Trading performance in a financial crisis: Momentum and the Covid-19 flash bear market

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Dedication

To my parents.

Abstract

Momentum strategies have proven to have robust profitability records, yielding substantial returns across several periods, geographies, and asset classes. Nevertheless, such an investment approach is hazardous since it suffers severe losses when the market returns positive after periods of bear markets with high volatility. Furthermore, it appears that in this last decade, momentum has lost its historical premium in terms of unit of return earned per unit of risk assumed. For the period going from January 2010 to December 2020, the momentum factor had a meager performance delivering a Sharpe ratio of 0.23, which is more than for times lower than the Sharpe ratio provided by the market (0.95). Focusing on the most recent financial crisis, results confirm that momentum crashed following the covid-19 bear market. The most significant loss occurred in April, the month in which the market rebounded following the stock market bottom. Consistently with the existing literature, the crash is caused by the large negative beta exhibited by the momentum strategy in declining markets. Thus when the market upswings following a financial crisis, momentum behaves like shorting a call option on the market. Interestingly, the analysis shows that this same optionality also exists after short periods of economic downturn, flash bear markets. Such findings are robust across different international equity markets and asset classes.

Keywords: Asset pricing, Momentum, Bear markets, Covid-19

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Chapter 1

Introduction

Over the years, momentum strategies have proven to have robust profitability records, yielding substantial returns across several time periods, geographies, and asset classes. The idea behind such a strategy is to ride the upward and downward trends generated by rising and falling securities by betting on the continuation of such movements in the short term. Thanks to its persistence and pervasiveness, it is considered one of the oldest and most prominent trading strategies.

Despite the outstanding positive performance yielded by momentum investing, some authors have noticed that the strategy "is not all roses". Momentum experiences occasional but severe crashes that could result in significant losses for an investor. Research published by Daniel and Moskowitz (2016) [1] (hereafter DM16) illustrates that momentum strategy crashes and goes through persistent negative returns in a situation of high market stress. They showed that such crashes are predictable, claiming that such an investment approach performs very poorly when there is an upswing in returns after a bear market with high expected volatility. The authors demonstrated a dramatic time variation in the winner and loser portfolio's betas around a crisis and identified this phenomenon as the source of such reversal. Such time-varying exposure to market risk infers that momentum strategies behave as selling call options on the market. Consequently, when the market rises after a financial crisis, momentum strategies crash because of their large negative beta. In this regard, momentum strategies' biggest crashes occurred when the market rebounded after the lows caused by three of the greatest financial crises ever experienced: the great depression, the dot-com bubble, and the Sub-prime crisis. In August 1932, the momentum portfolio lost 77.5% of its value. In January 2001, the strategy had a loss of 46.8%. Similarly, in April 2009, the strategy experienced a loss of 45.8%.

Times of crisis, economic downturns, and periods of uncertainty are very instructive. However, bears have different shapes and sizes, and particularly the 2020 pandemic-driven financial crisis has been very unusual. The covid-19 bear market has been the shortest in the SP500 history. In this regard, the most recent corona crisis offers the opportunity to extend and update some of the previously described evidence on momentum investing and its crashes. To begin with, despite the significant and positive alpha yielded by the momentum strategy over the market in this last decade, it appears that momentum has lost its historical premium in terms of unit of return earned per unit of risk assumed. For the period going from January 2010 to December 2020, the Sharpe ratio of the momentum portfolio is much lower than that of the market. Moreover, focusing on 2020, it is noticeable that the momentum strategy crashed following the covid-19 driven financial downturn. More precisely, 2020 appears twice among the list of the fifteen worst momentum monthly returns. Respectively, in April and November 2020, the Winner minus loser portfolio delivered a return of -28.2% and -26.2%.

Furthermore, I show that the momentum portfolio beta becomes large and negative when the market rebounds following periods of bear market (-1.277). Consistently with the methodology of DM16, the market is considered in a bear state if the past 24-month cumulative market return has been negative. Interestingly, the same optionality also exists after shorter periods of economic downturn, when the past six-month cumulative market return has been negative. Indeed, when the market returns positive after periods of flash bear markets, the momentum portfolio beta is -1.247, and thus the strategy suffers severe crashes also in this case. Moreover, using the VIX as a proxy measure of the future market variance, I find that in periods of bear market and flash bear market with high market volatility, the momentum strategy returns are particularly low. Finally, I extend the analysis carried on the US equity market to the United Kingdom, Japan, and Continental Europe equity markets and commodity futures and equity index futures. Intriguingly, the option-like features of momentum returns are also significant in commodities and the European and United Kingdom equity markets. Such findings hold as well for short periods of economic downturns, flash bear markets.

1.1 *Contribution and Research Questions*

The aim of this thesis is two-fold. First, it empirically investigates the cross-sectional momentum strategy's profitability and characteristics over the years. Furthermore, to assess whether the recent past performance of momentum is in line with its historical performance, a particular emphasis is set on the strategy's returns in the last four decades and throughout 2020, the year of the covid-19 financial crisis. Second, this work contributes to the research on momentum crashes, extending the time period of the analysis performed by DM16 [1] till the end of 2020. Thus, the main scope of this dissertation is to investigate whether momentum crashed throughout the 2020 bear market caused by the global covid-19 pandemic. Furthermore, given that the 2020 virus-driven bear market was the shortest ever manifested, I investigate whether momentum crashes are evident after short periods of economic downturn, "flash bear markets". Moreover, to check the robustness of the results obtained, the final part of the analysis investigates momentum crash patterns across different geographies (US, UK, Japan, and Continental Europe) and asset classes (equity country index futures and commodity futures).

With such premises in mind, the main research question that the present paper aims to answer is the following:

How did the Momentum strategy for the US common stock market perform during and just after the current covid-19 crisis? Was there a crash, and if so, is it comparable to the ones highlighted by Daniel and Moskowitz ?

Additionally, a set of sub-questions addressed through this project are:

- *How did the Momentum strategy behave during the last four decades?*
- *What is the WML portfolio's expected performance in different market environments (bear markets, flash bear markets, and times of high expected volatility)?*
- *To what extent does the market Beta of the momentum portfolio vary when the market upswings after periods of bear markets and flash bear markets ?*
- *How did the momentum strategy perform in different investment regions and asset classes during the year of the covid-19 crisis?*

The remainder of this dissertation is outlined as follows. Chapter 2 reviews the existing literature on momentum investing and momentum crashes. Next, Chapter 3 elaborates on the description of the dataset formation process and the methodology used for the empirical analysis. After that, Chapter 4 delivers the main results and the corresponding implications. Then, Chapter 5 challenges the robustness of the results obtained, investigating Momentum crash patterns across different geographies and asset classes. To conclude, Chapter 6 discusses the limitations of this work, provides future research suggestions, and presents some concluding remarks.

Chapter 2

Literature Review

The following chapter starts with a brief definition and explanation of momentum investing and then reviews the most relevant financial literature on the topic. I divided the contents such that Section 2.1 explains the strategy and briefly discusses different types of momentum. Next, Section 2.2 discusses the first empirical evidence and follows analyzing several other studies highlighting the strategy's persistence across different periods, markets and asset classes. After that, Section 2.3 discusses the possible sources and the economic rationale behind the momentum effect. Finally, Section 2.4 concludes the literature review with an in-depth focus on momentum crashes since it represents this dissertation's core topic.

2.1 *What is momentum ?*

Momentum is a trend-following investing approach, a technique in which traders bet that an asset price intensely moving in a given direction will continue to follow such trend in the near future. In this sense, recent winners will remain winners, while recent losers will continue to underperform. The strategy consists of constructing a long-short portfolio that buys assets with recent solid performance identified as the winners and sells the losers, which are assets that have recently underperformed. Such investing technique is fascinating since it goes against the number one, timeless advice for being profitable in the stock market, ”buy low and sell high”. While what momentum infers is buying high and selling higher.

Since the publication of the first relevant empirical study on momentum investing from Jegadeesh and Titman (1993) [2], the strategy has gained much traction and became a popular approach relevant for both industry practitioners and financial researchers. It is attractive for traders because its implementation has generated excess returns throughout different periods, across multiple geographical markets and asset classes. Moreover, it is an exciting research field for academics because the pervasiveness of momentum represents a severe challenge to the efficient market hypothesis proposed by Eugene Fama (1970) [3], to the extent that Fama refers to momentum as the premier anomaly contradicting its theory. The success of such an investment technique raised many questions. Suggesting that past prices are helpful to predict future performances, momentum defies financial markets' effective efficiency and thus represents one of the most researched financial puzzles. Additionally, due to the poor performances recorded by the traditional strategy during the subprime crisis (Daniel and Moskowitz 2016 [1]) researchers started seeking alternative momentum strategies with enhanced performance and lower downside risk, especially for periods of high market stress. Thus, in recent years, the studies on momentum focus on two perspectives: analyzing the underlying reasons driving the momentum effect and improving the classical momentum strategy's profitability by combining different approaches.

2.1.1 *Different types of momentum*

Research is continuously evolving, and over the years, academicians developed several versions of momentum investing based on different stock selection rules. Despite the fact that this dissertation focuses on cross-sectional momentum, for the sake of completeness, the following section lists and briefly distinguishes alternative momentum investing approaches.

The first alternative to cross-sectional momentum was the 52-week high momentum strategy introduced by George and Hwang (2004) [4]. In this case, stocks were selected based on the ratio of their current prices to past 52-week high prices. Even though this new version outperforms the basic strategy, both suffer from heavy losses in periods of high volatility. Consequently, to overcome such drawbacks, Blitz et al.(2011) [5] introduce the residual momentum. In this case, stocks are selected based on their residual returns, while the cross-sectional strategy relies on total relative returns. Residual returns are the proportion of stock returns not explained by the Fama and French factors. After that, Moskowitz et al. (2012) [6] developed the time-series momentum, also known as absolute momentum. In this approach, instead of focusing on relative returns, stocks are selected based on their own past returns. The main difference with the pure momentum strategy comes from the different selection processes. Given that the time series approach relies on absolute performance, it assigns more stocks to the winner (loser) portfolio in upwards (downwards) trending markets.

To conclude, another strain of literature focused on combining different investment strategies that ultimately outperform single momentum strategies. The most prominent combinations are value and momentum, cross-sectional and time-series momentum. (Serban 2010 [7]; Asness et al. 2013 [8]; Lim et al. 2018 [9]).

2.2 *Foundation of empirical evidence on the momentum effect*

The first evidence of momentum strategies' profitability dates back to 1993 when Jegadeesh and Titman [2] illustrated a positive relationship between past and future returns, claiming that past stock returns can be used to predict and form portfolios with positive alphas. More concretely, their study highlighted how from 1965 to 1989, strategies buying the best performing US common stocks over the past year 3 to 12 months and selling stocks that have experienced the poorest returns over the same period would have generated positive alphas over the next 3-12 months.

They are the earliest contributors and the most prominent authors for momentum investing. Their pioneering work set the theoretical and methodological foundations for a plethora of subsequent future studies. In fact, the methodology for portfolio construction introduced by Jegadeesh and Titman (1993) [2] will be referred to as the cross-sectional or pure momentum strategy, and, throughout the years, many researchers will adopt and enhance it. Their approach consisted of a J x K strategy in which stocks are selected depending on their formation period (J-months) returns, and held for the entire holding period (K-month). The authors ranked stocks each month into decile portfolios in ascending order based on their relative performance over a ranking period from t – J months up to month t-1 (with J ranging from the previous 3 to 12 months). The 10% of firms with the highest-ranking period return represent the "[W]inner" decile portfolio, while the lowest 10% goes into portfolio 1, the "[L]oser" portfolio. The next step involves implementing a self-financing long-short momentum portfolio, the "winner minus loser" portfolio (WML), consisting in going long on the winner decile while shorting the loser portfolio. Hence, WML symbolizes the spread in return between a portfolio containing past winners and a portfolio including past losers. Since the authors wanted to test the strategy's profitability for different time horizons, they followed an overlapping portfolio ranking period methodology, such that portfolios are held for the period K ranging from 3,6,9 to 12 months. Ultimately they demonstrated that the WML strategy yields an average return of about 1% per month for the following year. The most profitable WML portfolio was the one sorted on a 12 month formation period and held for the following 3 months, which generated a monthly return of 1.31%.

Interestingly, Jegadeesh and Titman (1993) noted that the momentum effect reverses, and the loser decile outperforms the winner portfolio over the long run. In this regard, they show that the strategy's positive excess returns in the first 12 months were outweighed by negative returns over the second and third years. Such findings are consistent with De Bondt and Thaler (1985) [10], which documented reversal effects for longer periods through a strategy referred to as contrarian. The principal difference between the contrarian and the momentum strategies is the holding period. The former holds stocks for 3 to 5 years while the latter holds them for 3 to 12 months. Building on their previous research Jegadeesh and Titman (2001) [11], to confirm the robustness of their result and demonstrate that they were not a product of data snooping, published a follow-up paper including additional data highlighting the continuing efficacy and profitability of momentum.

2.2.1 *Momentum around the globe, across alternative asset classes and time periods*

Subsequently, many academicians started investigating the persistence and pervasiveness of such investing approach confirming its profitability across different time periods, financial markets, and asset classes. Israel and Moskowitz (2013) [12] highlighted how momentum strategies were robust from 1927 to 1965 and from 1990 to 2012. Furthermore, the time consistency of the strategy is confirmed by Geczy and Samonov (2015) [13], in the so-called ”world’s longest back-test”, in which they illustrated momentum’s persistence from 1801 to 2012. Another broad strain of literature focused on exploiting the momentum effect for equities in different investment regions and different asset classes. For instance, Rouwenhorst(1998;1999)[14] [15] was the first to document momentum in the European equity market and emerging equity markets. Asness et al. (1997) [16] detect momentum in country indices, while Okunev and White (2003) [17] found momentum in currencies. Erb and Harvey (2006) [18] discovered momentum in Commodities, whereas Moskowitz et al. (2012) [6] observed the strategy’s profitability in exchange-traded futures contracts. Such evidence were integrated by Asness et al. (2013) [8], confirming the ubiquitous power of price momentum. They highlighted such effect in different stock markets (UK, Japan, and continental Europe) and across country indices, exchange-traded futures contracts, currencies, bonds, and commodities.

2.3 *Explaining momentum*

Since a strategy that generates profitable returns trading on past prices contradicts the Efficient Market Hypothesis (EMH), the existence of momentum represents a significant challenge to empirical asset pricing models. In short, the EMH introduced by Fama (1970) [3] infers that stocks follow a random walk and that current prices fully incorporate all present information. More concretely, the theory states past price series cannot predict future prices. Thus, trends in prices should not exist, and consequently, trading strategies based on historical prices, such as momentum, should be non-viable. Furthermore, since classic empirical asset pricing models such as the CAPM and the Fama and French 3-factor model cannot explain the profits generated by the WML portfolio, the strategy is considered an anomaly (Fama and French 1996 [19], Grundy 2001 [20]). Consequently, Carhartt extended the 3-factor model, adding momentum as a fourth risk factor (Carhart 1997 [21]).

The momentum phenomenon, among other investment-related anomalies, generated a debate on whether markets are efficient or not. Supporters of the traditional Market efficiency theory argue that such strategies yield higher returns as compensation for facing higher risks, concluding that momentum is linked to a yet unobserved risk factor. On the other hand, other studies building on the behavioural finance theory believe that markets are inefficient. According to Kanheman, and Tversky (1979) [22], in contrast with the assumptions underlying the

EMH, investors are not rational. They claim that investors' decision-making process and interpretation of information are influenced by psychological and cognitive bias, ultimately leading to security mispricing and arbitrage opportunities in the market.

Thus, over the years, the literature tried to explain the risk premia associated with the momentum effect through two contrasting theories, the behavioural and the risk-based approach; however, the question remains unresolved.

2.3.1 *Behavioural explanation*

From a Behavioural finance perspective, researchers argue that momentum profitability is attributable to securities mispricing caused by investors' irrational behaviour. Most of these explanations can be related to three particular behavioural biases, initial underreaction, overreaction, and the disposition effect.

Barberis et al. (1998) [23] argue that people respond slowly to new information, such as earning announcements; this tendency leads to an initial underreaction in security prices, the subsequent convergence to their intrinsic value generates the momentum effect. Next, Hong and Stein (1999) [24] suggest that underreaction is due to the gradual diffusion of information among investors. Such findings are consistent with Hong et al. (2000) [25], who demonstrated that momentum strategies are more profitable when stocks have a low analyst coverage and that momentum profitability decrease when company size increases.

Daniel et al. (1998) [26] support the overreaction theory, stating that investors' overreaction leads to a deviation of stock prices from their intrinsic value, ultimately causing momentum. More concretely, the author state that market overreaction is a consequence of investors' overconfidence and self-attribution. Overconfidence is defined as the tendency to overweight private information with respect to publicly available news. Consistent with these claims, Chui et al. (2010) [27] show that overconfidence affects momentum returns since the strategy appears to be more profitable in countries with a higher level of individualism.

Linked to the underreaction theory, some behavioural models support the idea that the disposition effect drives momentum (Grinblatt and Han, 2005 [28]). Such effect reflects investors' behavioural tendency of locking-in gains by selling winning investments before their peak while postponing the sale of losing investments driven by the hope of an eventual break-even point. Ultimately the disposition effect leads investors to overreact to negative news and underreact to positive information. More recently, Hur and Singh(2019) [29] build on such findings and claim that along with the disposition effect, the anchoring bias plays a crucial role in explaining the momentum puzzle.

2.3.2 *Rational explanation*

Many other studies attempted to solve the momentum puzzle through a risk-based approach, relying on the idea that its profitability results from higher risk premiums related to some market-specific factor or firm-specific characteristics.

For instance, Johnson (2002) [30] observed that past winners (losers) are positively (negatively) related to their expected growth rate. The author highlights a non-linear relationship between equity prices and growth rates. Johnson infers that the momentum effect exists because high past returns are related to higher growth rate risk, ultimately leading to higher expected return. Furthermore, Chordia and Shivakumar (2002) [31] investigated the strategy's profitability through a macroeconomic model. Their findings highlight that momentum payoffs depend on the economic cycle, suggesting that the strategy is profitable in expansionary periods while generating negative payoffs during periods of economic decline.

Subsequently, Cooper et al. (2004) [32] report similar results, inferring that momentum profits only in up-market states. Avramov et al. (2007) [33], claiming that momentum is only a compensation for risk, reinforce the rational explanations relating momentum gains to credit risk. In this regard, they highlight that the strategy is profitable only among non-investment grade firms. Asem and Tian (2010) [34] show that the strategy yields superior returns during market continuation times than in periods of trend interruptions and transition to different market states. Finally, DM16 [1] show that momentum experiences abysmal returns in periods of market stress. They claim that the momentum strategy's profitability can be seen as compensation to high systematic crash risk and volatility risk. Since momentum crashes are the core topic of this dissertation, such findings will be discussed in-depth in the following section.

2.4 *Momentum crashes*

There are no free lunches in finance, investors make a constant trade-off between risk and reward, and everything comes at a price. In this sense, momentum's impressive positive returns and Sharpe ratios are associated with significant risks; and ultimately, the strategy suffers occasional severe crashes.

Daniel and Moskowitz (DM16) published the most complete and comprehensive work on momentum crashes in 2016 [1]. The authors first analyzed momentum in US common stock over the 1927-2013 time period, confirming a substantial momentum premium over the last century. The WML portfolio average annual excess return is 17.9%, with a Sharpe ratio of 0.71. In contrast, the average excess market return is 7.6%, with a Sharpe ratio of 0.40. Nevertheless, DM16 document the presence of long periods over which past loser significantly outperformed past winners, and consequently a cross-sectional momentum strategy goes through persistent negative returns. More specifically, they argue that the momentum strategy's returns are negatively skewed, and the negative returns can be pronounced and persistent. They argue that crashes are a robust characteristic of the WML strategy and that a particular market environment characterizes such periods; thus, momentum crashes are predictable.

In this regard, DM16 document that the most severe crashes occured in periods of high market stress. Such periods are also known as ”panic states” and refer to when there is an upswing in returns after a bear market period with high ex-ante expected volatility. Momentum's most significant negative performance periods are the one going from June 1932 to December 1939 and the one going from March 2009 to March 2013. The starting dates coincide with the market bottoms reached after a stock market crash, respectively caused by the great depression and the subprime crisis. Furthermore, they probed that the main driver of the strong momentum reversal is the short side of the WML portfolio; therefore, crashes are mainly attributable to losers' performances. Specifically, during periods of panic states, stocks in the winner decile go up, but the loser portfolio goes up much higher; thus, the short side outperforms the long side, and as a result, the WML strategy experiences huge losses. For instance, over March and May 2009, the short side rose by 163%, the long side earned only 8%, while the market was up by 26%. Going back in history, DM16 identify the worst two months for a WML strategy, July and August of 1932; over such period, the market rose by 82%, the winner portfolio was up by 32%, while the loser decile increased by 232%.

Such findings are consistent with those of Cooper et al. (2004) [32] and Stivers and Sun (2010) [35]. The former observed that when the past three-year market return has been negative, the momentum premium falls. While the latter noted that the momentum premium is low when market volatility is high. Cooper et al. (2004) [32] came up with a behavioural interpretation to explain their results and the strategy's poor performance, stating that market rebounds are times when assets experience more mispricing. Nevertheless, DM16 infer that the momentum strategy's large negative returns are driven by large changes in the market beta of the WML portfolio. In this regard, they examine conditional risk measures, investigating the time-varying betas of the winner and loser momentum deciles.

2.4.1 *Time varying beta*

The investigation of how the mean return of the momentum portfolio is related to time variation in market beta represents a focal part of DM16 analysis. DM16 build on the previously existing literature and empirically demonstrate the intuitions of Kothari and Shanken (1992) [36] and of Grundy and Marty (2001) [20]. They both infer that the betas of past-return sorted portfolios have a great time-varying exposure to systematic factors. In this respect, when the formation period coincides with a bull market (bear market), past losers are likely to have lower (higher) beta than past winners. More concretely, when the market is going through a crash, low beta stocks perform better than high beta ones. Thus, in such a situation, the momentum portfolio would go long on low beta stocks (past winners) and short high beta stocks (past losers). Consequently, when the market rebounds quickly, past losers' expected returns are very high, and the strategy experiences huge losses because the momentum portfolio ends up having a conditionally large negative beta.

DM16 empirically confirmed the existence of dramatic time variation in the betas of momentum portfolios. Their study finds substantial beta variation principally for the loser decile, whose beta rises drastically in periods of high market volatility. More specifically, they show that, following a bear market, the beta of the WML portfolio, when the contemporaneous market return is positive, is more than double than when the contemporaneous market return is negative (up-market beta -1.51 vs down-market beta -0.70). This significant asymmetry in betas is present only in bear markets and is mainly driven by past losers. Furthermore, they conclude that the loser portfolio's time-varying beta makes the momentum strategy behave like a written call option on the market, in bear markets. Which is to say, when the market goes down, the strategy benefits a little, but then it yields huge losses once the market rebounds sharply. Additionally, in line with the strategy's option-like behaviour in bear markets, by using ex-ante volatility estimates, they show that the WML portfolio expected return is a decreasing function of the future market volatility. Thus, the momentum strategy performs very poorly during bear markets with high volatility. However, neither time-varying exposure to market risk nor time varying-exposure to volatility risk can explain the low returns earned by such strategies in panic states.

DM16 asserted their findings' robustness testing the consistency of their results for multiple periods, different equity markets, and alternative asset classes. They further find that the WML strategy suffers crashes in all markets and asset classes. They conclude that the driver of such reversals is the optionality of losers in bear markets, which is a common feature of momentum strategies since it is consistently present in different equity markets (Europe, the UK, Japan), and different assets (index futures, commodity, fixed income, currency).

2.4.2 *Market crash hedged momentum strategies*

Crashes are a crucial flaw that severely hinders the profitability of the cross-sectional momentum strategy. In this regard, some authors tried to develop new alternative models to hedge and protect the WML portfolio against the risk of such significant losses.

Jegadeesh and Titman (1993)[2] highlighted that the momentum portfolio performed very poorly in the pre-WWII period. Grundy and Martin(2001) [20] argued that this underperformance is due to the strategy's time-varying exposure to market and size factors. Subsequently, they were the first to suggest that momentum strategy's performance can be significantly enhanced by dynamically hedging the portfolio's exposure to market and size risk. In this regard, they showed that their hedged momentum portfolio outperforms in terms of average return and Sharpe ratio, the unhedged WML portfolio during the pre-WWII period. However, DM16 reviewed their approach and demonstrated that the strategy is not implementable since its construction is based on forward-looking betas. Because of the strong correlation between the beta of the future momentum portfolio and the future return of the market, the estimated performance of the ex-post hedged momentum portfolio ends up being upwardly biased. Furthermore, DM16 argue that an implementable version of the hedging strategy proposed by Grundy and Martin (2001) [20] based on ex-ante betas would not improve a pure momentum strategy's performance.

Barroso and Santa Clara (2015) [37] contributed to the research elaborating a different approach. They stated that investors should follow a risk-adjusted constant volatility strategy to mitigate the negative performance experienced by momentum strategies following a market crash. More concretely, they suggest scaling the amount invested in the WML portfolio targeting a precise volatility level based on the realized variance of daily returns in the past six months. The authors claim that implementing such a strategy would significantly improve the Sharpe ratio compared to a pure momentum strategy, eliminating large momentum crashes. In short, their risk-management strategy consisted of holding a momentum portfolio having constant volatility over time.

Recently Moreira and Muir (2017) [38] proposed volatility-managed portfolios, a volatility scaling approach close to the constant volatility introduced by Barroso and Santa Clara (2015) [37], that takes less risk when volatility is high and vice versa. They found significant and positive alphas for different popular equity strategies, including momentum, enhancing their performance relative to the standard unmanaged portfolios. More precisely, the volatility-managed portfolio scales monthly factor exposure by the inverse of the realized variance of daily portfolio returns in the previous month. They illustrate that future variance increases by far more than the expected returns after a variance shock, leading to a weaker risk-return trade-off. For this reason, they suggest reducing risk exposure when volatility is high until the risk-return trade-off becomes beneficial again.

In addition to their contribution to beta time variation of the WML portfolio and the predictability of momentum crashes, DM16 has also developed an alternative framework to reduce the strategy's crash risk. In this regard, they proposed a dynamically weighted version of the momentum portfolio, where the relative weights of the winner and loser deciles are based on their estimates for the forecasted return and variance of the cross-sectional momentum approach. Furthermore, they explain that the optimal dynamic strategy would coincide with the constant volatility model introduced by Barroso and Santa Clara if the Sharpe ratio of the momentum strategy were time-invariant. However, given that the return of a WML portfolio is negatively related to the forecasted WML volatility, the Sharpe ratio of the optimal dynamic portfolio does vary over time. To conclude their investigation and to assess the profitability of their model, DM16 compared the annualized Sharpe ratios of the dynamic strategy (1.19) with the baseline WML approach (0.682) and with the constant volatility strategy (1.04). They document that the proposed portfolio outperforms the constant volatility model, which ultimately outperforms the classic WML strategy. Furthermore, they show the efficacy of the dynamic momentum strategy in different investment regions and asset classes. Nonetheless, there are some methodological differences between volatility scaling and the DM16 dynamic portfolio. Mainly because in DM16, the optimal portfolio weights depend on the Sharpe ratio since they forecast both variance and return, while the former forecasts just the variance. Additionally, the methodology used by DM16 to forecast volatility is way more complex since they rely on the GJR-GARCH model proposed by Glosten et al. (1993) [39]. Also Barroso and Santa Clara (2015) [37] and Moreira and Muir (2017) [38] show that the profitability of their strategy is robust in several equity markets. However, despite its enhanced performance, DM16 recognize that the dynamic strategy takes on more leverage than a constant volatility approach and would generate higher transaction costs than the other two strategies.

To conclude, volatility-managed portfolios are profitable and convenient to manage volatility shocks because they are simple and easily implementable. Nevertheless, the dynamic portfolio proposed by DM16, despite its complex methodology, is tailored to reduce the downside risk of momentum crashes better and ultimately outperforms Moreira and Muir's method. Section 4.4 provides a more detailed overview of the methodologies behind market crash-hedged momentum strategies.

Chapter 3

Data and Methodology

The following chapter discusses the data retrieval procedure and describes the research design adopted for the empirical analysis. The principal scope of this dissertation is to extend the analysis done by Daniel and Moskowitz (2016) [1] and test whether the momentum strategy crashed during the 2020 Bear market. Consequently, data collection and the dataset construction intentionally emulate as precisely as possible the procedures adopted in DM16. However, since the crisis undergone by the market in 2020 is quite different from the ones highlighted by the authors, some methodological accommodation needs to be done.

This chapter is organized as follows. Section 3.1 introduces data sources for both the principal analysis and the robustness tests. Section 3.2 reviews the dataset formation process. To conclude, Section 3.3 describes the methodology and the regressions implemented to answer the research questions previously stated.

3.1 *Data*

The first subsection introduces the US equity data employed for the primary analysis. Moreover, to challenge the robustness of the findings yielded by the analysis, I replicate the results relying on international equity and other asset class data. Hence, the second subsection describes the dataset utilized to investigate whether the momentum crash patterns found in the US equity market are also persistent in other equity markets and asset classes.

3.1.1 *US Data*

The principal data sources are the Center for Research and Security Prices (CRSP) and Ken French's data library. The former was used to retrieve the Us common stocks' monthly returns for the entire time period (Jan 1927 - Dec 2020). The monthly returns are then used to construct the monthly momentum deciles portfolios. In contrast, I gathered the market return and the risk-free rate from Ken French's data library. Such metrics are respectively proxied by the value-weighted Index of all listed firms in CRSP and the one-month treasury bill rate.

DM16 used the realized daily market return variance annualized over the preceding six months as an additional explanatory variable to show that the expected return of the momentum strategy is a decreasing function of the futures market's variance. Hence, to investigate the relationship between the returns of the momentum portfolio and the expected market volatility, I needed to consider a forward-looking indicator of uncertainty. With more recent data, it is possible to rely on the daily data of the VIX Index, available on the Chicago Board Options Exchange website (CBOE), as a proxy measure of future market variance. Assuming that the monthly Index is equal to the daily rate at the beginning of each month and that such a daily VIX rate is valid throughout the month, I converted the daily series to a monthly series. The data series starts in January 1990 and ends in December 2020.

3.1.2 *International and non-equity data*

To assess the robustness of the results, I extend the analysis on momentum crashes to four different equity markets and two different asset classes. The data can be downloaded from the AQR Capital Management website and consist of the same sample used in Asness, Moskowitz, and Pederson (2013), which gets updated monthly following the original portfolio construction procedure. Note that the portfolio formation process is similar to the one used to construct the momentum deciles from US equity data, but the sorting is less extreme. Instead of taking the top and bottom deciles, Asness et al.'s momentum portfolio rely on terciles. Consequently, the WML portfolio consists of going long on the top third while short-selling the bottom third of securities based on their ranking period returns.[1]

More precisely, the international equity data refers to the US, UK, Japan, and Continental Europe equity markets. The non-equity data covers twenty-seven different commodity futures and Equity index futures across 18 developed equity markets. Furthermore, every single market and asset class has a different market index. Specifically, for international equity data, I considered the corresponding MSCI local index (US, UK, EU, JP). For the country index futures, I used the MSCI world index. While for commodities, I employed the Goldman Sachs Commodity Index (GSCI). All series start in January 1980 and end in December 2020.

3.2 *Portfolio Construction*

The dataset used for the analysis is formed in a manner broadly consistent with the deciles momentum portfolios formed by DM16. However, before describing the monthly momentum portfolio formation procedure, I need to outline some restrictions applied to the data sample. In particular, the universe includes only firms listed on the NYSE, AMEX, or NASDAQ as

[1]Please refer to the following link for more details regarding international and non-equity data and portfolio construction procedures www.aqr.com/library/data-sets/value-and-momentum-everywhere-factors-monthly.

of the formation date (CRSP exchange code of 1, 2, or 3) and considers only the returns of common stocks (CRSP share-code 10 or 11). Furthermore, to be considered in the portfolio construction process, firms must have a valid price and number of shares as of the formation date $(t-1)$. Observations with less than eight monthly returns over the past eleven months are considered missing. Firms that don't meet all these requirements are not included in any portfolio. Consequently, all firms meeting the requirements are ranked and sorted into deciles portfolios based on their cumulative returns over the ranking period.

Figure 3.1 represents the portfolio formation procedure for momentum returns in April 2020.

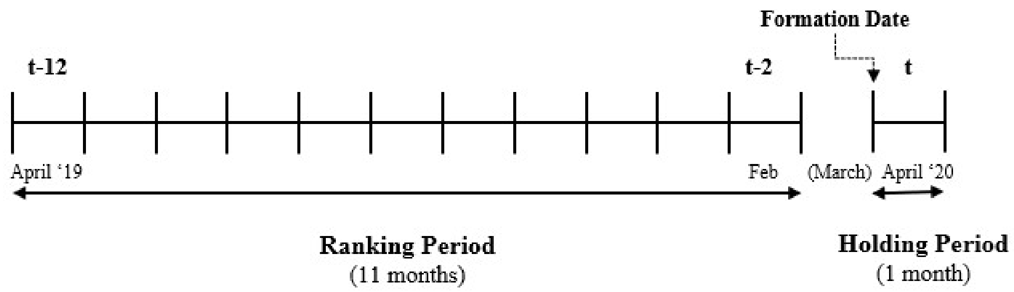

Figure 3.1: *Portfolio formation procedure*

The ranking period goes from 12 months before to one month before the formation date. Thus, the ranking returns for month t is the cumulative t-12 to t-2 month return. Based on such metric, firms are then placed into one of ten decile portfolios where portfolio 10 includes Winners (firms with the highest-ranking period return), while portfolio 1 represents the Losers. The difference between the returns of the Winner and Loser portfolios represents the self-financing "Winner Minus Loser" portfolio (WML).

The holding period returns are represented by the value-weighted returns of the firms included in the deciles, computed over the last trading day of the previous month through the last trading day of the current month. Hence, the holding period is one month. Portfolios are buy and hold within each month and are constantly rebalanced at the end of each month. Therefore portfolio membership does not change within a month, except in the case of delistings.

	Losers	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Winners
DM16	0.996	0.997	0.998	0.997	0.997	0.998	0.998	0.999	0.998	0.998

Table 3.1: *Correlation Matrix of momentum decile portfolios with DM16's portfolios*

To conclude, Table 3.1 presents the matrix of correlations between the self-constructed monthly decile portfolios' returns and those used by DM16 (Jan 1927-Dec 2012). The difference between the replicated momentum returns and the outcome from Daniel and Moskowitz

(2016) is not zero because of different ways in data processing and sample selection. Notice that the correlation between corresponding portfolios is never lower than 0.996.

3.3 *Methodology and Research Design*

The empirical investigation starts with an overview of the monthly momentum portfolio excess return characteristics over different periods. This initial analysis provides us with an estimate of the premium yielded by the strategy over the entire sample period (1927-2020) and compares returns over different decades. In this way, I can assess whether the results are consistent with the existing literature and the behaviour of such premium over time. Furthermore, to visualize better the premium yielded by the momentum strategy over the whole sample and different decades, I provide several plots representing the cumulative monthly returns for investments in the risk-free asset, the market portfolio, the bottom decile (past losers portfolio), and the top decile (past winners decile).

In addition to the average returns, I compute other relevant metrics such as the volatility, the skewness, and the annualized Sharpe Ratio of each portfolio decile. Moreover, I estimate the deciles' alpha and betas by fitting a full-period unconditional market model regression to the WML portfolio and to the other deciles. Hence, Regression 3.1 is simply a monthly time series regression, over the entire period, of each decile portfolio's excess return on the excess CRSP value-weighted index:

$$\tilde{R}_{WML,t} = \alpha_0 + \beta_0 \tilde{R}_{m,t} + \tilde{\varepsilon}_{,t} \tag{3.1}$$

Such specification will be repeated for different decades to estimate and compare the market betas and the intercept of the WML portfolio over time.

DM16 illustrated that returns earned by the momentum strategy are significantly lower in declining markets and that the most severe crashes occurred in periods of high market stress. Such periods are also known as ”panic states” and refer to an upswing in returns after a bear market period with high ex-ante expected volatility. More precisely, they showed that in such market states, there is a negative correlation between the market beta of the WML portfolio and the contemporaneous realized market return, demonstrating that the strategy follows the same behaviour of a short call option on the market. They investigated such optionality of momentum in bear markets through a set of monthly time series regression, in which the dependent variable is always the $\tilde{R}_{WML,t}$, the WML portfolio return in time t. Additionally, they used a combination of the following set of independent variables:

1. $\tilde{R}^e_{m,t}$: the market return, proxied by the excess CRSP value-weighted index return in month t.
2. $I_{B,t-1}$: an ex-ante Bear market indicator, a dummy variable that assumes the value of 1

when the past 24 months cumulative CRSP value-weighted index return is negative and zero otherwise.

3. $I_{U,t-1}$: an ex-ante Bull market indicator, a dummy variable that assumes the value of 1 when the past 24 months cumulative CRSP value-weighted index return is positive and zero otherwise.

4. $\tilde{I}_{U,t}$: a contemporaneous Up-market indicator, a dummy variable that assumes the value of 1 if the market return in month t is greater than the risk-free in month t, and zero otherwise.

5. $\hat{\sigma}^2_{m,t-1}$: an ex-ante estimate of the market volatility over the coming month, the variance of the daily returns of the market over the 126 days before time t.

However, since I want to extend such investigation to the 2020 virus-driven Bear market, it is necessary to consider that crises differ in terms of the severeness, causes, and time length. The 2020 Bear market started on February 19th, and the SP500 hit its bottom on March 23rd when the index lost approximately 33.9%. After approximately five months, on August 18th, the SP500 reached a new record high, fully recovering losses from the pandemic-driven crisis, a new bull market was born. To sum up, the covid-19 financial crisis had a length of just 1.1 months, while the two main bear markets in which DM16 highlighted an intense crash of the momentum strategy had a way longer length, 32.8 months for the great depression back in 1929 and 17 months for the 2007 financial crisis. Consequently, given that the covid-19 bear market was the shortest ever manifested, some adjustments to the variables need to be made.

In this regard, as an attempt to capture whether momentum crashes are also present after short but intense periods of economic downturn, I add two "Flash-Bear" market indicator as a new explanatory variables. Furthermore, as previously reported, with more recent data, it is possible to rely on the VIX Index as a proxy measure of future market variance. Consequently, I add three more independent variables to the setting:

1. $I_{FB(6),t-1}$: ex-ante Flash bear market indicator, assumes the value of 1 if the cumulative CRSP value-weighted index return in the past 6 months is negative, and zero otherwise.

2. $I_{FB(4),t-1}$: ex-ante Flash bear market indicator, assumes the value of 1 if the cumulative CRSP value-weighted index return in the past 4 months is negative, and zero otherwise.

3. $VIX_{m,t-1}$: the VIX index as an ex-ante estimate of the market volatility over the next month.

Regression 3.2 consists of a conditional CAPM with the standard Bear market indicator as an additional variable. In regression 3.3 and 3.4 respectively, I substitute the former indicator with the new 6-months and 4-months Flash-Bear market indicator variable:

$$\tilde{R}_{WML,t} = (\alpha_0 + \alpha_B I_{B,t-1}) + (\beta_0 + \beta_B I_{B,t-1})\tilde{R}_{m,t} + \tilde{\varepsilon}_{,t} \tag{3.2}$$

$$\tilde{R}_{WML,t} = (\alpha_0 + \alpha_{FB(6)} I_{FB(6),t-1}) + (\beta_0 + \beta_{FB(6)} I_{FB(6),t-1})\tilde{R}_{m,t} + \tilde{\varepsilon}_{,t} \tag{3.3}$$

$$\tilde{R}_{WML,t} = (\alpha_0 + \alpha_{FB(4)} I_{FB(4),t-1}) + (\beta_0 + \beta_{FB(4)} I_{FB(4),t-1})\tilde{R}_{m,t} + \tilde{\varepsilon}_{,t} \tag{3.4}$$

Such model analyzes the relationship and the differences between the expected returns and market betas of the WML portfolios for the two different bear market specifications introduced.

Next, to investigate the strategy's performance when the market rebounds following a bear market and to assess to which extent the market betas of the WML portfolio differ in different market states, in Regressions 3.5, 3.6 and 3.7, I added the contemporaneous upmarket indicator as an additional regressor:

$$\tilde{R}_{WML,t} = [\alpha_0 + \alpha_B I_{B,t-1}] + [\beta_0 + I_{B,t-1}(\beta_B + \tilde{I}_{U,t}\beta_{B,U})]\tilde{R}_{m,t} + \tilde{\varepsilon}_{,t} \tag{3.5}$$

$$\tilde{R}_{WML,t} = [\alpha_0 + \alpha_{FB(6)} I_{FB(6),t-1}] + [\beta_0 + I_{FB(6),t-1}(\beta_{FB(6)} + \tilde{I}_{U,t}\beta_{FB(6),U})]\tilde{R}_{m,t} + \tilde{\varepsilon}_{,t} \tag{3.6}$$

$$\tilde{R}_{WML,t} = [\alpha_0 + \alpha_{FB(4)} I_{FB(4),t-1}] + [\beta_0 + I_{FB(4),t-1}(\beta_{FB(4)} + \tilde{I}_{U,t}\beta_{FB(4),U})]\tilde{R}_{m,t} + \tilde{\varepsilon}_{,t} \tag{3.7}$$

With this setting, a negative $\beta_{B,U}$ ($\beta_{FB,U}$) would indicate that in bear markets (Flash-Bear markets), the momentum strategy is effectively shorting a call option on the market.

Since the value of an option increases with the market variance, such optionality further suggests that the expected return of the momentum portfolio should be negatively related to the future variance of the market. I test this Hypothesis through regressions 3.8, 3.9 and 3.10, specifically for Bear and Flash-Bear markets. Such specification is similar to the one used by DM16 to investigate market stress and momentum returns, the only difference (aside from the additional $I_{FB,t-1}$ indicator) is the adoption of the VIX as an estimate of the future variance of the market:

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_{B,t-1} I_{B,t-1} + \gamma_{VIXm} VIX_{m,t-1} + \gamma_{int} I_B VIX_{m,t-1} + \tilde{\varepsilon}_{,t} \tag{3.8}$$

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_{FB(6),t-1} I_{FB(6),t-1} + \gamma_{VIXm} VIX_{m,t-1} + \gamma_{int} I_{FB(6)} VIX_{m,t-1} + \tilde{\varepsilon}_{,t} \tag{3.9}$$

$$\tilde{R}_{WML,t} = \gamma_0 + \gamma_{FB(4),t-1} I_{FB(4),t-1} + \gamma_{VIXm} VIX_{m,t-1} + \gamma_{int} I_{FB(4)} VIX_{m,t-1} + \tilde{\varepsilon}_{,t} \tag{3.10}$$

As discussed earlier, DM16 found that in periods of high market stress, Bear markets with high volatility, momentum returns are particularly poor. The additional $I_{FB,t-1}$ allows us to investigate the relation between the expected return of the momentum strategy and market's variance in short but intense periods of economic downturn, such as the Coronavirus pandemic financial crisis.

Chapter 4

Results

The following chapter discusses the results yielded by the analysis of momentum in US common stocks over the 1927-2020 time period. A specific focus is set on the behaviour of the strategy throughout the covid-19 bear market and the relation between the WML portfolio and different market states.

The first Section 4.1 illustrates the characteristics of the momentum decile portfolio over time. More specifically, it assesses and compares the premiums yielded by momentum in the last four decades and in 2020. Section 4.2 investigates momentum's option-like behaviour and time varying betas in bear markets and "flash" bear markets. Next, Section 4.3 highlights the strategy's relation with different market states, focusing on panic periods which are bear markets with high ex-ante market variance. To conclude Section 4.4 discusses the methodologies at the basis of crash-proof momentum strategies.

4.1 *Momentum Characteristics overtime*

To begin with, Table 4.1 presents characteristics of monthly momentum decile portfolio excess returns over the full sample period from 1927:01 through 2020:12. WML is the zero-investment winner-minus-loser portfolio which is long the Decile 10 and short the Decile 1 portfolio. The average excess return, standard deviation, and alpha are in percent and annualized. SR indicates the annualized Sharpe Ratio. The α, t(α), and β are estimated from a full-period regression of each decile portfolio's excess returns on the CRSP value-weighted index. For all portfolios except WML, Sk_m indicates the full-period realized skewness of the monthly log returns to the portfolios. For WML, Sk_m is the realized skewness of $log(1+r_{WML}+r_f)$. This is because, the self-financing WML portfolio is constructed investing on margin. Thus, returns for WML, in addition to the gains resulting from both the long and short side, also consider that the margin posted earns interest at the risk-free rate, r_f.

Furthermore, Figure 4.1 plots the cumulative monthly returns over the entire sample period from 1927:01- 2020:12 for investments in the risk-free rate, the CRSP value-weighted index (market portfolio), the self-financing Winner minus Loser portfolio, the bottom decile portfolio (Losers), the top decile portfolio (Winners). The x-axis represents the dates, while the y-axis presents the cumulative return for each portfolio. Furthermore, assuming no transaction costs, the right-hand side of the graph illustrates the closing values for each of the four portfolios, given a $1 investment in January 1927.

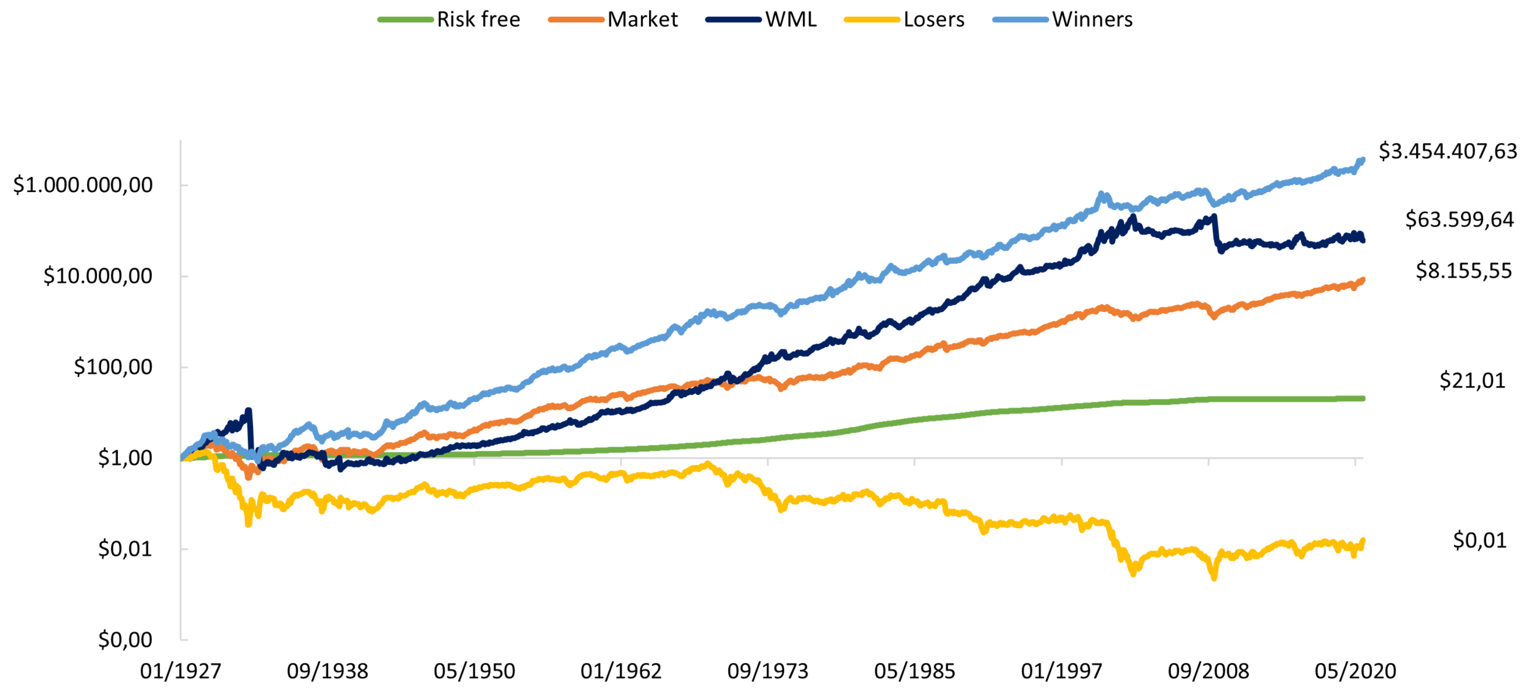

Figure 4.1: *Cumulative gains from investments 1927-2020*

Returns Statistics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	WML	Market
$r - r_f$	-1.4	3.2	3.8	6.9	7.8	7.6	9.3	10.6	11.7	15.8	17.2	8.1
σ	36.7	30.2	25.7	22.7	21.1	20.0	19.1	18.8	20.0	23.6	30.0	18.5
α	-14.7	-8.3	-6.2	-2.1	-0.8	-0.8	1.3	2.8	3.6	7.2	21.9	0
$t(\alpha)$	(-6.9)	(-5.4)	(-5.3)	(-2.3)	(-1.0)	(-1.3)	(2)	(4.3)	(4.3)	(5.2)	(7.5)	(0)
β	1.64	1.41	1.24	1.12	1.06	1.02	0.98	0.95	0.98	1.05	-0.59	1
SR	-0.03	0.10	0.14	0.30	0.37	0.37	0.48	0.56	0.58	0.66	0.57	0.43
$Sk(m)$	0.07	-0.18	-0.20	0.07	-0.11	-0.26	-0.65	-0.55	-0.76	-0.78	-4.83	-0.55

Table 4.1: *Momentum Portfolio Characteristics, Full-period 1927:01-2020:12*

First of all, in line with the existing literature, a substantial momentum premium appears over the last century. The winners have significantly outperformed the losers, with a mean excess return of 15.8%, against the -1.4% yielded by Decile 1. Consequently, the momentum WML portfolio had an annual average excess return of 17.2%, largely outperforming the market, which has an average excess return of 8.1%. The Beta of the momentum portfolio is negative, -0.59, and the unconditional CAPM alpha is 21.9% per year (t-statistic = 7.5). Considering a risk-adjusted perfomance metric, such as the Sharpe ratio, the WML portfolio had a higher rate of return per unit of risk with respect to the market. The momentum portfolio had a full period SR of 0.57, while that of the market was 0.43. Furthermore, observing the skewness an interesting pattern emerges. The winner portfolios are considerably more negatively skewed than the loser portfolios. Additionally, it is noticeable that the winners become more negatively skewed as we move to more extreme deciles. For the top winner decile portfolio, the monthly skewness is -0.78, while for the most extreme losers decile, the skewness is 0.07. Overall, the WML portfolio over this full sample period presents a monthly skewness of -4.83. Negative skewness indicates that the tail of the left side of the distribution is fatter than the tail on the right side; in this specific case, the left side of the distribution refers to negative returns. Such pattern supports the evidence that the high returns experienced by the winners deciles and by the momentum strategy are partly a compensation for taking on more skewness risk.

4.1.1 *Momentum in the last 4 decades*

To analyze how the strategy's premium behaved overtime, the following tables illustrate characteristics of monthly momentum decile portfolio excess returns for the last four decades individually. Respectively, table 4.2 refers to the time period going from 1980:01 through 1989:12, table 4.3 refers to the time period going from 1990:01 through 1999:12, table 4.4 refers to the time period going from 2000:01 through 2009:12, and table 4.5 refers to the time period going from 2010:01 through 2020:12. WML is the zero-investment winner-minus-loser portfolio which is long the Decile 10 and short the Decile 1 portfolio. The average excess return, standard deviation, and alpha are in percent and annualized. SR indicates the annualized Sharpe Ratio. The α, t(α), and β are estimated from a full-period regression of each decile portfolio's excess returns on the CRSP value-weighted index. For all portfolios except WML, Sk_m indicates the full-period realized skewness of the monthly log returns to the portfolios. For WML, Sk_m is the realized skewness of $log(1+rWML+rf)$. This is because, the self-financing WML portfolio is constructed investing on margin. Thus, returns for WML, in addition to the gains resulting from both the long and short side, also consider that the margin posted earns interest at the risk-free rate, r_f.

The roaring 80s and 90s

Figure 4.2 plots the cumulative monthly returns over the sample period from 1980:01- 1999:12 for investments in the risk-free rate, the CRSP value-weighted index (market portfolio), the self-financing Winner minus Loser portfolio, the bottom decile portfolio (Losers), the top decile portfolio (Winners). The x-axis represents the dates, while the y-axis presents the cumulative return for each portfolio. Furthermore, assuming no transaction costs, the right-hand side of the graph illustrates the closing values for each of the four portfolios, given a $1 investment in January 1980.

Having a closer look at the characteristics of the momentum decile portfolios through the 80s and the 90s, an even stronger premium emerges. From table 4.2 and 4.3, it is noticeable

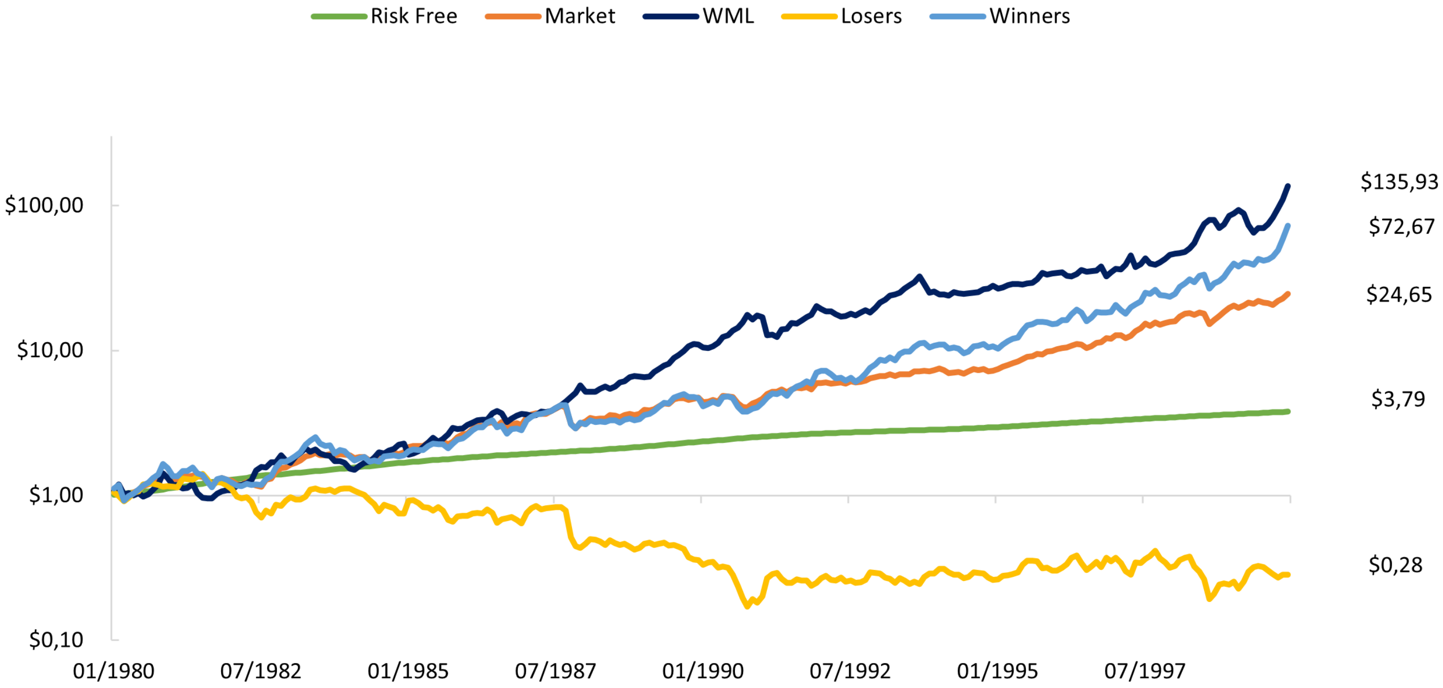

Figure 4.2: *Cumulative gains from investments 1980-1999*

Returns Statistics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	WML	Market
$r - r_f$	−15.6	−1.8	3.9	7.9	7.7	6.5	8.4	10.1	12.1	10.2	25.8	8.5
σ	24.7	20.8	18.4	16.6	16.0	16.6	18.2	18.5	20.8	23.6	21.3	16.9
α	−25.18	−10.56	−4.08	0.59	0.11	−1.58	−0.47	1.25	2.49	−0.49	24.68	0
$t(\alpha)$	(−4.9)	(−2.8)	(−1.3)	(0.23)	(0.06)	(−1.2)	(−0.3)	(0.6)	(0.9)	(−0.1)	(3.6)	(0)
β	1.12	1.01	0.94	0.86	0.89	0.96	1.04	1.04	1.13	1.25	0.13	1
SR	−0.63	−0.09	0.21	0.48	0.47	0.39	0.46	0.54	0.58	0.43	1.21	0.50
$Sk(m)$	−1.17	−0.59	−0.46	0.13	−0.41	−0.88	−0.95	−1.11	−1.41	−1.34	−0.75	−1.38

Table 4.2: *Momentum Portfolio Characteristics, 1980:01-1989:12*

Returns Statistics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	WML	Market
$r - r_f$	−2.9	−0.08	5.2	8.7	8.7	8.3	11.6	14.2	14.8	25.6	28.5	12.7
σ	29.1	22.3	18.4	15.8	14.4	14.3	13.1	13.8	15,6	23.7	21.3	13.8
α	−21.4	−15.41	−8.32	−3.13	−3.02	−3.54	0.64	2.48	1.55	7.47	28.94	0
$t(\alpha)$	(−3.10)	(−3.12)	(−2.26)	(−1.03)	(−1.37)	(−1.67)	(0.35)	(1.38)	(0.792)	(‘1.71)	(3.48)	(0)
β	1.45	1.20	1.06	0.93	0.92	0.92	0.86	0.92	1.04	1.42	−0.02	1
SR	−0.1	−0.003	0.28	0.55	0.6	0.57	0.88	1.02	0.95	1.08	1.12	0.92
$Sk(m)$	−0.13	−0.40	−0.34	−0.23	−0.62	−0.89	−0.66	−0.51	−0.49	−0.37	−0.86	−0.96

Table 4.3: *Momentum Portfolio Characteristics, 1990:01-1999:12*

that in such decades the WML portfolio overperformed the market by much more than the momentum strategy have outperformed the market over the entire period considered. More precisely, the WML portfolio (market) excess returns in the 80s and the 90s are respectively 25.8% and 28.5% (8.5% and 12.7%). Taking into consideration the realized volatility of returns, the momentum strategy in the period going from 1980:01 to 1989:12 had a Sharpe ratio of 1.21 against the value of 1.12 in the 90s. However, both the metrics are almost more than the double of the whole sample SR previously estimated which is 0.57. Concerning the skewness, the results align with the pattern found earlier. The winners become more negatively skewed as we move to more extreme deciles. Overall, the 80s and the 90s were outstanding decades for momentum investors. The discussed results are consistent with the full sample characteristics and with the existing literature.

The Twenty-first century: is momentum investing dead ?

Figure 4.3 plots the cumulative monthly returns over the sample period from 2000:01- 2020:12 for investments in the risk-free rate, the CRSP value-weighted index (market portfolio), the self-financing Winner minus Loser portfolio, the bottom decile portfolio (Losers), the top decile portfolio (Winners). The x-axis represents the dates, while the y-axis presents the cumulative return for each portfolio. Furthermore, assuming no transaction costs, the right-hand side of the graph illustrates the closing values for each of the four portfolios, given a $1 investment in January 2000.

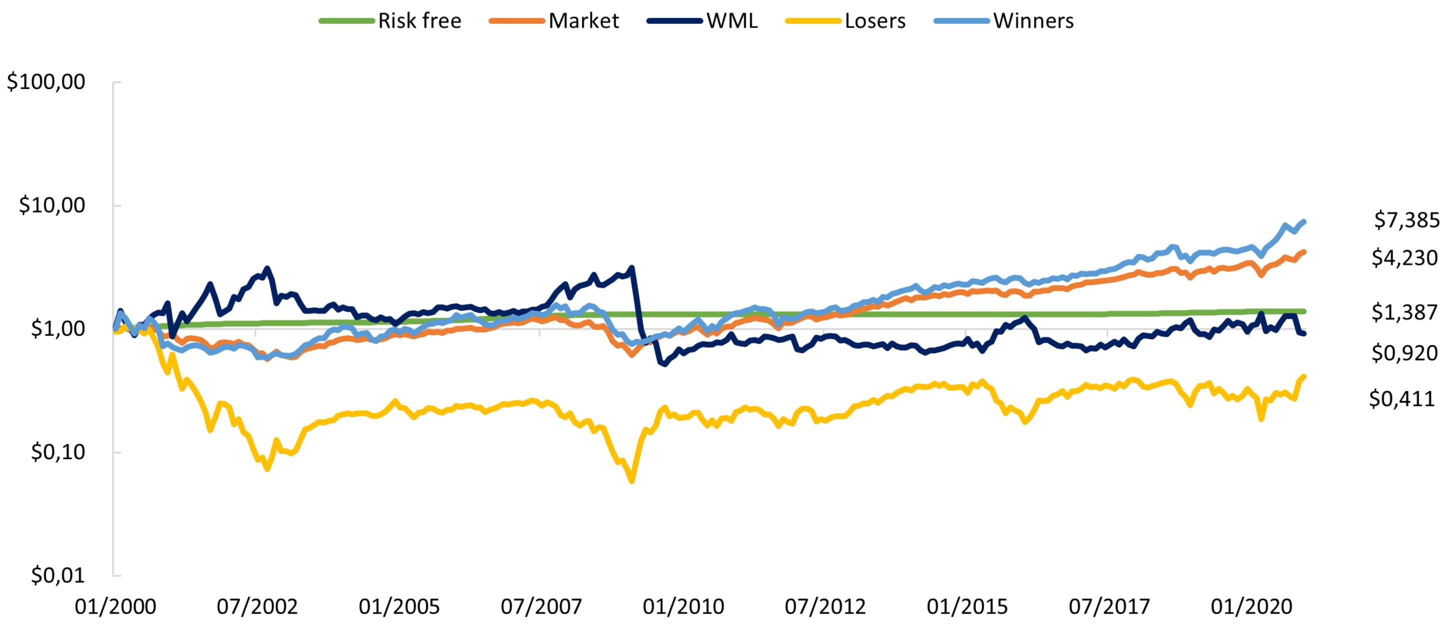

Figure 4.3: *Cumulative gains from investments 2000-2020*

Some more intriguing findings arise when we consider the first twenty years of the 2000s. Regarding the first decade of the twenty-first century, it is critical to notice that, on average, the market had a negative excess return of 1.7%.

Returns Statistics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	WML	Market
$r-r_f$	−7.9	−2.1	−2.9	−0.5	−0.1	0.4	1.1	0.3	−2.3	0.85	8.8	−1.7
σ	49.97	36.71	30.05	23.92	20.36	15.86	13.83	15.24	17.02	26.51	47.02	16.65
α	−3.67	1.10	−0.34	1.70	1.73	1.98	2.43	1.77	−0.94	2.81	6.49	0
$t(\alpha)$	(−0.389)	(0.17)	(−0.065)	(0.45)	(0.56)	(0.84)	(1.19)	(0.001)	(0.002)	(0.005)	(0.01)	(0)
β	2.40	1.82	1.50	1.25	1.07	0.84	0.73	0.80	0.82	1.08	−1.32	1
SR	−0.15	−0.05	−0.09	−0.021	−0.008	0.031	0.081	0.023	−0.140	0.033	0.187	−0.106
$Sk(m)$	0.18	−0.36	−0.33	−0.37	−0.57	−0.35	−0.89	−0.72	−1.14	−0.39	−1.79	−0.80

Table 4.4: *Momentum Portfolio Characteristics, 2000:01-2009:12*

The time period considered is very turbulent. More precisely, through these ten years, financial markets underwent two of the most severe financial crisis ever experienced, the dot-com bubble and the subprime mortgages crisis. The bear market of 2000-2002 lasted from February 2000 to October 2002; in 31 months, the SP500 declined by approximately 49%. On the other hand, the US bear market of 2007-2008 was slightly shorter but more intense. It was a 17-month bear market lasting from October 2007, till March 2009; in such period, the SP500 lost 56% of its value. Interestingly, in this kind of market condition, the WML portfolio returns exhibit a significantly higher volatility of 47.02% (the full period volatility estimate for the WML portfolio is 30.0%). Despite the unfavorable and extreme movements the market underwent in the decade, the momentum strategy on average overperformed the market, yielding an annual average excess return of 8.8%. However, the small Sharpe ratio (0.187) and the monthly skewness of -1.79 (which almost doubles the values of the 80s and the 90s) suggest that the strategy suffered from severe crashes. Such intuition is confirmed by DM16, which have shown that 7 out of the 15 worst momentum monthly returns took place in the first decade of the twenty-first century and are attributable to the dot-com bubble and 2008 financial crisis.

The most exciting findings emerge from the analysis of the last decade, which is the period going from January 2010 till December 2020. From table 4.5 we can observe that among the momentum portfolio deciles, winners (decile 10) on average still overperformed the remaining nine portfolios. Furthermore, the WML portfolio had a beta of -0.71, close to its total period value of -0.59. However, these last ten years have been quite rough for long/short momentum factor investors.

The WML had a disappointing performance, yielding an average annual excess return of 6.8%, while the market excess return has been 14.1%. Taking into account volatilities, the difference in terms of performance becomes even more pronounced. The market's Sharpe ratio (0.95) is more than four times momentum's factor Sharpe ratio (0.23). The short leg of the portfolio mainly drives such underperformance. Indeed from the previous tables, it is noticeable that historically past losers were characterized by having negative returns and negative alphas. While, in this last decade buying losers turned out to be a strategy more profitable than investing in the WML portfolio. The decile 1 portfolio had an annual average excess return of 12.6%

with a Sharpe ratio of 0.35. Nonetheless, the losers portfolio still yielded a negative alpha of 14.52% indicating that, compared to the market, investing in the decile 1 portfolio was too risky for the return earned (or has earned too little for its systematic risk). On the other hand, the WML portfolio had a positive and large alpha (16.93%). Such metric does not directly mean higher returns but it indicates that over this last decade momentum had good returns at a lower risk, relative to the market. It is important to bear in mind that the alpha is a measure of excess return on a market relative risk-adjusted basis, while the Sharpe ratio takes into consideration absolute risk relying on standard deviations to measure the volatility of returns. Consequently the SR, being a measure of unit of return earned per unit of absolute risk assumed by an investments, is a more meaningful performance metric. Noticeably, in this last considered decade, none of the ten deciles portfolios examined had a higher SR than the market. Furthemore, among all the different periods considered, it is the first time that the SR of the WML portfolio is much lower than that of the market. It appears that momentum has lost its historical premium.

Returns Statistics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	WML	Market
$r - r_f$	12.6	8.4	11.9	14.8	13.9	13.0	13.5	14.8	14.1	19.4	6.8	14.1
σ	35.63	26.46	20.44	17.43	15.69	14.85	14.60	14.81	15.16	20.52	28.54	14.77
α	−14.52	−13.40	−5.18	−0.56	−0.33	−0.63	0.05	1.33	0.70	2.40	16.93	0
$t(\alpha)$	(−2.13)	(−3.18)	(−1.67)	(−0.27)	(−0.224)	(−0.51)	(0.04)	(0.92)	(0.38)	(0.74)	(2.03)	(0)
β	1.91	1.54	1.21	1.08	1.01	0.96	0.95	0.95	0.94	1.20	−0.71	1
SR	0.35	0.32	0.58	0.85	0.89	0.88	0.92	1	0.93	0.94	0.23	0.95
$Sk(m)$	0.04	−0.75	−0.64	−0.79	−0.6	−0.76	−0.56	−0.35	−0.56	−0.48	−0.96	−0.28

Table 4.5: *Momentum Portfolio Characteristics, 2010:01-2020:12*

After the poor results achieved by momentum during these last years, many academics and institutional investors started questioning the strategy's viability in modern financial markets. They already knew that momentum is painful and that historically such an investment approach went through severe crashes. Furthermore, given that such underperformance is dictated by sudden and dramatic upswings following a period of bear market and thus are predictable, researchers and practitioners developed several momentum hedged strategies. Nevertheless, the meager performance exhibited by the original cross-sectional momentum raised many concerns and has caused many investors to wonder whether momentum-driven investing is dead. A comprehensive research that approaches such question was carried by Zimmerer et al.(2019) [40]. In light of their study, they stated that, as a risk factor associated with a positive risk premium, momentum, if implemented correctly, remains very much alive and profitable. However, they concluded that most simplistic traditional momentum investing approaches might never return to profitability. They highlighted four critical flaws generally common to most traditional momentum strategies: they rely on a single trend, they are uni-dimensional, they consider single asset classes and finally they employ a too short investment horizon. Consequently, the authors introduced an optimal design of a modern trend-following investment approach, named momentum 2.0, which relies on four pivotal elements to ensure the strategy's profitability:

1. Multiple lookback periods: it is not just about catching one trend. There are several overlapping trends whose relative attractiveness and predictive power fluctuate over time.

2. Multi-dimensional approach: combining trend direction with a measure of trend strength to better assesses trend's duration.

3. Multi-asset portfolio construction: since momentum returns across asset classes are uncorrelated, using a strategy with different assets delivers diversification benefits.

4. Appropriate investment horizon: momentum is associated with a long-term risk premium, a 10-year window is the most appropriate investment horizon.

The main point is that the premium yielded by momentum strategies did not disappear but became harder to capture.

4.1.2 *Momentum in 2020*

Figure 4.4 plots the cumulative monthly returns over the sample period from 2020:01 - 2020:12 for investments in the risk-free rate, the CRSP value-weighted index (market portfolio), the self-financing Winner minus Loser portfolio, the bottom decile portfolio (Losers), the top decile portfolio (Winners). The x-axis represents the dates, while the y-axis presents the cumulative return for each portfolio. Furthermore, assuming no transaction costs, the right-hand side of the graph illustrates the closing values for each of the four portfolios, given a $100 investment in January 2020. Momentum's underperformance in 2020 is apparent; among all the portfolios considered, the WML is the only one that lost value this last year.

To conclude this first section, table 4.6 illustrates momentum portfolio characteristics throughout 2020. In 2020 the market yielded an annual excess return of 24.84 %, which is more than double the return produced by the momentum factor (10.79%). The WML portfolio still exhibits a positive alpha of 40.9% indicating that momentum in 2020 had a return in excess of the reward for the assumed systematic risk. However, in terms of unit per return earned per unit of risk assumed, in 2020, momentum has largely underperfomed the market. The difference in performances becomes more marked when considering the Sharpe ratios. The market's SR is four-time as high as the WML's SR (0.89 vs 0.20). Despite the covid-19 financial crisis, the market performed particularly well in this last year, delivering a Sharpe ratio more than twice as big as its historical value which is 0.43. The results are consistent with the metrics discussed for the second decade of the new century. Also, in this case, the underperformance of the momentum factor is mainly attributable to the short leg of the portfolio. In 2020, investing in past losers, on a unit of return per unit of risk basis, turned out to be more fruitful than investing in the momentum factor. The decile 1 portfolio yielded an annual excess return of 44.54% with a SR of 0.6. Besides, it is remarkable that decile 10 had a stellar performance,

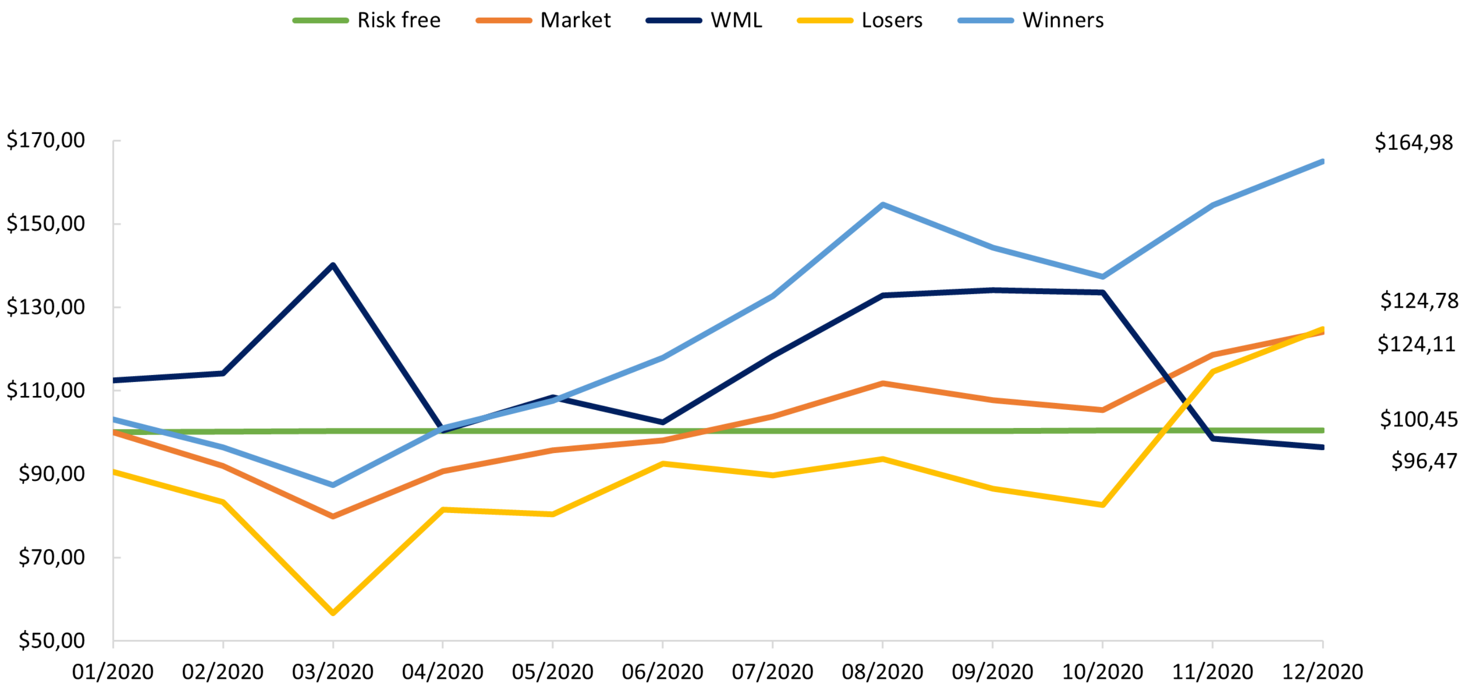

Figure 4.4: *Cumulative gains from investments 2020*

delivering a Sharpe ratio of 1.70. Such value is significantly larger than the historical Sharpe ratios delivered by both the winner decile and the WML portfolio.

Returns Statistics	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	WML	Market
$r - r_f$	44.54	21.36	14.93	20.27	13.88	16.60	14.99	21.67	19.36	55.34	10.79	24.84
σ	72.84	58.31	40.31	36.02	29.01	27.45	25.79	26.30	24.85	32.46	53.67	27.69
α	−12.36	−26.71	−17.75	−10.22	−11.27	−7.40	−7.69	−1.51	−2.34	28.54	40.90	0
$t(\alpha)$	(−0.318)	(−1.072)	(−0.948)	(−0.790)	(−1.402)	(−1.114)	(−1.409)	(−0.291)	(−0.381)	(2.076)	(0.899)	(0)
β	2.29	1.93	1.31	1.22	1.01	0.96	0.91	0.93	0.87	1.07	−1.21	1
SR	0.611	0.366	0.370	0.562	0.478	0.604	0.581	0.823	0.77	1.70	0.201	0.896
$Sk(m)$	0.019	−0.656	−0.830	−0.718	−0.527)	−0.721	−0.459	−0.297	−0.793	−0.337	−0.977	−0.524

Table 4.6: *Momentum Portfolio Characteristics, 2020:01-2020:12*

The last year has been a challenging and stormy period in which financial markets experienced high variance, and went through a ”flash” but painful bear market. In fact, by observing the portfolios’ sigmas, it is remarkable that returns’ volatilities in 2020 are substantially larger than their respective full-period averages. Furthemore, in 2020 momentum’s market beta assumed a value of -1.21, suggesting that when the market rebounds quickly momentum will crash because it has a conditionally large negative beta. Such numbers are similar to the most turbulent period previously investigated, the first ten years of the 2000s. Nevertheless, in 2020, the market and the losers decile portfolios experienced much more volatility. Such a situation perfectly matches the context that leads to momentum crashes described in DM16, periods of high market stress characterized by sudden upswings in the market return after a period of bear market. Thus, one would expect a crash of the momentum strategy in 2020. Indeed, we can confirm that the WML portfolio underperformed the market during the year of the covid-19 financial crisis.

Month	WML	Market
Jan	12.4	0.02
Feb	1.49	-8.01
Mar	22.5	-13.2
Apr	-28.2	13.6
May	7.81	5.59
Jun	-5.49	2.47
Jul	15.5	5.79
Aug	12.2	7.64
Sep	0.94	-3.62
Oct	-0.41	-2.09
Nov	-26.2	12.48
Dec	-2.08	4.64
AAR	10.79	24.84

Table 4.7: *Percentage Returns of momentum vs Market, 2020*

To better understand the returns pattern manifested by the momentum strategy in 2020, Table 4.7 presents the monthly returns (in %) of the market and the WML portfolio throughout the entire year. With AAR representing the average annual return. March and April 2020 are respectively the worse (-13.2%) and the best (13.6%) months experienced by the market in the last year. We can observe a reversed pattern for the monthly returns of the WML portfolio. The strategy recorded its best performance in March, earning a return of 22.5%, while the worst crash took place in April 2020 when momentum yielded a negative 28.2%. Similarly, in November, the WML portfolio failed again, recording a return of -26.2%. Interestingly both crashes occur in months in which the market rose, after two consecutive months of negative returns. To put into perspective and have a clearer idea of the entity of such crashes table 4.8 lists the 15 worst returns to the winner minus loser momentum portfolio over the 1927:01-2020:12 time period. Also tabulated are Mkt-2y, Mkt-6m, Mkt-4m, the two years, six, and four-month market returns leading up to the portfolio formation date. Mkt represents the contemporaneous market return. All numbers in the table are in percent.

Table 4.8 confirms that the momentum strategy crashed following the covid-19 crisis. As we can see, 2020 appears twice among the list of the 15 worst WML monthly returns. More precisely, April's crash ranked 12th, while November's ranked 14th. Furthermore, some interesting patterns emerge. Thirteen of the fifteen worst momentum returns occur when the lagged two-year market return is negative. Twelve (eleven) out of 15 occur when the lagged 6-month (4-month) market return is negative. All crashes occur in months in which the market experienced a contemporaneous positive return. To conclude, such a pattern suggests that the WML

Rank	Month	WML	MKT-2y	Mkt -6	Mkt-4	Mkt
1	1932 : 08	−77.5	−67.5	−18.3	−13.1	37.0
2	1932 : 07	−58.2	−74.7	−39.8	−42.2	33.8
3	2001 : 01	−46.4	10.5	−10.5	−15.1	3.6
4	2009 : 04	−45.8	−40.6	−30.0	−8.4	10.1
5	1939 : 09	−44.8	−21.5	−8.6	4.0	16.8
6	2009 : 03	−42.3	−44.9	−41.6	−22.5	8.9
7	1933 : 04	−40.7	−58.9	−24.3	−7.4	38.9
8	2002 : 11	−35.4	−36.2	−17.6	−10.2	6.0
9	1938 : 06	−32.4	−27.9	−14.5	−11.2	23.8
10	2009 : 08	−30.9	−27.3	22.9	25.4	3.3
11	1931 : 06	−29.3	−47.5	−20.1	−18.6	13.9
12	2020 : 04	−28.2	−0.9	−12.7	−17.8	13.6
13	1933 : 05	−26.9	−36.6	21.0	23.1	21.4
14	2020 : 11	−26.2	26.9	16.2	7.4	12.4
15	2001 : 11	−25.5	−19.8	−14.4	−13.8	7.7

Table 4.8: *Worst momentum monthly returns, 1927:01-2020:12*

portfolio has terrible results when markets rebound following a bear market, whether it is a long or a ”flash” period of economic downturn.

4.2 *Option like behaviour*

The following part of the analysis investigates more formally the beta variation and how the mean return of the WML portfolio is related to time variation in market risk. Table 4.9 presents the results of estimating three specifications of a monthly time-series regressions run over the period 1927:01-2020:12. Specifically column (1), refers to Regression 3.1, column (2) refers to Regression 3.2, and column (3) refers to regression 3.4. The equations are specified in Section 3.3. In every case, the dependent variable is the return on the WML portfolio. While $I_{B,t-1}$ is the bear market indicator variable, which in this case equals one if the cumulative past two-year return on the market is negative. The coefficients $\hat{\alpha}_0$ $\hat{\alpha}_B$ are multiplied by 100 (percent per month).[2] Using a similar specification, DM16 showed that the market beta of the momentum portfolio is strongly negatively correlated with the contemporaneous market return and that the return of the momentum portfolio is significantly lower in bear markets.

Column (1) in table 4.9 fits an unconditional CAPM to the momentum portfolio. The results are consistent with the existing literature. The market beta assumes a negative value of -0.592 with a t-statistic of -13.2. Additionally, the $\hat{\alpha}_0$ is positive (1.832% per month) and highly

[2]Significance codes: *** statistically significant at 0.1%; ** statistically significant at 1%; * statistically significant at 5%; ‘ statistically significant at 10%.

Coefficient	Variable	Estimated Coefficients (t-stats)		
		(1)	(2)	(3)
$\hat{\alpha}_0$	1	$1.832***$ (7.5)	$1.855***$ (7.4)	$1.73**$ (3.04)
$\hat{\alpha}_B$	$I_{B,t-1}$		$-1.726**$ (-2.8)	-0.144 (-0.1)
$\hat{\beta}_0$	$\tilde{R}_{m,t}$	$-0.592***$ (-13.232)	-0.106‘ (-1.8)	-0.071 (-0.6)
$\hat{\beta}_B$	$I_{B,t-1} * \tilde{R}_{m,t}$		$-1.073***$ (-12.8)	$-0.750***$ (-3.9)
$\hat{\beta}_{B,U}$	$I_{B,t-1} * I_{U,t} * \tilde{R}_{m,t}$			$-0.456*$ (-1.7)
R^2_{adj}		0.133	0.257	0.268

Table 4.9: *Market Timing regression results*

statistically significant (t-statistic = 7.5) , confirming a strong premium over the full period.

In column (2), I add the indicator variable $I_{B,t-1}$ to investigate how the market beta of the WML portfolio varies in bear markets. In line with the findings of DM16, the $\hat{\beta}_B$ is negative and highly statistically significant (t-statistic = -12.8). It indicates that momentum's market beta is -1.073 lower in bear markets. Furthermore, the coefficient $\hat{\alpha}_B$ indicates that the premium yielded by the strategy is significantly lower in such periods. The intercept is almost zero but remains positive. More specifically the alpha in declining markets is equal to $\hat{\alpha}_0 + \hat{\alpha}_B$ which is 0.129% per month.

In column (3), I include an auxiliary variable, the $I_{U,t}$ to capture the extent to which the up- and down-market betas of the momentum portfolio differ. When the contemporaneous market return is negative, the WML portfolio beta ($\hat{\beta}_0 + \hat{\beta}_B$) is equal to -0.821. However when the market rebounds during or following periods of declining markets momentum's beta becomes -1.277 ($\hat{\beta}_0 + \hat{\beta}_B + \hat{\beta}_{B,U}$). The coefficient $\hat{\beta}_{B,U}$ is negative and statistically significant (t-statistic = -1.7), meaning that in bear markets, momentum is effectively shorting a call option on the market. Which is to say, when the market bounces back after a financial crisis, the WML portfolio suffers severe crashes. Overall the results yielded by this first set of regressions are highly consistent with the research carried out by Daniel and Moskowitz [1].

4.2.1 *Optionality in Flash Bear Markets*

In this section, to capture whether momentum crashes manifested after short but intense periods of economic downturn, we replace the bear-market indicator variable with the two new "Flash-Bear" market indicators. Such change allows us to investigate the variation of the WML portfolio market beta in short bear markets. Table 4.10 presents the results of estimating three monthly time-series regressions run over the period 1927:01-2020:12. Specifically column (1), refers to Regression 3.1, column (2a) refers to Regression 3.3 and column (3a) refers to regression 3.6. The equations are specified in Section 3.3. In all cases, the dependent variable is the return on the WML portfolio, and $I_{FB(6),t-1}$ is the first "flash" bear market indicator variable, which in this case equals one if the cumulative past six-month return on the market is negative. The coefficients $\hat{\alpha}_0$ $\hat{\alpha}_B$ are multiplied by 100 (percent per month). Table 4.11, ceteris paribus, considers an even shorter period of declining market, $I_{FB(4),t-1}$ equals one if the cumulative past 4-month return on the market is negative. Here, column (1), refers to regression 3.1, column (2b) refers to regression 3.4 and column (3b) refers to regression 3.7. The equations are specified in Section 3.3. [3]

Coefficient	Variable	Estimated Coefficients (t-stats)		
		(1)	(2a)	(3a)
$\hat{\alpha}_0$	1	1.832∗∗∗	1.800∗∗∗	1.365∗
		(7.5)	(6.5)	(2.1)
$\hat{\alpha}_B$	$I_{B,t-1}$		−0.68	0.22
			(−1.3)	(0.2)
$\hat{\beta}_0$	$\tilde{R}_{m,t}$	−0.592∗∗∗	−0.080	−0.086
		(−13.232)	(−1.2)	(−0.6)
$\hat{\beta}_B$	$I_{B,t-1} * \tilde{R}_{m,t}$		−0.950∗∗∗	−0.642∗∗∗
			(−11.1)	(−3.4)
$\hat{\beta}_{B,U}$	$I_{B,t-1} * I_{U,t} * \tilde{R}_{m,t}$			−0.519∗
				(−2.0)
R^2_{adj}		0.133	0.222	0.244

Table 4.10: *Market Timing regression results IBT6M*

Coefficient	Variable	Estimated Coefficients (t-stats)		
		(1)	(2b)	(3b)
$\hat{\alpha}_0$	1	1.832∗∗∗	1.728∗∗∗	1.83∗∗
		(7.5)	(6.0)	(2.8)
$\hat{\alpha}_B$	$I_{B,t-1}$		−0.19	−0.945
			(−0.3)	(−0.8)
$\hat{\beta}_0$	$\tilde{R}_{m,t}$	−0.592	−0.21∗∗	−0.041
		(−13.232)	(−3.1)	(−0.2)
$\hat{\beta}_B$	$I_{B,t-1} * \tilde{R}_{m,t}$		−0.664∗∗∗	−0.656∗∗∗
			(−7.5)	(−3.4)
$\hat{\beta}_{B,U}$	$I_{B,t-1} * I_{U,t} * \tilde{R}_{m,t}$			−0.113
				(−0.4)
R^2_{adj}		0.133	0.173	0.211

Table 4.11: *Market Timing regression results IBT4M*

For both flash bear market indicators (the six and the four-month) bear market indicator,

[3] Significance codes: *** statistically significant at 0.1%; ** statistically significant at 1%; * statistically significant at 5%; ‘ statistically significant at 10%.

the results in columns (2a) and (2b) are partly consistent with earlier discussed findings. The coefficients of the new pair indicators, $\hat{\beta}_B$, are negative and highly statistically significant, indicating a consistent time variation in the beta of the momentum portfolio in short bear markets. Momentum's beta is -0.950 (-0.664) lower when the past cumulative six (four) month market return is negative. In such periods, the intercept declines but remains well above one. However, the coefficients $\hat{\alpha}_B$ are not significant anymore.

Intriguingly, some differences emerge from the results between column (3a) and (3b). The beta of the momentum portfolio, when the contemporaneous market return is negative, is similar for the two "flash" bear markets considered (-0.728 and -0.697). However, outcomes diverge when the market return at time t returns to be positive. When the market rebounds, following a flash bear market lasting 6 month, momentum's beta is -1.247 ($\hat{\beta}_0 + \hat{\beta}_B + \hat{\beta}_{B,U}$). In this case the coefficient $\hat{\beta}_{B,U}$ is negative, -0.519, and statistically significant (t-statistic = -2). In contrast, for declining markets lasting four months, the coefficient $\hat{\beta}_{B,U}$ is still negative, -0.113, but it is not statistically significant anymore. Consequently, the momentum's beta in such circumstances is closer to zero -0.81.

The discussed findings suggest that when the market bounces back after periods in which the past cumulative six (or more) months market return is negative, the WML portfolio suffers severe crashes. Consistently with the 24-month bear market indicator, momentum investing is effectively shorting a call option on the market also for more concise bear markets lasting only six months. Interestingly, such optionality did not manifest for the shortest bear market considered, the coefficient is of the right sign but is not statistically significant. In other words, I cannot confirm that the WML portfolio crashes when there is an upswing in the market's return following bear markets lasting only four months.

4.3 *VIX and momentum returns*

The findings earlier discussed indicate that the WML portfolio, in bear markets, behaves like shorting a call option on the market. Furthermore, given that the value of a call option is positively related to the market variance, such optionality suggests that the expected returns of the momentum strategy should be a declining function of the future variance of the market. The following section investigates this supposition.

In Table 4.12 we use the VIX, as an estimate of the market variance, combined with the bear-market indicator $I_{B,t-1}$ used in the previous section to forecast future WML returns. Each column presents the estimated coefficients and t-statistics for a monthly time-series regression, over the entire period 1927:01-2020:12, based on Regression 3.8, specified in section 3.3. The coefficients $\hat{\gamma}_0$ and $\hat{\gamma}_B$ are multiplied by one hundred and are in percent per month. [4]

[4] Significance codes: *** statistically significant at 0.1%; ** statistically significant at 1%; * statistically significant at 5%; ' statistically significant at 10%.

Coefficient				
	(1)	(2)	(3)	(4)
$\hat{\gamma}_0$	1.60∗∗	4.72∗∗∗	4.46∗∗	0.727
	(2.8)	(3.4)	(3.0)	(0.4)
$\hat{\gamma}_B$	−2.66‘		−0.829	
	(−1.8)		(−0.4)	
$\hat{\gamma}_{VIX}$		−0.179∗∗	−0.16∗	
		(−2.7)	(−2.1)	
$\hat{\gamma}_{int}$				−0.578∗∗∗
				(−3.7)

Table 4.12: *Momentum return and the VIX Index*

From columns (1) and (2), it is noticeable that both the bear market indicator and the VIX independently forecast future momentum returns. Both coefficients, $\hat{\gamma}_B$ and $\hat{\gamma}_{VIX}$ are negative and statistically significant, suggesting that in periods of high market stress (i.e., bear-markets and high market volatility), momentum strategy performs poorly. Column (4) considers the interaction between the two variables to capture the performance of the WML portfolio in periods of bear-market with high market volatility. The interaction effect coefficient $\hat{\gamma}_{int}$, is highly statistically significant (t-statistic= -3.7), and remains negative (-0.578), indicating that momentum's returns are particularly low in periods of bear-markets with high volatility. To conclude even though, I relied on the VIX as a forward-looking indicator of the market's variance, while DM16 used the variance of the daily returns of the market over the 126-days just before the start of month t, the results yielded by the analysis are consistent with existing literature.

4.3.1 *Flash Bear Markets*

In Table 4.13 I use the VIX, as an estimate of the market variance, combined with the bear-market indicator $I_{FB(6),t-1}$ used in the previous section to forecast future WML returns. Each column presents the estimated coefficients and t-statistics for a monthly time-series regression, over the entire period 1927:01-2020:12, based on Regression 3.9, specified in section 3.3. The coefficients $\hat{\gamma}_0$ and $\hat{\gamma}_B$ are multiplied by one hundred and are in percent per month. While, ceteris paribus, Table 4.14 presents the results of Regression 3.10, where the bear-market indicator $I_{FB(4),t-1}$ equals one if the cumulative past 4-month return on the market is negative. [5]

In contrast with the previously used bear-market indicator, $I_{B,t-1}$, both the new flash bear market indicators do not seem to forecast future momentum returns. From column (1) of Table 4.13 and Table 4.14 The coefficients $\hat{\gamma}_{B(6)}$ and $\hat{\gamma}_{B(4)}$ are negative, but not statistically significant.

[5] Significance codes: *** statistically significant at 0.1%; ** statistically significant at 1%; * statistically significant at 5%; ‘ statistically significant at 10%.

However the most interesting results comes from column (4), which considers the interaction between the VIX and the flash bear-market indicator variables.

Coefficient				
	(1)	(2)	(3)	(4)
$\hat{\gamma}_0$	$1.68**$	$4.72***$	$4.63**$	0.688
	(2.8)	(3.4)	(3.2)	(0.3)
$\hat{\gamma}_{B(6)}$	-1.86		-0.308	
	(-1.5)		(-0.2)	
$\hat{\gamma}_{VIX}$		$-0.179**$	$-0.171*$	
		(-2.7)	(-2.2)	
$\hat{\gamma}_{int(6)}$				$-0.385*$
				(-2.5)

Table 4.13: *Market Timing regression results IBT6M*

This setting is an attempt to capture the performance of the WML portfolio in periods of flash bear-market with high market volatility. The interaction effect coefficient $\hat{\gamma}_{int(6)}$, is now statistically significant (at a 0.05 significance level and of t-statistic= -2.5) and assumes a negative value of -0.385. The same reasoning holds also for the coefficient $\hat{\gamma}_{int(4)}$ which has a value of -0.321 (t-statistic = -2.1). The results are consistent with those from Section 4.3. and suggest that in periods of high market stress, as indicated by flash bear-markets and high market variance momentum's returns are low.

Coefficient				
	(1)	(2)	(3)	(4)
$\hat{\gamma}_0$	$1.48*$	$4.72***$	$4.88***$	1.49
	(2.4)	(3.4)	(3.4)	(0.6)
$\hat{\gamma}_{B(4)}$	-0.98		0.65	
	(-0.8)		(0.5)	
$\hat{\gamma}_{VIX}$		$-0.179**$	$-0.197**$	
		(-2.7)	(-2.6)	
$\hat{\gamma}_{int(4)}$				$-0.321*$
				(-2.1)

Table 4.14: *Market Timing regression results IBT4M*

4.4 *Crash-proof momentum strategies*

The final part of this chapter builds on the evidence previously mentioned in Section 2.4, concerning market crash-hedged momentum strategies. More specifically, the following Section focuses on explaining the methodology behind the crash-proof momentum portfolios introduced by Barroso and Santa Clara (2015) [37], DM16 [1], and by Moreira and Muir (2017) [38]. Although it would be interesting to investigate the performance of these strategies during the most recent covid-19 bear market, such analysis goes beyond the scope of this dissertation. Anyway, describing the methods at the basis of the implementation of a crash-proof momentum strategy, the following Section is helpful for potential future research addressing this area.

As earlier described, the constant-volatility approach presented by Barroso and Santa Clara (2015) [37] and the volatility managed portfolios proposed by Moreira and Muir (2017) [38] are pretty similar. The former suggests scaling the amount invested in the WML portfolio targeting a precise level of volatility over time. The latter proposes to scale the portfolio's exposure by the inverse of the realized variance to reduce risk-taking during times of high volatility. In practice, both strategies manage portfolio's crash risk by targeting a constant level of volatility rather than a constant notional exposure. Thus, the following subsection describes the methodology behind volatility scaling and highlights the differences between the constant volatility and the volatility-managed portfolios. To conclude, the last subsection discusses the dynamic strategy, which is a more complex strategy specifically designed by DM16 to counter and mitigate momentum crashes [1]. In this case, the additional source of complexity comes from the fact that the strategy dynamically adjusts the weight on the momentum portfolio using both the forecasted return and variance of the strategy.

Before diving into the strategies' methodologies, let us first define the investment environment designed. Assuming that an agent, operating in a discrete time setting with T periods going from 1 to T, can trade in two assets, a risky asset which is the WML portfolio, and a risk-free asset, corresponding to the one-month treasury bill rate. Further assuming that he can trade in or out of the risky asset with no cost involved, he can freely assign a fraction w_t of the amount invested to the momentum portfolio and a fraction $1 - w_t$ to the risk-free asset. Thus, the agent can manage the portfolio by determining how to allocate the value of the managed portfolio between these two assets at the beginning of each period. In this way, in turbulent periods, the agent could decrease its portfolio risk exposure (w_t) by assigning more weight to the risk-free asset.

4.4.1 *Volatility scaling*

Volatility scaling is an asset allocation approach aiming at achieving a stable level of volatility in different market states. Such a technique involves leveraging and deleveraging the portfolio risk exposure according to time-varying expected volatility. By targeting a constant level of volatility, investors can maximize expected returns based on a fixed level of volatility over time, protecting their portfolios from crash or fat-tail risk.

The distribution of returns of the momentum strategy is characterized by a high excess kurtosis and a sizeable negative skewness, implying a very fat left tail. Such a feature suggests significant crash risk, indicating relatively long periods over which the momentum strategy experiences severe losses or crashes. Barroso and Santa Clara (2015) [37], and Moreira and Muir (2017) [38], show that volatility scaling reduces the probability of extreme losses by limiting the tail risk of extreme returns. In practice, both strategies construct a crash risk-managed portfolio by targeting a constant level of volatility rather than a constant notional exposure. Furthermore, Barroso and Santa Clara highlight that the most crucial benefit from risk managing the momentum portfolio comes from the improvements in the higher-order moments, which indicates a reduction in crash risk. The authors show that a constant volatility momentum strategy reduces the excess kurtosis from 18.24 to 2.68, and increases the skewness from -2.47 to -0.42.

The momentum managed portfolio return is equal to:

$$r^{\sigma}_{WML,t+1} = w_t \tilde{r}_{WML,t+1} \tag{4.1}$$

Where *wt* is the weight corresponding to the value of the managed portfolio invested in the momentum portfolio. While $\tilde{r}_{WML,t+1}$ is the buy-and-hold momentum strategy excess return.

In the constant volatility model proposed by Barroso and Santa Clara [37], the weight is equal to:

$$w_t = \frac{\sigma^2 target}{\hat{\sigma}^2_{WML,t}} \tag{4.2}$$

Here, $\sigma^2 target$ is a constant representing the target level of volatility[6], while $\hat{\sigma}^2_{WML,t}$ is an estimate of the monthly volatility of the momentum portfolio at time t. In their principal analysis Barroso and Santa Clara calculate the variance using the daily returns over the previous six months:

$$\hat{\sigma}^2_{WML,t} = 21 \frac{\sum_{j=0}^{125} r^2_{WML,d_{t-1}-j}}{126} \tag{4.3}$$

Where $r_{WML,d}$ are the daily returns of momentum. Thus the authors use the realized variance in the previous six months to scale the exposure to the risky momentum portfolio. Following this methodology, they showed that for the time period 1927:03–2011:12 on average, the weight is 0.90, indicating a slightly less than full exposure to momentum[7].

[6]They chose a target corresponding to an annualized volatility of 12%.

[7]Their results are robust also using the one-month and three-month realized variances as well as exponentially weighted moving average (EWMA).

In the volatility managed portfolio proposed by Moreira and Muir (2017) [38], the weight is equal to:

$$w_t = \frac{c}{\hat{\sigma}^2_{WML,t}} \tag{4.4}$$

Here, the term c is a constant that controls the strategy's average risk exposure. Moreira and Muir set c so that the unconditional volatility of the risk-managed portfolio is equal to the volatility of the buy and hold momentum portfolio[8]. Furthermore, in their main analysis, they use the realized variance over the previous month as a proxy for the conditional variance of the momentum portfolio over the month t, $\hat{\sigma}^2_{WML,t}$. More specifically, the realized variance is computed as the square of the monthly standard deviation, where the monthly standard deviation is calculated using daily returns:

$$\hat{\sigma}^2_{WML,t} = \sum_{d=1/22}^{1} (r_{WML,t+d} - \frac{\sum_{d=1/22}^{1} r_{WML,t+d}}{22})^2 \tag{4.5}$$

Following such methodology, Moreira and Muir illustrated that the volatility managed momentum portfolio has lower standard deviation during times of recession and crises, which are characterized by high volatility. Furthermore, they showed that following a significant market crash such as that in October 2008, the strategy initially gets out of the market to avoid an unfavorable risk-return trade-off, and then it returns to the market only once the spike in volatility decreases [9].

The results of Barroso and Santa Clara (2015)[37] and Moreira and Muir (2017) [38] indicate that volatility scaling momentum returns involves taking substantially less risk during recessions and market crises, demonstrating that such a strategy performs exceptionally well in avoiding large momentum crashes. Furthermore, a key feature of volatility scaling is its simplicity; since it does not rely on any parameter estimation, it can easily be implemented by investors in real-time.

4.4.2 *Dynamic weighting strategy*

In addition to their contribution on momentum crashes, DM16 has also developed an optimal weighting approach for the momentum portfolio to reduce the strategy's crash risk. They propose an approach that dynamically calibrates the weight placed on the risky asset, the momentum portfolio, based on maximizing the strategy's Sharpe ratio.

[8] They denote that the term c has no effect on the strategy's Sharpe ratio, and thus the fact that they uses the full sample to compute c did not impact their results.

[9] Their results are consistent also using the inverse of the expected variance estimated from an AR(1) and the inverse of the realized volatility rather than the inverse of the realized variance to scale the portfolio's returns.

Dynamic weighting requires the estimation of both the conditional mean return $\tilde{r}_{WML,t}$ and the conditional variance $\hat{\sigma}^2_{WML,t}$ of the momentum strategy over the coming month. More precisely, they use their results from the regression of the WML returns on the interaction term between the bear market indicator $I_{B,t-1}$ and the market variance over the preceding six months (similar to the specification used in column (4) of table 4.12 in Section 4.3). Furthermore to forecast the volatility, they fit the GJR-GARCH model proposed by Glosten et al. (1993) [39] to the daily momentum returns[10].

Thus, in DM16's framework the agent's objective function is to maximize the full-period in-sample unconditional Sharpe ratio of the managed portfolio, giving an optimal weight on the momentum portfolio at time t of:

$$w_t = (\frac{1}{2\lambda})\frac{\tilde{r}_{WML,t}}{\hat{\sigma}^2_{WML,t}} \tag{4.6}$$

The formula indicates that the weight assigned to the WML portfolio at time t should be proportional to the expected excess return over the next period and inversely proportional to the forecasted variance. Where, λ is a constant scalar that controls the unconditional risk and return of the dynamic portfolio.[11]

To assess the profitability of their model, DM16 compared the annualized Sharpe ratios of the dynamic strategy (1.19) with the baseline WML approach (0.682) and with the constant volatility strategy (1.04). They document that the proposed portfolio outperforms the constant volatility model, which ultimately outperforms the classic WML strategy; it holds across different periods and asset classes. Furthermore, they explain that the optimal dynamic strategy would coincide with the constant volatility model introduced by Barroso and Santa Clara if the Sharpe ratios of the momentum strategy were time-invariant. However, given that the return of a WML portfolio is negatively related to the forecasted WML volatility, the Sharpe ratio of the optimal dynamic portfolio does vary over time. Additionally, while the baseline buy and hold WML strategy has a stable weight of 1. The dynamic strategy presents weights varying between a maximum of 5.37 and a minimum of -0.604. This is another significant difference denoted by DM16: the dynamic weighting strategy has weights that are 3.6 times more volatile than the constant volatility strategy. Furthermore, for volatility scaling strategies, the weight can not be negative, instead in DM16's approach the weight goes below zero in 82 out of the 1,035 months full sample period considered (1927:01-2013:03), which are the months in which forecasted return on the WML strategy is negative.

[10] For a more detailed explanation of the design of the dynamic strategy adopted by DM16 see Appendix C." Maximum Sharpe ratio strategy" and Appendix D. "GJR-GARCH forecasts of volatility" in their paper "Momentum Crashes" [1].

[11] In their primary analysis, they pick λ such that the volatility of the dynamic strategy is equal to that of the CRSP value-weighted index over the entire sample, which is 19%.

Compared to the volatility scaling approaches, the methodology adopted by DM16 is more complicated. While in the former, it is sufficient to pick a target volatility and estimate the realized variance over the preceding month. Dynamically weighting needs estimating both the expected excess return and the expected variance over the next period. Nevertheless, despite its enhanced performance, DM16 recognize that their strategy takes on more leverage and would generate higher transaction costs than a volatility scaling approach. To conclude, volatility-managed portfolios are profitable and convenient to manage volatility shocks because they are simple and easily implementable. However, the dynamic portfolio proposed by DM16, despite its complex methodology, is specially tailored to reduce the downside risk of momentum crashes and ultimately outperforms volatility scaling strategies.

Chapter 5

Robustness Tests

To challenge the robustness of the previously discussed results, the following chapter extends the study on the US common stocks to other investment regions and asset classes. Such analysis allows us to evaluate momentum's performance in different international equity and asset classes during and after the 2020 covid-19 crisis and to check whether its trend has been consistent with the strategy's behavior in the US common stock market. International equity data covers the US, UK, Continental Europe, and Japan. While non-equity data covers equity country index futures and commodities. Please refer to subsection 3.1.2 for more details regarding the data. It should be noted that here, the US equity momentum portfolio is different from the WML portfolio analyzed in Chapter 4. The sorting of the momentum portfolios investigated in this section is based upon terciles. Thus, the WML_{P3-P1} portfolios are long the top tercile, and short the bottom tercile of stocks ranked on their returns from month t-12 through month t-2.

5.1 *Momentum in 2020 across equities and asset classes*

This first section investigates and compares the strategy's behavior across different investment regions and asset classes throughout the 2020 covid-19 crisis. Table 5.1 provides us the annual average excess returns (in percentage) yielded by the WML_{P3-P1} in 2020 and their respective market return for all the equity geographies (US, UK, EU, JP) and asset classes considered (CM, FUT).

	(US)	(UK)	(EU)	(JP)	(CM)	(FUT)
WML_{P3-P1}	15.39	19.23	11.05	5.23	-32.46	4.25
Market	24.84	-10.11	4.84	13.68	-17.66	16.47

Table 5.1: *2020 momentum annual average excess return across geographies and asset classes*

First of all, the US WML_{P3-P1} in 2020 had an average annual excess return of 15.39%, still underperforming the market, which yielded a return of 24.84%. However, the momentum portfolio based on terciles did better than the previously considered deciles sorted WML portfolio, which in 2020 had an excess return of 10.79%. Surprisingly the UK WML_{P3-P1} portfolio in 2020 had an outstanding performance. In the United Kingdom, the strategy delivered an average annual excess return of 19.23%, while the market had a negative return of 10.11%. Momentum preserved its premium also in Continental Europe. While the market gained only 4.84% in 2020, the EU momentum portfolio yielded a return of 11.05%. Concerning Japanese equity, the JP WML_{P3-P1} delivered a performance of 5.23%, whereas the market index yielded a double-digit return of 13.68%. This last result is not surprising since Aness et al. (2013) [8] showed that the momentum effect historically failed to generate positive profits in the Japanese market.

Regarding the other asset classes, commodities WML_{P3-P1} had a disastrous performance of -32.46%, losing almost more than double the Goldman Sachs Commodity Index (-17.66%). Furthermore, in 2020 momentum underperformed its relative market also in the equity country index futures market. The MSCI world index delivered a performance of 16.47%, while the equity futures WML_{P3-P1} had a meager annual return of 4.25%.

The heterogeneity in return patterns across international equities and asset classes are in line with the findings of Zimmerer et al. (2019) [40]. To summarize, in 2020, momentum portfolio underperformed the market in four out of the six international asset classes considered. The worse crash occurred in the commodity market, followed by the equity country futures market and the US and Japanese equity markets. However, the WML_{P3-P1} performed very well in the UK and Continental Europe. Noticeably, in 2020 momentum had a stellar performance in the United Kingdom, delivering an average annual return of 19.23%. Consistently such findings suggest that using a strategy that relies on different assets would provide diversification benefits and ultimately enhance the performances of the momentum portfolio.

5.2 *Momentum's optionality and market-variance effects outside the US*

In this last section, I investigate whether momentum crash patterns observed in the US common equities are also present in the other asset markets. Panel A through C in tables 5.2, 5.3, and 5.4 present the result of the analysis. The regressions are similar to the one specified in section 3.3 but for different stock market universes; here, the dependent variable is always the $\tilde{R}_{WML_{P3-P1},t}$, the terciles WML portfolio return at time t.

Respectively Panel A investigates the variation in the alpha and beta of the strategy in bear markets and refers to the following specification:

$$\tilde{R}_{WML_{P3-P1},t} = (\alpha_0 + \alpha_B I_{B,t-1}) + (\beta_0 + \beta_B I_{B,t-1})\tilde{R}_{m,t} + \tilde{\varepsilon}_{,t} \tag{5.1}$$

Panel B investigates the strategy's optionality in bear markets and refers to the following specification:

$$\tilde{R}_{WML_{P3-P1},t} = [\alpha_0 + \alpha_B I_{B,t-1}] + [\beta_0 + I_{B,t-1}\beta_B + \tilde{I}_{U,t}\beta_{B,U}]\tilde{R}_{m,t} + \tilde{\varepsilon}_{,t} \tag{5.2}$$

Panel C includes an additional explanatory variable, the realized daily market variance, annualized, over the preceding six months. Such setting investigates the relation between the $\tilde{R}_{WML_{P3-P1},t}$ and the market's variance:

$$\tilde{R}_{WML_{P3-P1},t} = [\alpha_0 + \alpha_B I_{B,t-1} + \alpha_V \sigma^2_{m,t-1}] + [\beta_0 + I_{B,t-1}\beta_B + \sigma^2_{m,t-1}\beta_V]\tilde{R}_{m,t} + \tilde{\varepsilon}_{,t} \tag{5.3}$$

The only difference between the three tables stands in the bear-market indicator used. Please note that specifications in table 5.2 include the standard $I_{B,t-1}$ as an ex-ante Bear market indicator. While regressions, in table 5.3 rely on the $I_{FB(6),t-1}$, 6-month flash bear-market indicator. Finally, specifications in table 5.4 consider the $I_{FB(4),t-1}$, 4-month flash bear-market indicator. [12]

Panel A of table 5.2 shows that, in bull markets, the abnormal returns of the momentum strategy are significantly positive for all regions and asset classes except for Japan. Furthermore, the coefficients $I_B\tilde{R}_{m,t}$ are negative and highly statistically significant, indicating that the beta of the momentum portfolio is notably lower in bear markets. Such results hold across all the other stock markets and asset classes considered. More precisely, in the US and JP stock markets, the cross-sectional momentum strategy has betas 0.56 lower during bear markets. The EU momentum strategy beta drops by 0.47, while in the UK, it falls by 0.4. Also, the market betas of the momentum strategy implemented in the commodities and equity futures asset classes are notably more negative in bear markets.

Panel B of table 5.2 investigates whether the cross-sectional momentum strategies in all equity regions and asset classes exhibit conditional betas and payoffs similar to writing call options on the respective index market. The coefficient $I_B\tilde{R}_{m,t}I_{U,t}$ is of the right sign for all of the assets considered except for equity futures. However, for this subsample, the strategy exhibits statistically significant optionality only for the European and Japanese equity markets and for commodities.

In Panel C, $\hat{\sigma}^2_m$ assesses the relation between market variance and the future abnormal return

[12]Significance codes: *** statistically significant at 0.1%; ** statistically significant at 1%; * statistically significant at 5%; ‘ statistically significant at 10%.

of momentum strategies. Such coefficients are not statistically significant but are of the right sign (negative) for the UK, EU, JP, and CM markets. Moreover, $\hat{\sigma}^2_m \tilde{R}_{m,t}$ indicates that higher ex ante market variance is associated with more negative momentum strategy beta. This relation is highly statistically significant in the US and EU equity markets. Such outcomes indicate that the strategy shows a conditionally large negative beta in periods of market stress, characterized by high ex-ante market variance. Such a situation will ultimately cause an underperformance of the momentum strategy if the market return at time t is positive.

Overall the results are consistent with the findings earlier discussed and with the research of DM16 [1].

Coefficient						
	(US)	(UK)	(EU)	(JP)	(CM)	(FUT)
$\hat{\alpha}_0$	6.90∗	11.50∗∗∗	7.45∗∗	1.08	7.02∗	5.29∗∗
	(2.5)	(3.9)	(2.9)	(0.3)	(1.9)	(2.7)
I_B	−3.74	−3.96	1.12	0.69	−3.69	1.57
	(−0.5)	(−0.7)	(0.2)	(0.1)	(−0.6)	(0.3)
$\tilde{R}_{m,t}$	0.106	−0.009	0.06	0.237∗∗∗	0.46∗∗∗	0.15‘
	(0.8)	(−0.18)	(1.6)	(5.0)	(8.7)	(1.8)
$I_B\tilde{R}_{m,t}$	−0.56∗∗∗	−0.40∗∗∗	−0.47∗∗∗	−0.56∗∗∗	−0.76∗∗∗	−0.31∗∗∗
	(−5.4)	(−4.9)	(−8.0)	(−8.3)	(−9.6)	(−4.7)
Panel B						
$\hat{\alpha}_0$	6.90∗	11.50∗∗∗	7.45∗∗	1.08	7.02∗	5.29∗∗
	(2.5)	(3.9)	(2.9)	(0.3)	(1.9)	(2.7)
I_B	−4.03	−3.94	0.5	0.98	−2.95	0.9
	(−0.6)	(−0.7)	(0.1)	(1.8)	(−0.5)	(0.1)
$\tilde{R}_{m,t}$	0.106	−0.009	0.06	0.237∗∗∗	0.46∗∗∗	0.15‘
	(0.8)	(−0.18)	(1.6)	(5.0)	(8.7)	(1.8)
$I_B\tilde{R}_{m,t}$	−0.404	−0.16	−0.22∗	−0.23	−0.30‘	−0.29∗
	(−1.6)	(−0.8)	(−1.9)	(−1.3)	(−1.9)	(−2.0)
$I_B\tilde{R}_{m,t}I_{U,t}$	−0.20	−0.33	−0.57∗∗	−0.47∗	−1.08∗∗∗	0.13
	(−0.6)	(−1.3)	(−3.1)	(−2.2)	(−4.7)	(0.6)
Panel C						
$\hat{\alpha}_0$	6.80∗	12.07∗∗	9.04∗∗∗	1.80	8.32∗	3.23
	(2.0)	(3.0)	(3.3)	(0.4)	(2.0)	(1.2)
I_B	−4.36	−3.94	−3.87	0.98	−2.95	−0.51
	(−0.6)	(−0.7)	(0.9)	(0.1)	(−0.5)	(−0.1)
$\hat{\sigma}^2_m$	0.02	−0.01	−0.04	−0.01	−0.04	0.09
	(0.2)	(−0.1)	(−1.0)	(−0.3)	(−0.7)	(1.3)
$\tilde{R}_{m,t}$	0.08	0.03	0.19∗∗∗	0.24∗∗∗	0.50∗∗∗	0.10∗
	(1.1)	(0.4)	(4.4)	(4.1)	(8.0)	(2.0)
$I_B\tilde{R}_{m,t}$	−0.51∗∗∗	−0.41∗∗∗	−0.34∗∗∗	−0.56∗∗∗	−0.73∗∗∗	−0.27∗∗∗
	(−4.7)	(−4.9)	(−5.9)	(−8.1)	(−9.0)	(−3.8)
$\hat{\sigma}^2_m\tilde{R}_{m,t}$	−4.31∗	−1.04	−4.59∗∗∗	−0.09	−1.08	−2.97‘
	(−2.1)	(−0.7)	(−6.9)	(−0.1)	(−1.3)	(−1.9)

Table 5.2: *Time series regressions for other asset classes and for international Equity markets*

5.2.1 *Flash bear markets*

To conclude, table 5.3 and table 5.4 present the results of time series regression, for international equities and other asset classes, using respectively the new flash bear market indicators, $I_{B,6m}$ and $I_{B,4m}$.

Coefficient						
	(US)	(UK)	(EU)	(JP)	(CM)	(FUT)
$\hat{\alpha}_0$	7.37$*$	9.83$**$	9.31$***$	3.45	7.78$*$	6.17
	(2.4)	(3.2)	(3.6)	(1.0)	(2.1)	(2.9)
$I_{B,6m}$	−2.99	1.24	−6.33	−6.12	−11.49$*$	−2.80
	(−0.5)	(0.2)	(−1.5)	(−1.2)	(−2.0)	(−0.7)
$\tilde{R}_{m,t}$	0.15	0.02	0.03	0.23$***$	0.42$***$	0.15‘
	(1.1)	(0.4)	(0.7)	(4.9)	(7.5)	(1.7)
$I_{B,6M}\tilde{R}_{m,t}$	−0.43$***$	−0.33$***$	−0.37$***$	−0.52$***$	−0.65$***$	−0.22$***$
	(−4.5)	(−4.4)	(−6.2)	(−7.8)	(−8.1)	(−3.4)
Panel B						
$\hat{\alpha}_0$	7.37$*$	9.83$**$	9.31$***$	3.45	7.78$*$	6.17
	(2.4)	(3.2)	(3.6)	(1.0)	(2.1)	(2.9)
$I_{B,6M}$	−0.18	1.24	−8.34	−4.82	−11.49$*$	0.82
	(−0.01)	(0.2)	(−0.9)	(−0.4)	(−0.2)	(0.09)
$\tilde{R}_{m,t}$	0.15	0.02	0.03	0.23$***$	0.42$***$	0.15‘
	(1.1)	(0.4)	(0.7)	(4.9)	(7.5)	(1.7)
$I_{B,6M}\tilde{R}_{m,t}$	−0.479$*$	0.07	−0.36$**$	−0.52$**$	−0.38$*$	−0.19
	(−2.1)	(0.4)	(−2.9)	(−3.0)	(−2.2)	(−1.4)
$I_{B,6M}\tilde{R}_{m,t}I_{U,t}$	0.28	−0.47$*$	−0.51$**$	−0.11	−0.95$***$	−0.014
	(0.9)	(−2.0)	(−2.6)	(−0.5)	(−3.98)	(−0.07)

Table 5.3: *Time series regressions for other asset classes and for international Equity markets(IBT6M)*

Panel A in table 5.3 shows that momentum strategy returns are lower when the cumulative market return in the past six months is negative. This result holds for each region and asset class except for the UK equity market, but only in the commodities market is the coefficient significant. Interestingly in panel A of table 5.4, considering an even shorter bear market, the coefficient $I_{B,4m}$ is negative for all the assets considered, except for the equity futures asset classes (FUT). With this setting, the estimates for the UK and EU equity markets become significant at the 5% level, indicating that in these equity markets, the momentum strategy returns are significantly lower when the cumulative market return in the past four months is negative. Such results are weakly consistent with the earlier evidence that market-adjusted momentum returns are lower in periods of bear and flash bear markets. Nevertheless, in line with results of table 5.2, the coefficients $I_{B,6m}\tilde{R}_{m,t}$ and $I_{B,4m}\tilde{R}_{m,t}$ are both negative and statistically significant for all asset classes considered. Thus, the momentum portfolio's market beta is notably more negative for both flash bear markets specifications. Such findings are highly consistent with the evidence presented earlier in Section 4.2.

Coefficient						
	(US)	(UK)	(EU)	(JP)	(CM)	(FUT)
$\hat{\alpha}_0$	8.62∗∗	14.81∗∗∗	11.5∗∗∗	2.21	6.16‘	5.45∗∗
	(2.8)	(4.7)	(4.4)	(0.6)	(1.6)	(2.5)
$I_{B,4m}$	−5.57	−11.7∗	−9.38∗	−3.74	−7.25	0.297
	(−1.0)	(−2.3)	(−2.3)	(−0.7)	(−1.2)	(0.08)
$\tilde{R}_{m,t}$	0.10	−0.08	−0.04	0.13∗∗	0.40∗∗	0.19∗
	(0.7)	(−0.7)	(−0.9)	(2.8)	(2.9)	(2.2)
$I_{B,4m}\tilde{R}_{m,t}$	−0.336∗∗∗	−0.18∗	−0.27∗∗∗	−0.36∗∗∗	−0.64∗∗∗	−0.263∗∗∗
	(−3.5)	(−2.3)	(−4.4)	(−5.2)	(−7.9)	(−4.1)
Panel B						
$\hat{\alpha}_0$	8.62∗∗	14.81∗∗∗	11.5∗∗∗	2.21	6.16‘	5.45∗∗
	(2.8)	(4.7)	(4.4)	(0.6)	(1.6)	(2.5)
$I_{B,4m}$	−3.16	−11.05∗	−7.49∗	−2.37	−6.67	0.62
	(−0.2)	(−2.3)	(−2.0)	(−0.4)	(−1.2)	(0.07)
$\tilde{R}_{m,t}$	0.10	−0.08	−0.04	0.13∗∗	0.40∗∗	0.19∗
	(0.7)	(−0.7)	(−0.9)	(2.8)	(2.9)	(2.2)
$I_{B,4m}\tilde{R}_{m,t}$	−0.36	0.036	−0.18	−0.56∗∗	−0.36∗	−0.295∗
	(−1.6)	(0.2)	(−1.5)	(−3.1)	(−2.1)	(−2.2)
$I_{B,4m}\tilde{R}_{m,t}I_{U,t}$	0.17	−0.40‘	−0.47∗	0.09	−1.01∗∗∗	0.09
	(0.5)	(−1.6)	(0.1)	(0.4)	(−4.1)	(0.4)

Table 5.4: *Time series regressions for other asset classes and for international Equity markets (IBT4M)*

Let's now focus on Panel B of tables 5.3 and 5.4 which investigate whether the optionality present in momentum strategies in bear markets are also present in flash bear markets. Interestingly the coefficients $I_{B,6M}\tilde{R}_{m,t}I_{U,t}$ and $I_{B,4M}\tilde{R}_{m,t}I_{U,t}$ for the US momentum portfolio are positive. Despite not being statistically significant, Such outcome is inconsistent with the results presented earlier in table 5.2, and the analysis carried out in section 4.2 for the decile sorted WML US market portfolio. With this new subsample and methodology, the tercile sorted US momentum strategy does not manifest any optionality when the market return upswings following periods of flash bear markets. However, momentum optionality appears to be present in all the other equity regions and asset classes considered for both flash bear market indicators. Indeed, the estimates of $I_{B,6M}\tilde{R}_{m,t}I_{U,t}$ and $I_{B,4M}\tilde{R}_{m,t}I_{U,t}$ are all negative, but are statistically significant only for commodities and for the UK and EU markets.

In summary, there are strong momentum effects in each region and asset classes considered except Japan. Similar to the behavior manifested by the US WML portfolio analyzed in Chapter 4, there is a significant time variation in the betas of the momentum portfolios in bear markets and periods of high ex-ante market variance. Thus in panic periods, the momentum strategy exhibits a conditionally negative beta in all the other equity markets and asset classes considered. The option-like features of momentum returns are strong and significant in commodities and the European and United Kingdom equity markets. Such findings also hold for short periods of economic downturns, flash bear markets. They further suggest that cross-sectional momentum strategies manifest significantly lower returns when the market returns profitable after panic periods of declining markets and high volatility.

Chapter 6

Limitations and Conclusions

6.1 *Limitations*

Despite having carried out the analysis with care and attention, this research suffers from certain limitations. Firstly, I used monthly returns of US common stocks to construct the WML portfolio. Moreover, I assumed that the monthly rate for the VIX index is equal to the daily rate at the beginning of each month and that such a daily rate remains valid throughout the month. In this way, I converted the daily series of the VIX index into a monthly series. Using higher-frequency data would have yielded more timely and precise estimates of returns and volatilities. Second, the returns and performance statistics presented in this study should be interpreted with caution. They are not representative of a real-life implementable strategy since they do not account for transaction costs. Third, this analysis focuses solely on cross-sectional momentum. It would be interesting to extend the study to investigate the behavior of different types of momentum strategies, such as residual or time-series momentum.

6.2 *Conclusions and avenues for future research*

DM16 showed that momentum investing is particularly risky and suffers severe crashes following periods of economic recessions. The main objective of such master thesis was to extend their sample till the end of 2020 to assess whether the cross-sectional momentum strategy also crashed during the year of the covid-19 financial crisis.

Firstly, the analysis confirms a substantial premium over the entire sample period considered. Consistently with the existing literature, such a result holds for all the equity markets and asset classes considered, except for Japan. However, focusing on the last decade, it appears that momentum has lost its historical premium in terms of unit of return earned per unit of risk assumed. Indeed, for the period going from January 2010 to December 2020, the WML portfolio had a meager Sharper ratio of 0.23 while the market delivered a SR of 0.95. Focusing on 2020, this dissertation confirms that momentum crashed throughout the year of the covid-

19 financial crisis. The most terrible performance occurred in April when the market returned to be profitable following the economic decline caused by the global pandemic; in such period, the strategy had a return of -28.2%. April's 2020 crash ranked 12th among the list of the worst fifteen monthly returns experienced by the WML portfolio over the whole sample period analyzed.

The second part of this dissertation examines momentum's option-like behavior described by DM16. The analysis shows that the strategy exhibits significantly lower abnormal returns and more negative betas in bear markets. Furthermore, once the market returns to be positive, the WML portfolio ends up having large negative exposure to systematic risk. Such features indicate that in bear markets, momentum is effectively shorting a call option on the market. This is to say when the market bounces back after a financial crisis, the WML portfolio suffers severe crashes. Collectively the results appear consistent with the findings of DM16. However, given that the covid-19 crisis was the shortest bear market experienced in the SP500 history, I introduced two new indicator variables to capture short periods of economic downturn, flash bear markets. The results confirm a notable time variation in the betas of the momentum portfolio in flash bear markets. Interestingly, the strategy's optionality also holds when the market bounces back after periods in which the past cumulative six-month market return is negative. While when the past cumulative four-month market return is negative, the optionality is of the correct sign but is not statistically significant anymore. Moreover, using the VIX index, I showed that momentum's returns are remarkably lower in periods of high ex-ante market variance and that the strategy performs very poorly in bear markets and flash bear markets, with high market volatility.

As a robustness test, I extended the analysis carried out on the US common stocks to other investment regions and asset classes. The strategy exhibits significantly more negative betas in bear markets, flash bear markets, and periods of high ex-ante market variance in all the different markets considered. In terms of excess returns, in 2020, the momentum portfolio underperformed the market in four out of the six international asset classes considered. However, in the UK and EU equity markets, the WML portfolio delivered excess returns that exceed the market's expectations. The present findings suggest that using a strategy relying on different equity markets and asset classes would provide diversification benefits and ultimately improve the performances of the momentum portfolio.

Looking forward, there are several ways in which this research can be developed. Future works should investigate and compare the different types of momentum strategies' behavior in this last decade. It would be interesting to see whether the crash patterns exhibited by the cross-sectional momentum strategy are also present in different types of momentum. Furthermore, it would be interesting to assess how the hedging strategies built to reduce momentum's crash risk, such as the volatility managed portfolios and the DM16 dynamic hedging strategy, behaved throughout the shortest bear market in the SP500 history, the 2020 financial crisis.

Future research should also investigate and compare the performance of various risk factors in times of short but intense periods of economic downturn. To conclude, future investigations are necessary to examine the performance of a momentum 2.0 approach in different market environments and periods of high market stress.

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Summary

Introduction and Research Questions

Over the years, momentum strategies have proven to have robust profitability records, yielding substantial returns across several time periods, geographies, and asset classes. The idea behind such a strategy is to ride the upward and downward trends generated by rising and falling securities by betting on the continuation of such movements in the short term. Thanks to its persistence and pervasiveness, it is considered one of the oldest and most prominent trading strategies. Despite the outstanding positive performance yielded by momentum investing, some authors have noticed that the strategy ”is not all roses”. Momentum experiences occasional but severe crashes that could result in significant losses for an investor. Research published by Daniel and Moskowitz (2016) [1] (hereafter DM16) illustrates that momentum strategy crashes and goes through persistent negative returns in a situation of high market stress. The authors demonstrated a dramatic time variation in the winner and loser portfolio’s betas around a crisis and identified this phenomenon as the source of such reversal. Such time-varying exposure to market risk infers that momentum strategies behave as selling call options on the market. Consequently, such crashes are predictable, momentum strategies, because of their large negative beta performs very poorly when there is an upswing in returns after a bear market with high expected volatility. In this regard, momentum strategies’ biggest crashes occurred when the market rebounded after the lows caused by three of the greatest financial crises ever experienced: the great depression (August 1932 -77.5%), the dot-com bubble (January 2001 -46.8%), and the Sub-prime crisis (April 2009 -45.8%). Times of crisis, economic downturns, and periods of uncertainty are very instructive. However, bears have different shapes and sizes, and particularly the 2020 pandemic-driven financial crisis has been very unusual. The covid-19 bear market has been the shortest in the SP500 history. In this regard, the most recent corona crisis offers the opportunity to extend and update some of the previously described evidence on momentum investing and its crashes. Thus, the aim of this thesis is two-fold. First, it empirically investigates the cross-sectional momentum strategy’s profitability and characteristics over the years. Second, this work contributes to the research on momentum crashes, extending the time period of the analysis performed by DM16 [1] till the end of 2020, to include the latest covid-19 bear market. Furthermore, given that the 2020 virus-driven bear market was the shortest ever manifested, I investigate whether momentum crashes are evident after short periods of economic downturn, ”flash bear markets”. Finally, to check the robustness of the results obtained, the final part of the analysis investigates momentum crash patterns across different geographies (US, UK, Japan, and Continental Europe) and asset classes (equity country index futures and commodity futures). With such premises in mind, the main research question that the present paper aims to answer is the following:

How did the Momentum strategy for the US common stock market perform during and just after the current covid-19 crisis? Was there a crash, and if so, is it comparable to the ones highlighted by Daniel and Moskowitz ?

Additionally, a set of sub-questions addressed through this project are:

- *How did the Momentum strategy behave during the last four decades?*
- *What is the WML portfolio's expected performance in different market environments (bear markets, flash bear markets, and times of high expected volatility)?*
- *To what extent does the market Beta of the momentum portfolio vary when the market upswings after periods of bear markets and flash bear markets ?*
- *How did the momentum strategy perform in different investment regions and asset classes during the year of the covid-19 crisis?*

To begin with, it appears that momentum has lost its historical premium in terms of unit of return earned per unit of risk assumed. For the period going from January 2010 to December 2020, the Sharpe ratio of the momentum portfolio is much lower than that of the market. Moreover, focusing on 2020, it is noticeable that the momentum strategy crashed following the covid-19 driven financial downturn. More precisely, 2020 appears twice among the list of the fifteen worst momentum monthly returns. Respectively, in April and November 2020, the Winner minus loser portfolio delivered a return of -28.2% and -26.2%. Furthermore, I show that the momentum portfolio beta becomes large and negative when the market rebounds following periods of bear market (-1.277). Interestingly, the same optionality also exists after shorter periods of economic downturn, when the past six-month cumulative market return has been negative. Indeed, when the market returns positive after periods of flash bear markets, the momentum portfolio beta is -1.247, and thus the strategy suffers severe crashes also in this case. Moreover, using the VIX as a proxy measure of the future market variance, I find that in periods of bear market and flash bear market with high market volatility, the momentum strategy returns are particularly low. Finally, I extend the analysis carried on the US equity market to the United Kingdom, Japan, and Continental Europe equity markets and commodity futures and equity index futures. Intriguingly, the option-like features of momentum returns are also significant in commodities and the European and United Kingdom equity markets. Such findings hold as well for short periods of economic downturns, flash bear markets.

Literature Review

Momentum is a trend-following investing approach, in which traders bet that an asset price intensely moving in a given direction will continue to follow such trend in the near future. The strategy consists of constructing a long-short portfolio that buys assets with recent solid performance identified as the winners and sells the losers, which are assets that have recently underperformed. The first evidence of momentum strategies' profitability dates back to 1993 when Jegadeesh and Titman [2] illustrated a positive relationship between past and future returns, claiming that past stock returns can be used to predict and form portfolios with positive alphas. Their pioneering work set the theoretical and methodological foundations for a plethora of subsequent future studies. In fact, the methodology for portfolio construction introduced by Jegadeesh and Titman (1993) [2] will be referred to as the cross-sectional or pure momentum strategy. Many academicians started investigating the persistence and pervasiveness of such investing approach confirming its profitability across different time periods, financial markets, and asset classes.The time consistency of the strategy is confirmed by Geczy and Samonov (2015) [13], in the so-called "world's longest back-test", in which they illustrated momentum's persistence from 1801 to 2012. Another broad strain of literature focused on exploiting the momentum effect for equities in different investment regions and different asset classes. Such evidence were integrated by Asness et al. (2013) [8], confirming the ubiquitous power of price momentum. They highlighted such effect in different stock markets (UK, Japan, and continental Europe) and across country indices, exchange-traded futures contracts, currencies, bonds, and commodities.

Since a strategy that generates profitable returns trading on past prices contradicts the Efficient Market Hypothesis (EMH), the existence of momentum represents a significant challenge to empirical asset pricing models. The momentum phenomenon, among other investment-related anomalies, generated a debate on whether markets are efficient or not. Supporters of the traditional Market efficiency theory argue that such strategies yield higher returns as compensation for facing higher risks, concluding that momentum is linked to a yet unobserved risk factor. On the other hand, other studies building on the behavioural finance theory believe that markets are inefficient. They claim that investors' decision-making process and interpretation of information are influenced by psychological and cognitive bias, ultimately leading to security mispricing and arbitrage opportunities in the market. Thus, over the years, the literature tried to explain the risk premia associated with the momentum effect through two contrasting theories, the behavioural and the risk-based approach; however, the question remains unresolved.

There are no free lunches in finance, momentum's impressive positive returns and Sharpe ratios are associated with significant risks; and ultimately, the strategy suffers occasional severe crashes. DM16 published the most complete and comprehensive work on momentum crashes in 2016 [1]. DM16 document the presence of long periods over which past loser significantly outperformed past winners, and consequently a cross-sectional momentum strategy goes through persistent negative returns. They argue that crashes are a robust characteristic of the WML strategy and that they are predictable. DM16 document that the most severe crashes occured in periods of high market stress. Such periods are also known as ”panic states” and refer to when there is an upswing in returns after a bear market period with high ex-ante expected volatility. Furthermore, they probed that crashes are mainly attributable to losers' performances. Specifically, during periods of panic states, stocks in the winner decile go up, but the loser portfolio goes up much higher; thus, the short side outperforms the long side, and as a result, the WML strategy experiences huge losses. DM16 infer that the momentum strategy's large negative returns are driven by large changes in the market beta of the WML portfolio. In this regard, they examine conditional risk measures, investigating the time-varying betas of the winner and loser momentum deciles. The betas of past-return sorted portfolios have a great time-varying exposure to systematic factors. Thus, in periods of economic downturns, the momentum portfolio would go long on low beta stocks (past winners) and short high beta stocks (past losers). Consequently, when the market rebounds quickly, past losers' expected returns are very high, and the strategy experiences huge losses because the momentum portfolio ends up having a conditionally large negative beta. Furthermore, they conclude that the dramatic time variation found in the loser portfolio's market beta makes the momentum strategy behave like a written call option on the market, in bear markets. Which is to say, when the market goes down, the strategy benefits a little, but then it yields huge losses once the market rebounds sharply. Additionally, in line with the strategy's option-like behaviour in bear markets, by using ex-ante volatility estimates, they show that the WML portfolio expected return is a decreasing function of the future market volatility. Thus, the momentum strategy performs very poorly during bear markets with high volatility. DM16 asserted their findings' robustness testing the consistency of their results for multiple periods, different equity markets, and alternative asset classes. They further find that the WML strategy suffers crashes in all markets and asset classes. The driver of such reversals is the optionality of losers in bear markets, which is a common feature of momentum strategies since it is consistently present in different equity markets, and different assets.

Some authors tried to develop new alternative models to hedge and protect the WML portfolio against the risk of such significant losses. Barroso and Santa Clara (2015) [37], and Moreira and Muir (2017) [38], show that volatility scaling reduces momentum's probability of extreme losses by limiting the tail risk of extreme returns. In practice, both strategies construct a crash risk-managed portfolio by targeting a constant level of volatility rather than a constant notional exposure. To conclude DM16 have also developed an alternative framework to reduce the strategy's crash risk. In this regard, they proposed a dynamically weighted version of the momentum portfolio, where the relative weights of the winner and loser deciles are based on the maximixation of the strategy's Sharpe ratio using their estimates for the forecasted return and variance of the cross-sectional momentum approach. Despite its complex methodology DM16 empirically demonstrate that dynamic hedging outperforms volatility scaling.

Data and Methodology

Data collection and the dataset construction intentionally emulate as precisely as possible the procedures adopted in DM16. However, since the crisis undergone by the market in 2020 is quite different from the ones highlighted by the authors, some methodological accommodation needs to be done. The principal data sources are the Center for Research and Security Prices (CRSP) and Ken French's data library. The former was used to retrieve the Us common stocks' monthly returns for the entire time period (Jan 1927 - Dec 2020). The monthly returns are then used to construct the monthly momentum deciles portfolios. In contrast, I gathered the market return and the risk-free rate from Ken French's data library. To investigate the relationship between the returns of the momentum portfolio and the expected market volatility, as a proxy measure of future market variance I considered the daily data of the VIX Index, available on the Chicago Board Options Exchange website (CBOE). To conclude and assess the robustness of the results, I extend the analysis on momentum crashes to four different equity markets and two different asset classes. The data can be downloaded from the AQR Capital Management website. The international equity data refers to the US, UK, Japan, and Continental Europe equity markets. The non-equity data covers twenty-seven different commodity futures and Equity index futures across 18 developed equity markets. Concerning the portfolio formation procedure, the ranking period goes from 12 months before to one month before the formation date.Then, based on such metric, firms are placed into one of ten decile portfolios where portfolio 10 includes Winners, while portfolio 1 represents the Losers. The holding period is one month. Portfolios are buy and hold within each month and are constantly rebalanced at the end of each month. The difference between the returns of the Winner and Loser portfolios represents the self-financing "Winner Minus Loser" portfolio (WML).

The empirical investigation starts with an overview of the monthly momentum portfolio excess return characteristics over different periods. In addition to the average returns, I compute other relevant metrics such as the volatility, the skewness, and the annualized Sharpe Ratio of each portfolio decile. Moreover, I estimate the deciles' alpha and betas by fitting a full-period unconditional market model regression to the WML portfolio and to the other deciles. Furthemore, as an attempt to capture whether momentum crashes are also present after short but intense periods of economic downturn, I add two "Flash-Bear" market indicator as a new explanatory variables.

1. $I_{FB(6),t-1}$: ex-ante Flash bear market indicator, assumes the value of 1 if the cumulative CRSP value-weighted index return in the past 6 months is negative, and zero otherwise.

2. $I_{FB(4),t-1}$: ex-ante Flash bear market indicator, assumes the value of 1 if the cumulative CRSP value-weighted index return in the past 4 months is negative, and zero otherwise.

The second set of regressions consist of a conditional CAPM with a bear market indicator as an additional variable. Such model analyzes the relationship and the differences between the expected returns and market betas of the WML portfolios for the two different bear market specifications introduced. After, to investigate the strategy's performance when the market rebounds following a bear market and to assess to which extent the market betas of the WML portfolio differ in different market states, in the next set of regressions I added a contemporaneous upmarket indicator as an additional regressor. Then, since the value of an option increases with the market variance, the strategy's optionality further suggests that the expected return of the momentum portfolio should be negatively related to the future variance of the market. To conclude and to challenge the robustness of the results, using similar specifications, I extended the analysis carried out on the US common stocks to other investment regions and asset classes.

Results

First of all, in line with the existing literature, a substantial momentum premium appears over the last century. The winners have significantly outperformed the losers, with a mean excess return of 15.8%, against the -1.4% yielded by Decile 1. Consequently, the momentum WML portfolio had an annual average excess return of 17.2%, largely outperforming the market, which has an average excess return of 8.1%. The Beta of the momentum portfolio is negative, -0.59, and the unconditional CAPM alpha is 21.9% per year (t-statistic = 7.5). Considering a risk-adjusted perfomance metric, such as the Sharpe ratio, the WML portfolio had a higher rate of return per unit of risk with respect to the market. The momentum portfolio had a full period SR of 0.57, while that of the market was 0.43. Furthermore, observing the skewness an interesting pattern emerges. The winner portfolios are considerably more negatively skewed than the loser portfolios. Winners become more negatively skewed as we move to more extreme deciles. Such pattern supports the evidence that the high returns experienced by the winners deciles and by the momentum strategy are partly a compensation for taking on more skewness risk. Having a closer look at the characteristics of the momentum decile portfolios through the 80s and the 90s, an even stronger premium emerges. The WML portfolio (market) excess returns in the 80s and the 90s are respectively 25.8% and 28.5% (8.5% and 12.7%). Taking into consideration the realized volatility of returns, in the 80s the momentum strategy had a Sharpe ratio of 1.21 against the value of 1.12 in the 90s. However, both the metrics are almost more than the double of the whole sample SR previously estimated which is 0.57. Concerning the skewness, the results align with the pattern found earlier.

Some more intriguing findings arise when we consider the first twenty years of the 2000s. The time period considered is very turbulent. More precisely, through these ten years, financial markets underwent two of the most severe financial crisis ever experienced, the dot-com bubble and the subprime mortgages crisis. Regarding the first decade of the twenty-first century, it is critical to notice that, on average, the market had a negative excess return of 1.7%. Interestingly, in this kind of market condition, the WML portfolio returns exhibit a significantly higher volatility of 47.02% (the full period volatility estimate for the WML portfolio is 30.0%). However, the momentum strategy on average overperformed the market, yielding an annual average excess return of 8.8%. Nevertheless, the small Sharpe ratio (0.187) and the monthly skewness of -1.79 (which almost doubles the values of the 80s and the 90s) suggest that the strategy suffered from severe crashes. Such intuition is confirmed by DM16, which have shown that 7 out of the 15 worst momentum monthly returns took place in the first decade of the twenty-first century. The most exciting findings emerge from the analysis of the last decade, which is the period going from January 2010 till December 2020. The WML had a disappointing performance, yielding an average annual excess return of 6.8%, while the market excess return has been 14.1%. Taking into account volatilities, the difference in terms of performance becomes even more pronounced. The market's Sharpe ratio (0.95) is more than four times momentum's factor Sharpe ratio (0.23). The short leg of the portfolio mainly drives such underperformance. In this last decade buying losers turned out to be a strategy more profitable than investing in the WML portfolio. Noticeably, in this last considered decade, none of the ten deciles portfolios examined had a higher SR than the market. I consider the SR over alphas, because since the former is a measure of unit of return earned per unit of absolute risk assumed by an investments, it is a more meaningful performance metric. Among all the different periods considered, it is the first time that the SR of the WML portfolio is much lower than that of the market. Thus, it appears that momentum has lost its historical premium.

To conclude this first section, I investigated momentum portfolio's characteristics throughout 2020. In 2020 the market yielded an annual excess return of 24.84 %, which is more than double the return produced by the momentum factor (10.79%). The WML portfolio still exhibits a positive alpha of 40.9%. However, in terms of unit per return earned per unit of risk assumed, in 2020, momentum has largely underperfomed the market. The market's SR is four-time as high as the WML's SR (0.89 vs 0.20). Also, in this case, the underperformance of the momentum factor is mainly attributable to the short leg of the portfolio. In 2020, investing in past losers, on a unit of return per unit of risk basis, turned out to be more fruitful than investing in the momentum factor. This last year has been a challenging and stormy period in which financial markets experienced high variance, and went through a "flash" but painful bear market. Furthemore, in 2020 momentum's market beta assumed a value of -1.21, suggesting that when the market rebounds quickly momentum will crash because it has a conditionally large negative beta. Such a situation perfectly matches the context that leads to momentum crashes described in DM16, periods of high market stress characterized by sudden upswings in the market return after a period of bear market. Thus, one would expect a crash of the momentum strategy in 2020. Indeed, we can confirm that the WML portfolio crashed during the year of the covid-19 financial crisis. Analysing the returns pattern manifested by the momentum in 2020, it is noticeable that the strategy recorded its best performance in March, earning a return of 22.5%, while the worst crash took place in April 2020 when it yielded a negative 28.2%. Similarly, in November, the WML portfolio failed again, recording a return of -26.2%. Interestingly both crashes occur in months in which the market rose, after two consecutive months of negative returns. To put into perspective and have a clearer idea of the entity of such crashes I listed the 15 worst returns to the momentum portfolio, 2020 appears twice in this list. More precisely, April's crash ranked 12th, while November's ranked 14th.

The next part of the analysis investigates more formally the beta variation and how the mean return of the WML portfolio is related to time variation in market risk. The results are consistent with the existing literature. The market beta assumes a negative value of -0.592 with a t-statistic of -13.2. Additionally, the $\hat{\alpha}_0$ is positive (1.832% per month) and highly statistically significant (t-statistic = 7.5) , confirming a strong premium over the full period. Then, I added the indicator variable $I_{B,t-1}$ to investigate how the market beta of the WML portfolio varies in bear markets. In line with the findings of DM16, the $\hat{\beta}_B$ is negative and highly statistically significant (t-statistic = -12.8). Indicating that momentum's market beta is -1.073 lower in bear markets. Furthermore, the coefficient $\hat{\alpha}_B$ indicates that the premium yielded by the strategy is significantly lower in such periods. The intercept is almost zero but remains positive. I included an auxiliary variable, the $I_{U,t}$ to capture the extent to which the up-and down-market betas of the momentum portfolio differ. When the contemporaneous market return is negative, the WML portfolio beta is equal to -0.821. However when the market rebounds during or following periods of declining markets momentum's beta becomes -1.277. The coefficient $\hat{\beta}_{B,U}$ is negative and statistically significant (t-statistic = -1.7), meaning that in bear markets, momentum is effectively shorting a call option on the market. Which is to say, when the market bounces back after a financial crisis, the WML portfolio suffers severe crashes. Overall the results yielded by this first set of regressions are highly consistent with the research carried out by DM16 [1].

Next, to capture whether momentum crashes manifested after short but intense periods of economic downturn, I replaced the bear-market indicator variable with the two new "Flash-Bear" market indicators. The coefficients of the new pair indicators, $\hat{\beta}_B$, are negative and highly statistically significant, indicating a consistent time variation in the beta of the momentum portfolio in short bear markets. Momentum's beta is -0.950 (-0.664) lower when the past cumulative six (four) month market return is negative. In such periods, the intercept declines but remains well above one. When the market rebounds, following a flash bear market lasting 6 month, momentum's beta is -1.247. In this case the coefficient $\hat{\beta}_{B,U}$ is negative, -0.519, and statistically significant (t-statistic = -2). In contrast, for declining markets lasting four months, the coefficient $\hat{\beta}_{B,U}$ is still negative, -0.113, but it is not statistically significant anymore. Consequently, the momentum's beta in such circumstances is closer to zero -0.81. In short the discussed findings suggest that when the market bounces back after periods in which the past cumulative six (or more) months market return is negative, the WML portfolio suffers severe crashes. Consistently with the 24-month bear market indicator, momentum investing is effectively shorting a call option on the market also for more concise bear markets lasting only six months. Interestingly, such optionality did not manifest for the shortest bear market considered, the coefficient is of the right sign but is not statistically significant.

The findings earlier discussed indicate that the WML portfolio, in bear markets, behaves like shorting a call option on the market. Furthermore, given that the value of a call option is positively related to the market variance, such optionality suggests that the expected returns of the momentum strategy should be a declining function of the future variance of the market. Both the bear market indicator and the VIX independently forecast future momentum returns. Both coefficients, $\hat{\gamma}_B$ and $\hat{\gamma}_{VIX}$ are negative and statistically significant, suggesting that in periods of high market stress (i.e., bear-markets and high market volatility), momentum strategy performs poorly. The interaction effect coefficient $\hat{\gamma}_{int}$, which is designed to capture periods of high market stress, is highly statistically significant (t-statistic= -3.7), and remains negative (-0.578), confirming that momentum's returns are particularly low in periods of bear-markets with high volatility. However, both the new flash bear market indicators do not seem to forecast future momentum returns. The coefficients $\hat{\gamma}_{B(6)}$ and $\hat{\gamma}_{B(4)}$ are negative, but not statistically significant. Nevertheless, considering the interaction between the VIX and the flash bear-market indicator variables, I find that the interaction effect coefficient $\hat{\gamma}_{int(6)}$, is now statistically significant (at a 0.05 significance level and of t-statistic= -2.5) and assumes a negative value of -0.385. The same reasoning holds also for the coefficient $\hat{\gamma}_{int(4)}$ which has a value of -0.321 (t-statistic = -2.1). The results suggest that in periods of high market stress, as indicated by flash bear-markets and high market variance momentum's returns are low.

Robustness Tests

To challenge the robustness of the previously discussed results, I extended the study on the US common stocks to other investment regions and asset classes. Such analysis allows us to evaluate momentum's performance in different international equity and asset classes during and after the 2020 covid-19 crisis and to check whether its trend has been consistent with the strategy's behavior in the US common stock market. International equity data covers the US, UK, Continental Europe, and Japan. While non-equity data covers equity country index futures and commodities.

In 2020, momentum portfolio underperformed the market in four out of the six international asset classes considered. The worse crash occurred in the commodity market, followed by the equity country futures market and the US and Japanese equity markets. However, the WML_{P3-P1} performed very well in the UK and Continental Europe. Noticeably, in 2020 momentum had a stellar performance in the United Kingdom, delivering an average annual return of 19.23%. Consistently such findings suggest that using a strategy that relies on different assets would provide diversification benefits and ultimately enhance the performances of the momentum portfolio.

The last section of the chapter investigate whether momentum crash patterns observed in the US common equities are also present in the other asset markets. Overall the results are consistent with the findings earlier discussed and with the research of DM16 [1]. There are strong momentum effects in each region and asset classes considered except Japan. Similar to the behavior manifested by the US WML portfolio analyzed in Chapter 4, there is a significant time variation in the betas of the momentum portfolios in bear markets and periods of high ex-ante market variance. Thus in panic periods, the momentum strategy exhibits a conditionally negative beta in all the other equity markets and asset classes considered. The option-like features of momentum returns are strong and significant in commodities and the European and United Kingdom equity markets. Such findings also hold for short periods of economic downturns, flash bear markets. They further suggest that cross-sectional momentum strategies manifest significantly lower returns when the market returns profitable after panic periods of declining markets and high volatility.

Conclusions

The main objective of such master thesis was to extend the sample used in DM16 till the end of 2020 to assess whether the cross-sectional momentum strategy also crashed during the year of the covid-19 financial crisis.

Firstly, the analysis confirms a substantial premium over the entire sample period considered. Consistently with the existing literature, such a result holds for all the equity markets and asset classes considered, except for Japan. However, focusing on the last decade, it appears that momentum has lost its historical premium in terms of unit of return earned per unit of risk assumed. Indeed, for the period going from January 2010 to December 2020, the WML portfolio had a meager Sharper ratio of 0.23 while the market delivered a SR of 0.95. Focusing on 2020, this dissertation confirms that momentum crashed throughout the year of the covid-19 financial crisis. The most terrible performance occurred in April when the market returned to be profitable following the economic decline caused by the global pandemic; in such period, the strategy had a return of -28.2%. April's 2020 crash ranked 12th among the list of the worst fifteen monthly returns experienced by the WML portfolio over the whole sample period analyzed.

The second part of this dissertation examines momentum's option-like behavior described by DM16. The analysis shows that the strategy exhibits significantly lower abnormal returns and more negative betas in bear markets. Furthermore, once the market returns to be positive, the WML portfolio ends up having large negative exposure to systematic risk. Such features indicate that in bear markets, momentum is effectively shorting a call option on the market. This is to say when the market bounces back after a financial crisis, the WML portfolio suffers severe crashes. Collectively the results appear consistent with the findings of DM16. However, given that the covid-19 crisis was the shortest bear market experienced in the SP500 history, I introduced two new indicator variables to capture short periods of economic downturn, flash bear markets. The results confirm a notable time variation in the betas of the momentum portfolio in flash bear markets. Interestingly, the strategy's optionality also holds when the market bounces back after periods in which the past cumulative six-month market return is negative. While when the past cumulative four-month market return is negative, the optionality is of the correct sign but is not statistically significant anymore. Moreover, using the VIX index, I showed that momentum's returns are remarkably lower in periods of high ex-ante market variance and that the strategy performs very poorly in bear markets and flash bear markets, with high market volatility.

As a robustness test, I extended the analysis carried out on the US common stocks to other investment regions and asset classes. The strategy exhibits significantly more negative betas in bear markets, flash bear markets, and periods of high ex-ante market variance in all the different markets considered. In terms of excess returns, in 2020, the momentum portfolio underperformed the market in four out of the six international asset classes considered. However, in the UK and EU equity markets, the WML portfolio delivered excess returns that exceed the market's expectations. The present findings suggest that using a strategy relying on different equity markets and asset classes would provide diversification benefits and ultimately improve the performances of the momentum portfolio.

Despite having carried out the analysis with care and attention, this research suffers from certain limitations. Firstly, I used monthly returns of US common stocks to construct the WML portfolio. Moreover, I assumed that the monthly rate for the VIX index is equal to the daily rate at the beginning of each month and that such a daily rate remains valid throughout the month. In this way, I converted the daily series of the VIX index into a monthly series. Using higher-frequency data would have yielded more timely and precise estimates of returns and volatilities. Second, the returns and performance statistics presented in this study should be interpreted with caution. They are not representative of a real-life implementable strategy since they do not account for transaction costs. Third, this analysis focuses solely on cross-sectional momentum.

Looking forward, there are several ways in which this research can be developed. It would be interesting to assess how the hedging strategies built to reduce momentum's crash risk, such as the volatility managed portfolios and the DM16 dynamic hedging strategy, behaved throughout the shortest bear market in the SP500 history, the 2020 financial crisis. Future research should also investigate and compare the performance of various risk factors in times of short but intense periods of economic downturn.