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MOMENTUM CRASHES IN US STOCKS, RECENT EVIDENCE DURING THE COVID-19 CRISIS

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UNIVERSITY OF OULU ABSTRACT OF THE MASTER'S THESIS
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Abstract

Cross-sectional momentum has been one of the most persistent return anomalies to provide high levels of abnormal returns in most markets and asset classes over long time periods. While scientific literature is still inconclusive on the core cause of the anomaly, a significant amount of research has been published confirming the existence of abnormal returns related to the phenomenon.

Momentum also has its downsides, or its moments, as previous researchers have expressed it. The strategy occasionally experiences large streaks of negative returns, which can wipe out a significant part of the value of momentum portfolios within only a few months. These momentum crashes can take decades to recover from for the strategy and are an important consideration for both researchers and investors seeking to profit from the abnormal returns or diversification benefits that the strategy has provided.

As momentum crashes have been found to happen during rebounding markets after market crashes, this thesis studies the momentum crash following the recent market downturn caused by the COVID-19 pandemic and takes a modern look at both momentum and momentum crashes in the US stock market by studying three different momentum strategies formed in previous research with data from January 1990 to March 2022. It also introduces a risk-managed momentum strategy that scales the weights of a traditional 1st decile momentum strategy based on the lagged value of the VIX index compared to its ten-year simple rolling average, up to the previous month.

The results show that momentum portfolios had large negative returns in the year following the market downturn caused by the COVID-19 crisis at the start of the year 2020. The negative returns for all studied momentum portfolios were caused by the highly positive returns of the shorted portfolio in the strategy during a market recovery period, similar to prior research results on momentum crashes. The Vix-based risk-managed momentum strategy successfully lowered the effects of momentum crashes compared to its base strategy and provided statistically significant abnormal returns and higher Sharpe ratios compared to the three traditional momentum portfolios throughout the studied time period. Successfully using a lagged value of a market-based index to predict the volatility of momentum has both practical implications, as well as possibly interesting implications for future research on momentum.

The traditional 1st decile momentum strategy saw significantly larger losses during momentum crashes compared to 3rd decile momentum strategies; however, the 1st decile portfolio still has higher mean returns than 3rd decile momentum portfolios over a long time period. This suggests that managing the downside risk of aggressive momentum strategies has been extremely important during the 21st century to maximize the benefits of the return anomaly.

Keywords

momentum, momentum crash, risk-managed momentum

Additional information

CONTENTS

FIGURES

TABLES

1 INTRODUCTION

Momentum has been one of the most persistent and significant stock return anomalies over the past several decades, and a large amount of research has been written on the subject. Momentum has been a well-known return anomaly in the US stock market ever since the end of the 20^{th} century and has been later found to exist across a significant amount of asset classes globally.

Despite being well-researched and widely documented, the return anomaly has persisted and has been shown to provide statistically significant risk-adjusted excess returns and Sharpe Ratios when compared to the relevant benchmark market portfolios globally over long periods of time. There are relatively few cases studied in large markets, where statistically significant momentum does not seem to exist over long time periods.

However, momentum also has significant downsides. The returns of the momentum strategy have been found to have significant kurtosis, and there are short periods of massively negative returns found across the scientific literature on the topic. These momentum crashes can cause the value of a momentum investor's portfolio to reduce so drastically that it would take investors with poor timing decades to recuperate their losses if they invested in momentum right before a crash occurred.

Momentum has also behaved somewhat differently in the past decade compared to the results of previous studies in the US stock market. The profitability of the classical t-12 to t-2 decile cross-sectional momentum portfolios formed from US stocks where past winners are bought long, and past losers are sold short show significantly different results over the past decade compared to long-term momentum studies. Unlike previous times of economic growth, the overall profitability of the classic momentum portfolios during a period of significant growth and high stock market returns has not been all that impressive.

Generally during economic upturns and long-term bull markets, crash periods following economic crises excluded, is where the momentum strategy provides significant risk-adjusted abnormal returns, and these periods of high returns are what cause the anomaly to have its impressive excess returns over long periods of time, despite the downsides of the strategy like massive momentary negative returns caused by momentum crashes. This leads to questions about whether something about momentum has fundamentally changed as the return anomaly has now been well-known for almost 3 decades, or whether the anomaly still behaves similarly to the findings of previous research and is being affected by other outside factors that have caused a somewhat long-term slump in its returns since the financial crisis of 2008.

One potential explanation for the poor returns of momentum since the financial crisis could be the unprecedented long period of extremely low interest rates that followed the 2008 financial crisis. This could logically cause more investors to seek investment opportunities in stocks due to bonds offering poor returns during these periods, and a potential reason for the poor returns of momentum would be this having a causal effect with the shorted portfolio of momentum performing exceptionally poorly during this period as a result of more investors seeking to buy even poorly performing stocks due to lessened returns on bonds as the common alternative investment option.

Alternatively, perhaps investor behaviour has fundamentally with regards to the factor. This could be based on increased investor knowledge of the behaviour of the factor, and new technologies such as algorithmic trading becoming more common, or the overall reduction in trading costs that has happened since the factor was brought into wide public scientific knowledge by Jegadeesh and Titman (1993).

The increasing amount of research and general knowledge about momentum might cause fundamental changes in the return anomaly. This may also be especially relevant, since the strategy has generally been found to be more viable in practice to institutional investors due to lower average trading costs, which help offset the significantly high turnover of assets in momentum portfolios. Grinblatt and Keloharju (2000) and Baltzer, Jank and Smajlbegovic (2019) both found when studying stock market holdings in Finland and Germany respectively, that foreign institutional investors were the investors that were the most likely to trade on momentum. Considering the higher level of sophistication among these investors, it stands to reason that their behaviour in the market may fundamentally change faster than that of retail investors as more scientific information is published on the subject.

This also leads into questions regarding momentum crashes. If momentum has been less profitable in the past decade and there seem to be some changes in its behaviour, how do these changes reflect on momentum crashes? If the returns of momentum strategies have reduced significantly over the past decade, does this mean momentum crashes would also be reduced in severity? Perhaps the increased knowledge about the subject could have changed investor behaviour to the point where momentum crashes do not exist anymore, or alternatively become even more severe? Or perhaps despite the reduced excess returns of momentum in recent years, momentum crashes still occur similarly to previous findings, and are perhaps even caused by to the exact same reasons as have been previously studied.

Momentum crashes may also get worse as a potential outcome of investors being more aware of the downsides of momentum strategies, as more research gets published on the subject, due to the nature of short-selling. As noted by Kent and Moskowitz (2016), momentum crashes are mostly driven by the shorted loser portfolio having significant positive returns during the market recovery period following a sharp downturn in the US stock market caused by economic crises. As more investors become aware of momentum crashes and seek to avoid them, this could lead into less investors selling short the stocks in the loser portfolio in the periods following momentum crashes, driving the positive returns of the portfolio to be even higher during recovery periods, which would cause the returns for the momentum strategy to suffer even more as this is the shorted portfolio in the strategy. These effects could lead to traditional momentum investors without tail-risk adjustments in their strategy experiencing even larger losses than before.

Several previous researchers such as Barroso and Santa-Clara (2015) and Kent and Moskowitz (2016) have also proposed risk-adjusted decile momentum strategies as a result of their findings about momentum crashes. These strategies have managed to keep the upside of high returns of the 1st decile momentum strategy, while limiting the downside of momentum crashes. This paper will also construct a risk-managed momentum strategy based on the past value of the CBOE Volatility Index ("VIX") as an estimate of volatility and scale the classical 1st decile momentum strategy with it to see the results of the strategy including how well it has survived the most recent momentum crashes.

The strategy is inspired by the findings of Barroso and Santa-Clara (2015), who find that scaling the weight of the first decile WML portfolio based on an estimate of current period volatility produces statistically significant risk-adjusted returns, and significantly reduces the severity of momentum crashes.

While the strategy introduced in this paper differs significantly in some respects, such as the source of the volatility estimation used to scale the portfolio, the core idea of scaling the weights of a 1st decile momentum portfolio, based on an estimate of current period volatility to reduce the impact of momentum crashes, and aim for abnormal returns this way compared to traditional momentum strategies is similar. To the best knowledge of the author, the strategy used in this paper has not been published before its release.

This paper will form various momentum portfolios based on the well-known data set provided by Kenneth R. French (2022) in his data library. The usage of this publicly available data ensures that the results and findings of this paper are robust and can be repeated easily for further studies on the topic, or related topics.

As different methods for forming traditional momentum portfolios have been used in previous research, the paper will study several different types of momentum portfolios which are formed monthly to see if significant differences can be observed between the different types of portfolios. The four main types of momentum portfolios associated with previous research that will be formed for the paper are as follows:

Traditional 1st decile portfolios formed during t-12 to t-2, where the stocks in the top decile of returns is bought long, and stocks in the bottom decile of returns are sold short, as used by Barroso and Santa-Clara (2015), Kent And Moskowitz (2016) among others.

The more modern monthly 3rd decile momentum factor formed by Fama and French (2018), which constructs six value-weighted portfolios using independent sorts on stock returns and size and constructs the momentum portfolio by taking the average of the returns of the big and small high prior return portfolios and deducts the average returns of the big and small low prior return portfolios.

A similar method to the one used by Carhart (1997) which calculated the returns of stocks monthly and split the stocks into three portfolios. The top 30%, the median 40% and the bottom 30%. The average equally-weighted returns of the top portfolio is then calculated, and the average equally-weighted return of the bottom portfolio is deducted from it.

A risk-adjusted momentum strategy, where traditional decile portfolios are formed during t-12 to t-2. This portfolio then scales the weights of the long and shorted portfolio based on the value of the VIX index at the beginning of the previous period, which is compared to its 10-year rolling average during the same time period.

Chapter 3 will go more in-depth on the methods used to form the portfolios.

1.1 Purpose and Motivation of the Thesis

The purpose of this Thesis is to study and add to existing literature on momentum, primarily through studying momentum crashes, and also studying the phenomenon during recent years. The paper aims to find whether recent momentum crashes have occurred similar to the time periods following past market crises that have been documented in prior research, and to assess whether the previous behaviours and the patterns that have been found and researched about the return anomaly have applied in the US stock market during and after the recent period of stock market downturns in the US stock market caused by the COVID-19 pandemic.

Momentum crashes have significant relevance to scientific literature related to the momentum strategy and are an important, if negative, part of the momentum strategy. Therefore, they are an important part of the momentum puzzle to understand for the purpose of being able to predict and make accurate assessments related to momentum at large.

Additionally, the paper aims to study whether fundamentally different investor behaviour has been observed during the recent COVID-19 crisis, and to study potential reasons or correlations for the different behaviour based on existing, priorly researched or novel phenomena related to the return anomaly. If sound proof is found that investor behaviour seems to have fundamentally changed from recent crises, the paper will attempt to pinpoint any existing causality or correlation for the potential differences between investor behaviour during the recent crisis, and prior investor behaviour which has been researched during previous crises.

The paper aims to also add to the existing literature on risk-managed momentum strategies by forming a new type of strategy based on previous findings, and studying its performance, up to and including the COVID-19 crisis, and to see whether there are major differences in performance of the portfolio which could also apply to other similar risk-managed strategies.

The paper aims to study how US stocks have behaved during the period of high volatility that has followed the initial stock market crash at the start of the COVID-19 pandemic early in the year 2020 Through the performance of these portfolios, and if the investor behaviour in the market has changed from previous crises, as more research has been published on the behaviour of momentum during these specific times.

The paper will also include analysis of returns of the winner portfolios and loser portfolios in various momentum strategies separately from the portfolios themselves, this is aimed at analysing the drivers behind potential new momentum crashes, or any other phenomenon of interest found in the empirical part of the thesis.

The paper will also study the scaling of the multiplier related to the Vix-based risk-managed momentum strategy, and how effectively it has scaled the returns of its base strategy.

1.2 Structure of the thesis

The thesis starts with an analysis on the significant amount of prior literature written about momentum, momentum crashes and various asset pricing models. It aims to summarize the key prior research related to the main topics and themes of the paper.

Chapter three will introduce and go over the data and methodology used for the empirical part of the paper in detail. The chapter starts with going over the data used for the paper, then goes over the VIX-Index and the VIX-based risk-managed momentum portfolio formation, then goes into the formation methods for all portfolios used to obtain the empirical results. After that the chapter will discuss the theoretical framework of drawdowns which are used in the study, and then go over the sub-periods used to study momentum crashes, followed by the Fama-French 5-factor model.

Chapter four will include the empirical results. The chapter will also include analysis and commentary on the empirical results obtained. The chapter will assess various returns, one-year sub-period returns during momentum crash periods and statistical measures of the formed momentum portfolios during the COVID 19-crisis, the period following the financial crisis of 2008 and long-term results from 1990, which is the first available point of data for the VIX Index. The chapter will also include analysis on the individual winner and loser portfolios to study whether the portfolios have behaved similarly to prior research during the COVID-19 crisis, and to further analyse the empirical results and returns of the various momentum strategies.

Finally, chapter five will conclude the paper. It will include conclusions based on the empirical results of the study, and suggestions for future research on the subject, if applicable.

2 PREVIOUS RESEARCH

This section will outline relevant previous research related to momentum and momentum crashes, and the theoretical research related to the framework of the asset pricing models which are relevant to the empirical part of this paper. These include the Capital Asset Pricing Model, Fama-French three-factor model, the Carhart four-factor model, the Fama-French 5-factor model and the Fama-French six-factor model.

The section will be divided to three parts, prior research that primarily focuses on momentum, prior research that primarily focuses on momentum crashes, and prior research that relates to asset pricing models. Past research on momentum is included to better categorize and understand the factors related to momentum crashes, and to be able to draw conclusions of the current state of momentum and its related crashes based on findings in past research.

2.1 Momentum

Jegadeesh and Titman (1993) brought the momentum anomaly into general knowledge and spotlight within the scientific community. After studying a significant amount of contrarian strategies which were being discussed a significant amount in academia, they studied portfolios of buying past winners and selling past losers in a medium holding time of 3 to 12 months. In their study, they built portfolios based on buying stocks that had performed well long and shorting stocks that had performed poorly during the previous 12 months. They then formed various portfolios with varying holding times and assessed the excess returns of the portfolios with this method. They found significant abnormal returns across the portfolios. They found significant excess returns on portfolios formed with this method during the years 1965-1989 that were traded in NYSE and AMEX. They also note that the price changes that occur during the holding periods may not be permanent. They found that the stocks in relative strength portfolios that had experienced high returns during the holding time, suffer from negative abnormal returns starting approximately 12 months after the formation date, which was a trend that continued up to the 31st month. An example portfolio that had generated an excess cumulative return of 9,5% during the holding period of a year but lost more than half of its value in the following 24 months. They found the most successful zero-cost strategy to be the strategy that selects stocks based on their previous 12-month returns and holds the stocks for 3 months. The strategy generally has a high turnover, 84.8% semi-annually in one of the example portfolios, which would make trading costs significant in using the strategy in practice. However, even adjusting the results to have 0,5% one-way transaction costs still resulted in an annual profitability of 9,29%, which was also statistically significant, meaning momentum survived trading costs with these assumptions. They also found statistically significant negative returns during January, the strategy lost approximately 7% on average each January, but achieved positive abnormal returns in every other month. They however found the effect to be dependent on firm size. The January-effect on momentum portfolios was not statistically significant for large firms, while it applied to smaller firms. They found that the profitability of the strategy could not be explained by lead-lag effects that would be a result of delayed investor reactions to common factors in stock prices. Evidence was, however, found that at least part of the profitability could be explained with delayed price-reactions to company-specific information by the market. (Jegadeesh & Titman, 1993)

Grobys (2016) studied European stock returns and formed various momentum portfolios of German stocks between 2000-2014. German stocks are used to study the return anomaly in a European setting. He forms traditional 12-2 momentum portfolios, as well as 6-2 and 12-7 portfolios to study the momentum effect in stocks within the EMU. The findings of the study suggest that strong momentum-based abnormal returns existed in German stocks during the period. The traditional 12-2 momentum strategy had a mean monthly return of 1,91 during the time period, and provided positive risk-adjusted returns, significantly outperforming the market portfolio return as a zero-cost strategy. His research also found that significant negative returns happened in all the studied momentum portfolios following the 2008 market crash caused by the financial crisis, which shows that momentum crashes also occur in the European markets. However, he also notes that the financial sector faced extraordinary conditions during this time due to the simultaneous effects of the financial crisis, and the European debt crisis both occurring during the time period. To test whether these had significant effects a dummy variable was formed and found to be statistically insignificant, meaning the study found the crises to have virtually no impact on the profitability of various momentum strategies. (Grobys, 2016)

Asness, Frazzini, Israel and Moskowitz (2014) find that momentum has offered strong risk-adjusted returns for a very long time period and aim to dispel some criticism towards momentum as an investment strategy. They find that even though momentum as an investment strategy has high volatility, risk-adjusted returns have also favoured momentum over other popular factor investment strategies. However, they also note that rather than competing with the different factor models' excess returns, combining them such as using momentum and value together is likely the better solution. They also note that approximately half of the returns in momentum strategy come from the shorted portfolio, however momentum can still be used as a factor for long-only investors to capture the excess returns. They also found momentum to be a relevant driver of excess returns for both large and small stocks, although the effect was stronger in small cap stocks. They also find that momentum provides excess returns even when factoring in trading costs. Traditionally, one of the criticisms of the momentum strategy has been that it's a high turnover strategy, so the excess returns might be limited by, or even completely removed by the trading costs involved in the momentum portfolio. They refer to Frazzini, Israel, and Moskowitz (2012), who studied factor investing generally, including momentum, from the perspective of taking the trading costs of a large institutional investor, AQR, into account when evaluating the success of various factor investment styles. They found that the per-dollar trading costs of momentum were quite low, despite the high turnover, and that momentum easily survives transaction costs in this scenario. However, previous studies such as Lesmond, Schill and Zhou (2003) have taken the perspective of an average investor and found that momentum's excess returns were much more seriously hampered in this scenario, as the trading costs for the average investor far exceed those paid by large institutional investors. They also note that momentum suffers from very large drawdowns occasionally, such as spring 2009 following the financial crisis where the returns in US stocks were highly negative. Return crashes are the most significant in momentum strategies of all the individual factor investing strategies, however they also note that using momentum and value factors together to form a portfolio can significantly mitigate these large drawdowns. They also note that conversely, momentum does extremely well on market upswings, and that it's not decided yet whether momentum falls under the category of risk-based or behavioral theory to explain its excess returns. (Asness et al. 2014)

Novy-Marx (2012) finds momentum's profitability to mostly be driven by the performance of the stocks in portfolios during t-12 to t-7, rather than winner stocks carrying on providing positive abnormal returns, and loser stocks having abnormally poor returns during the formation period of Momentum portfolios. He finds that Momentum strategies which are based on intermediate past performance perform significantly better than those based on recent past performance. he also found that the predictive power of intermediate returns had not diminished similarly to the predictive power of recent returns during more recent years. The results were consistent outside US equities and found to be true in other asset classes as well, where the Sharpe Ratios of strategies which were based on trading according to an intermediate time horizon were significantly higher than those of strategies that traded on more recent past performance. This was especially true in the largest and most liquid stocks in the US market, which is a market that generally exhibits more momentum than most other markets. The conclusion of the findings was that Momentum is driven significantly more by past performance in the intermediate horizon, than returns in the recent past. (Novy-Marx, 2012)

Novy-Marx (2015) argues that Momentum returns are mainly driven by fundamental momentum, he finds price momentum to simply be an expression of earnings momentum, which simply reflects the tendency of stocks with strong earnings announcements to outperform stocks of companies which have announced weak earnings. Using cross-sectional regressions of the returns of firms onto both past performance and earnings surprises, the earnings surprises predict cross-sectional variation in returns significantly well, while past performance can be replaced with earnings surprises in predictive power. The effect is even more noticeable in time-series momentum. When testing the results against risk-corrected price momentum strategies, he found the risk-corrected earnings momentum strategies to outperform price momentum strategies significantly. (Novy-Marx, 2015)

Frazzini, Israel and Moskowitz (2012) study the effects of trading costs on various asset pricing anomalies. They study a data set featuring live trades from large institutional investors, featuring nearly a trillion dollars of trades in the data. They also study implementation shortfalls of trading strategies due to trading costs, which allows them to gauge the tradeoff between the trading costs and the opportunity costs of not fully implementing the investment strategies for investors of different fund sizes. They found that value and momentum survived the trading costs of a large institutional investor, and also benefit significantly from trading cost optimization, whereas short-term return reversals did not survive trading costs at a reasonable fund size. Their conclusion is that value and momentum appear to be both robust and implementable in portfolios, at least for large institutional investors. (Frazzini et al. 2012)

The momentum strategy has also had its fair share of criticism in academia. Lesmond, Schill and Zhou (2003) studied momentum trading strategies and found that the high turnover of stocks related to the strategy caused significant trading costs, to the point that the return anomaly no longer had excess returns from the perspective of an average investor due to the high trading expenses. They found the highest amount of abnormal returns to be found specifically in the stocks that had the highest trading costs associated with then and concluded that the profitability of momentum strategies is illusory and not applicable in real-world investment scenarios from the point of view of an average investor. They conclude that their findings suggest that the market is efficient when pricing stocks, and what drives momentum profits in an academic setting is the significant trading costs associated with trading the outlier stocks that have performed extremely well, or extremely poorly in the past months. The outlier stocks that form the basis of the portfolios used in momentum strategies were often not traded on NYSE and tended to disproportionately be smaller stocks with large trading costs, including large bid-ask spreads and short-sale costs, a notable cost facing individual investors would also be the tax effects of selling profitable stocks from the portfolio. They found that relative strength strategies, which had been generally found to produce larger gross profits in academic literature also had the highest relative trading costs, and this would explain most the strategies' abnormal returns in academic literature. They found that none of studied popular momentum strategies at the time survived the trading costs of the applied LDV estimate, the returns of the strategies became either negative, or statistically insignificant. (Lesmond et al. 2003)

Antoniou, Doukas and Subrahmanyam (2013) study whether investor sentiment affects the profitability of momentum investment strategies. They found that news that contradict the current investor sentiment causes significant cognitive dissonance in investors, resulting in underpricing of losers during a period of optimistic investor sentiment, and underpricing winners during a period of pessimistic investor sentiment. They find that momentum profits are significantly higher during periods of optimistic investor sentiment and are driven in significant part by strong momentum in the loser portfolio. They also found that small investors are specifically slow to sell the loser portfolio stocks from their holdings during periods of optimistic investor sentiment. During periods of optimistic investor sentiment, they found the momentum strategy to generate average monthly returns of 2%, whereas when the investor sentiment is pessimistic, momentum returns drop to a monthly average of only 0,34%. They also study the long-run behaviour of the portfolios after the sentiments by studying the returns of optimistic and pessimistic momentum portfolios five years after formation. They found that momentum profits to reverse significantly after optimistic periods, with the strategy providing an average monthly return of -0,49% after an optimistic period, whereas the returns do not reverse after a pessimistic period. They found the main driver for the strong momentum profits during periods of optimistic investor sentiment to be mainly driven by continual underperformance of the shorted loser portfolio. When removing the companies with negative earnings surprises during optimistic periods, the profitability of the momentum strategy lowered significantly, by approximately 0,91%. They also study data for trades during the time period of 1983 to 2008, finding that smaller investors seem to be significantly more impacted by cognitive dissonance during an optimistic period. Whereas large investors will sell their holdings quickly after a negative announcement is made by the company, smaller investors are much slower to sell their holdings during the studied time periods. This prolongs the pricing of bad news in the value of the stock. Their findings generally suggest that larger institutional investors are more aware of the effects of market sentiment on stock prices, and generally react faster to new information in their trades. Their evidence was found to support the view that smaller investors specifically display a larger amount of cognitive dissonance and play a key role when contributing to momentum in general when the investor sentiment is optimistic. (Antoniu et al. 2013)

Asness, Moskowitz, and Pedersen (2008) study value and momentum strategies' excess returns in significant detail across various markets and asset classes. Most studies until then had focused on US equities, and a much smaller number of studies had been performed on whether the excess returns from momentum and value strategies existed on the global scale, and across various asset classes. They found momentum and value premia in all their studied equity portfolios formed in eight different markets, as well as finding value and momentum in government bonds, and value effects in various currencies. Strong co-movement between the two factors across asset classes was also found. Value effects were found to be negatively correlated with momentum effects, and momentum effects were found to be positively correlated with other asset classes' momentum effects even if the asset classes were unrelated, value effects were also found to be positively correlated in similar way across a significant amount of asset classes. They also find measures of liquidity risk to be positively related with momentum, and negatively related with value strategies' excess returns, and estimate that negative correlation between the two factors might be driven by the opposing exposure to liquidity risk. they however found that the liquidity risk cannot completely explain the value or momentum premium, or their negative correlation on its own. (Asness et al. 2008)

Moskowitz, Ooi, and Pedersen (2012) study Time series momentum across various asset classes, and find significant time series momentum in equity indices, currencies, commodities, and bond futures for 58 considered instruments. They find significant and persistent returns for 1 to 12 months, that partially reverses after the holding period. Their findings were consistent with sentiment theories that suggest initial underreaction, and delayed overreaction to prices by investors. Their findings were robust across various subsamples and holding periods. Their diversified portfolio consisting of various time series momentum strategies across various asset classes delivered significant abnormal returns and had minimal exposure to standard asset pricing factors. They also study trading activities of speculators and hedgers and find that speculators tend to profit from time series momentum at the expense of hedgers. The findings differ from the traditional cross-sectional momentum in the way the portfolios are formed, rather than using cross-sectional momentum portfolios where portfolios are formed based on relative performance to the stock's peers during the past year. In the time series momentum approach, the strategy focuses solely on the security's own past returns. The time-series variant of the momentum strategy however still delivers statistically significant abnormal returns across a significant amount of asset classes, suggesting that momentum exists in investor behaviour even outside the traditional cross-sectional framework. (Moskowitz et al. 2012)

Asness (2011) studies momentum in the Japanese market, which had been noted as an exception to the trend of finding statistically significant momentum returns in most global markets and a significant amount of asset classes, this had caused some academics to question the robustness of momentum. While a univariate momentum strategy failed to provide excess returns, using multivariate analysis especially related to value, which has been found to have a significant negative correlation with momentum, the results of the study show that momentum in Japan still fits the general framework of global findings in momentum quite well, rather than being a significant outlier where the behaviour of momentum is considerably different. He also notes that value has provided the largest returns in Japan compared to U.S., U.K., or European markets, and with a negative correlation to momentum strategies, the momentum strategies having weaker returns in Japan is reasonable within the general framework of how momentum and value have been studied to interact. (Asness, 2011)

Baltzer, Jank and Smajlbegovic (2019) study the German stock market data to find patterns on investors who trade on momentum and contrarian trading in different investor groups. Using securities holding statistics, they study which investor types end up being the buyers and sellers during and after the financial crisis of and the following momentum crash of 2008-2009 and analyse whether and how this trading affected the momentum crash of 2009 in the German market. They found significant increases in sales of stocks in the loser portfolio by foreign investors and institutional investors during large market downturns, such as the great recession and shortly before the momentum crash of 2009, and found evidence supporting the overreaction explanation for the post-financial crisis momentum crash in noting that a significant amount of loser stocks were sold during 2008, and this overreaction is hypothesized to cause a significant return reversal in the portfolio, which would be a significant cause of the momentum crash. They also generally found strong evidence that institutional investors such as mutual funds and other foreign investors on the German markets trade on momentum, whereas private smaller investors generally trade as contrarians. The degree of their contrarian trading becomes smaller when investors are more sophisticated, which is proxied by financial wealth in their study, as well as home bias They found that momentum trading to be strong specifically among the loser portfolio, and that the quantity of executed trades increases significantly during phases of large market volatility, and market downturns. Only the sale of stocks in the loser portfolio was affected by bad economic states, whereas the winner portfolio was largely unaffected by the current economic state and market volatility. They also found a predictor of momentum profitability reversals in stocks contained in the loser portfolios of institutional investors being sold excessively, and that trading volume in the loser portfolio significantly increased during market downturns and during high periods of market volatility. They also find that more sophisticated institutional investors are more likely to take advantage of the momentum effect, and the less sophisticated private investors take contrarian views, predicting against it. Momentum was highly profitable in Germany over the studied period of 1965-2012, meaning that the institutional investors benefitted significantly from momentum, while private investors would generally lose returns consistently betting against it. (Baltzer et al. 2019)

Cooper, Gutierrez and Hameed (2004) study overreaction theories in short-run momentum profitability. They find that momentum profitability is significantly tied to positive market states, where the previous three-year return of the stock market has been positive. Momentum strategies with a six-month holding period generated statistically insignificant negative monthly returns of -0,37% during negative market states, while generating statistically significant positive returns of 0,93% during positive market states during 1929-1995. The momentum profits during positive market states, as well as the returns during negative market states both eventually suffer from long-term return reversal. They also found a significant between lagged market states and momentum profits, where momentum profits are high following the highest periods of lagged market returns, and profitability is low following poor lagged market returns. The relationship isn't linear however, and profitability was highest during the second quintile, a period of rapid market growth at the start of an economic upswing, the profits however remained statistically significant even at the highest levels of the lagged market state. They find the long-run return reversal to be consistent with prior research that suggests the excess returns of momentum strategies may be related to investor overreaction and find that prior research by Chordia and Shivakumar (2002) which attempted to explain the excess returns of momentum based solely on macroeconomic variables was not robust in its findings. (Cooper et al. 2004)

Ehsani. and Linnainmaa (2019) study the momentum factor and find it to aggregate autocorrelations found in all other factors. They argue that momentum is not a distinct factor by itself but is a factor that's dependant and explained by movement of other factors. They argue that rather than being a factor that is unrelated to the other factors, momentum is a factor that relates directly to all of them. They find that a momentum strategy built inside factors describes average returns sorted by prior year returns even better than the commonly used UMD factor. They also find that factor momentum explains other forms of momentum in stock pricing, such as industry momentum, intermediate momentum, and industry-adjusted momentum. They find that momentum strategies indirectly time factors, when the factors are positively autocorrelated, the strategy profits and when the autocorrelation becomes negative the strategy loses. The autocorrelations of other factors abruptly turning negative would explain momentum crashes in this case. They found that the profitability of cross-sectional momentum strategies is almost entirely based on the autocorrelation inherent in factor returns, and that the characteristics on the returns change based on the changes in the autocorrelation of factor returns. As factor returns significantly autocorrelated, this would necessitate the existence of momentum. They found that factor momentum returns explained both standard cross-sectional momentum and is in fact a strategy that bets on positive autocorrelations in factor returns, if the autocorrelations remain positive the strategy is profitable, and when they turn negative the strategy suffers significantly. They also specifically found momentum crashes to happen when the autocorrelations in factors abruptly stop being positive. (Ehsani & Linnainmaa, 2019)

Grinblatt and Keloharju (2000) study investor behavior with a unique data set of Finnish stock holdings that study investors exhibiting momentum. They find that foreign investors tend to invest on momentum, while a significant number of domestic investors are contrarians. They found the behavioural patterns of both sets of investors to be extremely strong, suggesting that the behavioural types are common in a large proportion of investors within their categories, rather than them being anomalies within a small group. They found the portfolios of foreign investors to outperform portfolios of domestic investors, even when controlling for behavioural differences, and for foreign investors to generally be more sophisticated than domestic investors. Foreign investors, such as investment banks and various professionally managed funds pursued momentum strategies, but their higher performance is also not limited to momentum and their holdings were found to significantly outperform domestic investors' returns even when looking at the holdings' momentum-adjusted performance. Conversely, domestic investors showed statistically significant negative performance in their portfolios which was not fully explained by heir contrarian behaviour, even when controlling for the negative returns of contrarian behaviour, Finnish households performed significantly more poorly than the foreign investors on the market. They also found significant behavioural differences between Finnish households, and Finnish institutional investors, which are considered to be more sophisticated investors. The more sophisticated the investors were, the less they exhibited contrarian behaviours, which generally result in poor returns when compared to momentum and other more sophisticated investment strategies. They also note that these strategies are not limited to momentum, and foreign investors often exhibited more sophisticated investor behaviour and had superior returns in other methods as well. Finnish institutional investors' performance and behaviour was in the middle ground between the foreign investors that generally traded with more sophisticated strategies such as momentum, and domestic household investors which exhibited extreme contrarian behaviour. Finnish institutional investors' trade performance and assumed level of sophistication was also in the middle ground between these two extremes. (Grinblatt & Keloharju, 2000)

Chordia and Shivakumar (2002) find that the profitability of the momentum strategy can be explained by lagged macroeconomic variables, and the abnormal returns of the momentum strategy are no longer statistically significant when these macroeconomic variables are accounted for. They suggest that time-varying expected returns are one the contributors to momentum's excess returns. (Chordia & Shivakumar, 2002)

2.2 Momentum crashes

Barroso and Santa-Clara (2015) found that while momentum offered investors a higher Sharpe Ratio than other factor model investment styles such as value or size, it also had the largest crashes, especially in the periods of rapid growth following large economic crises. In some cases, these crashes were so steep that it could take investors several decades to recuperate their losses, which might be unacceptable to investors with moderate or high risk-aversion profiles, or investors who are only looking to invest for short periods of time. In their backtesting they found that in the aftermath of the financial crisis in 2009, their momentum strategy had experienced a crash of -73,42%, and in 1932 an even larger crash of a -91.59% return in the span of just two months. They also suggest a modified momentum strategy based on a constant volatility to limit the negative effects of momentum crashes, and to provide higher excess returns and Sharpe Ratios than the traditional momentum strategies have been able to produce. (Barroso & Santa-Clara, 2015)

Kent and Moskowitz (2016) also study the phenomenon of momentum crashes extensively in their study, researching the effect on US stocks and find that momentum crashes during and after market crisis periods are mostly driven by the loser portfolio producing significant positive returns in post-crash periods of positive market movements. As this is the shorted portfolio in the traditional WML-portfolio based momentum strategy, where the top decile of stocks ranked on their performance during t-12 to t-2 are long, and the bottom decile is shorted, this will result in significantly negative returns for the strategy during these time periods. These periods of high positive returns for the shorted portfolio showed to be the main driver behind the large crashes observed slightly after market crisis periods, that the traditional momentum strategy suffers from. The shorted losers portfolio showed to have a significantly higher beta than the long winners portfolio had during these time periods. The winner portfolio also provided positive returns, but a much smaller amount than the strategy was losing returns from its shorted portfolio. The betas varied highly over time but showed to behave in this way consistently in post-crisis periods and caused significant crashes for the momentum strategy during these time periods as a result. (Kent & Moskowitz, 2016)

Daniel, Jagannathan and Kim (2012) also study the tail risk of momentum strategies. They find that momentum has historically generated significant positive returns with little systematic risk. They also find that momentum strategies suffer from infrequent but severe drawdowns. They found that during 13 months of their total of 978 months of research, the losses of the strategy exceeded 20% on a monthly level. They found that the turbulent state of the losses was forecastable during the months that had the most severe losses. They found the monthly momentum strategy's average returns to be 1,12% per month with a Sharpe Ratio above the market portfolio, and positive monthly alpha compared to the market portfolio with respect to the Fama-French 3-factor model. However, they also find significant excessive kurtosis, and also negative skewness due to the large drawdowns that occur infrequently in the strategy but are highly significant. The largest negative monthly return of the portfolio was as large as -79%. They note that the beta of the momentum strategy returns differs significantly depending on the current market conditions, and whether the market is currently turbulent or calm. To improve the strategy, they suggest a hidden Markov model, that predicts whether the market's state between the calm and turbulent states and note that the large drawdowns happen during the market being in the turbulent state. They also find that the strategy does not have corresponding extremely large gains during the turbulent period, even when the market continues to depreciate rather than starting to recover. (Daniel et al. 2012)

Dierkes and Krupski (2022) study momentum crashes and their predictors and attempt to construct an indicator that predicts momentum crashes and isolates them from bull markets for momentum by combining systematic and momentum-specific risk factors. They note that momentum crashes occur in rebounding bear markets, while the market is recovering from a significant crash, and the large tail risks these crashes are a large downside of the momentum factor in general. While the average monthly returns are high for the strategy when studying it over long time periods, the high kurtosis and negative skewness of the factor can cause losses of over 90% in momentum portfolios during periods following a crisis, such as in the few months after the 1932 US stock market crash. They also found that the crashes are driven by the previous loser portfolio, which is shorted in the strategy, having significant returns during these periods, and causing the overall strategy's returns to crash during these periods of rapid recovery from a crisis. They introduce a crash indicator strategy to limit the negative returns of momentum crashes, which is based on both systematic risk, and momentum-specific risk. Instead of limiting the downside by a constant volatility approach, or a stop-loss strategy as had been done in previous research, their strategy reverses the weights during momentum crashes when they're predicted to occur by their crash indicator strategy. The weights of the portfolios are then reversed during a momentum crash, making the strategy invest in past losers, and sell the past winners short during those periods. They found their crash indicator strategy to have a higher Sharpe Ratio than the corrective risk-limiting measures in previous research in both US and non-US regional portfolios, and to be more implementable in practice with ex-ante information than the strategy provided by Daniel and Moskowitz (2016). (Dierkes & Krupski, 2022)

Avramov, Cheng and Hameed (2014) study the momentum strategy's returns in periods of market illiquidity and find that the strategy's returns vary significantly with market illiquidity. They find that illiquid periods in the market are followed by massively negative returns for momentum strategies, and that market illiquidity is a significant predictor for negative momentum returns. They found that the role of market illiquidity had been overlooked significantly compared to other factors that had been studied to explain momentum crashes. They also conversely find momentum to perform extremely well during periods of high liquidity and suggest that the current state of liquidity in the market significantly affects the momentum strategy's profitability. They note that momentum going long on past winners, and shorting losing stocks results in momentum being long on more liquid stocks, and short on less liquid stocks that have performed poorly in the past year. They find that momentum returns are at their worst during periods of illiquidity, when the illiquidity gap between the winner portfolio and the winner portfolio widens considerably. This causes the loser portfolio to earn a significantly higher return during the holding period in return to compensate for illiquidity, while the effect is the opposite in the winner portfolio. Since the loser portfolio is shorted in the strategy, this is one of the core drivers of momentum crashes, meaning the shorting of the loser portfolio which has high returns during these periods is one of the main causes of the negative returns during momentum crashes. They suggest that the liquidity gap between the well-performing stocks and poorly performing stocks is at its largest during periods of illiquidity on the market, and that the liquidity gap being one of the main drivers of momentum crashes. They also study the effects of illiquidity on portfolios consisting purely of large stocks, which have a market capitalization above the median for NYSE companies and have a stock price above 5$. They find statistically significant risk-adjusted momentum returns in the sample. In the sample of large stocks, they also find that market illiquidity significantly predicts negative returns, making the findings more robust. (Avramov et al. 2014)

Han, Zhou and Zhu (2016) propose a stop-loss strategy to reduce the negative effects that momentum crashes have on the investment factor's returns. They found that at a stop-loss level of 15%, the maximum monthly losses are reduced approximately two thirds during the worst historical months of the strategy, and this results in the investment strategy's Sharpe ratios more than doubling. In their strategy, instead of holding the stocks to the end of the month, they do not hold all the traded stocks to the end of the month. Instead, if a pre-determined level of negative returns is triggered during the month, the stock is sold from the portfolio without replacing the stock until the next month's balancing. The stop-loss strategy significantly increased the average return of the strategy compared to a traditional momentum strategy, almost doubling the monthly returns from 0.99% per month to 1.93% per month, and significantly reducing the volatility of the strategy. This raised the Sharpe ratio of the strategy to 0.399 from the traditional portfolio's 0.165, over doubling it during the sample period of 1926-2013. The 3-factor Fama-French model's alpha of the stop-loss strategy also significantly exceeded the alpha of the traditional momentum portfolio, almost doubling at 1.97 compared to the traditional momentum portfolio's alpha of 1.14. Both the alphas were highly statistically significant. The stop-loss strategy also significantly changes the monthly drawdowns from the traditional momentum strategy. The returns of some of the worst months in the traditional momentum strategy, which happen in the aftermath of a crisis, are significantly reduced, or in one of the four cases even positive. The positive return on one of the worst months of the traditional strategy was driven by the good performance of the stocks that did not get sold as a part of the stop-loss strategy. The stop-loss strategy also changed which months had the worst returns significantly from the traditional momentum strategy and reduced the negative monthly returns during the worst months of the strategy significantly. They also conclude that the crash risk cannot explain the excess returns of the momentum strategy due to the findings that show that limiting the volatility of the strategy with a stop-loss level of 15% significantly increased the profitability and reduced its volatility. They also highlight the importance of using daily information when investing with a momentum strategy in a similar way as they employed in their stop-loss strategy, to alter the levels of risk and increase the profitability of the strategy. (Han et al. 2016)

2.3 Asset pricing models

This section will outline prior research related to various asset pricing models and asset pricing frameworks, which describe investor behaviour based on past empirical research. The chapter starts with addressing the efficient market hypothesis, which is a framework related to a significant amount of asset pricing models. It then describes various asset pricing models in chronological order, starting from the Capital Asset Pricing Model, and ending with the Fama-French 6-factor model.

2.3.1 Efficient market hypothesis

The efficient market hypothesis is a fundamental framework for a significant amount of later asset pricing models. Fama (1970) popularized the theory, his main hypothesis was that modern efficient markets can predict and fully reflect all publicly available information in asset pricing. He then conducted several types of tests to support this. Weak form tests, where historical prices are used. Semi-strong form tests, which tested whether prices efficiently adjust to other publicly available information such as earnings announcements and stock splits. Strong form tests were used to test whether other investors with exclusive access to information were considered when pricing assets in the market. The results concluded that while there were some exceptions, for the most part the efficient market hypothesis held true.

The theory also closely relates to momentum, as according to the efficient market hypothesis prior returns should not be able to predict future returns. Whether the abnormal returns of momentum are evidence against the efficient market hypothesis is still not completely clear up to this date. However, several researchers, perhaps most notably Jegadeesh and Titman (1993) suggest that the existence of abnormal returns of momentum offers contrary evidence to market efficiency, and the abnormal returns may be based on investors behaving in a way that contradicts parts of the efficient market hypothesis.

2.3.2 Capital asset pricing model

The capital asset pricing model is an important theoretical framework for describing the relationship between systematic risk and return expectation for investors, as well as studying asset correlations and co-movement in modern markets. The model was developed during the early 1960's by Treynor (1962), Sharpe (1964), Lintner (1965) and Mossin(1966). The theory was based on the modern portfolio theory introduced by Harry Markowitz.

The capital asset pricing model assumes investor rationality and efficient capital markets, which allows researchers and other users of the model to draw conclusions from its parameters, both actual and implied, which are widely used for further financial models and practical economic decision-making. The Capital asset pricing model can be expressed by the following equation:

$$E(r_i) = R_f + \beta_i(E(R_m) - R_f) \tag{1}$$

where $E(r_i)$ is the expected return of asset i, $R_f$is the risk-free rate of return, $\beta_i$is the beta coefficient of asset i, and $E(R_m)$is the expected return of the market.

The capital asset pricing model has been widely used as the basis for a significant amount of asset pricing models, including the Fama-French factor models and Carhart 4-factor models which will be described in the following chapters.

2.3.3 Fama-French 3-Factor Model

Fama and French (1993) add two new risk factors to the capital asset pricing model to explain stock market returns more accurately, expanding on their research done in the previous year that found that the capital asset pricing model did not accurately reflect certain factor returns. They add the size factor SMB (small minus big) which is the difference between returns on portfolios built from small stocks, and portfolios built from large stocks. They also add the value factor HML (high minus low) which is the monthly difference in the simple average returns of two portfolios with high BE/ME, or low stock price relative to its book value, and two portfolios with low BE/ME, or high stock price relative to its book value. They add these new factors to the core capital asset pricing model to improve the mode. The new factors were found to explain average returns on stocks significantly better than simply using the capital asset pricing model. The Fama-French 3-factor model can be expressed by the following equation:

$$E(r_i) - r_f = \alpha_i + \beta_i(R_m - R_f) + s_i SMB(_i) + h_i HML + \varepsilon_i \quad (2)$$

where α_i is the intercept of the model, $E(r_i) - r_f$ is the expected return over the risk-free return of asset *i*, $\beta_i(R_m - R_f)$ is the expected excess return of the market, $s_i SMB(_i)$ is the size factor, which is a portfolio that takes a long position in small stocks, and short position on large stocks, $h_i HML$ is the value factor, which is a portfolio takes a long position in stocks with low stock price relative to their book value, and a short position in stocks with a high stock price relative to their book value. ε_i is the error term of the regression. (Fama & French, 1993)

2.3.4 Carhart 4-factor model

Carhart (1997) expanded on the Fama-French 3-factor model, his 4-factor model included another factor which had been researched recently and brought into the spotlight by Jegadeesh and Titman (1993). He studied a significant amount of mutual funds and found that the previous findings of statistically significant returns buying past winners and selling past losers during a one-year window was had statistically significant excess returns. He constructed a fourth factor, momentum, which was denoted as PR1YR and constructed by taking a long position in a portfolio constructed from the equally weighted average returns of firms with the highest 30 percent past returns during t-12 to t-1 and taking a short position in in a portfolio constructed from firms with the lowest 30 percent past returns during t-12 to t-1. The momentum factor PR1YR was constructed from these returns, and he found the 4-factor model to explain return variation significantly better than the Fama-French 3-factor model.

The Carhart 4-factor model can be expressed by the following equation:

$$E(r_i) - r_f = \alpha_i + \beta_i(R_m - R_f) + s_i SMB(_i) + h_i HML + p_i PR1YR + \varepsilon_i \quad (3)$$

where $p_i PR1YR$ is the momentum factor. The factor uses value-weighted fund returns, and takes a long position in the stocks in the highest 3rd decile, and a short position in the lowest 3rd decile of prior t-12 to t-1 returns. Carhart built the momentum factor based on prior research earlier in the decade. The 4-factor model was found to have higher explanatory power over returns observed in the market than the three-factor model of Fama and French, and accounted for momentum, which was a relatively new factor and a hot topic of research at the time.

2.3.5 Fama-French 5-Factor Model

In 2015, Fama and French propose a 5-factor model, adding two more variables to their highly regarded three-factor model from over twenty years prior to the publication of the five-factor model.

They add the factor RMW(Robust minus weak), which is a factor that takes a long position in stocks that have a robust operating profitability, and a short position in stocks with weak operating profitability, independently sorted by size and profitability.

They also add another factor, CMA(Conservative minus aggressive), which takes a long position in stocks that invest conservatively, and a short position in stocks that invest aggressively, independently sorted by size and investment aggressiveness.

The five-factor model offers a better amount of explanatory power to explain the sources of stock market returns compared to the three-factor model.

Somewhat interestingly the model did not include momentum as one of its factors, which was a factor with a significant amount of prior research done on it at the time and was widely accepted as an asset pricing anomaly. The 5-factor model also did not include other phenomenon such as the low volatility anomaly or assumed that it incorporates into the other five factors which explain a significant amount of stock returns.

The Fama-French 5-factor model can be expressed by the following equation:

$$E(r_i) - r_f = \alpha_i + \beta_i(R_m - R_f) + s_i SMB(_i) + h_i HML + r_i RMW + c_i CMW + \varepsilon_i \qquad (4)$$

where $r_i RMW$ is the Robust minus weak factor that takes a long position in stocks that have a robust operating profitability, and a short position in stocks with weak operating profitability. $c_i CMW$ is the conservative minus aggressive factor, which takes a long position in conservatively investing stocks, and a short position in aggressively investing stocks. (Fama&French, 2015)

2.3.6 Fama-French 6-factor Model

Fama and French (2018) add momentum to the previous Fama-French 5-factor model. They test a significant amount of different asset pricing models using a squared Sharpe ratio model in their paper and find that the 6-factor model slightly outperforms the 5-factor model.

Interestingly, they state that momentum was added by popular demand, and they were somewhat reluctant to add the factor. They worried that adding momentum to satisfy popular demand, and with the factor lacking robust empirical theory behind it might result in a significant amount of "data dredging" for other factors, more than can perhaps be sorted through in a statistically reliable way.

The Fama-French 6-factor model can be expressed by the following equation:

$$E(r_i) - r_f = \alpha_i + \beta_i(R_m - R_f) + s_i SMB(_i) + h_i HML + r_i RMW + c_i CMW + u_i UMD + \varepsilon_i \qquad (5)$$

where $u_i UMD + \varepsilon_i$ is the momentum factor, a monthly updated portfolio that sorts stocks by their returns at the end of t-1 based on their previous returns during t-12 to t-2.

3 DATA AND METHODOLOGY

This chapter describes the data and empirical methods used in the paper in detail. The chapter starts with describing the data used for the paper, and then goes over details of the formation of various portfolios for the study, before going over the methodology used to evaluate the performance of various portfolios. The chapter includes a deeper look into the used data, the VIX-based risk-managed momentum strategy, portfolio formation, drawdowns, sub-periods used to analyse momentum crashes and the Fama-French 5-factor model.

3.1 Data

The thesis focuses on studying cross-sectional price momentum in the US stock market. The data used will be monthly and daily returns from January 1990, the data will also be divided into sub-periods to inspect how various momentum strategies have performed during later time periods.

The monthly and daily data used to form the momentum portfolios is obtained from the data library of Kenneth R French. The data set has been widely used in previous research and is kept up to date with high-quality data.

Daily data is used to be able to accurately assess the regression coefficients for the relatively short time periods of momentum crashes. Using monthly data for these time periods would not give accurate results due to this especially when it comes to studying the Fama-French 5-factor regression coefficients due to the large number of variables in the model.

The daily data is slightly different from monthly data as the data library uses daily rebalanced portfolios, however Kent (2014) goes over the differences between his daily data with monthly rebalanced portfolios, and the data of Kenneth R French which contains daily rebalanced portfolios and finds the summary statistics and the data to be highly similar in general. This suggests that the regression coefficients of the monthly data can be approximated by the daily data during periods of momentum crashes using the daily returns with only minor reductions in accuracy.

The historic data for the VIX index is downloaded from the website of the Chicago Board Options Exchange. The data set contains daily closing, opening, high and low points for the CBOE Volatility Index (VIX). The data set contains daily observations for the closing prices of the VIX index from January 1990 to March 2022, which are used to build the multiplier for our risk-managed momentum strategy.

The data set used to form the classical momentum portfolio consists of ten monthly portfolios formed by prior returns from January 1927 to February 2022. The portfolios are constructed from NYSE stock data and rebalanced monthly using prior returns from t-12 to t-2. The last two months of returns is not included to remove the effect of short-term return reversal from returns, and to include a formation period consistent with a significant amount of prior research. The portfolios include US stocks traded in NYSE, NASDAQ and AMEX. The stocks must have valid returns at t-13 and t-2, and any missing returns are required to be indicated by the missing price code used by CRSP. (French, 2022)

The data set used to form the second, more modern momentum portfolio used by Fama and French (2018) consists of six portfolios formed monthly on size and momentum. The portfolios are constructed from NYSE, AMEX and NASDAQ stock returns and sorted individually by former prior t-12 to t-2 return and market equity (ME). To be included in a portfolio The prior return sort uses 70th percentile of prior returns for the winner portfolio, and the 30th percentile of prior returns to form the loser portfolio. The size sort uses the NYSE median market equity as its breakpoint. The stocks must have valid returns at t-13 and t-2, and any missing returns are required to be indicated by the missing price code used by CRSP. (French, 2022)

3.2 The Chicago Board Options Exchange Volatility Index (VIX)

The modern VIX index measures the expected volatility of the market by aggregating a significant amount of put and call options based on the S&P 500 index. The VIX index calculates the weighted prices of the put and call options across a significant range of strike prices.

Through this method, the index provides a market estimate of future 30-day volatility of the S&P 500, which is an index that tracks the 500 largest companies in US stock exchanges.

The components of the index are put and call options which have more than 23 days, but less than 37 days to expiration. The index uses the midpoint between the quoted bid and ask prices for the options selected by its process, leaving out any options with no available bid prices.

When introduced in 1993, the index originally measured the expectation of the volatility of S&P 100. After ten years in 2003, the index was updated to reflect the S&P 500 instead of S&P 100.

3.3 Risk-adjusted momentum strategy: VIX-scaled WML portfolio

This paper will also introduce a risk-adjusted momentum strategy that scales the weights of the traditional first decile momentum portfolio based on the current value of the VIX index at the beginning of the previous period compared to its 10-year rolling average during the same time period.

The strategy is inspired by the results of Barroso & Santa-Clara(2015), who show that scaling the WML portfolio weights based on their estimation of current period volatility based on the realized volatilities of past periods provides statistically significant abnormal returns, and significantly reduces the effect of momentum crashes on the portfolio returns.

Our strategy has some key differences, however. The risk-adjusted strategy presented in this paper uses the value of the VIX index at the start of month t-1, compared to its 10-year rolling average, to estimate the volatility as the difference of the current value of the VIX index from its long-term average for the current period. and scales the WML portfolio weights for time period t accordingly.

The core source of the volatility estimate is fundamentally quite different from predicting volatility based on past momentum returns as Barroso and Santa-Clara did, since the VIX is a forward-looking market estimate of volatility based on option pricing in the current time period.

The portfolio scaling is hence known well in advance, during the portfolio formation period, which makes the strategy fully implementable with ex-ante information and usable in a real-world trading setting. However, the usual caveat of high trading costs related to momentum still exists for the strategy. Retail investors may lose a significant portion of potential excess returns to trading fees, while institutional investors would likely benefit more from the strategy.

The strategy remains self-financing, as the long and short positions remain equal regardless of the volatility scaling, and hence keeps up with one of the core rules of momentum portfolios. The portfolios can theoretically be scaled infinitely, however in practice the scaling varies between 0,36 and 2,09.

The return data for the VIX index is available from January 1990. This is also the starting month for the portfolio in our data. While the time period is shorter than the other portfolios included in the study, it still contains several momentum crashes. And perhaps quite interestingly, a generally poor performance period for traditional momentum portfolios to study potential differences in return from.

3.3.1 The original formation of the VIX-based risk-managed momentum strategy

The VIX-based risk-managed momentum strategy was originally implemented as an effort to create a new risk-managed momentum strategy, that had similarities between a previously researched strategy, but with a new variable introduced to further add to scientific literature.

As this paper is written on US stocks, testing the results VIX which is a market-based index that fundamentally aims to predict future volatility, and provides an option market-based estimate of future volatility that is inherently forward-looking seemed like an interesting prospect to study, since various timings could be studied with relative ease. Since no equivalent strategies were found on a quick search, regardless if the strategy was highly successful or not, it could also have interesting contributions for the scientific literature on momentum.

The VIX-based strategy originally started as a strategy that checked the monthly value of VIX on its first trading day during t-1 and compared it to the 10-year simple moving average of those values. The strategy immediately provided significant abnormal returns compared to the traditional 1st decile momentum portfolio, which it is based on.

3.3.2 Improving the VIX-based risk-managed momentum strategy

While the initial findings were interesting, the strategy was deemed not to be quite robust due to the inherent volatility of the VIX.

Simply using the values of the first trading day in a month in the case of a volatile index such as the VIX would inevitably cause a lot of randomness in the values, and in the worst-case scenario, the excess returns found this way might have been a partial cause and might also have been the core cause of the excess returns the strategy provided.

To ensure the results and the strategy was robust, we changed the daily values to averages. The 10-year rolling average values were changed to be the monthly average value of the VIX, and the current estimate of volatility was changed to being the average closing value of the ten first trading days of VIX at t-1, the period for most months ends approximately halfway into the month.

Later it was found that adding slightly more delay rather than simply using the average monthly closing value at t-1 as the approximation of volatility increased the efficiency of the strategy significantly, which is an interesting finding and may suggest that scaling momentum strategies with the difference of the value of VIX from its long-term average works better with a slight delay from simply using the average from the whole period of t-1 as the estimate.

The exact optimized timing and scaling for this strategy will remain the subject of potential further research.

3.4 Portfolio formation

We form four different portfolios. Three are based on prior research and one is a risk-managed momentum portfolio found during the writing process of this thesis, to study whether there have been significant differences in the behaviour in cross-sectional momentum in US stocks. We study the different types of momentum portfolios to see if there are major differences in the performance of the different portfolio types. This section will describe the portfolios that are used to study these effects.

3.4.1 Traditional decile momentum portfolio

The first type of momentum portfolio is the traditional decile portfolio, which is formed during t-12 to t-2 and rebalanced monthly. Stocks in the top decile of returns are bought long, and stocks in the bottom decile of returns are sold short. This method has previously been used in a significant number of previous studies, including Barroso and Santa-Clara (2015), and Kent and Moskowitz (2016).

For clarity in naming, this paper will assign simple and descriptive new names to the three portfolios being formed, as past research has occasionally formed portfolios with various methods which have varied depending on publication time as the naming convention for momentum portfolios, this paper will use WML for the 1st decile traditional momentum strategy, VixWML for the Vix-based risk-managed momentum strategy, Car3dec for the 3rd decile momentum strategy similar to the strategy of Carhart (1994), and FF3dec for the Fama-French 3rd decile momentum strategy.

Value-weighted portfolios are used to form the momentum portfolio to eliminate the effects of small stocks dominating the decile portfolios, consistent with a significant amount of prior research.

The return of the momentum portfolio is then calculated as: winner portfolio less the loser portfolio and risk-free rate, where the winner portfolio is the decile portfolio with the highest t-12 to t-2 prior returns, and the loser portfolio is the portfolio with the lowest t-12 to t-2 prior returns.

The returns of the first portfolio can be expressed by the following equation:

$$WML = P10 - P1 \tag{6}$$

where $P10$ is the decile portfolio with the highest value-weighted prior t-12 to t-2 returns, and $P1$ is the decile portfolio with the lowest value-weighted prior t-12 to t-2 returns.

3.4.2 Modern Fama-French momentum portfolio

The second type of portfolio formed is the more modern monthly momentum factor used by Fama and French (2018). This method constructs six portfolios using independent sorts on stock returns and size. The winner portfolio is then constructed by sorting stocks to the 70th percentile of prior t-12 to t-2 return breakpoints, and sorting stocks individually by size to the NYSE median market equity, forming separate portfolios of small stocks and big stocks. The winner portfolio is then constructed as the intersection of these two portfolios. The loser portfolio is constructed by sorting stocks to the 30th percentile of prior t-12 to t-2 return breakpoints, and sorting stocks individually by size to the median NYSE market equity, and the loser portfolio is constructed as the intersection of these two portfolios. The momentum portfolio is then formed by taking the average of the returns of the big and small high prior return portfolios and deducts the average returns of the big and small low prior return portfolios. (French, 2022)

The returns of the second portfolio, expressed as FF3dec can be expressed by the following equation:

$$FF3dec = (high.small + high.big)/2 - (low.small + low.big)/2 \tag{7}$$

where $high.small$ is a 3rd decile portfolio sorted individually by prior returns and size, including small stocks with high prior returns, $high.big$ is a 3rd decile portfolio sorted individually by prior t-12 to t-2 returns and size, including large stocks with high prior t-12 to t-2 returns, $low.small$ is a 3rd decile portfolio sorted by low prior returns and size individually, including small stocks with low prior t-12 to t-2 returns. $low.big$ is a 3rd decile portfolio sorted by low prior returns and size individually, including large stocks with low prior t-12 to t-2 returns.

3.4.3 Carhart-type momentum portfolio

The third type of portfolio is a similar method to the one used by Carhart (1997) which calculates returns of stocks monthly and splits the stocks into three portfolios instead of decile portfolios. The three portfolios are the top 30%, the median 40% and the bottom 30% of value-weighted stock returns. The returns are calculated for the top portfolio consisting of value-weighted stocks with the highest prior returns during t-12 to t-2, and the the bottom portfolio consisting of value-weighted stocks with the lowest prior returns during t-12 to t-2 is formed by taking the equally-weighted average return of the bottom portfolio, and deducting it from the top portfolio.

The returns of the third portfolio, expressed as Car3dec can be expressed by the following equation:

$$Car3dec = (P10 + P9 + P8)/3 - (P1 + P2 + P3)/3 \tag{8}$$

where $P10$, $P9$ and $P8$ are decile portfolios with the highest prior t-12 to t-2 value-weighted returns, and $P1$, $P2$ and $P3$ are decile portfolios with the lowest prior t-12 to t-2 value-weighted returns.

3.4.4 VIX-based risk-managed momentum strategy

The fourth portfolio is a traditional 1st decile portfolio, that is scaled by a multiplier obtained by calculating the average value of the VIX during the first ten trading days in the previous month, and dividing the 10-year rolling average of the value of the VIX, ending at t-1 with it

The returns of the fourth portfolio, expressed as VixWML can be expressed by the following equation:

$$VixWML = \frac{Vix10yravg_{(t-1)}}{Vix10davg_{(t-1)}} WML \quad (9)$$

where $Vix10yravg_{(t-1)}$is the simple moving monthly average value of the VIX index of the previous 120 months, ending at t-1, and $Vix10davg_{(t-1)}$ is the daily average value of the VIX during the first ten trading days in the month t-1, and WML is the traditional 1st decile momentum strategy.

3.5 Drawdowns

Drawdowns represent the reduction in the value of an asset from its previous maximum cumulative return value during a given time period.

The previous maximum cumulative return value in the series during the time period, or peak is computed, and the current cumulative return value of the asset is compared to the peak value.

A through is calculated similarly to represent the lowest value during the time period after the initial return. In the case of a positive return, if the value is higher than the peak, a new peak is achieved. If the return is lower than the peak, the value becomes the current level of drawdown for its time period. In the case of a negative return, if the cumulative return value is lower than the current through, a new through is achieved. If the cumulative return value is higher than the current through, the value becomes the current level of drawdown for its time period. A drawdown for a time period can be calculated by the following equation:

$$Drawdown = \frac{peak_t - CV_n}{peak_t} * 100\% \ , CV_n < \ peak_t \quad (10)$$

where CV_n is the current value of the asset at time n, and $peak_t$ is the largest cumulative return value of the asset during time period t.

A maximum drawdown is the largest drawdown during its time period, maximum drawdowns describe the largest continuous reduction in the value of an asset since reaching its previous peak during a given time period. A maximum drawdown during time period t can be calculated by the following equation:

$$MaxDrawdown = \frac{peak_t - trough_t}{peak_t} * 100\% \quad (11)$$

where $peak_t$ is the largest cumulative return value of the asset during time period t, and $through_t$ is the lowest cumulative return value of the asset during time period t.

The length of a drawdown describes the amount of time periods that the cumulative return value of an asset took to reach its previous peak value and gives meaningful insight to investors and researchers on how long recuperating the lost value after a series of negative returns took.

Drawdowns and maximum drawdowns will be used extensively in this paper. The aim is to use drawdowns as a measure of potential consecutive negative returns during observed time periods that simple monthly returns do not capture, as they simply calculate individual returns.

The length of a drawdown, and the value of a maximum drawdown will be used to analyse the severity and the time it takes for a momentum portfolio to recover from momentum crashes.

3.6 Momentum crash data sub-periods

We locate the momentum crash-subperiods in the data by using drawdowns. Momentum crashes have historically occurred right after a trough is reached in the market portfolio. Periods of momentum crashes will be studied from the month following the market portfolio reaching its through.

This paper will study the magnitude and timing of any potential momentum crashes that occurred during the COVID-19 crisis, and to compare the event to previous similar events, such as the momentum crash that followed the Financial Crisis of 2008

The goal will be to study any differences or similarities between previous momentum crashes, and to also attempt to study the drivers behind any potential momentum crashes that have occurred.

The methodology used in the paper is inspired by event study methodology. Similar methodology will be used to study momentum crashes, albeit there will be slight differences due to the nature of momentum crashes compared to the usual effects studied by event studies.

Event studies are a widely researched topic with a significant amount of prior research available. This paper will use a well-known framework similar to the one used by Campbell, Lo and MackKinlay (1998), who built a seven-part framework for conducting event studies. The framework and its usage in this paper will consist of the following:

1. Event definition where the event of interest is defined and the relevant time period to study it is identified.

2. Selection criteria, where the selection criteria of firms relevant to the study is identified.

3.Normal and abnormal returns, where abnormal returns are calculated ex post over the security's normal return over the time period.

4. Estimation procedure, where parameters of the model are estimated using an estimation window consisting of a subset of the data, which generally excludes the event period.

5. Testing procedure, where the parameter estimates for the abnormal returns and normal performance model are calculated, with an emphasis of correctly defining the null hypothesis.

6. Empirical results, where the empirical results and possible diagnostics are presented.

7. Interpretation and conclusions, where the insights provided by the empirical results are gone over, and potential additional analysis is added.

Since this paper is focused on studying long-term US stock returns, the firms included are stocks traded in NYSE, AMEX and NASDAQ, that have been sorted into momentum portfolios based on their prior returns and/or market equity.

The paper will not define abnormal returns similar to event studies but will instead look at the Fama French 5-factor model coefficients, and descriptive statistics such as mean return, mean annualized geometric return, volatility and Sharpe ratios and compare these to long-term values to attempt to determine abnormal returns during event periods.

The event window used for this paper will be 12 months after a trough is reached in the market portfolio, and the post-crash market recovery period begins. Previous research indicates that momentum crashes have conventionally happened shortly after these periods.

3.7 Fama-French 5-factor model

The Fama-French 5-factor model will be the main factor model used in this paper. Using the 5-factor model allows us to study the exposure of various momentum portfolios to the risk factors of the Fama-French 5-factor model.

The Fama-French 5-factor model can be expressed by the following equation:

$$E(r_i) - r_f = \alpha_i + \beta_i\left(R_m - R_f\right) + s_i SMB(_i) + h_i HML + r_i RMW + c_i CMW + \varepsilon_i \qquad (12)$$

The Market factor $\beta_i\left(R_m - R_f\right)$ will be denoted as MKT in this thesis.

4 EMPIRICAL RESULTS

This chapter presents the empirical findings and results based on the data and methodology described in the previous chapter. The chapter will begin by analysing the long-term descriptive statistics, Fama-French 5-factor model regression results, and cumulative returns of the momentum strategies described in chapter 3.4 from January 1990 to March 2022. It will then analyse the drawdowns of the various momentum strategies and the market portfolio from the same time period to analyse the timing and severity of drawdowns experienced in various strategies. It will then analyse the correlations of the various strategies, including the market portfolio by analysing the correlation matrix. The chapter will then analyse the momentum crashes related to the financial crisis and COVID-19, by analysing the returns, descriptive statistics and regression results of 12-month time periods following the maximum drawdown of the cumulative monthly market returns as described in chapter 3.6. The chapter will end with an initial analysis on the potential to further improve the VixWML strategy by scaling its multiplier further.

4.1 Empirical results - January 1990 to March 2022

This chapter presents the results and long-term statistics found in the study for the various momentum portfolios and the market portfolio, beginning with the descriptive statistics of the momentum portfolios.

Table 1: Descriptive statistics from January 1990 to March 2022

Statistic	WML	VixWML	Car3dec	FF3dec	MKT
$\bar{r}$ (monthly)	0.82	1.25	0.36	0.47	0.73
Min	-45.21	-31.19	-35.51	-34.30	-17.23
Max	23.81	28.80	14.69	18.20	13.65
$\bar{r}$ (annualized)	5.40	12.28	2.51	4.27	7.87
σ	28.83	25.76	18.82	16.34	15.10
Sharpe Ratio	0.25	0.48	0.10	0.19	0.41
Skewness	-1.33	-0.22	-1.31	-1.42	-0.59
Kurtosis	5.77	1.80	6.82	10.18	1.24

Table 1 reports the descriptive statistics of four monthly momentum strategies from January 1990 to the end of March 2022. Returns are expressed as percentages. $\bar{r}$ (monthly) is the monthly simple mean return, $\bar{r}$ (annualized) is the annualized geometric mean return of the portfolio during the time period. σ is the annualized volatility, calculated by multiplying the monthly portfolio volatility by $\sqrt{12}$. Sharpe Ratios are also annualized by multiplying the monthly Sharpe ratios by $\sqrt{12}$. Min is the smallest monthly value in the data denoting the worst monthly return, Max is the largest monthly value in the data denoting the largest monthly return. Kurtosis is the unbiased excess kurtosis of the distribution.

Table 1 shows that the VIX-based risk-managed momentum strategy has outperformed traditional momentum strategies in most statistics during the long-term time period of January 1990 to March 2022. VixWML has significantly reduced skewness and kurtosis compared to all traditional momentum strategies and has a higher Sharpe ratio, nearly doubling the Sharpe ratio of WML, and being 4.8 times larger than that of Car3dec.

The returns returns of VixWML are also higher compared to all the other strategies. We can see that the monthly mean returns are significantly higher in the 1st decile strategies of WML and VixWML compared to the 3rd decile strategies. However, the annualized mean geometric return of WML is only slightly above FF3dec. This is due to the Geometric mean taking into account the sharp downturns caused by the unmanaged momentum crashes in the strategy, which cause significant losses in the strategy beyond what the simple monthly mean return would suggest.

Notably, these results show several momentum crashes during the time period, and end in a very recent momentum crash (as shown in chapter 4.4). and will show significantly worse results for the portfolios than longer-term momentum studies such as Barroso&Santa-Clara(2015) show. While the time period is unfortunate for momentum portfolios, especially the traditional 1st decile strategy, even without the most recent crash momentum strategies have not produced similar risk-adjusted returns during the 21st century compared to older data.

Table 2: Regression results from January 1990 to March 2022

Coefficient	WML	VixWML	Car3dec	FF3dec
α	1.07**	1.46***	0.55**	0.61**
	(2.50)	(3.66)	(2.03)	(2.49)
MKT-RF	-0.52***	-0.37***	-0.36***	-0.27***
	(-3.81)	(-3.64)	(-4.17)	(-3.67)
SMB	0.06	0.01	-0.06	0.07
	(0.30)	(0.07)	-(0.50)	(0.61)
HML	-1.04***	-0.87***	-0.67***	-0.57***
	(-4.89)	(-5.15)	(-5.52)	(-5.12)
RMW	0.44*	0.32	0.25	0.16
	(1.71)	(1.59)	(1.55)	(0.98)
CMA	0.48	0.29	0.39*	0.33
	(1.39)	(1.06)	(1.77)	(1.56)
Adj. R^2	0.18	0.14	0.20	0.15

Table 2 reports the Fama-French 5-factor model regression coefficients for 4 different monthly rebalanced momentum strategies from January 1990 to the end of March 2022. The alphas are monthly and reported as percentages. The t-statistics are corrected for heteroskedasticity using the heteroskedasticity-robust standard errors with the methodology of White (1980). T-values are reported in parenthesis. * Signifies statistical significance at the 10% level, ** statistical significance at the 5% level, and *** statistical significance at the 1% level.

Table 2 reports vWML having the highest long-term alpha of the portfolios, which also increases in significance and is statistically significant at the 1% level compared to the traditional momentum strategies. All portfolios have a highly statistically significant negative loading with the market factor, the traditional 1st decile momentum strategy is significantly more negatively loaded with the market than the other observed momentum strategies. All portfolios also have a highly statistically significant negative coefficient with the value factor, consistent with previous research on momentum. The traditional 1st decile portfolio has the highest negative exposure to value, approximately double the exposure of the Fama-French momentum portfolio. Notably, the value factor coefficient is significantly lower in both the 3rd decile momentum portfolios compared to the 1st decile momentum strategies.

The loadings on other Fama-French 5-factor model risk factors are smaller and generally statistically insignificant. The adjusted R^2 for all the momentum strategies is at a low level, which implies that the standard Fama-French 5-factor model does not explain the returns of any of the momentum portfolios particularly well.

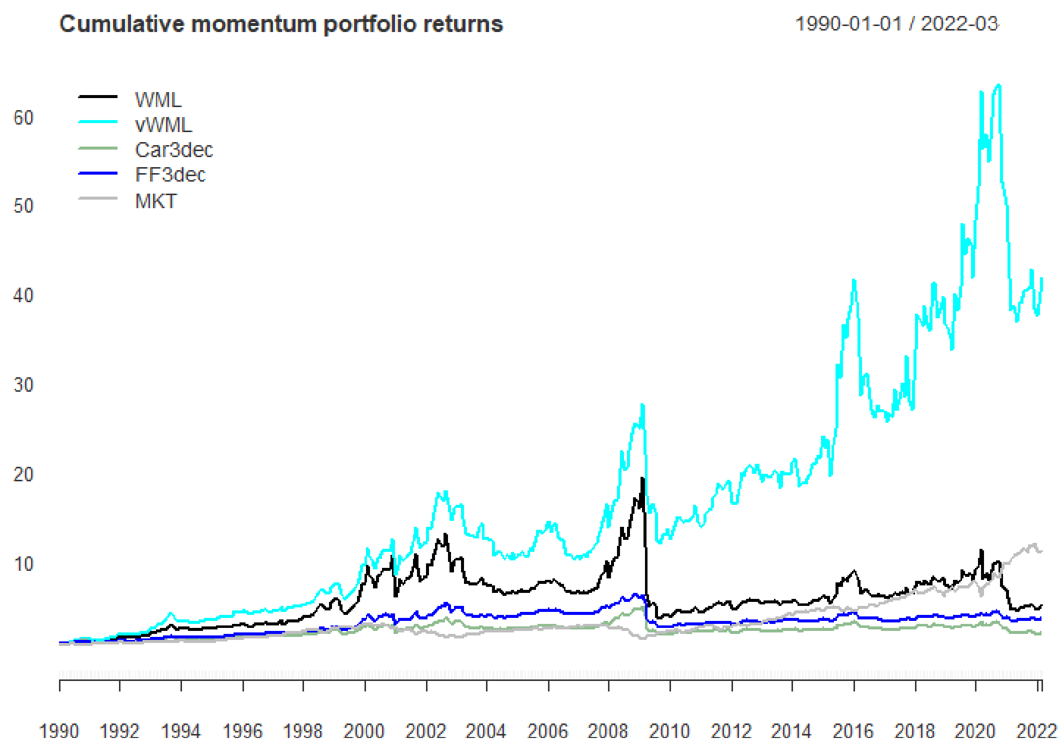

Figure 1: Cumulative monthly returns from January 1990 to March 2022

Figure 1 shows the cumulative monthly returns of the various momentum portfolios and the market portfolio, from January 1990 to March 2022. VixWML has outperformed the traditional strategies significantly over the time period, however the figure also shows that there have been large negative returns recently in all the studied momentum portfolios. An investor who invested 1$ in VixWML at January 1990 would have gained a cumulative return equivalent to 40.9$ by March 2022, while the similar cumulative return for traditional strategies is significantly lower, with WML being at 4.46 $, Car3dec at 1.22 $ and FF3dec at 2.8 $, and the market portfolio being at 10.49 $. However, it is notable that these cumulative return figures end at a likely highly unfavourable time for momentum, as the data ends shortly after a significant downturn for all the strategies.

Notably, only the risk-managed momentum strategy has beaten the market portfolio over this time period. The main driver behind this are the sharp negative returns of momentum during 2009-2020 and 2020-2021. The 1st decile momentum strategy had outperformed the market before each of these periods, after which the significant and quick negative returns cause it to crash below the market in cumulative returns. The cumulative return figure emphasizes the importance of managing the downside risk of momentum during these volatile time periods. Further, the recovery of momentum after the crash of 2008 has not been a quick one for the traditional momentum strategies, and the market returns often outpace the returns for them, suggesting that the profitability of momentum has not been great over a long recent time period, even excluding momentum crashes.

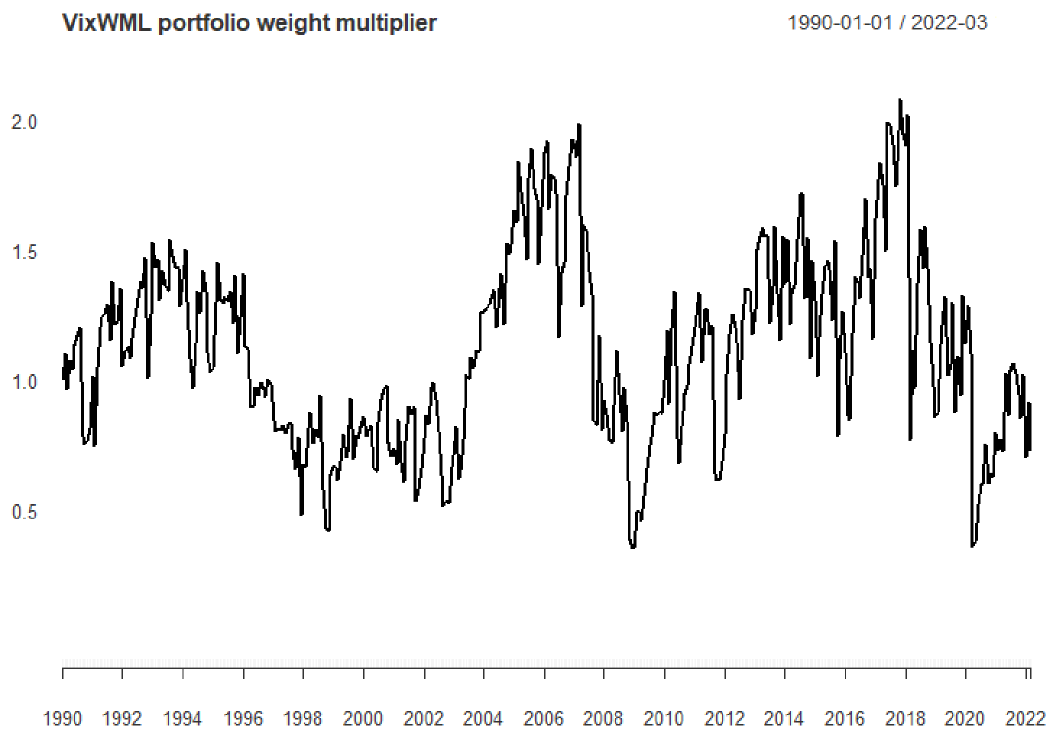

Figure 2: VixWML portfolio weight multiplier

Figure 2 shows the time series for the multiplier for portfolio weights calculated for the VixWML strategy. The mean of the multiplier throughout the period is 1,12, meaning the strategy has a slightly higher than normal exposure to the 1st decile momentum. We can see the multiplier lowering significantly during the tech bubble crash of 2000-2002, during and after the financial crisis of 2008 and during and after the 2020 market drawdown caused by COVID-19, suggesting the multiplier predicts and lowers the effects of momentum crashes on the strategy. During periods of low volatility, the multiplier goes up to 2,09 and lowers down to a minimum of 0,36 during periods of high volatility.

4.2 Drawdowns

This chapter studies the drawdowns of the various momentum strategies and the market portfolio. Previous research has indicated momentum crashes to happen quickly after market downturns, this chapter will present and analyse the results related to drawdowns in the data.

Table 3: Largest drawdowns from January 1990 to March 2022

Drawdowns	Start	Trough	Recovery	Depth	Months
	Panel A: MKT				
1	2007-11	2009-02	2012-03	50.39	53
2	2000-09	2002-09	2006-10	45.09	74
3	2020-02	2020-03	2020-07	20.21	6
4	1998-07	1998-08	1998-11	17.39	5
5	1990-06	1990-10	1991-02	16.96	9
	Panel B: WML				
1	2009-03	2009-09	<NA>	80.69	158
2	2002-10	2004-08	2008-06	51.32	69
3	2001-01	2001-01	2001-09	42.11	9
4	1999-03	1999-05	1999-11	30.69	9
5	2001-10	2001-11	2002-05	28.07	8
	Panel C: VixWML				
1	2009-03	2009-09	2015-07	56.10	77
2	2002-10	2004-12	2008-05	42.96	68
3	2020-11	2021-05	<NA>	41.86	18
4	2016-02	2017-02	2019-08	38.16	43
5	2001-01	2001-01	2001-09	31.19	9
	Panel D: Car3dec				
1	2009-03	2009-09	<NA>	61.69	158
2	2002-10	2004-08	2008-06	37.57	69
3	2000-03	2001-01	2001-09	29.14	19
4	1990-11	1991-05	1993-02	25.77	28
5	1999-03	1999-05	1999-11	18.87	9
	Panel E: FF3dec				
1	2008-12	2009-09	<NA>	57.65	161
2	2002-10	2004-08	2008-06	31.74	69
3	2000-03	2001-01	2001-09	27.41	19
4	2001-10	2001-11	2002-05	16.42	8
5	1990-11	1991-02	1991-12	15.42	14

Table 3 reports the largest drawdowns and their lengths of the momentum strategies and market portfolio, sorted by drawdown size from January 1990 to March 2022. Drawdowns are expressed as percentages. Start describes the starting date of the drawdown, Trough describes the timing of the through of the associated drawdown, Recovery describes the timing of reaching a new peak from the associated drawdown, Depth describes the depth of the drawdown, Months describes the amount of months that the drawdown lasted before a new peak was reached.

Table 3 reports the largest drawdowns during the sample period and show two very interesting things. Firstly, the only studied momentum strategy that has recovered to its old pre-2009 momentum crash value before the 2020 negative returns was VixWML. All the traditional momentum strategies still have not reached a new peak from 2009, meaning investors with poor timing that invested right before the momentum crash of 2009 would still not have recuperated their initial investment 13 years later. Figure 1 shows that in the 1st decile strategies, this is mainly due to the massive negative returns experienced in the 2009 momentum crash, which further shows the importance of the phenomenon for momentum strategies.

Secondly, the trough of the market portfolio predicts the beginning of large drawdowns for momentum portfolios well in the data set. For the 2009 and 2002 market troughs, the largest drawdowns for all momentum portfolios begin the next month. This is consistent with previous findings of momentum crashes occurring shortly after market crashes as the market starts recovering. For the momentum crash, we also notice that the through of the drawdown for all momentum strategies happened within the next year, after which they started recovering from their lowest value.

4.3 Strategy correlations

This chapter will analyse the correlation matrix of the momentum portfolios and the market portfolio to study the related coefficients.

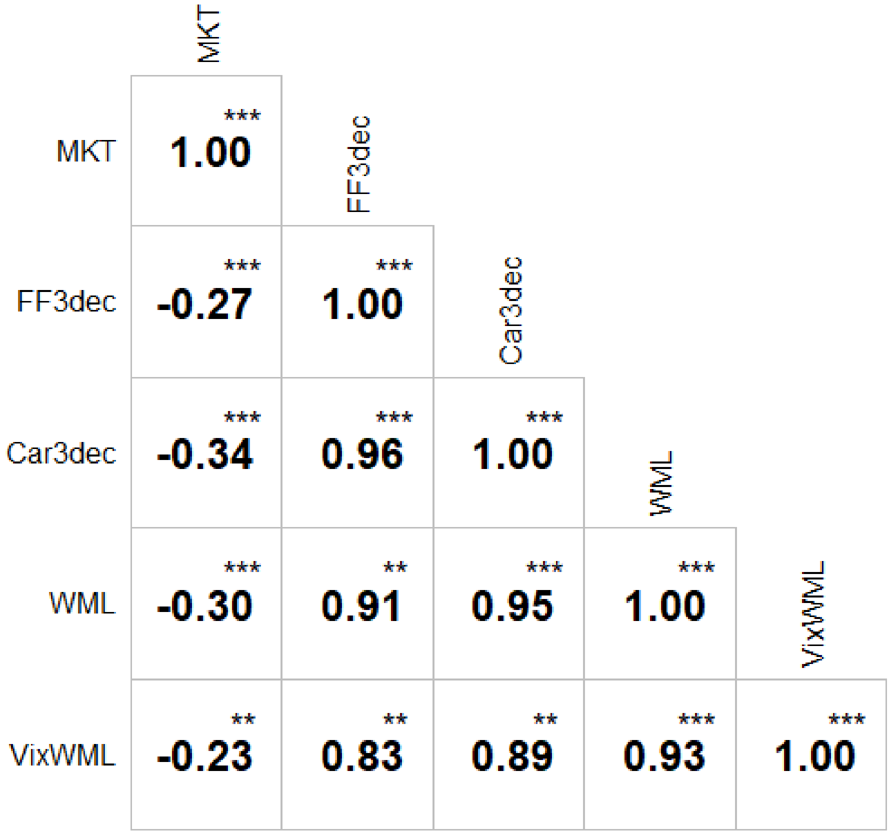

Figure 3: Correlation matrix of monthly momentum strategies and the market portfolio

Figure 3 shows the correlation matrix for the various strategies and market returns from January 1990 to March 2022. The various types of momentum portfolios are highly correlated with each other and are all statistically significantly negatively correlated with the market. VixWML has the lowest correlation with other momentum strategies and has the lowest negative correlation with the market of all the studied momentum strategies.

4.4 Momentum strategy statistics – COVID-19 crisis momentum crash period

This chapter will analyse the performance of momentum portfolios during the 12-month sub-period following the COVID-19 market drawdown, from April 2020 to the end of March 2021.

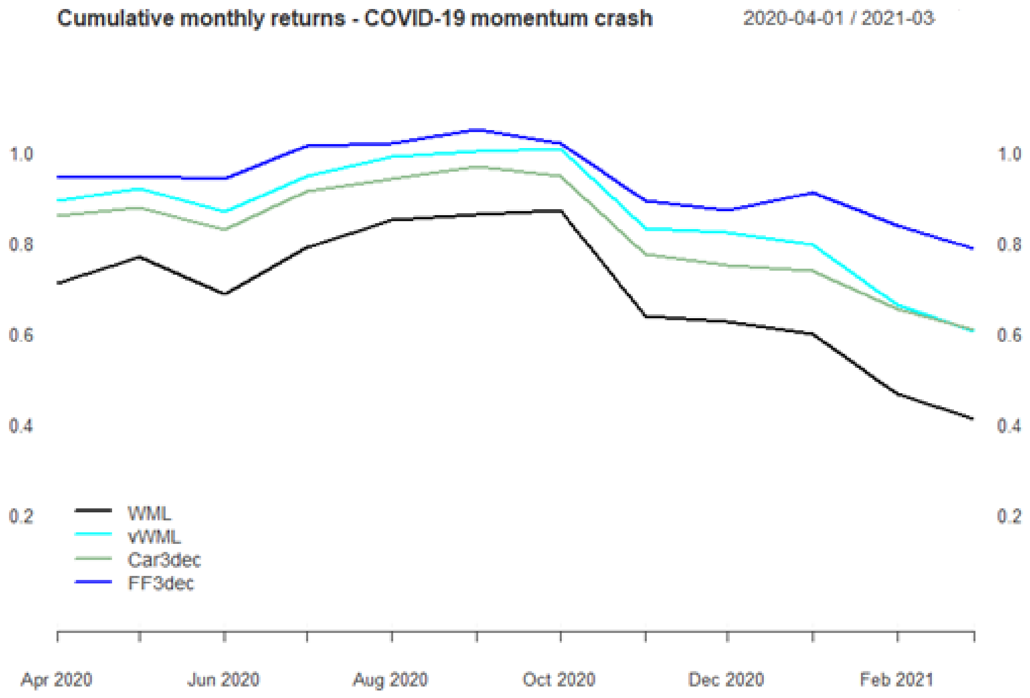

Figure 4: Cumulative monthly momentum strategy returns from April 2020 to March 2021

Figure 4 shows the cumulative monthly returns of momentum strategies, following the market through of 2020 caused by the COVID-19 crisis. We notice that all the momentum strategies have had negative returns over the period, however the returns occur over a longer period of time than during the 2009 momentum crash.

WML experienced significant losses during the time period, losing over half of its value. The losses are lower in VixWML as the value of the VIX-multiplier was low throughout most of the period, which means the multiplier for portfolio weights was low. the traditional 3rd decile portfolios lost less than the traditional 1st decile portfolio, which is consistent with previous findings about momentum crashes, while their crashes are significantly lower than those of traditional 1st decile momentum strategies, their mean return is lower during the good periods for momentum, as showed in Table 1.

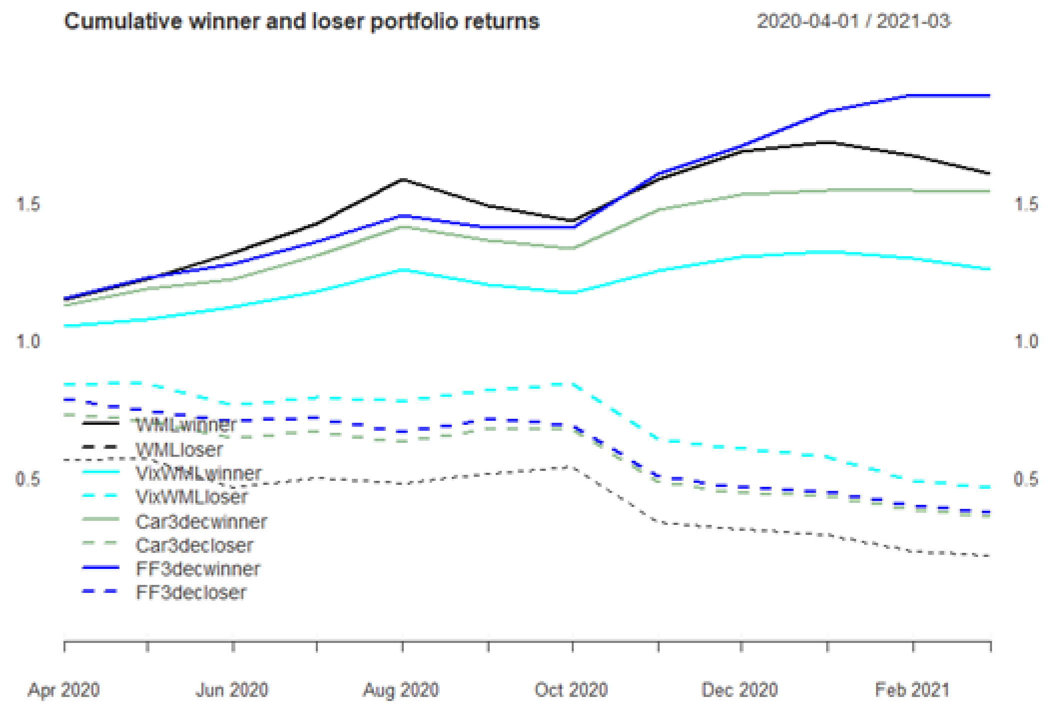

Figure 5: Cumulative monthly returns of winner and loser portfolios from April 2020 to March 2021.

Figure 5 shows the cumulative monthly returns of winner and loser portfolios from April 2020 to March 2021. Returns in the figure are shown as they contribute to the overall strategy, so negative cumulative returns for the shorted loser portfolios are caused by the loser portfolio having positive returns.

The cumulative winner and loser portfolio returns for the 2020 momentum crash show us the drivers behind the poor returns of momentum portfolios. Previous research has shown that the main drivers behind momentum crashes are the shorted portfolios experiencing high positive returns during market recovery periods.

This also happened during the period following the COVID-19. We can see that the winner portfolios are generating positive returns in all the momentum portfolios, but the loser portfolios are causing higher negative returns for the strategy, causing the overall strategies to suffer significantly. This is driven by the high positive returns of the loser portfolios during market recovery periods, which are shorted in the strategy, consistent with prior research.

The driver behind momentum crashes seems to still be the same as during periods following previous economic crises, even after a significant amount of research has been published on the phenomenon.

Table 4: Regression results on daily returns during From April 2020 to March 2021

Coefficient	WML	VixWML	Car3dec	FF3dec
α	-4.62*	-3.38*	-2.61	-1.87
	(-1.77)	(-1.96)	(-1.59)	(-1.43)
MKT	-0.20*	-0.01	-0.19***	-0.1**
	(-1.79)	(-0.12)	(-2.95)	(-2.04)
SMB	-0.03	0.07	-0.04	0.18*
	(-0.11)	(0.48)	-(0.28)	(1.69)
HML	-1.99***	-1.16***	-1.39***	-1.25***
	(-10.97)	(-9.13)	(-11.55)	(-10.74)
RMW	-0.18	-0.09	-0.05	-0.22
	(-0.54)	(-0.47)	(-0.28)	(-1.45)
CMA	0.69**	0.20	0.32*	0.35**
	(2.25)	(1.12)	(1.88)	(2.56)
Adj. R^2	0.73	0.68	0.78	0.80

Table 4 reports the Fama-French 5-factor model regression coefficients for 4 different daily momentum strategies from April 2020 to the end of March 2021. The alphas are transformed to monthly by multiplying the alphas by 21 and reported as percentages. The t-statistics are corrected for heteroskedasticity using the heteroskedasticity-robust standard errors with the methodology of White (1980). T-values are reported in parenthesis. * Signifies statistical significance at the 10% level, ** statistical significance at the 5% level, and *** statistical significance at the 1% level.

The regression results for the crash period in April 2020 to March 2021 show a large difference in alphas from the long-term alphas displayed in Table 2. The alphas become highly negative during the time period, although they are only statistically significant at the 10% level for the 1st decile portfolios.

As this is a market recovery period, the negative exposure to MKT in all portfolios but VixWML, and HML for all portfolios also explain some of the poor returns during the period, as the returns for both the factors are positive during the time period.

Interestingly, CMA becomes a statistically significant factor for FF3dec and WML, suggesting co-movement with conservative stocks for the strategies during the time period.

The adjusted R^2 of the model also significantly increases during the crash period from its long-term average for all momentum portfolios, implying that during the crash period the Fama-French 5-factor model has had higher explanatory power on the returns of all the momentum portfolios compared to the regression results of the entire studied time period.

Table 5: Descriptive statistics from April 2020 to March 2021

Statistic	WML	VixWML	Car3dec	FF3dec	SMB	HML	RMW	CMA	MKT
$\bar{r}$ (monthly)	-6.05	-3.73	-3.73	-1.80	2.44	0.59	0.43	0.08	3.89
Min	-28.75	-17.34	-18.17	-12.44	-3.17	-4.92	-3.62	-3.21	-3.63
Max	15.13	9.07	10.18	7.64	6.99	7.41	6.35	4.78	13.65
$\bar{r}$ (annualized)	-58.57	-39.17	-39.05	-20.99	32.83	6.32	4.84	0.73	64.58
σ	49.19	28.60	27.79	19.47	11.18	14.14	9.88	7.96	18.06
Sharpe Ratio	-1.48	-1.57	-1.61	-1.11	2.61	0.49	0.52	0.12	2.89

Table 5 reports the descriptive statistics of four monthly momentum strategies from, and the Fama-French 5-factor model factors from April 2020 to the end of March 2021. $\bar{r}$ (monthly) is the monthly simple mean return, $\bar{r}$ (annualized) is the annualized geometric mean return of the portfolio during the time period. σ is the annualized volatility, calculated by multiplying the monthly portfolio volatility by $\sqrt{12}$. Sharpe Ratios are also annualized by multiplying the monthly Sharpe ratios by $\sqrt{12}$. Min is the smallest monthly value in the data denoting the worst monthly return, Max is the largest monthly value in the data denoting the largest monthly return.

Table 5 shows the descriptive statistics of the monthly momentum strategies and FF5 factors from April 2020 to the end of March 2021. The returns of all momentum portfolios have been highly negative, while the return of MKT has been highly positive during the time period, suggesting that the market has recovered at a fast rate during this time period. The returns of other FF5 factors are also positive during the time period, notably the size factor has a large positive return for the time period.

The volatility of momentum strategies has been high for the time period and the Sharpe ratios are highly negative, especially when compared to their long-term positive averages.

4.5 Momentum strategy statistics – Financial crisis momentum crash period

This chapter will analyse the performance of momentum portfolios during the 12-month sub-period following the market drawdown caused by the financial crisis, from March 2009 to the end of February 2010. The goal is to study any potential differences and similarities causing the negative returns for momentum during the 2020-2021 time period discussed in chapter 4.4.

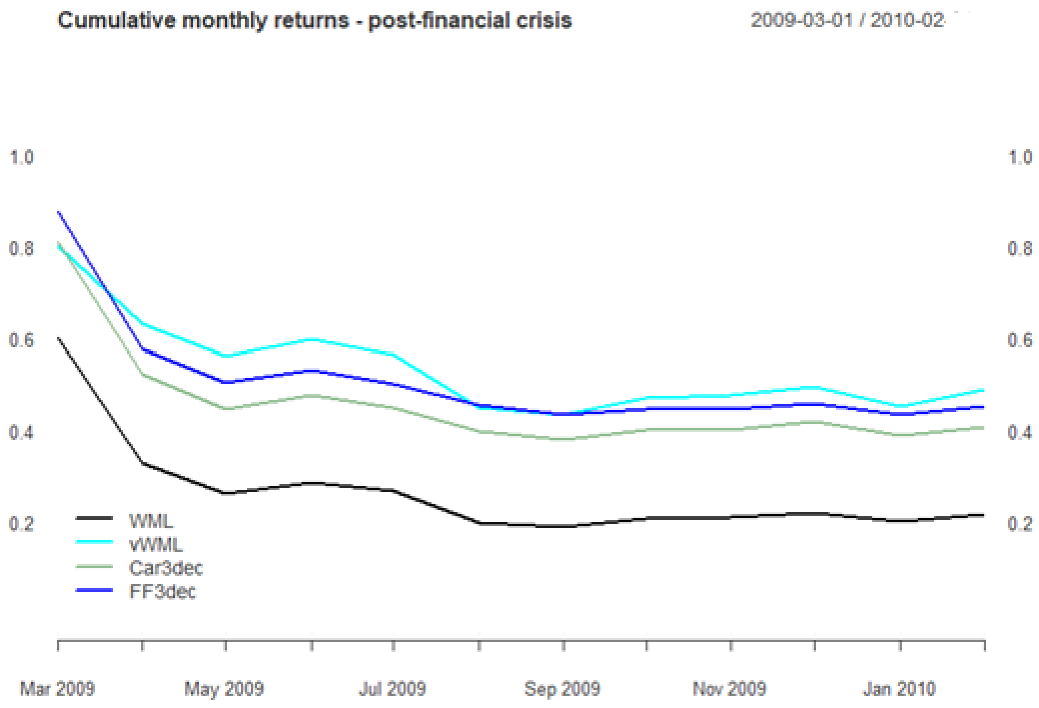

Figure 6: Cumulative monthly returns of momentum strategies from March 2009 to February 2010.

Figure 6 shows the cumulative monthly returns of momentum strategies, following the market through of 2009 caused by the financial crisis. All the momentum strategies have had significant negative returns over the period, with the largest negative returns focused on the early two months in the time period. The momentum crash of 2009 was a lot more abrupt than the negative returns that occurred during the 2020-2021 12-month sub-sample.

WML experienced the most significant negative returns during the time period, experiencing a drawdown of approximately 80%. The losses are lower in VixWML, approximately at the level of the 3rd decile portfolios as the value of the VIX-multiplier was low during the time period, which means the multiplier for portfolio weights was low and the negative returns are lessened by this scaling.

the traditional 3rd decile momentum portfolios experienced higher negative returns than during the 2020-2021 subsample, losing over half their value during the momentum crash. The negative returns for the 3rd decile portfolios also occurred extremely quickly after the start of the observation period, unlike in the 2020-2021 subsample.

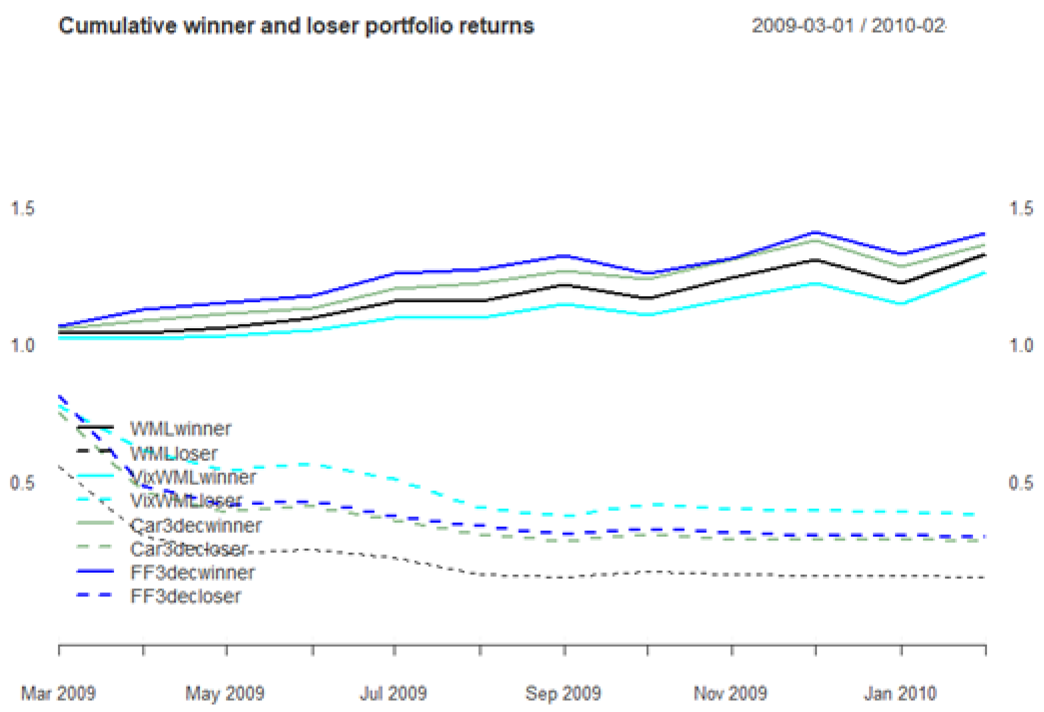

Figure 7: Cumulative monthly returns of winner and loser portfolios from March 2009 to February 2010.

Figure 7 shows the cumulative monthly returns of winner and loser portfolios during the momentum crash sub-period of 2009-2010. Returns in the figure are shown as they contribute to the overall strategy, so negative cumulative returns for the shorted loser portfolios are caused by the loser portfolio having positive returns.

The cumulative winner and loser portfolio returns for the 2009-2010 subsample show similar results as presented in Figure 4. The driver behind the negative returns of momentum portfolios during momentum crash periods are the loser portfolios contributing significant negative returns to the strategy. However, in the 2009-2010 subsample the returns caused by the loser portfolios are even higher in magnitude compared to the 2020-2021 subsample and focused significantly on the first two months in the data.

As the loser portfolios have significant positive returns during the market recovery period, the overall strategy that shorts them experiences significant negative returns during these time periods. While the winner portfolios have contributed positive returns into the strategy, the overall return is negative due to the higher negative return contributions of the loser portfolios.

The timing difference suggests there may be fundamental differences between the momentum crash of 2009 and the negative returns experienced during 2020 and 2021, even if the general results and the drivers behind the negative returns are similar.

Table 6: Descriptive statistics from March 2009 to February 2010

Statistic	WML	VixWML	Car3dec	FF3dec	SMB	HML	RMW	CMA	MKT
$\bar{r}$ (monthly)	-9.87	-5.12	-6.29	-5.69	1.10	1.56	-0.06	0.22	3.81
Min	-45.21	-20.95	-35.51	-34.30	-4.92	-4.20	-2.92	-2.20	-3.36
Max	9.40	8.42	6.86	5.49	7.04	7.63	4.17	3.30	10.18
$\bar{r}$(annualized)	-78.20	-50.70	-58.85	-54.53	13.34	19.66	-0.86	2.46	55.13
σ	65.05	38.25	43.01	37.80	12.00	11.83	6.73	6.13	14.50
Sharpe Ratio	-1.82	-1.61	-1.76	-1.81	1.10	1.58	-0.11	0.41	3.14

Table 6 reports the descriptive statistics of four monthly momentum strategies, and the Fama-French 5-factor model factors from March 2009 to the end of February 2010. $\bar{r}$ (monthly) is the monthly simple mean return, $\bar{r}$ (annualized) is the annualized geometric mean return of the portfolio during the time period. σ is the annualized volatility, calculated by multiplying the monthly portfolio volatility by $\sqrt{12}$. Sharpe Ratios are also annualized by multiplying the monthly Sharpe ratios by $\sqrt{12}$. Min is the smallest monthly value in the data denoting the worst monthly return, Max is the largest monthly value in the data denoting the largest monthly return.

Table 6 shows the descriptive statistics of the monthly momentum strategies and FF5 factors from March 2009 to the end of February 2010. The mean returns of all studied momentum portfolios have been extremely negative during this time period, while the mean return of MKT has been extremely high during the market recovery period. HML also saw significant positive returns during this time period, which is notable due to its negative factor loading with the momentum portfolios.

The volatility of momentum strategies has also been very high during the time period, and the Sharpe ratios of all studied momentum strategies are all highly negative for the time period.

WML suffered the most during this period, whereas VixWML and the 3rd decile momentum strategies suffered from smaller, but still significant negative returns during this time period. Due to its low scaling multiplier during the 2009 market recovery period, VixWML manages to reduce the losses, but still ends up with a significant period loss of approximately half of its value during the time period.

Table 7: Regression results on daily returns From March 2009 to February 2010

Coefficient	WML	VixWML	Car3dec	FF3dec
α	-5.2*	-2.69	-3.59*	-3.68**
	(-1.92)	(-1.59)	(-1.93)	(-2.47)
MKT-RF	-0.36*	-0.14	-0.35***	-0.33***
	(-1.85)	(-1.23)	(-2.71)	(-3.24)
SMB	0.15	0.04	0.04	0.01
	(0.54)	(0.27)	(0.20)	(0.05)
HML	-1.98***	-1.04***	-1.29***	-0.82***
	(-7.47)	(-7.38)	(-7.75)	(-6.43)
RMW	0.00	0.27	-0.19	-0.21
	(0.00)	(1.10)	(-0.77)	(-1.12)
CMA	2.85***	1.37***	2.19***	1.6***
	(6.13)	(4.61)	(6.20)	(5.49)
Adj. R^2	0.64	0.57	0.65	0.59

Table 7 reports the Fama-French 5-factor model regression coefficients for 4 different daily momentum strategies from March 2009 to the end of February 2010. The alphas are transformed to monthly by multiplying the alphas by 21 and reported as percentages. The t-statistics are corrected for heteroskedasticity using the heteroskedasticity-robust standard errors with the methodology of White (1980). T-values are reported in parenthesis. * Signifies statistical significance at the 10% level, ** statistical significance at the 5% level, and *** statistical significance at the 1% level.

The FF5 factor loadings during this time period have some key differences to the 2020-2021 subsample time period, but generally behave similarly. Alphas become significantly negative for the period, although only statistically significantly at the 5% level for FF3dec, and statistically significant at the 10% level for Car3dec and WML.

The loadings with HML become more negative compared to the long-term levels and are highly statistically significant. This explains a significant amount of the negative returns as the return of HML during the period was highly positive. The loadings with

MKT also contribute to the negative returns, although they are statistically significant at the 1% level only for the 3rd decile strategies Card3dec and FF3dec, and at the 10% level for WML.

The largest difference between the 2020-2021 momentum crash subsample period is the relatively large positive loadings with CMA on all the studied momentum portfolios, suggesting co-movement with conservative stocks during the financial crisis.

The R^2 of the Fama-French 5-factor model for all the studied momentum strategies increases significantly during this time period from their long-term average as well, albeit not by quite as much as in the 2020-2021 subsample. This suggests the Fama-French 5-factor model explains momentum returns significantly better during momentum crash periods compared to its explanatory power over longer time periods.

4.6 Further scaling of VixWML

Initial results with optimizing VixWML further show that the strategy predicts negative returns well. This means the multiplier can be attempted to be scaled further to optimize the strategy. One such method is to increase the multiplier of the strategy would be to add an exponential scaling to the multiplier of the strategy. The scaled VixWML can be expressed by the following equation:

$$VixWMLscaled = (\frac{Vix10yravg_{(t-1)}}{Vix10davg_{(t-1)}})^{x} WML \tag{13}$$

Where $(\frac{Vix10yravg_{(t-1)}}{Vix10davg_{(t-1)}})^{x}$ is the exponentially scaled multiplier for the strategy.

The exact optimization of the strategy of this method will have to be done in future research, however for the initial results we can set the value of ^{x} to be 2 for a reasonable scaling multiplier.

Using the exponential scaling of 2 for the multiplier of the strategy results in an increase in the annualized Sharpe ratio to 0,6. The annualized mean return of the strategy increases to 17,4%. The monthly Fama-French 5-factor model alpha of the strategy increases significantly to 1,98. The annualized volatility of the strategy increases to 30,4.

The increases in mean return, alphas and Sharpe ratios are interesting, and while there is a relatively minor increase in volatility, the initial results suggest that the strategy can be significantly optimized with further scaling. One notable downside of this scaling however is the large positions scaling the multiplier further would create, however this downside is significantly reduced by the fact that the strategy remains self-financing due to the long positions and short positions always being of equal size. Further optimization of the strategy will remain the subject of future research.

5 CONCLUSIONS

This thesis analysed momentum crashes and the performance of various momentum strategies including a VIX-based risk-managed momentum strategy from January 1990 to March 2022, with an emphasis of studying a potential momentum crash following the market downturn caused by the COVID-19 crisis at the start of 2020. The thesis also analysed a risk-managed momentum strategy to study if the VIX-based risk-managed momentum strategy could outperform traditional momentum portfolios in the long term and during momentum crashes.

Overall the results of this thesis provide more information about the current state of momentum, which can be used for both institutional investors and scientific literature on the topic.

The findings related to momentum crashes in the empirical data suggests that momentum portfolios experienced large negative returns following the market downturn which ended in March 2020, similarly to previous momentum crashes. In the following year all studied momentum strategies saw significant losses driven by the negative returns contributed to the strategy by the shorted loser portfolios, similar to previously studied momentum crashes. The Fama-French 5-factor model regression coefficients exhibited similar behaviour as during the 2009-2010 momentum crash sub-period with alphas for the period becoming highly negative, albeit only statistically significantly for some momentum portfolios and commonly at the 10% significance level. The negative factor loadings with HML became even larger during both sub-periods, and the negative factor loading with MKT during a recovery market where MKT saw significant positive returns were also drivers for the poor performance during these sub-periods.

While there are no exact limits of what constitutes a momentum crash, the evidence suggests that the losses experienced by all momentum strategies during this period exhibited similar characteristics to previous momentum crashes, studied both in this paper and in previous research. The traditional 1st decile portfolio lost over half of its value during the year following the market downturn, whereas the 3rd decile portfolios and the risk-managed momentum strategy experienced smaller, but still significant losses, all driven by the shorted loser portfolios of the strategy in a recovery market.

The timing of the negative returns also had differences from the 2009 momentum crash, with the negative returns being highly focused on the initial two months in the 2009 momentum crash, whereas the negative returns were more evenly distributed for momentum portfolios during the 2020-2021 sub-period. This suggests that there may be at least partially different drivers for the negative returns during these periods, and future research should be conducted with sector-sorted cross-sectional momentum portfolios to check for the possibility of the unique nature of the COVID-19 crisis contributing differently to the stock returns of various sectors being a partial cause for the overall poor performance of momentum during the time period.

The findings show that momentum strategies have had poor performance compared to their long-term average so far during the 21st century, mainly driven by several momentum crashes, but also the poor recovery from the 2009-2010 momentum crash. None of the traditional momentum strategies had fully recovered from the 2009-2010 momentum crash before the highly negative returns experienced during the 2020-2021 period following the market drawdown in 2020 caused by the COVID-19 crisis. The only portfolio that had outperformed the market in cumulative returns and Sharpe ratio was the risk-managed momentum portfolio.

The VIX-based risk-managed momentum strategy outperformed all traditional momentum portfolios during long time periods, the Sharpe ratios and Fama-French 5-factor model alpha and mean returns of the strategy are higher than that of any other studied momentum portfolio. The risk-managed momentum strategy also reduces the negative skewness and kurtosis of the returns significantly compared to all traditional momentum strategies. The losses during momentum crash periods are smaller than the comparable 1st decile portfolio due to the low scaling caused by the high estimated volatility during the crash periods.

The VIX-based risk-managed momentum strategy adds to the scientific literature on risk-managed momentum. Consistent with other similar strategies from prior research such as the constant volatility strategy by Barroso and Santa-Clara (2015) it outperforms traditional momentum strategies by scaling momentum with scaling the weights of a 1st decile momentum portfolio with an estimate of the volatility of the period, while being fully implementable with ex ante information. The outperformance of the 1st decile during momentum crashes is caused by the high estimated volatility of the periods, which causes the multiplier of the strategy to be low and for the strategy to not have full exposure to momentum during crashes due to this. The positive results and risk-adjusted abnormal returns during an otherwise poor period for momentum signal the importance of managing the volatility of momentum strategies.

The optimal timing and scaling of the multiplier for the Vix-based risk-managed momentum strategy can also be subject to future research, as both of these likely have a significant amount of potential for optimization. Initial results of scaling the strategy further show promising results, with the mean returns, alphas and Sharpe ratio of the strategy increasing further. The core causality behind using the past value of the VIX compared to its long-term average estimate working so well to predict momentum returns can also be the subject of future research, as a market-based estimate of future volatility accurately scaling the weights of momentum portfolios to create excess returns may offer interesting implications for the literature on momentum.

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