7%	-6.3%	19.87%	1.38	-0.85

Table 2: The table shows the long-run performance of the momentum strategy which buys the past winners and sells the past losers (*WML*) and the market portfolio proxied by the *GSCI*. Reported are the maximum and minimum one-month returns observed in the sample, the mean average return (annualized), the (annualized) standard deviation, excess kurtosis, and skewness. The sample returns are from 1979:01 to 2024:04.

my strategy as it gains annually 2%. The unsettling finding based on the table is that the skewness is higher for the GSCI by far. The momentum still has negative skewness that the volatility scaling aims to mitigate however, the market portfolio appears to be more prone to crashes. It leads to the conclusion that the WML strategy is underperforming but it's not due to huge periodical crashes but rather consistently losing money as the winners underperform and losers outperform. Still, managing the risk of the momentum portfolio proves to be important as the distribution has pronounced negative skewness.

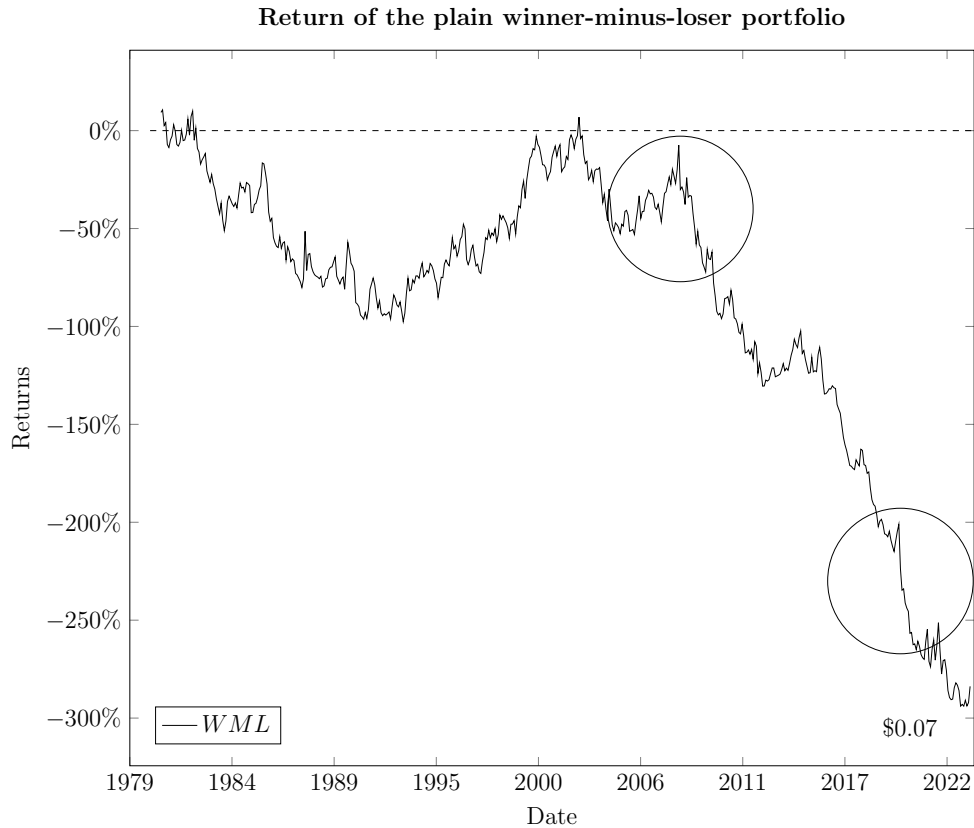


Figure 1: Plotted are the cumulative returns to the plain winner-minus-loser portfolio over the full sample period 1979:01 to 2024:04. In the plot I also mark the final dollar value for the portfolio, given a \$1 investment in 1979:01. The circles highlight the two worst periods of the momentum strategy when it experienced the biggest crashes over the entire time horizon I examined.

5.1.2 Characteristics of the crashes

Taking a look again at [Figure 1](#), although the flow of negative returns seems to be constant, the return profile is still characterized by huge crashes that further deteriorate the performance. The highlighted crashes happened amidst the financial crisis and the COVID crisis. Looking at [Table 3](#), the COVID period was full of turmoil in the commodity sector marking some of the worst crashes appearing among the top 15 worst months. Previously I mentioned that the biggest crashes in equity markets tend to happen when the market rebounds ([Daniel and Moskowitz, 2016](#)) nevertheless, we cannot observe a similar tendency in this case. An interesting observation is that the worst-performing months happen usually after a big rally or sell-off in the market portfolio. This might indicate that the market state factors can contain additional information. Another characteristic of the crashes, compared to other markets, is they are smaller in volume as these negative returns do have a significant impact however, they do not eliminate entirely the cumulated returns. On the other hand, the losses are more stable meaning that in [Table 3](#) the 15th worst month's return is still more than half of the worst month's return in absolute value. In [Barroso and Santa-Clara \(2015\)](#), the gap between the samely ranked returns is much wider.

Worst monthly momentum returns				
Rank	Month	MOM	$MKT R_{-2y}$	$MKT R_t$
1	2008:7	-22.7%	56.7%	13.5%
2	2020:4	-22.6%	-69.8%	-10.0%
3	1988:6	-20.1%	13.4%	-1.2%
4	2021:11	-16.3%	34.6%	6.0%
5	1991:2	-16.1%	6.9%	-10.3%
6	2010:4	-15.9%	-30.1%	3.5%
7	1997:1	-15.6%	19.1%	-5.6%
8	1982:6	-14.9%	-17.5%	-5.4%
9	2022:6	-14.3%	95.5%	5.3%
10	1986:6	-14.3%	-34.8%	-11.9%
11	2012:9	-14.0%	26.3%	6.0%
12	2002:2	-13.8%	-24.5%	5.7%
13	1985:7	-13.8%	-12.4%	-4.3%
14	2022:7	-11.9%	72.2%	-15.6%
15	2006:5	-11.5%	44.4%	-3.8%

Table 3: The table lists the 15 worst monthly returns of the momentum strategy over the 1979:01 - 2024:04 time period. The table also lists the the past two-year market returns (MKT_{-2y}) and the contemporaneous market return (MKT_t).

5.2 Volatility scaled strategies

5.2.1 Constant volatility scaling

Figure 2 shows us the annualized volatility of the momentum strategy in each month. The strategy is characterized by high volatility spikes that happen throughout the whole sample period. The 1990s is the only exception as the volatility in those years till 2006 seems to be more contained. Hence we can make the assumption that when the momentum strategy experiences high volatility then the strategy underperforms just like what we see in Figure 1 between 1980 and 1990 and also in the 2010s. While in the calmer periods, the momentum strategy slowly but steadily accumulates returns. As shown by Barroso and Santa-Clara (2015), the volatility is more predictable based on past volatility. Using Equation (6), I calculate the past 126 days' volatility of the WML strategy and scale the returns to it based on Equation (5). The constant volatility scaling should prove to be efficient as it can avoid major spikes and the negative returns associated with them.

Figure 3 somewhat support this theory. Looking at the chart, it shows us that based

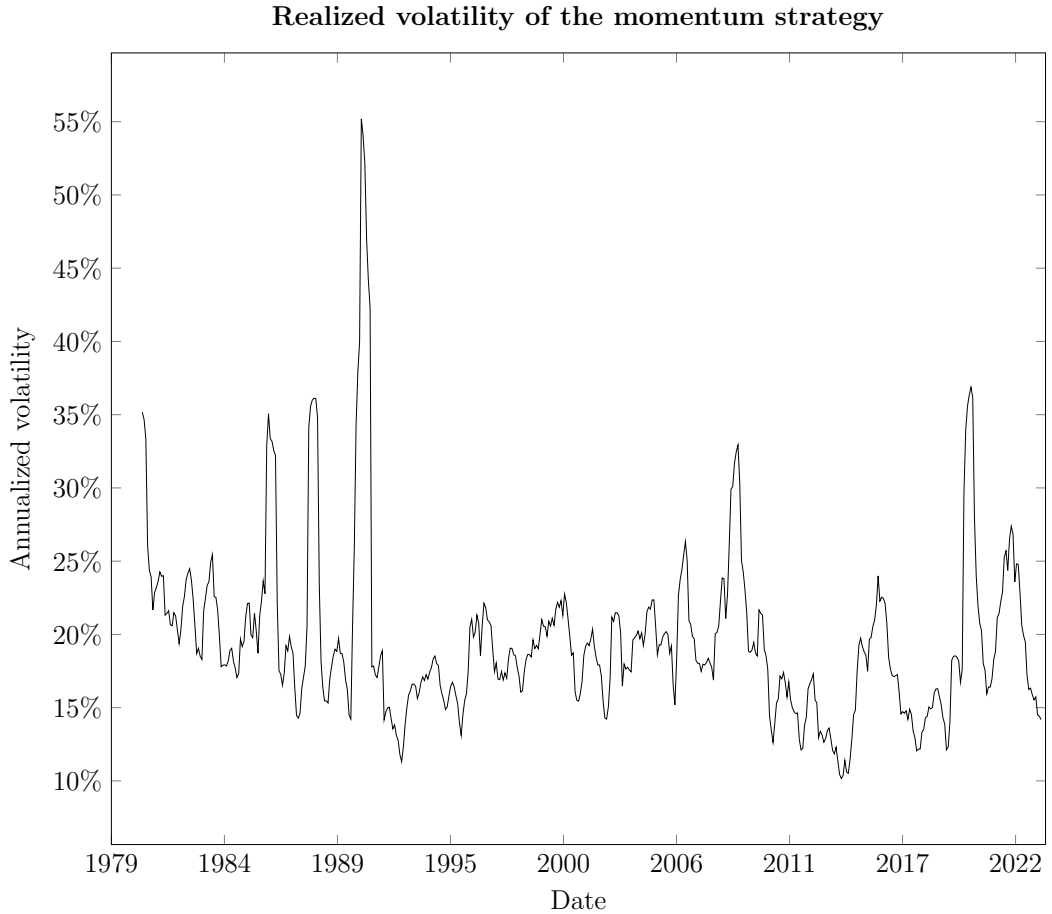


Figure 2: The figure shows the realized volatility of momentum strategy obtained from daily returns in each month from 1979:01 to 2024:04. The volatility is annualized, calculated by $\sigma_{MOM,t} = \sqrt{252 \frac{\sum_{j=1}^{21} r_{MOM,d-j,t}^2}{21}}$.

Risk-return relationship of the momentum and market portfolio

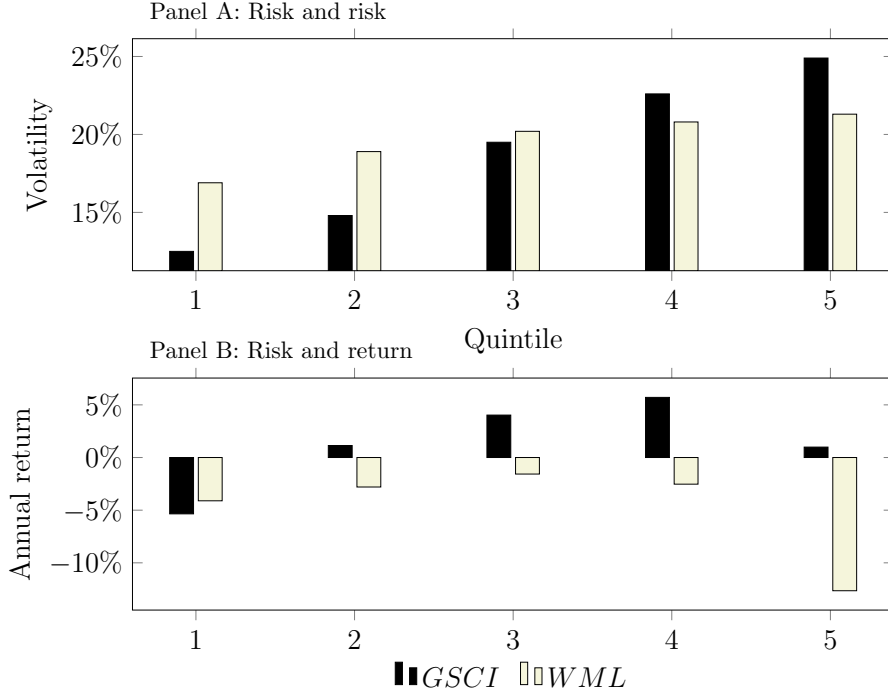


Figure 3: The figure highlights the performance of the market index (*GSCI*) and momentum strategy (*WML*) conditional on realized volatility in the previous six months. Returns are sorted into quintiles according to volatility in the previous six months, Quintile 1 represents the months with the smallest volatility while Quintile 5 contains the months that are most volatile. Panel A presents the following year's volatility computed from daily returns, Panel B shows the cumulative returns. The sample period is from 1979:01 to 2024:04.

on the previous six months' return volatility defines the next one-year return volatility. It can be observed in both the market portfolio and the WML strategy as well. On the flip side, the risk-return relationship is not so straightforward. The least volatile periods tend to lose money on average in case of both investments. This partially goes against what we saw in [Figure 1](#) and [Figure 2](#). The most interesting finding in this table is in connection with *Quintile 5*. Although we cannot see a simple explanation for the other quintiles' behavior, it's still plain and simple that after the most volatile months, neither the momentum strategy nor the market performs well. The former one yields an annual -12.65% return on average. Those months are the ones that truly drag down the performance.

5.2.2 Dynamic volatility scaling

In the case of the dynamic volatility scaling the most important thing is the forecast of the expected return of the WML strategy as we use it as part of the scaling methodology. Following [Daniel and Moskowitz \(2016\)](#), I use the same regression described earlier ([Equation \(8\)](#)). The results of the regressions can be seen in [Table 4](#) from columns 1 to 3. In line with my previous findings, the bear market indicator solely does not explain

any variation in the returns. This was also the conclusion based on Table 3 as the crashes are not really related to whether the market actually went up or down before. However, we can see in the 2nd and 3rd regressions that the market volatility explains more in the variation of the returns. In both regressions, it stays significant at a 5% significance level while the coefficient does not change meaningfully which is a sign of its robustness. The bear market indicator's t-statistics increases however, it doesn't become a significant variable at the conventional significance levels just like the interaction between the two variables. The coefficient of the market volatility is negative backing the results that high volatility decreases the expected returns.

My enhanced regression is based on Equation (9) and the results in Table 4 can be seen in the last 3 columns. Just like in Huang (2022)'s paper the momentum gap negatively predicts the returns and it's significant at 5% significance level. The widening between the best-performing and worst-performing assets eventually results in a reversal that can be partially predicted by the momentum gap also in commodity markets. Just like the bear indicator, the past market return is omissible, at least it cannot explain meaningfully

Regressions for momentum return estimation

Coefficients	Regressions					
	(1)	(2)	(3)	(4)	(5)	(6)
α	-0.004 (-1.23)	0.005 (1.6)	0.011 (2.4)	0.016 (1.6)	-0.006 (-2.6)	0.026 (2.3)
γ_1	-0.004 (-0.9)		-0.011 (-1.7)			-0.006 (-0.9)
γ_2		-2.012 (-4.2)	-2.931 (-4.0)			-3.372 (-4.7)
γ_3			1.227 (1.23)			2.269 (2.5)
γ_4				-0.040 (-2.0)		-0.034 (-1.7)
γ_5					0.011 (1.2)	0.026 (2.0)

Table 4: This table lists the estimated coefficients (Newey-West t-statistics) for a set of time series regressions based on the following regression specifications: (1) $R_{MOM,t} = \gamma_0 + \gamma_1 * I_{Bear,t-1} + \gamma_2 * \sigma_{GSCI,t-1}^2 + \gamma_3 * I_{Bear,t-1} * \sigma_{GSCI,t-1}^2 + \epsilon_t$ where $I_{Bear,t-1}$ is the bear market indicator and $\sigma_{GSCI,t-1}^2$ is the variance of the GSCI's daily returns over the previous 6 months and (2) $R_{MOM,t} = \gamma_0 + \gamma_1 * I_{Bear,t-1} + \gamma_2 * \sigma_{GSCI,t-1}^2 + \gamma_3 * I_{Bear,t-1} * \sigma_{GSCI,t-1}^2 + \gamma_4 * MG_{10th,90th} + \gamma_5 * MKT R_{-2y} + \epsilon_t$ where MG is the momentum gap which is the difference between the 90th and 10th percentiles of the formation period returns and $MKT R_{-2y}$ is the GSCI's cumulative return for the past 2 years. Each regression is estimated using monthly data over the 1979:01 - 2024:04 sample period.

the variation of the WML returns. As per the last column, it contains all of the variables altogether. The market volatility's coefficient doesn't change moreover, the t-statistics of the variable even increases. The momentum gap also remains negative but its t-statistics drops to -1.7. However, the interaction variable and the market return variable become significant at the 5% significance level indicating that the market state factors have value to add to my expected return calculations. Another item to highlight is the α in the regressions. According to the results, after controlling for all these variables, there still remains some variation that they cannot explain as the α is significant in multiple regressions. Finding additional variables can be a way to further enhance my strategies.

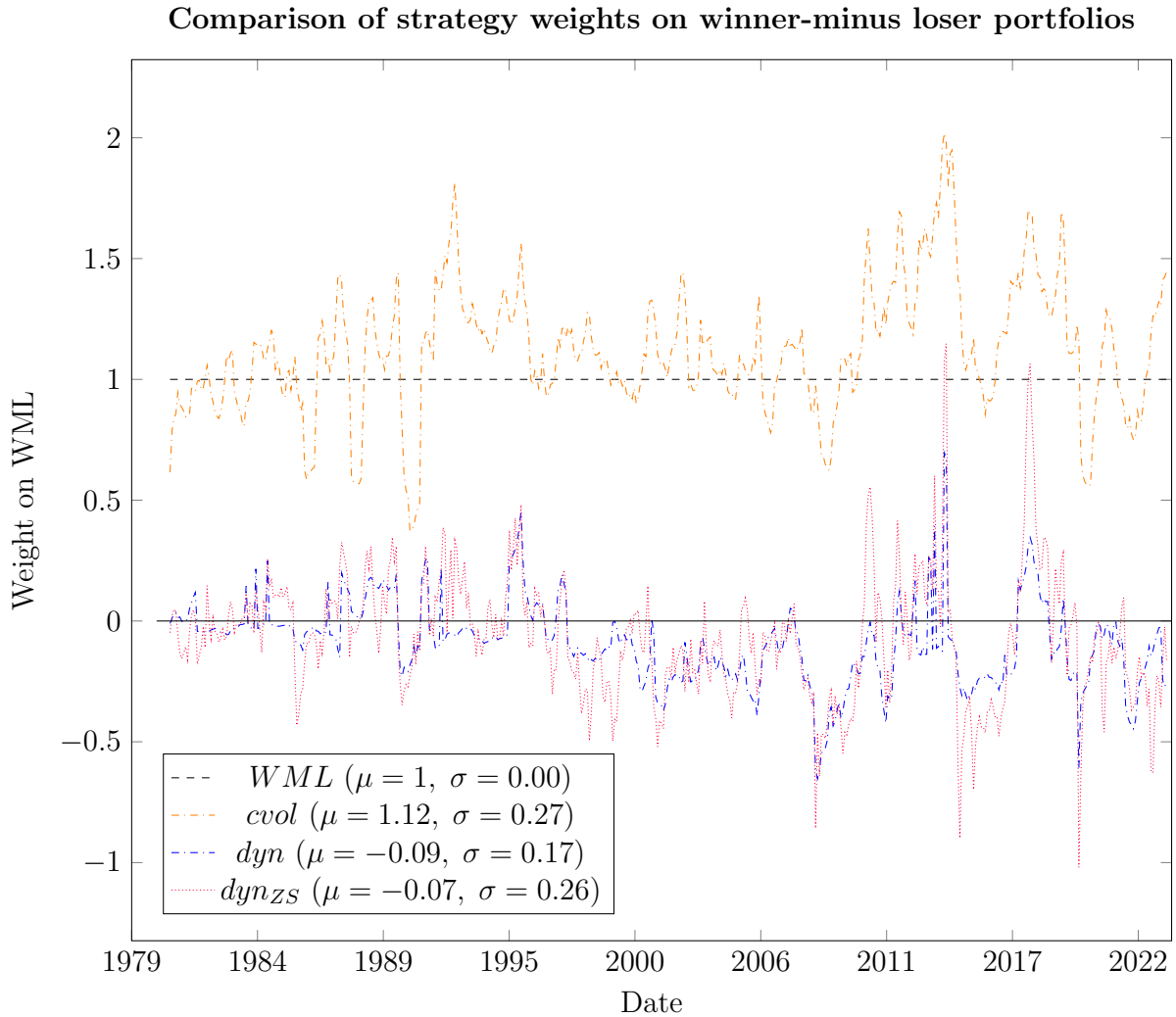


Figure 4: The figure shows the variation in different weights on the WML portfolios throughout my sample period from 1979:01 to 2024:04. I examine 3 different volatility scaling methodologies: (1) the constant volatility strategy ($cvol$), (2) the dynamic strategy (dyn) and (3) the enhanced dynamic strategy (dyn_{zs}). The figure legend reports the time series mean and standard deviation for the WML weight for each portfolio.

5.2.3 Weights of the strategies

In the next sections, I used the results of the third and sixth regressions from Table 4 to calculate the expected returns for Equation (7). In Figure 4, the w of the different strategies are plotted through the entire sample period. By definition, the $cvol$, referring to constant volatility scaling, cannot go below zero and it fluctuates around one. On the other hand, the dynamic strategies are mostly negative. This is driven by the fact that the regressions forecast negative returns in a lot of cases but the returns are not too big that's why these scales do not vary on a wider range than $cvol$. In case of the constant volatility scaling the time-series pinpoints exactly the period when there was higher volatility based on Equation (6). The huge spikes before 1990 can be seen also in this figure, and the strategy takes a position that is less than one signaling that the volatility is too high hence the return is more likely to be negative. The dynamic scales turn negative almost constantly during the financial crisis and also in the 2010s. The enhanced dynamic scaling varies more and it takes bigger values in terms of absolute value. Overall, the weights appear to be in line with the preliminary analysis.

5.2.4 Performance of the volatility scaled strategies

Table 5 shows the comparison of performance between the four momentum strategies. The constant volatility scaling methodology improves the performance by almost +2% annually although the return is still negative which is expected because its w cannot go negative. This scaling reduces also the excess kurtosis and its skewness is slightly

Comparison of different volatility scaled momentum strategies' performance

Strategy	WML	$cMOM$	$dMOM$	$dMOM_{ZS}$
Maximum	24.3%	27.9%	7.6%	14.6%
Minimum	-22.7%	-20.9%	-9.0%	-6.4%
Mean	-6.3%	-4.7%	2.1%	2.8%
Standard deviation	19.9%	21.2%	4.4%	5.7%
Kurtosis	1.38	1.13	11.72	16.32
Skewness	-0.85	0.21	2.08	8.06

Table 5: The table presents the result of 4 differently scaled momentum strategies, namely (1) the plain momentum strategy (WML), (2) the constant volatility scaled momentum strategy ($cMOM$), (3) the dynamic scaled momentum strategy ($dMOM$) and (4) the enhanced dynamic volatility scaled momentum strategy ($dMOM_{ZS}$). WML is the baseline winner-minus-loser momentum strategy. $cMOM$ is momentum scaled to a constant volatility level by its six-month past volatility. $dMOM$ and $dMOM_{ZS}$ are momentums scaled by their forecasted returns relative to their realized variances over the preceding 126 trading days. The difference between the scalings is in the regression of the forecasted returns, $dMOM$ uses a bear market indicator and market volatility based on the last 126-days daily volatility (Equation (8)) while the $dMOM_{ZS}$ strategy incorporates additional dependent variables, namely the momentum gap and the past 2-years cumulative market return (Equation (9)). The results are annualized. The analysis is performed on the whole sample period starting from 1979:01 to 2024:04.

Cumulative performance of the volatility scaled momentum strategies

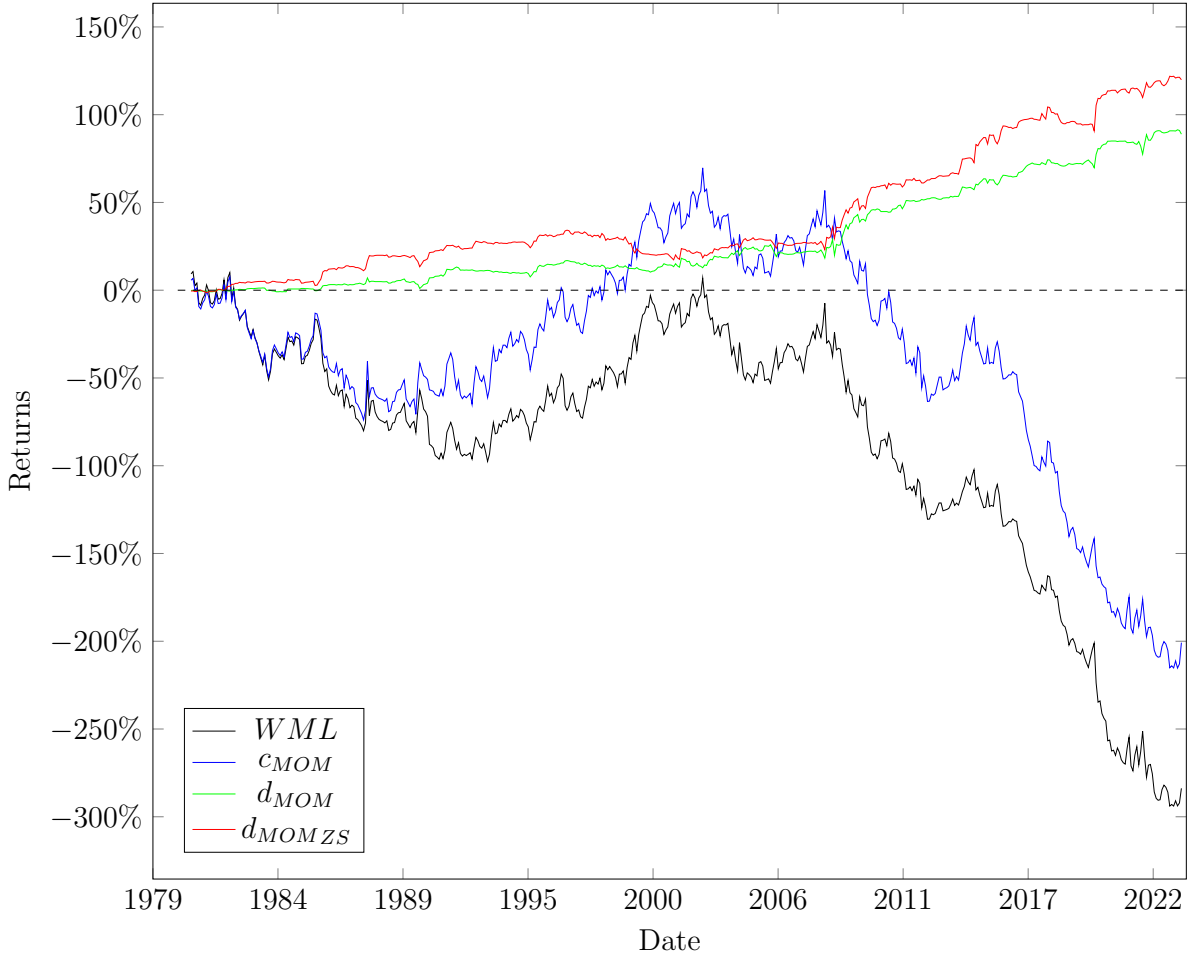


Figure 5: This figure displays the cumulated performance of each of the volatility scaled momentum strategies and the plain momentum for the full sample period from 1979:01 to 2024:04. The following strategies are comprised: *WML*, *cMOM*, *dMOM*, and *dMOM_{ZS}*. *WML* is the baseline winner-minus-loser momentum strategy. *cMOM* is momentum scaled to a constant volatility level by its six-month past volatility. *dMOM* and *dMOM_{ZS}* are momentums scaled by their forecasted returns relative to their expected variances. The difference between the scalings is in the regression of the forecasted returns, *dMOM* uses a bear market indicator and market volatility based on the last 126 days daily volatility while *dMOM_{ZS}* contains two additional dependent variables, the momentum gap and the past 2-years cumulative market return.

positive indicating that the risk management works. Most of the crashes are avoided through scaling with past volatility. In Figure 5, *cMOM* performs well in the previously mentioned 1990s period when the cumulative return improves a lot reaching into positive return territory. However, in the 2010s and 2020s, the overall performance of the strategy falls short. Its volatility is slightly higher than the plain *WML* strategy which can be understood by looking at Figure 4 as *cMOM*'s w ranges between 0.5 and 2 so although it avoids crashes which makes the strategy less volatile it also takes part in the rallies with a multiplier. Daniel and Moskowitz (2016) found similar characteristics but this elevated volatility comes with a greater increase in returns resulting in a higher Sharpe ratio.

The dynamic volatility scaled strategies yield positive return at the end of the sample period and it stays positive all times. $dMOM$ ends up generating a 2.1% annual return while my enhanced strategy outperforms it by 0.7 %pt. Both strategies have relatively low standard deviation which was already pointed out earlier. It's due to the fact that the expected return regressions calculate pretty small negative returns hence resulting in small ws . The return distributions are positively skewed meaning that the right tail is longer which is especially true for $dMOM_{ZS}$ as it has an extreme right skewness of 8.06. In [Figure 5](#) the dynamic strategies go hand in hand however the $dMOM_{ZS}$ slowly outperforms the conventional $dMOM$ by [Daniel and Moskowitz \(2016\)](#). After 2010, when the WML and $cMOM$ started to accumulate massive losses, the dynamic strategies continuously gain money by consistently earning small amounts of positive returns. The biggest jump can be seen in 2020, in the COVID era as the only sharp increase happened that time. Overall, the dynamic volatility scaled strategies outperformed the plain winner-minus-loser portfolio and the constant volatility scaled portfolio as well. Due to the methodology, the overall volatility of the momentum is contained, and by forecasting the expected return, the performance is highly increased.

6 Conclusion

The previously documented momentum anomaly ([Miffre and Rallis, 2007](#); [Bianchi et al., 2016](#); [Xu and Wang, 2021](#)) in commodity markets seems to perform well below the market portfolio in my sample period. The crashes occur more frequently than in equity markets and they are more widespread meaning that it does not only occur when the market rebounds ([Daniel and Moskowitz, 2016](#)). The momentum strategy experiences huge spikes of volatility in this 45-year-long time horizon. Especially the years before the 1990s and after the 2010s seem to experience more volatility. The risk-return relationship tells us that the biggest crashes happen after the most volatile periods which is why managing the risk of the portfolio is a good idea. In line with other articles, I find that the volatility-scaled strategies outperform the plain momentum. They reduce the excess kurtosis and negative skewness in other words the tail risk. The dynamic strategies by allowing them to have negative weights, perform an almost 3% annual return which is an improvement of around 8 %pt over the WML strategy.

These results reflect the findings of the previous works done by researchers. Although the overall performance of the momentum strategy is negative, risk management plays a huge role in improving the momentum strategy. The correlation between past and future volatilities is pervasive in the commodity future markets as well. The risk profile is different than what we saw in equity markets but the tools, developed in that market, are efficient here as well. The results partially support the well-established literature but it imposes a few questions about the momentum strategy in a longer time horizon.

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