ERASMUS UNIVERSITY ROTTERDAM
ERASMUS SCHOOL OF ECONOMICS
Bachelor Thesis Economics & Business

Momentum Crashes:

A look into the latest bear markets.

Author: Oren Justin Ventura
Student number: 564345
Thesis supervisor: dr. Marc Gabarro Bonet
Second reader: **[**title and name of second reader]
Finish date: July 4, 2023

The views stated in this thesis are those of the author and not necessarily those of the supervisor, second reader, Erasmus School of Economics or Erasmus University Rotterdam.

ABSTRACT

This thesis explores the phenomenon of momentum, more specifically the recent potential underperformance of momentum in periods following bear markets. The study focuses on data on the US stock market in the years 2014-2022. Results show that a momentum strategy based on a trailing 12-month formation period underperformed in holding periods following market bottoms, with the bottom decile of stocks outperforming the top decile, causing a Winner-Minus-Loser portfolio to experience periods of negative profits while the market recovers. These results are seemingly stronger when considering equal-weighted portfolios, with these portfolios performing worse than value-weighted momentum portfolios overall as well. The shortcomings of a momentum strategy that shorts the bottom decile following bear markets are thus highlighted, and the potential of buying past-losers instead is brought to light.

Keywords: momentum, market anomalies, asset pricing, momentum crashes

JEL codes: G11, G12

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 Introduction

The thesis explores evidence of “momentum crashes”, that is, the poor performance in terms of cumulative returns of momentum investment strategies following bear markets, in the most recent stock market crashes. In this study, the cumulative returns of momentum strategy portfolio, or the buying of “past winners” as well as the short selling of “past losers” is examined and compared to other portfolio benchmarks during these periods. As for the relevance of the study, the results shed light on the underperformance of momentum strategies after the most recent bear markets which differ in scale/degree and either strengthen the findings of past studies or refute them.

The momentum strategy is generally considered to be pioneered by Jegadeesh and Titman (1993), where they found that a strategy consisting of going long on well-performing stocks (past-winners) and shorting poorly performing stocks (past-losers) provided considerable and significant positive returns. Many replications have shown that this holds true for several different asset classes and time periods as well, leading momentum to be considered an anomaly in asset pricing. One of these papers by Daniel and Moskowitz (2016) confirms the findings of Jegadeesh and Titman (1993) among others, but also reveals another discovery regarding momentum strategies. To be specific, they find that following periods of market drawdowns, the momentum strategy underperforms the market considerably, resulting in a “momentum crash”. They attribute most of the poor performance to the fact during the market recoveries and periods of high volatility, the past-losers portfolio of stocks rose considerably more than both the market and the past-winners. Since the traditional momentum strategy entails shorting the past losers, this results in the overall returns of the strategy to underperform or even be negative. Hence, one takeaway from their paper is that the momentum strategy performs poorly in periods following a bear market. An additional and similar paper also come to the same findings and conclusions regarding momentum crashes following market declines (Barroso and Santa-Clara, 2015).

Given these findings, it is natural to see if it can be applied to more recent samples of data. Daniel and Moskowitz (2016) mainly emphasize the worst of the crashes (i.e The Great Depression and the 2008-2009 Financial Crisis), whereas it may be of greater interest to the modern investor whether the same patterns persist in contemporary markets with crises that are not as extreme. Hence, for this paper, the use of more recent cases compared to the ones explored by Daniel and Moskowitz (2016) will be explored. The bear markets considered in this thesis differs from the ones they examined in terms of novelty as well as the degree of the market drawdown (length and overall negative performance). Simply put, they looked at a large timeframe consisting of data from 1927 up to 2013, and my sample will account exclusively for bear markets past 2013 up to the present day. Currently, my time period of interest are the months following recent stock market declines seen after the publication of Daniel and Moskowitz’s (2016) paper, from the most recent decline throughout 2022 as well as the bear markets in 2020 (COVID-19), 2018 (Q4 crash), and 2015-16 (flash crashes)

As these bear markets occurred more recently, they provide better insight to the modern performance of momentum portfolios given more concurrent market conditions, such as historically low interest rates, potentially better understanding and prevention of crises, and higher investment by retail investors and lower transaction costs brought by the rise of electronic trading. Additionally, shorter timeframes (i.e up to a year) will be looked at when it comes to the market rebound and the performance of the momentum strategy. Previous literature looked at much longer time horizons (several years) for the momentum portfolio, hence it may be of interest to examine shorter term cumulative gains from the strategy for swing traders as opposed to long-term holders. The analysis of the results will hopefully serve as confirmation or perhaps a potential contradiction to existing knowledge. Overall, my study will aim to answer:

"How do recovery periods following more recent market drawdowns affect the performance of a momentum strategy?".

The method to study the research question closely follows that of existing literature, where the momentum strategy is comprised of portfolios of stocks allocated to either a winner or loser portfolio. Stocks are firstly ranked based on their cumulative returns from 12 months to one month prior to the formation date of the portfolio, which is end of the month with the day of the lowest closing price in each bear market. This ranking then determines the winner and loser portfolios, with the top decile considered the "Winners" and the bottom decile considered the "Losers". And, as mentioned earlier, the strategy entails buying the winner portfolio and selling the losers portfolio. An examination of the performance of momentum portfolios in terms of average returns over the sample period will firstly be conducted to report the contemporaneous performance of momentum overall. Afterwards, in the subperiod studies, the cumulative returns of 1$ invested over a period following each market drawdown is measured as the strategy's performance, which is then compared to the performance of simply investing that dollar in the market portfolio to determine relative performance. An additional study of value versus equal weighted momentum portfolios is also conducted to report differences in performance. Stock data will be based on the United States' equity market sourced from the Center for Research in Security Prices (CRSP) with access provided by EUR.

I expect my findings to be consistent with that of Daniel and Moskowitz (2016), where periods following market drawdowns and high volatility result in poor or even negative performance for a momentum strategy. Additionally, as the market drawdowns are considered in my study are not as severe, the degree of market crash is also expected to not be as drastic. My results in combination with the previous literature can potentially shed light on the fact that a reverse momentum strategy (i.e buying the loser's portfolio instead) could offer lucrative returns following bear markets, which is a strategy that is not necessarily popular and is one that goes against investors' intuition as buying past losers does not readily come to one's mind. Finally, as this paper exclusively studies recent momentum performance, there is a high chance of divergence from the results of previous literature, and leaves room for future research to explain any discrepancies brought up.

CHAPTER 2 Theoretical Framework

The following chapter firstly describes momentum as an investment strategy with a brief history of its emergence, followed by proposed explanations of how such a strategy is profitable. Then the idea of momentum crashes is introduced and explained, as well as some theoretical background behind the differences between equal and value-weighted portfolios. The last subsection describes the expected outcomes of this study based on the established knowledge.

2.1 Momentum

2.1.1 Evidence of Momentum

“Momentum” refers to an investing strategy that is considered to be a market anomaly with lucrative returns. It can be described as the tendency of stocks to continue their past performance into the future, indicating a violation of the weak-form market efficiency outlined by Fama and French (1970) as future returns could now seemingly be predicted by past performance. The seminal paper on momentum by Jegadeesh and Titman (1993) has shown that buying previously well-performing stocks and selling poor-performing stocks generated significant positive returns in the medium-term (3-12 months). What initially started as research to confirm the findings of De Bondt and Thaler (1985) that suggested that stock prices overreact to new information, Jegadeesh and Titman (1993) ended up paving the way for later research on momentum investing strategies and its implications on investors’ behaviour. The strategy in their paper entails ranking NYSE and AMEX stocks by their cumulative returns over the previous 1-4 quarters excluding the latest previous month. The top decile is then bought, and the bottom decile is sold, resulting in a “winner-minus-loser” portfolio which is held over 1-4 quarters and that realizes significant abnormal returns over their studied period (1965-1989). Jegadeesh and Titman (1993) also relate the profitability of their strategies to market underreaction to firm-specific information. They then conclude with suggestions for further research, which was met with future papers on the topic of momentum strategies as well as potential explanations being done.

For example, Rouwenhorst (1998) replicates and expands the study of these momentum strategies internationally, showing that the profits can also be found in 12 European markets. Chui, Titman and Wei (2000) examined momentum profits in Asian markets, finding that with the exception of Japan, profits from momentum can also be found. Chan, Jegadeesh, and Lkonishok (1999) also provides evidence of momentum on the international scale, this time for market indexes. As for other asset classes, Carhart (1997) expands the study of momentum with the past performance of mutual finds. He finds that buying the best performing mutual funds and shorting the worst over the previous year yielded a positive return as well, or a persistence in mutual fund performance. Straying away from equities, evidence of momentum was also found in commodity futures (Miffre and Rallis, 2007) and foreign currency exchange markets (Okunev and White, 2003). Much more recently, Liu, Tsyvinski, and Wu (2022) also find momentum profits when looking at the past performance of cryptocurrencies. These consistent findings suggest that momentum is indeed a seemingly robust investing strategy, but also that there may be a common factor in asset pricing or investor behaviour that can be found across both countries and asset classes that drives momentum profits.

2.1.2 Explanations of Momentum

Studies aiming to explain the basis of momentum profits generally fall into either behavioural-based or risk-based models. The following paragraphs will summarize the essence of these two explanations.

On the behavioural side, studies following Jegadeesh and Titman (1993) develop theories/models of underreaction and overreaction as the stimulants of momentum, insinuating a serial correlation of stock returns driven by individual biases and the sluggishness to incorporate new information. Early theories include Daniel et al. (1998), who attribute momentum profitability to investor overconfidence and biased self-attribution, suggesting that public signals cause stock prices to drift from their fundamental value in the direction of their private signal that was established by investors' prior research (i.e a buy signal is confirmed if the publicly-available return turns out to be positive, leading to positive momentum). Their study is also one of the first to suggest a reversal of momentum in the long run as prices return to their fundamental value. There is also Hong and Stein (1999) who unify underreaction and overreaction to construct a model of two types of investors including so-called "news-watchers" and "momentum-traders", with the former basing price targets based on privately observed news and the former on past and current prices. The news-watchers drive the underreaction as new information is slowly digested, whereas the momentum-traders drive the overreaction as they tend to push past winners above fundamental values further. Hong, Lim, and Stein (2000) found that the profitability of momentum strategies declines with firm size and more importantly that they work better among stocks with low analyst coverage. Their results are consistent with the proposal that information (especially negative) takes time to be digested to the investing public, which results in the profitability of these momentum strategy. Other studies such as Barberis, Shleifer, and Vishny (1998) develop the findings of underreaction as well as overreaction to form a model of investor sentiment in an attempt to explain several market anomalies including momentum. Jegadeesh and Titman (2001) revisit their momentum strategy but focuses on the long-term performance of momentum strategies. They found that in their sample period of 1965 to 1998, the momentum returns were on average negative during the second through fifth years after formation of the portfolio, which serves as evidence for the long-term reversal of momentum strategies.

As for the risk-based explanations, the sources of momentum are seeked while still assuming investors are rational. Here, theories propose that momentum profits arise from the compensation for the higher risk one would take with a momentum strategy, referring to the Arbitrage Theory of Ross (1976) who propose that expected returns are a positive function of the excess return of the market multiplied the risk factor of the asset (β). Conrad and Kaul (1998) were the first to show that the cross-sectional variance in mean returns, or the risk, is what potentially generates the observed profits of the momentum strategy. Johnson (2002) uses a simple single-firm model show that shocks in expected growth rates, which can increase or decrease risk and therefore affect asset pricing, could explain market anomalies related to underreaction, including momentum. Sagi and Seasholes (2007) suggest that momentum is stronger in firms with higher book-to-market ratios as these firms have better growth options. They reason that these growth options are riskier than the rest of the firm's already established revenue streams, resulting in the overall firm to be riskier, hence driving momentum profits as investors would demand a higher expected return as compensation. Finally, Avramov et al. (2007) examine momentum profits depending on the firms' credit rating. Including only firms with an S&P rating of B or worse produced significant profits in a momentum strategy whereas including only firms with a BB rating or better showed no significant momentum effects, once again suggesting that momentum arises from a higher undertaking of risk.

2.2 Momentum Crashes

Despite their strong returns, Daniel and Moskowitz (2016) reveal that momentum strategies can suffer from occasional periods of drastic negative returns or "crashes". The worst of the crashes occurred when the market rose drastically after the trailing two-year market return was negative, with the two worst sustained periods of underperformance being the market recoveries following the 1932 and 2009 market bottoms. Additionally, the cause of the crashes was credited to the performance of the loser portfolio, which rose drastically more than the winner portfolio resulting in the overall winner-minus-loser portfolio return to be negative as the losers were short-sold. This finding is in line with Avramov et. al (2013) who observe that the profitability of various investing anomalies, including momentum, is attributable to the performance of the worst-rated stocks under financial distress. These stocks are expected to continue performing poorly hence shorting them would lead to profits, however as Daniel and Moskowitz (2016) have shown, such a position leads to large losses in market recoveries.

Their paper also confirms previous research conducted by Cooper et. al (2004) which showed that from 1929-1995, average monthly momentum profits following three-year positive market returns was 0.93% versus -0.37% following negative market returns. Cooper et al (2004) themselves also confirm the findings of Jegadeesh and Titman (2001) that momentum profits are reversed in the long run, which further suggests momentum strategies as medium-term investments that can in fact suffer from occasional periods of losses. On the other hand, Stivers and Sun (2010) look at market volatility and find evidence that higher market volatility negatively predicts momentum profits. This suggests that the higher volatility that is associated with bear markets would predict a reversal in momentum profits. This study was followed up by Wang and Xu (2015), who confirm that market volatility has significant power to forecast momentum payoffs, much more so than other variables. Additionally, the theme of the loser stocks being responsible for the momentum premium is continued, where the time-series predictive power of profits turned out to revolve around the loser stocks.

This then begs the question on whether these crashes can be forecasted in advance. Daniel and Moskowitz (2016) use bear market indicators and ex ante volatility estimates in their same study to construct a robust dynamic momentum strategy that approximately doubles the Sharpe ratio of the WML portfolio. Baltzer, Jank, and Smajlbegovic (2019) look at the sales volume of losers to predict momentum crashes. They report a substantial increase in the selling volume of past loser stocks by momentum traders over the course of the 2007-2009 financial crisis, whose market recovery caused some of the largest momentum crashes. Their findings indicate that these excessive sales pushed prices below their fundamental value, and ultimately led to the reversal in momentum profits when markets recovered or a momentum crash.

2.3 Equal vs. Value-Weighted Portfolios

The various literature also contains differing portfolios weighting strategies, with studies generally choosing either an equal-weighted or a value-weighted strategy based on market capitalizations. For example, the seminal paper by Jegadeesh and Titman (1993) consists of portfolios that are equally weighted, whereas Daniel and Moskowitz (2016) opted for value-weighted portfolios when they first explored momentum crashes. This thesis will explore the performance of momentum portfolios based on both weighting philosophies.

DeMiguel et al. (2007) shed light on the outperformance of equal-weighted investment strategies, showing that equal-weighted (1/N) portfolios performed better than 14 weighing alternatives, including a value-weighted strategy. Plyakha et al. (2016) directly tackle the question of why an outperformance occurs, attributing the higher returns to a bearing of additional systematic risk with the equal-weighted portfolio and a higher alpha because of the rebalancing of the portfolio in order to maintain equal weights. This is in line with the risk-based explanations of momentum, where the source of momentum profits is similarly attributed to a higher undertaking of risk. Therefore, one could expect that an equal-weighted momentum portfolio would perform better than a value-weighted one as a result. Korajczyk and Sadka (2004) incorporate a model including trading costs into momentum strategies, finding that when ignoring these costs, equal-weighted strategies indeed performed better than their value-weighted counterparts in their sample data from 1967 to 1999. When trading costs were included however, the equal-weighted strategy performed worse.

2.4 Research Expectations

Now that the previous knowledge has been tackled, the main research question this paper aims to answer will be restated:

“How do recovery periods following more recent market drawdowns affect the performance of a momentum strategy?”

Referring to the studies done by Cooper et al (2005), Stivers and Sun (2010), and closely following the paper of Daniel and Moskowitz (2016), the same findings of a poor performance of a momentum portfolio following the most recent market drawdowns are expected. Hence, the first hypothesis proposed is:

H1: Market recovery periods will result in a momentum crash in the years following the observations of Daniel and Moskowitz (2016).

Additionally, the studies of Avramov et al. (2013) and Daniel and Moskowitz (2016) lead one to expect that the underperformance will be as a result of the short-side or the losers. Here, the holding period cumulative returns (losses) would be driven by the losers outperforming the winners portfolio despite the latter still yielding positive returns, and as the losers are shorted the entire WML portfolio would yield a negative return. This is opposed to another possible case, where the WML portfolio would yield a negative return due to the winners portfolio performing badly. Thus, the second hypothesis expected is:

H2: The losers portfolio will experience a substantial rise in value during the holding period.

This thesis lastly introduces additional, equal-weighted momentum portfolios to compare with the baseline value-weighted portfolios to explore any difference in the performance as well as the momentum crashes. Given the suggestion of Plyakha et al. (2016) that equal-weighted portfolios bear higher risk and the trading costs study of Korajczyk and Sadka (2004), one would expect comparatively larger returns in equal-weighted momentum portfolios without trading costs. At the same time, this risk would suggest a larger downside potential in the case of a momentum crash, hence the third hypothesis proposed is:

H3: The equal-weighted momentum strategy will perform better than the value-weighted strategy on average but will experience larger momentum crashes.

CHAPTER 3 Data

The data obtained for the purposes of this research paper is taken from the Center for Research in Security Prices (CRSP). CRSP data was accessed through Wharton Research Data Services (WRDS) with access provided from the university. Monthly and daily stock data from 2014-2022, which are the years following the paper of Daniel and Moskowitz (2016), are considered for this study. The monthly data is used to form the portfolios based on the previous months before the formation date as well as the calculation of the overall performance of momentum, whereas as the daily data is used to calculate and display the cumulative returns for the subperiod studies in the months following the formation date. As for the actual data, the date, PERMNO (unique company ID) holding period return (RET), price, and shares outstanding were taken. RET will be considered for the cumulative returns as it includes any dividend distributions whereas the closing price alone does not. The last two were used to calculate the market capitalization, which was then used to weigh the stocks in the portfolios and their subsequent returns.

Additionally, following the procedure of Daniel and Moskowitz (2016), only data from common shares as they are generally the most accessible security for investors. On the CRSP database, the conditional statements of a Share Code (shrcd) equal to 10 or 11 can be added to the search query to achieve this. Table 1 below contains a few summary statistics of the resulting monthly data that was eventually used in the formation of the momentum portfolios.

Table 1: Descriptive statistics of the data used in the study.

	Mean	Median	Standard Deviation	Minimum	Maximum
Number of Firms, Yearly	4084.56	3955 (2020)	302.72	3857 (2018)	4625 (2022)
Market Capitalization ($)	7780758	674462.7	44500000	88.33 (PSTV, Jul. 2019	2900000000 (AAPL, Dec. 2021)

Source: CRSP. In parenthesis is additional information of each observation, with either the year for each observation in the Number of Firms (i.e the median of 3955 coincided with the year 2018) or the stock ticker and the month (i.e the max market cap was achieved by Apple (ticker: AAPL) on December 2021.

To identify the market crashes and compare the returns of the momentum portfolios to the market, the CRSP Index File on the S&P500 was also taken. More specifically, daily data of the return and the price level of the S&P 500 was extracted. The CRSP directly bases their data on the Standard & Poor Statistical Service, where events such as a quarterly rebalancing (i.e adding/removing of firms from the index) are already incorporated into the index level. Other sources of data include the Fama/French Data Library for the risk-free interest rates used to calculate the Sharpe Ratios.

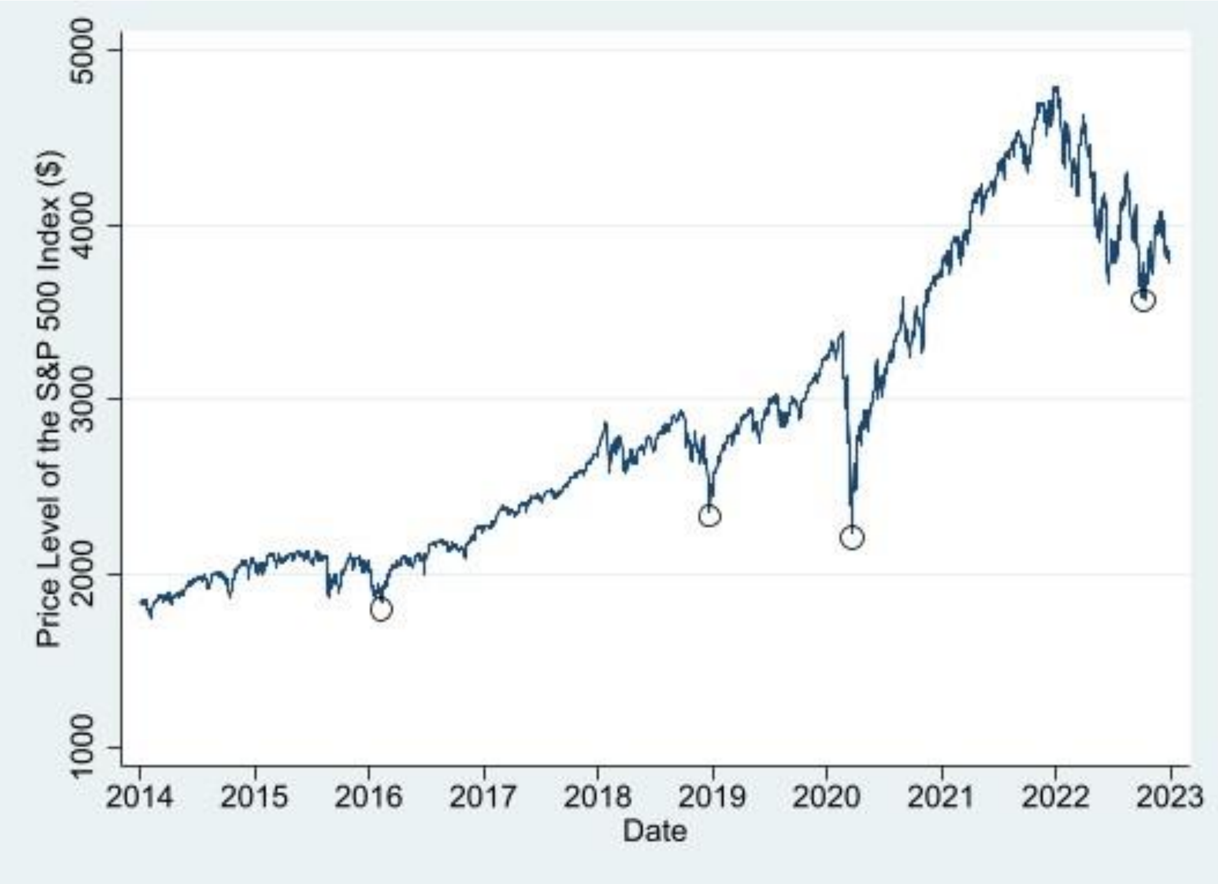
CHAPTER 4 Method

The momentum strategy utilized for this study closely follows that of the traditional cross-sectional strategy first illustrated by Jegadeesh and Titman (1993), as did Daniel and Moskowitz (2016). More specifically, stocks are ranked by their trailing 12-month cumulative return, excluding the immediate previous month. This month is omitted as to avoid the short-term reversals shown by Jegadeesh (1990) and Lehmann (1990), hence the monthly returns are summed up from T-12 up to T-2 with T entailing the formation month. Firms are then placed into deciles with the best-performing stocks, the “Winners”, placed in decile 10 and the worst-performing stocks, the “Losers”, placed in decile 1, effectively creating the portfolios that are desired for the momentum strategy. For stocks to be eligible to be placed in one of the portfolios however, they must have a valid share price at the formation date and at least 8 monthly return observations in the cumulative return consideration period. The WML portfolio simply consists of a long position on the winners and a short position on the losers, effectively subtracting the returns of the losers from the winners.

As for the resulting performance of the momentum strategy, the weighted-average or the value-weighted return of the top and bottom decile will be first be considered. The weights will be based off the market capitalization of each firm as of the formation date, which is simply calculated as the closing price multiplied by the number of shares outstanding. In some cases, the closing price is unavailable in the provided dataset and instead reports the bid-ask average price with a negative sign, in which case the absolute value of the observation is taken as to avoid negative market capitalizations. In the equal-weighted portfolio, the simple average of the returns of all the winners and losers is taken over the holding period. No trading costs will be considered. Depending on the application, the holding period cumulative return, or performance, of these portfolios will be calculated using the monthly and daily datasets.

Finally, to identify the momentum crashes, periods of recovery of the market following considerable retractions or bear markets are given more attention. These periods are discerned by the market bottoms in using the price level of the S&P 500 index during the observed time frame of 2014-2022. An illustration can be seen in in the following figure which depicts the daily price level of the S&P 500, the proxy considered for the performance of the market, over this paper’s observed time frame.

Figure 1: Price level of the S&P 500, 2014-2022.



Note: Graph made using daily data on the S&P 500, sourced from the CRSP. Circles indicate the market bottoms, or the lowest price level achieved during a drawdown.

The market bottoms are indicated above by a marker. These points also correspond to a date with a price level that is below the level that it was in the previous 12 months. This results in the following four bear markets considered in this study:

1. 2015-2016 stock market selloff
2. 2018 Q4 crash
3. COVID-19 recession in 2020
4. Ongoing 2022 stock market decline

Thus, the periods following these bottoms are more closely examined in terms of the performance of a momentum strategy to reveal any evidence of a momentum crash.

CHAPTER 5 Results & Discussion

The results section starts off by examining the overall performance of momentum over the sample period of 2014-2022. Afterwards, the subperiod study is conducted where the bear markets outlined in the previous section will be given more attention to find evidence of a momentum crash. Then, the equal-weighted portfolios are introduced in order to compare the performance between the equal and value-weighted momentum portfolios. Finally, the section concludes with a discussion of the results in relation to the previously established knowledge and literature.

5.1 Overall Momentum Performance

Table 2: Momentum performance during 2014-2022, value weighted.

		Holding Period				
Portfolio		1 Month	3 Months	6 Months	12 Months	24 Months
Winners	Mean (%)	1.59**	1.60***	1.47***	1.54***	1.66***
	T-Stat.	(1.80)	(3.13)	(3.97)	(5.42)	(9.61)
	Standard deviation (%)	8.59	4.93	3.50	2.61	1.47
	Maximum (%)	26.3	22.3	14.3	9.05	5.05
	Minimum (%)	-21.1	-11.9	-7.14	-2.61	-1.65
	Excess return over the S&P 500 (%)	0.762	0.713**	0.717***	0.916***	0.293***
	T-Stat.	(0.736)	(1.89)	(2.50)	(4.28)	(2.45)
	Beta	-0.171	1.70***	1.80***	2.27***	3.00***
	Sharpe Ratio	0.177	0.312	0.401	0.567	1.08
Losers	Mean	-0.689	-0.258	0.0447	0.917**	1.23***
	T-Stat.	(-0.642)	(-0.412)	(0.0913)	(2.57)	(6.22)
	Standard deviation (%)	10.5	6.05	4.64	3.27	1.67
	Maximum (%)	39.1	16.7	12.7	9.70	4.28
	Minimum (%)	-24.6	-18.1	-8.15	-8.88	-2.14

	Excess return over the S&P 500 (%)	-1.52	-1.04**	-0.689*	0.537**	-0.513***
	T-Stat.	(-1.22)	(-2.00)	(-1.63)	(2.26)	(-3.35)
	Beta	-0.369	1.88***	2.31***	2.76***	2.94***
	Sharpe Ratio	-0.0883	-0.0534	-0.00361	0.261	0.689
WML	Mean	2.28***	1.86***	1.42***	0.626***	0.436***
	T-Stat.	(2.56)	(3.67)	(3.90)	(2.69)	(2.98)
	Standard Deviation (%)	8.66	4.89	3.46	2.14	1.24
	Maximum (%)	22.9	18.9	9.51	9.07	2.90
	Minimum (%)	-26.8	-9.00	-8.89	-3.52	-3.89
	Excess return over the S&P 500 (%)	1.45*	0.940*	0.458	-0.733***	-0.0823
	T-Stat.	(1.51)	(1.61)	(1.03)	(-2.84)	(-0.577)
	Beta	0.198	-0.177	-0.509*	-0.486**	0.0654
	Sharpe Ratio	0.255	0.367	0.393	0.263	0.291

Note: This table includes the average monthly returns, standard deviations, maximum/minimums, excess returns over the stock market (S&P500), CAPM betas, and Sharpe Ratios of value-weighted momentum portfolios for various holding periods after a formation period consisting of the previous 12-1 months prior to the formation date. All values in three significant figures. Data sourced from the CRSP. Stars indicate significance levels (one-sided) based on the T-statistics directly below (* p<0.10, **p<0.05, ***p<0.01).

Table 2 above presents the overall performance of the portfolios in a momentum strategy of various holding periods following a 12-month formation period for the entire sample period of 2014-2022. Investing in stocks in the top decile, the “Winners”, yields a value-weighted average monthly return of between 1.47% (6 months) and 1.66% (24 months) with all holding periods showing statistical significance of a mean return greater than 0 at the 1% level except for the 1-month holding period, which is significant at the 5% level. On the other hand, investing in the bottom “Losers” results in various monthly returns depending on the holding period, seemingly increasing with a longer holding period as seen with an initial negative return of -0.689% per month for the 1-month holding period to a 1.23% for the 24-month holding period. Statistical significance also seems to increase with the holding period, with only the 12 and 24-month holding periods showing significance. As for the main WML portfolio, the opposite trend can be seen with a performance of 2.28% in the 1-month strategy decreasing to 0.44% in the 24-month strategy. Interestingly, the holding period of 6 months is the moment at which the Losers portfolio starts being profitable on average, which also coincides with the moment at which the WML portfolio stops being more profitable than the Winners portfolio. All mean monthly returns for this portfolio are positive and statistically significant.

To paint a better picture of the performance of momentum over this time period, included in the table is a comparison to the average monthly return of the S&P 500 over each holding period as well. The Winners portfolio outperformed the S&P 500 in each holding period as seen with the positive "excess return over the S&P 500" row, with the largest difference in the mean returns coming from the 12-month holding period with 0.916% and the difference dropping to only 0.293% for the 24-month holding period. Only the 1-month holding period excess return does not show statistical significance. The story changes for the Losers portfolio, where the mean difference in returns is negative with the largest difference at -1.52% per month in the 1-month holding period, then seemingly increasing with the holding period with a sudden jump to 0.537% in the 12-month holding period. Here, the 1-month holding period also does not show statistical significance. Finally, the WML portfolio outperforms the S&P 500 in the shorter holding periods, with the highest difference being the 1-month holding period with a significant 1.45% average premium over the market then decreasing to 0.458% in the 3-month holding period. The excess return then drops for the longer holding periods to a significant -0.733% difference per month for the 12-month and a miniscule and insignificant difference in the 24-month holding period.

As for the other reported values, the beta of the returns of each portfolio to the returns of the market was also included in the table. Here the market was again considered to be the S&P 500, hence the beta points to the sensitivity of each portfolio to the performance of the market. For holding periods greater than the 1-month period, the betas were positive and significant, and increased with the holding period for both the Winners and Losers portfolio. Interestingly, looking at the WML portfolio betas, the only significant values were negative (-0.509 in the 6-month and -0.486 in the 12-month) suggesting the Losers portfolio had the larger betas compared to the Winners portfolio. This is discussed more in the later subsections.

Lastly, the Sharpe Ratios are also reported as the last value for each portfolio. For the Winners portfolio, the Sharpe Ratio increased with the holding period, whereas the Losers portfolio showed no evident trend. The shorter holding periods of 1-6 months had values that were quite small and negative which is in line with Daniel and Moskowitz (2016) and their losers portfolio Sharpe Ratio, however the longer time periods of 12 and 24-months showed much larger and positive values. An important thing to note is that with the higher holding periods, the standard deviations tended to decrease which would result in higher T-statistics and Sharpe Ratio as well.

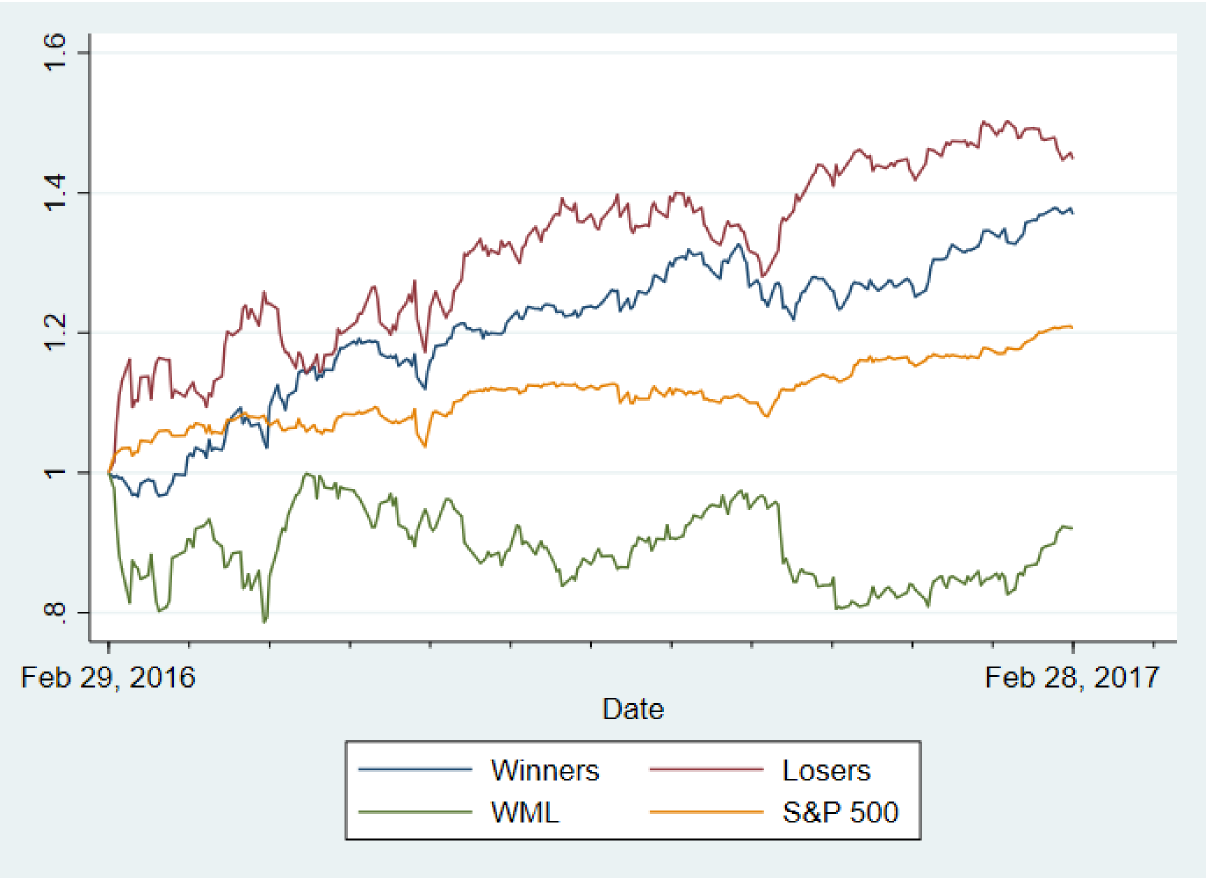
Overall, momentum strategies have continued being profitable following Daniel and Moskowitz (2016). The most profitable strategy on average that was examined turned out to be the 1-

month holding period after a 12-month formation period, however the worst loss is larger in magnitude in absolute terms compared to the best return (-26.8% and 22.9% respectively). This now hints at potential momentum crashes, where the strategy risks some periods of considerable losses. These periods will be more closely examined in the next sections.

5.2 2015-2016 Market Selloff

The first bear market following the sample period of Daniel and Moskowitz (2016) (up to 2013) is the 2015-2016 market selloff, where the S&P 500 dropped 12.2% from the price level of 2128.28 on the 20th of July 2015 to 1867.61 on the 25th of August 2015. The market recovered back up to the level of 2109.79 on the 3rd of November 2015 only to drop 13.3% 1829.08 on the 11th of February 2016, or an overall decrease of 14.2% between July 2015 and February 2016.

Figure 2: Momentum crash 2016.



Note: Daily returns of each portfolio following a formation date of 29th of February 2016 up to 28th of February, 2017. Portfolios are value-weighted; weights based on the market capitalization on the formation date. Each tick on the x-axis represents one month.

Table 2 serves as a visual representation of an investment that entails buying 1$ worth of the Winners, Losers, and the Winner-Minus-Loser portfolios as well as the S&P 500 which serves as our benchmark for the performance of these portfolios over time. February 29th was the last day in

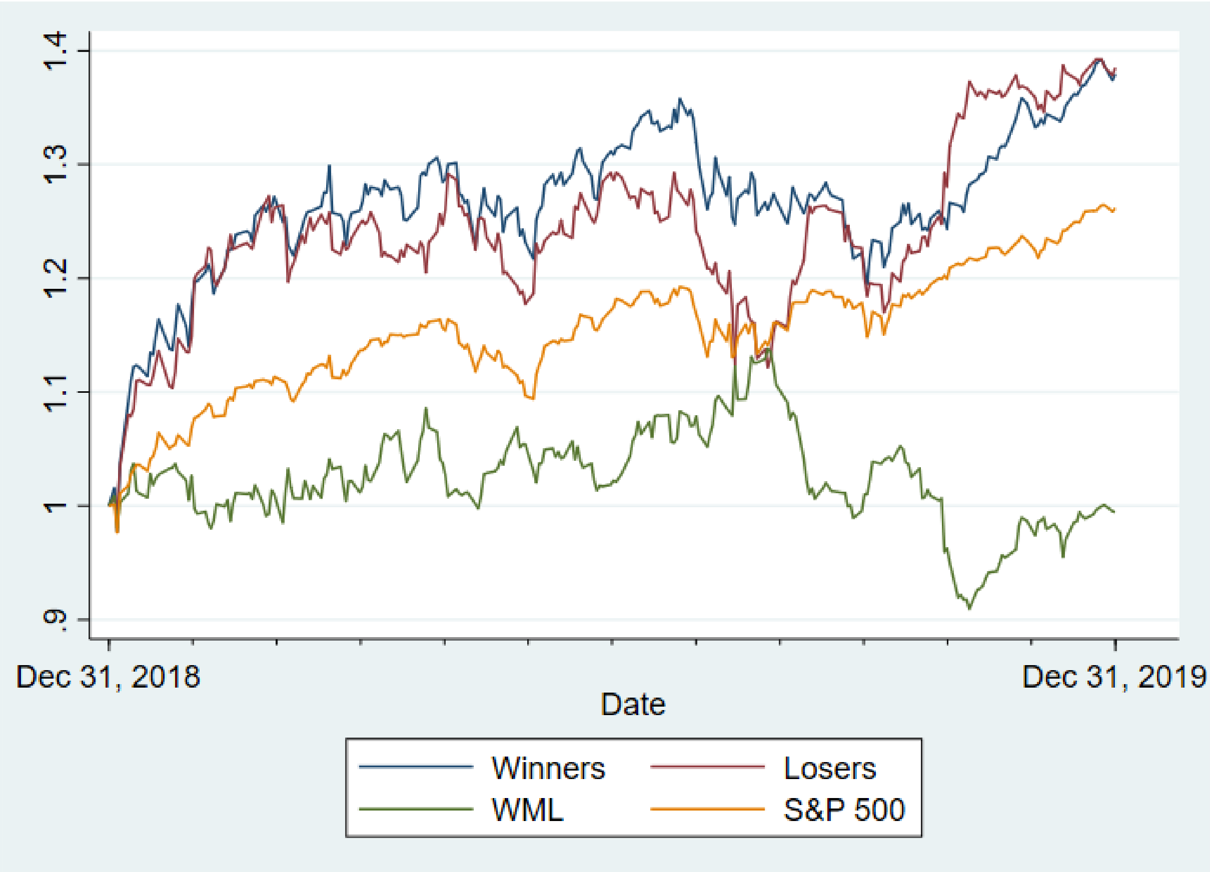
February of 2016, and thus is the formation date and the start of the holding period return considered. The first observation here is that immediately after the onset of the investment, the Losers portfolio experienced a considerable increase in value as seen with the red line. The increase is more than that of the S&P 500 (in yellow) and is the opposite of that of the Winners portfolio (in blue), which experienced negative returns for the first couple of weeks. The Losers continued showing strong returns throughout the holding period of 12 months in total, seemingly outperforming the Winners portfolio and the S&P 500 almost the entire time and ending off at a value of $1.45 a year after the formation date with a maximum of $1.50 (Feb. 3rd, 2017). The Winners and the S&P 500 investment ended off at $1.37 and $1.21 respectively, which is also around the same as their maximum values. Seeing as the Losers portfolio managed to outperform the Winners, the WML portfolio did expectantly suffer from negative returns from the start. In fact, after the initial crash of the strategy, it started to recover in the month of May 2016 only to reach just shy of a breakeven value ($0.99) only to continue its losses for the remaining period. Here, the WML portfolio suffered from a minimum value of $0.786 (Apr. 27th, 2016), with similar lows being reached later in the holding period ($0.80 around January of 2017) and ending off at a value of $0.921 at the end of the holding period. Consequently, the case of a momentum crash is evident, with the WML portfolio strictly underperforming the S&P 500 for the entire holding period with a mean difference of -$0.218 (largest difference of -$0.358, 7th of January 2017) and suffering from overall negative returns.

As the sustained underperformance of the WML portfolio may be driven by the first few day returns following the formation date, an additional alternative graph for the 2016 bear market is included in the appendix. Figure 6 in the appendix consists of momentum portfolios formed on an alternative formation date of December 30th, 2015, or 2 months before the original formation in Figure 2. Here, the WML portfolio performs better in the month of January, however when the market bottom is reached in February and the month of March comes around, a similar large rise in the Losers portfolio is seen. This sudden increase once again leads the WML portfolio to underperform the S&P 500 for the remainder of the holding period, suggesting that the underperformance is not a result of the choice of formation date and has more to do with the performance of the Losers portfolio in market recovery periods.

5.3 2018 Q4 Crash

The next bear market that is looked at is the decline seen in the last quarter of the year 2018. From the high of 2930.75 on the 20th of September 2018, the S&P 500 dropped all the way down to 2351.10 on Christmas Eve, or the 24th of December 2018 (-19.8%). For the year, the S&P 500 was down around 6.20% which is the worst year since the 2008 financial crisis 10 years earlier, and the month of December in particular was the worst December since 1931. Seeing as this bear market seems to mirror the two bear markets that Daniel and Moskowitz (2016) have shown to cause the worst returns for momentum, it is interesting to see whether the story is the same for 2018.

Figure 3: Momentum crash 2018.



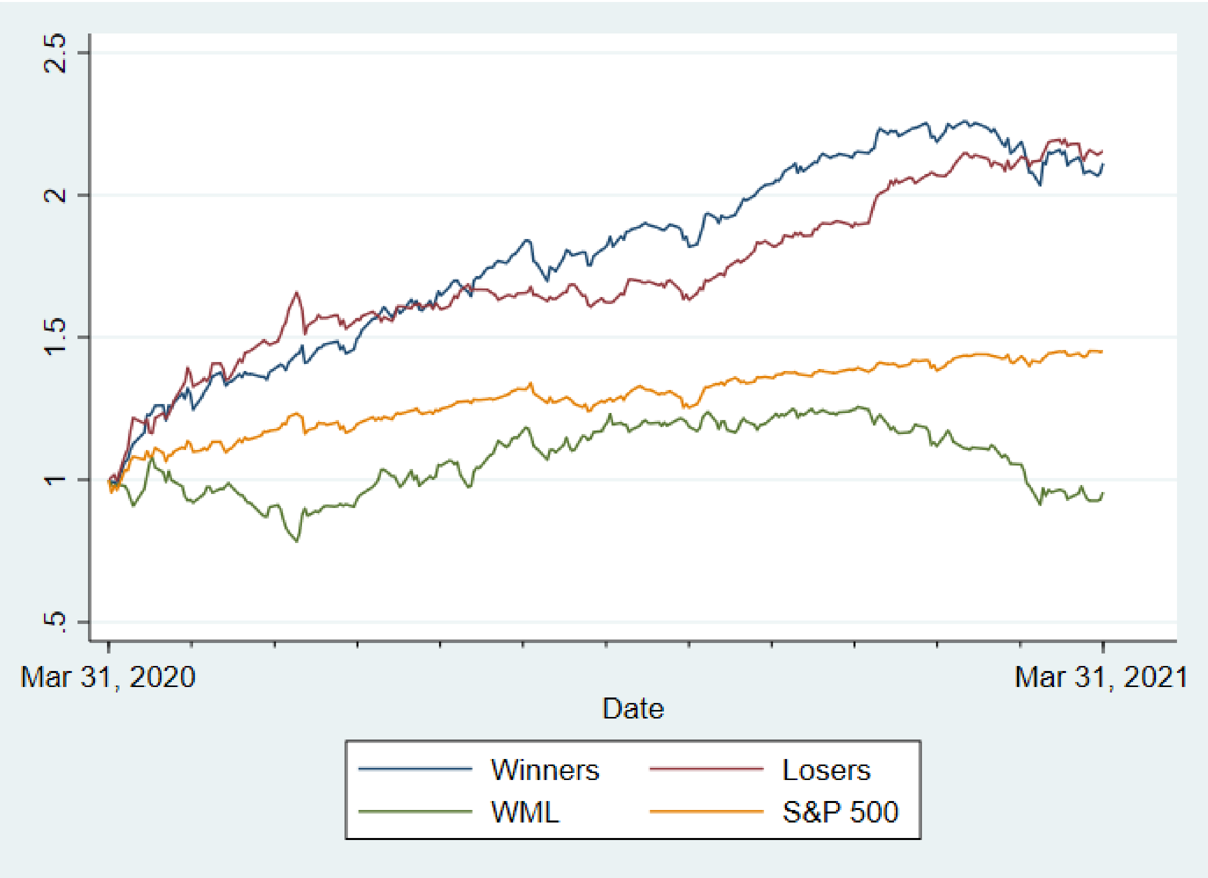
Note: Daily returns of each portfolio following a formation date of 31st of December, 2018 up to 31st of December, 2019. Portfolios are value-weighted; weights based on the market capitalization on the formation date. Each tick on the x-axis represents one month.

Contrary to the 2016 selloff, the Winners and Losers portfolio for 2018 had similar price movements after the initial formation date as seen in Figure 3, with both portfolios increasing considerably and more than the S&P 500. The Winners had persistent periods of better performance than the Losers portfolio as seen with the WML portfolio showing positive returns with a peak of \$1.14 on Aug. 27th, 2019, as a result of the Losers portfolio dropping substantially up to that date. From that low of \$1.12 however, the Losers portfolio eventually outperforms the Winners portfolio for the remaining holding period, reaching just shy of \$1.40 around the end. This recovery ended up erasing the profits of the WML portfolio, as it dropped all the way down to 91 cents on the 8th of November. From there, it would recover back to around breakeven for the remaining holding period. While the WML portfolio itself did not result in negative returns as much as 2016 selloff, it still mostly underperformed the S&P 500 for the entire holding period with a mean difference of -\$0.128 and the largest difference of -\$0.308 on the 8th of November as well. For the case of the 2018 bear market, it's not as clear cut as the 2016 selloff in terms of a momentum crash as there are periods of profitability for the WML portfolio, however it still generally underperforms the market and the month of September 2019 in particular represented the second worst monthly return (-21.3%) across the entire sample period, only behind the month of November 2020 (see Table 3, Appendix A).

5.4 2020 COVID-19 Recession

The selloff from the onset of the COVID-19 pandemic was the most severe in terms of its degree and speed in the entire sample period. From the high of 3386.15 on Feb. 18, 2020 to the bottom of 2237.40 Mar. 23, 2020, the S&P 500 fell 33.9% in only around a month.

Figure 4: Momentum Crash 2020.



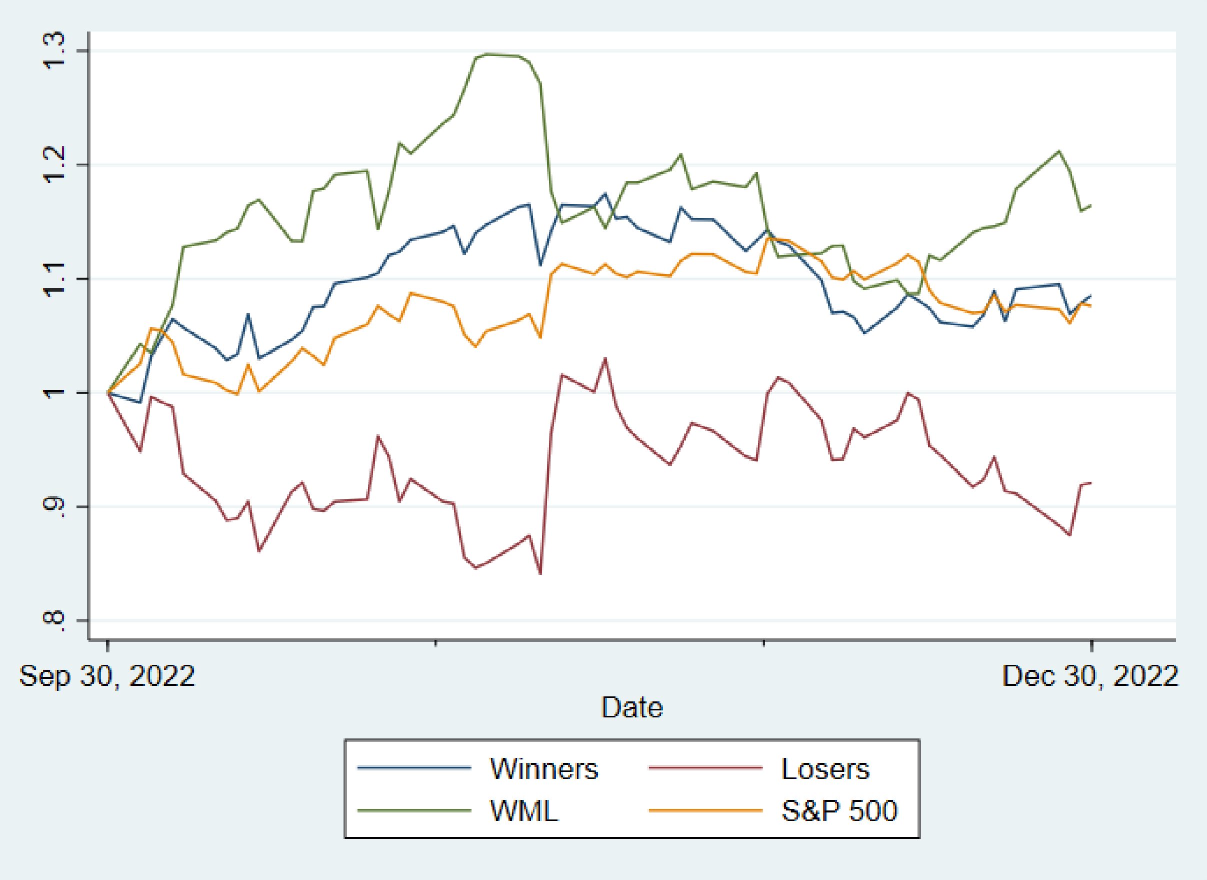
Note: Daily returns of each portfolio following a formation date of 31st of March, 2020 up to 31st of March, 2021. Portfolios are value-weighted; weights based on the market capitalization on the formation date. Each tick on the x-axis represents one month.

Here, the Winners, Losers, and the S&P 500 investment yielded the highest return compared to the other time periods, with both the Winners and Losers reaching levels above $2 and the S&P 500 reaching $1.45 for the 12-month holding period. Both the Winners and Losers portfolio started off strong, both gaining around the same rate until the Losers started outperforming the Winners after around a month, resulting in a low of $0.783 on the 8th of June. The situation is then reversed in the coming months with the Winners outperforming the Losers, resulting in some profits for the WML portfolio with a max of \$1.26 on Dec. 31st, 2020. This is unfortunately reversed once again near the end of the holding period, with the Winners suffering some losses and eventually leading the WML to overall suffer from a loss (ending at \$0.931). Once again, the WML portfolio mostly underperforms the S&P 500 despite being profitable for a considerable period. The mean difference of -\$0.212 is similar to that of the 2016 selloff, but the largest difference was –\$0.527 at the end of the holding period, resulting in the largest divergence compared to the other studied bear markets. Also, the months of July and later November 2020 represent the highest and lowest single month returns (-26.8% and 22.9% respectively) for a momentum strategy across the entire observation set (see Table 3, Appendix A), overall suggesting a momentum crash once again.

5.5 2022 Stock Market Decline

The last and most recent bear market considered in this study is the ongoing 2022 stock market decline. From the first trading day of 2022 (January 3rd), the S&P 500 fell from 4796.56 down to a low of 3577.03 on October 12th, or a loss of 25.4%. While this loss is greater than the 2016 and 2018 bear markets, it occurred over a longer period of time with intermittent periods of recovery as seen earlier in Figure 1. Additionally, due to the recency of this specific period, the holding period is cut short as the data only runs up to the end of 2022 representing a holding period after the formation date of only 3 months.

Figure 5. Momentum Crash 2022.



Note: Daily returns of each portfolio following a formation date of 30th of September, 2022 up to 30th of December, 2022. Portfolios are value-weighted; weights based on the market capitalization on the formation date. Each tick on the x-axis represents one month.

As seen in Figure 5, this short period holding period following the market bottom for 2022 is considerably different to all previously examined bear markets. Most notably, the WML portfolio was not only profitable, but outperformed the S&P 500 for some periods during the 3-month holding period of October to December of 2022. Upon closer inspection, the Losers portfolio suffered losses from the start while the Winners rose after a slight drawdown under $1, with the Losers portfolio staying at levels under both the Winners and Losers portfolio. As a result, the WML portfolio reflects the ideal momentum results with the benefits of the positive returns from the past winners as well as benefitting from the negative returns of the past losers. Compared to the S&P 500, the WML portfolio had a higher return of $0.0865 on average, with a maximum difference of 25.3 cents (3rd of November) and a minimum of -3.42 cents on the 13th of December when the S&P 500 outperformed the WML portfolio for some days. On the other hand, the other subperiods studied previously showed the WML portfolio strictly underperforming the market if the holding period was to be trimmed to only the first 3 months after the formation date. Hence, the case of 2022 suggests no considerable momentum crash, with the Winners portfolio showing positive returns, the Losers portfolio showing losses, and the WML portfolio mostly outperforming the S&P 500 in a shorter 3-month holding period.

The figures above describe the performance of value-weighted portfolios. In the Appendix, an additional study was performed looking at simpler, equal-weighted portfolios. In these portfolios, stock equities are no longer weighted according to their market capitalizations, rather their returns are all treated with equal weight, or an equal investment in each of the stocks is made. In other words, the average of the returns of the stocks in each portfolio is taken. While the conclusions on whether each respective bear market caused a market crash remains the same, the performance of the Winners and Losers portfolio and the degree of the market crashes are different. As seen in Figure 7 in Appendix B and visually comparing it to Figure 2, the 2016 bear market saw the Winners portfolio performing worse in the equal-weighted portfolio compared to the value-weighted portfolio, as the former more closely followed the S&P 500. On the other hand, the Losers portfolio performed quite similarly, maintaining similar price movements compared to the value-weighted portfolio. Overall, the WML portfolio performed worse in the equal-weighted portfolio as a result of the worse performance of the winners. The story is different with the 2018 and 2020 bear markets. In the case of 2018, the Losers portfolio performed better in the first half and struggled more in the latter half as seen in Figure 8, while in 2020 both portfolios performed much better as seen in Figure 9. In both cases, the WML portfolios performed worse, with its value dropping to levels under $0.50 near the end of the 2020 period. The 2022 subperiod shown in Figure 10 still shows no considerable crash in the WML portfolio in the equal-weighted case.

5.6 Equal vs. Value-Weighted

Finally, the overall performance of equal-weighted momentum portfolios can now be compared to the initial value-weighted portfolios examined in Section 5.1. A similar table to Table 2, Table 4, has been included in the Appendix, with the "Return over the S&P 500" row replaced with the mean monthly difference compared to the value-weighted returns.

The first noticeable difference is the fact that the Winners portfolios all underperformed their value-weighted counterparts, with the "Difference with the value weighted portfolio" row showing strictly negative values and all but the 1 month holding period portfolio being significantly less than zero at the 1% level. Additionally, the Losers portfolio performed better, with all equal-weighted portfolios outperforming the value-weighted Losers. As a result, the WML portfolios all performed worse in the equal-weighted case, with statistically significant lower returns at the 5% level for the 1-month holding period and the 1% level for the rest. The lower returns are also quite considerable in size, with the mean difference ranging from -0.846% up to -1.48% depending on the holding period. Momentum profits thus seemingly disappear as the holding periods increase, as the while the mean monthly return decreases with longer holding periods in the same fashion as the value-weighted case, the smaller initial return in the 1-month period causes the holding periods from 12-months up to be negative. The 24-month holding period results in a significantly negative return of -0.594% on average, as the seemingly Losers portfolio performs better than the Winners.

5.7 Discussion

Starting with the overall momentum performance results in Table 2, the results in this study do show that there are significant positive momentum profits that can be found even with the most recent stock market data. The initial findings of Jegadeesh and Titman (1993) are continued, with all holding periods following a trailing 12-month formation period resulted in significantly positive monthly returns on average. Additionally, the mean monthly returns also decrease with the holding period in a similar fashion, with the 1-month holding period showing the highest magnitude and it decreasing as the holding period increases in the same manner of Jegadeesh and Titman (1993). The same can also be said when comparing the returns to the S&P 500, with the outperformance of the WML portfolio also decreasing on average with the holding period. This is consistent with the literature agreeing that momentum is a shorter-term investment strategy, with the potential for eventual reversals in the long term (Daniel et al., 1998, Jegadeesh and Titman, 2001). Moreover, only in the holding periods of 1 and 3 months are the WML portfolios more profitable than simply buying the Winners, with the longer holding periods suffering more as the Losers portfolio becomes profitable. Thus, these results suggest that a shorter holding period is more optimal in terms of returns, however the shorter holding periods also come with higher volatilities as seen with the decreasing standard deviations with the holding period, implying a higher undertaking of risk as well.

As for the subperiod studies, the bear markets of 2016, 2018, and 2020 all result in a momentum crash compared to an investment in the S&P 500, with only the recent 2022 bear market not showing any signs of underperformance. With the exception of 2022, the other three subperiods showed that in a 12-month holding period following a bear market, a $1 investment the WML portfolio consistently underperformed the same investment in the S&P 500 and experienced some periods of negative returns. All subperiods studied have a trailing-12-month return that is negative as of their formation date, with the bear markets of 2016 and 2020 specifically having a negative trailing-24-month negative return. Again, with the exception of 2022, these momentum crashes are in line with the studies of Daniel and Moskowitz (2016) who have shown that the worst of the crashes they examined coincided with periods where the lagged 2-year market return was negative, and Cooper et al (2005) who have shown that average monthly momentum returns were negative when the lagged 3-year return was negative, reinforcing their discoveries that negative momentum can be somewhat predicted by the return of the market. In the case of this study, the bear markets of 2016 and 2020 resulted in the worst of the crashes with similar lows of around -21.4% and -21.7% respectively within the first 3 months of the holding period, and both had a previously mentioned 2-year negative lagged return. The performance of the WML portfolio is even worse in the 2020 subperiod when equal-weighted returns are considered, with lows below the -50% level around the end of the holding period as seen in Figure 9. For 2018, the 1-year lagged return was negative and momentum profits were also negative in the first 3 months although not the as large of a degree as the other two. This perhaps leaves room to suggest that the 1-year lagged return could also predict whether momentum returns would be positive or negative.

Focusing in on the individual performances of the portfolios, there is evidence that reinforces the idea that the profits from momentum are as a result of the performance of the losers portfolio as suggested by the studies of Avramov et al. (2013) and Wang and Xu (2014). As seen in Table 2, the Losers portfolios had higher standard deviations and beta than the Winners portfolios in each of the holding periods, indicating a higher volatility in the monthly returns. In the subperiod study, this can be somewhat visually seen with the Losers portfolio roughly following the Winners portfolio's performance line, with periods of fluctuating over and underperformance in 2018 and 2020 or outperforming the Winners portfolio entirely in 2016. The crossing of the Losers portfolio in the fluctuating periods of performance is what eventually dictated the direction of momentum profits for the holding periods of 2018 and 2020. Additionally, the Losers portfolio overall had lower average monthly returns, with only the longer holding periods of 12 and 24 months resulting in statistically significant returns. However, in the subperiod studies it is evident that the Losers had periods of better performance than the Winners, overall outperforming them in at the end of the holding periods (with the exception of 2022). Thus, these periods are very much in line with the scenarios of the momentum crashes illustrated by Daniel and Moskowitz (2016), where the Losers portfolio's sudden run of gains causes the overall WML portfolio to underperform as these stocks are shorted.

To answer the hypotheses, once again with the exclusion of the 2022 bear market, there is evidence that the bear markets of following the study of Daniel and Moskowitz (2016) do negatively affect momentum profits. The holding periods after the 2016, 2018, and 2020 market bottoms resulted in a underperformance of the WML portfolio in comparison the stock market (S&P 500) and thus resulted in a market crash. Therefore, Hypothesis 1 is confirmed in this study thanks to these cases. As for Hypothesis 2, in the same three periods the Losers portfolio did indeed outperform the Winners portfolio for considerable periods, which caused the WML portfolio to experience negative returns. The bear market of 2016 in particular strongly confirms this hypothesis, with the Losers portfolio outperforming the Winners portfolio almost through the entire holding period. The other two bear markets are slightly more ambiguous however, and as the case of 2022 suggests the complete opposite, hence the second hypothesis can only be somewhat confirmed by these subperiods. However, when looking at the average or equal-weighted returns of these portfolios, both hypotheses are more strongly confirmed, with the WML portfolio underperforming to a greater extent—to the point of no actual periods of profitability in the holding period and the Losers consistently performing better than the Winners (again with the exception of 2022).

As an additional observation, the Losers portfolio shows strong returns in the recovery periods following the market bottom of all but 2022, with no considerable prolonged periods of drawdowns under the initial investment of $1 but reaching levels of up to $2.79 like in the case of the equal-weighted 2020 portfolio in Figure 9. This in combination with the confirmation of the second hypothesis of the outperformance of the Losers portfolio relative to the Winners hopefully sheds light on a potential alternative investment. If the Losers portfolio was bought instead of short sold, investors can take advantage of the reversal of traditional momentum strategies. This can also be of interest for investors who may not have the ability or are averse to short selling in the first place, whether that be due to borrowing costs, margin calls, or limited access to capital markets causing only long positions.

Finally, the last hypothesis regarding the differences between the equal and value-weighted momentum strategies cannot quite be confirmed. Overall, the equal-weighted WML portfolios actually performed worse as compared to the value-weighted case, as the Winners performed worse while the Losers simultaneously performed better in each holding period following a 12-month formation period. Comparing the results in Table 4 in Appendix B with that of Korajczyk and Sadka (2004), the Losers portfolio similarly performed better in the equal-weighted versus the value-weighted case, however the Winners portfolio performed worse while it contrastingly performed better in their study. Hence, the results in this thesis are at odds with the literature and the third Hypothesis of the better performance of equal-weighted momentum portfolios cannot be confirmed. The second half of the hypothesis, the worse momentum crashes in the equal-weighted cases, could be confirmed as seen with the worse performance of the WML portfolio compared to the value-weighted cases, however the larger momentum crashes could simply be a result of the worse performance of the equal-weighted portfolios overall. Thus, the results in this study suggest that equal-weighted momentum portfolios would yield lower returns than value-weighted momentum portfolio, both overall and in momentum crashes.

This then begs the question of why a discrepancy has occurred. Firstly, Korajczyk and Sadka (2004) sampled CRSP data from 1967 to 1999, while this study exclusively uses a much more recent sample set of 2014 to 2022. The diverging results from their study may suggest that there has been a change in equal-weighted momentum returns because of the time period, with the results in this study being indicative of different market conditions today compared to the past. Additionally, the construction of the momentum portfolios differs, with Korajcyzk and Sadka (2004) conducting a monthly rebalancing of each portfolio in their study while this study does not. And, as Plyakha et al (2016) suggest, the rebalancing of equal-weighted portfolios does result in higher alphas compared to value-weighted portfolios without rebalancing, hence the better performance of the equal-weighted portfolios in their case may be because of the monthly rebalancing. This however does not explain the underperformance of the WML portfolio as a result of the worse performance of the Winners. There is thus future research that can be done to explore this disagreement to determine whether this is a result of changing times or a difference in modus operandi.

CHAPTER 6 Conclusion

This thesis studies momentum, and more specifically the phenomenon of momentum crashes, in more recent data, bringing existing knowledge on the subject up to date. Previous research conducted by Daniel and Moskowitz (2016) pointed out these periods of the underperformance of traditional momentum strategies up to the year 2013, and this paper conducted a similar study to examine cases in the wake of their study. This paper also considers the possibility of equal-weighted momentum portfolios in addition to the standard value-weighted portfolios used in their paper. Overall, the main question that was aimed to be addressed was: “How do recovery periods following more recent market drawdowns affect the performance of a momentum strategy?”.

Thought the course of this study, data from the CRSP was taken from the years 2014 up to and including 2022. The momentum portfolios were constructed in the same manner as the seminal paper on momentum by Jegadeesh and Titman (1993). The Winners and Losers portfolios were based on the performance of stocks in a trailing 12-month formation period and various holding periods afterwards, with both the value-weighted and later equal weighted-returns of these portfolios examined. Additionally, the main periods of interest to examine momentum crashes more closely were the bear markets of 2016, 2018, 2020, and the ongoing one in 2022.

The results show evidence of momentum crashes in all bear markets except for 2022, with the Winner-Minus-Loser portfolio showing signs of underperformance with periods of negative returns and/or returns lower than the S&P 500 in their respective holding periods. Hypotheses 1 and 2 made in this paper are confirmed, with the periods of market recovery after a bear market negatively affecting the profits of a momentum strategy through the outperformance of the Losers portfolios in relation to the Winners. This sheds light on a potential alternative investment scenario where an investor can buy the losers portfolio after a market bottom, which in the subperiods excluding 2022 would result in a considerable profit. Additionally, the stylized fact of more severe momentum crashes when the two-year market return was negative illustrated by Daniel and Moskowitz (2016) with the cases of the 2016 and 2020 bear markets. Hypothesis 3 however, is not exactly confirmed as equal-weighted momentum portfolios seemingly underperformed value-weighted portfolios in general. Overall, momentum investment strategies still showed significantly positive returns in general in the entire sample period.

Some of the limitations of this study include the fact that the most recent bear market, the 2022 stock market decline, is potentially still in progress. At the time of this study, the market bottom used still holds, but there is always the potential that a lower price level for the S&P 500 can be reached. The CRSP only provides data annually, so the data for this study is capped at the last trading day of 2022 (December 30). This results in a shorter holding period of the start of October up to the end of 2022, while the conclusions may change once the data for 2023 is released. Future research can address this problem with the benefit of hindsight and after market conditions are more clear.

REFERENCES

Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2007). Momentum and credit rating. *The Journal of Finance*, *62*(5), 2503–2520. https://doi.org/10.1111/j.1540-6261.2007.01282.x

Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2013). Anomalies and financial distress. *Journal of Financial Economics*, *108*(1), 139–159. https://doi.org/10.1016/j.jfineco.2012.10.005

Baltzer, M., Jank, S., & Smajlbegovic, E. (2019). Who trades on momentum? *Journal of Financial Markets*, *42*, 56–74. https://doi.org/10.1016/j.finmar.2018.08.003

Barberis, N., Shleifer, A., & Vishny, R. (1997). *A Model of Investor Sentiment*. https://doi.org/10.3386/w5926

Barroso, P., & Santa-Clara, P. (2015). Momentum has its moments. *Journal of Financial Economics*, *116*(1), 111–120. https://doi.org/10.1016/j.jfineco.2014.11.010

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chan, L. K. C., Jegadeesh, N., & Lakonishok, J. (1999). The profitability of Momentum Strategies. *Financial Analysts Journal*, *55*(6), 80–90. https://doi.org/10.2469/faj.v55.n6.2315

Chui, A. C. W., Titman, S., & Wei, K. C. J. (2000). Momentum, legal systems and ownership structure: An Analysis of Asian Stock Markets. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.265848

Conrad, J., & Kaul, G. (1998). An anatomy of trading strategies. *Review of Financial Studies*, *11*(3), 489–519. https://doi.org/10.1093/rfs/11.3.489

Cooper, M. J., Gutierrez, R. C., & Hameed, A. (2004). Market states and momentum. *The Journal of Finance*, *59*(3), 1345–1365. https://doi.org/10.1111/j.1540-6261.2004.00665.x

Daniel, K., & Moskowitz, T. (2016). *Momentum Crashes*. https://doi.org/10.1016/j.jfineco.2015.12.002

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor psychology and security market under- and overreactions. *The Journal of Finance*, *53*(6), 1839–1885. https://doi.org/10.1111/0022-1082.00077

De Bondt, W. F., & Thaler, R. (1985). Does the stock market overreact? *The Journal of Finance*, *40*(3), 793–805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

DeMiguel, V., Garlappi, L., & Uppal, R. (2007). Optimal versus naive diversification: How inefficient is the 1/*n*portfolio strategy? *Review of Financial Studies*, *22*(5), 1915–1953. https://doi.org/10.1093/rfs/hhm075

Fama, E. F. (1970). Efficient Capital Markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383. https://doi.org/10.2307/2325486

Hong, H., & Stein, J. (1997). *A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets*. https://doi.org/10.3386/w6324

Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of Momentum Strategies. *The Journal of Finance*, *55*(1), 265–295. https://doi.org/10.1111/0022-1082.00206

Jegadeesh, N, & Titman, S. (1993). Returns to buying winners and selling losers: Implications for Stock Market Efficiency. *The Journal of Finance*, *48*(1), 65–91. https://doi.org/10.1111/j.1540-6261.1993.tb04702.x

Jegadeesh, N., & Titman, S. (2001). Profitability of Momentum Strategies: An evaluation of alternative explanations. *The Journal of Finance*, *56*(2), 699–720. https://doi.org/10.1111/0022-1082.00342

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of Finance*, *45*(3), 881–898. https://doi.org/10.1111/j.1540-6261.1990.tb05110.x

Johnson, T. C. (2002). Rational momentum effects. *The Journal of Finance*, *57*(2), 585–608. https://doi.org/10.1111/1540-6261.00435

DeMiguel, V., Garlappi, L., & Uppal, R. (2007). Optimal versus naive diversification: How inefficient is the 1/*n*portfolio strategy? *Review of Financial Studies*, *22*(5), 1915–1953. https://doi.org/10.1093/rfs/hhm075

Lehmann, B. N. (1990). Fads, Martingales, and market efficiency. *The Quarterly Journal of Economics*, *105*(1), 1. https://doi.org/10.2307/2937816

Liu, Y., Tsyvinski, A., & Wu, X. (2022). Common risk factors in cryptocurrency. *The Journal of Finance*, *77*(2), 1133–1177. https://doi.org/10.1111/jofi.13119

Miffre, J., & Rallis, G. (2007). Momentum Strategies in Commodity Futures Markets. *Journal of Banking & Finance*, *31*(6), 1863–1886. https://doi.org/10.1016/j.jbankfin.2006.12.005

Okunev, J., & White, D. (2003). Do momentum-based strategies still work in foreign currency markets? *The Journal of Financial and Quantitative Analysis*, *38*(2), 425. https://doi.org/10.2307/4126758

Plyakha, Y., Uppal, R., & Vilkov, G. (2012). Why does an equal-weighted portfolio outperform value- and price-weighted portfolios? *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1787045

Ross, S. A. (1976). The arbitrage theory of Capital Asset Pricing. *Journal of Economic Theory*, *13*(3), 341–360. https://doi.org/10.1016/0022-0531(76)90046-6

Rouwenhorst, K. G. (1998). International Momentum Strategies. *The Journal of Finance*. https://doi.org/10.2307/2327804

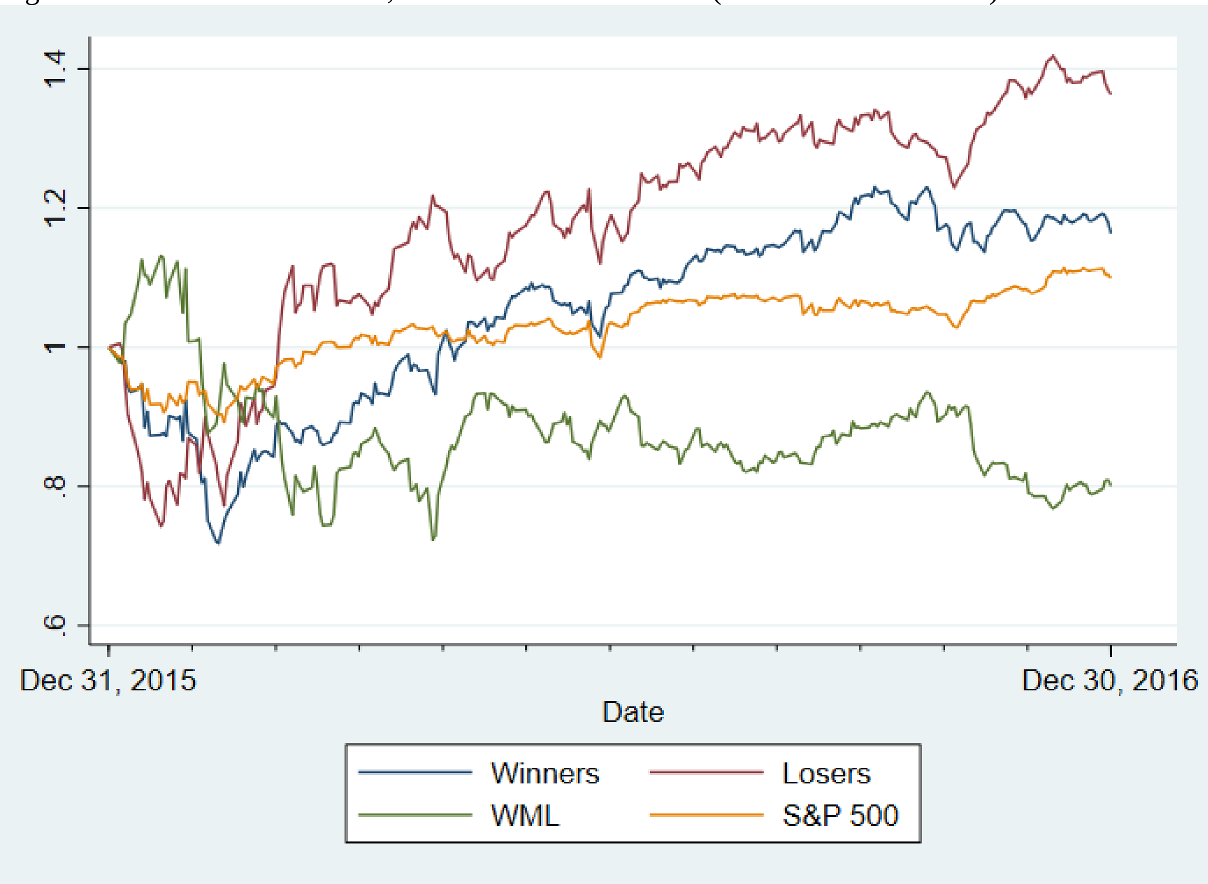
Sagi, J., & Seasholes, M. (2007). Firm-specific attributes and the cross-section of Momentum. *Journal of Financial Economics*, *84*(2), 389–434. https://doi.org/10.1016/j.jfineco.2006.02.002

Stivers, C., & Sun, L. (2010). Cross-sectional return dispersion and time variation in value and momentum premiums. *Journal of Financial and Quantitative Analysis*, *45*(4), 987–1014. https://doi.org/10.1017/s0022109010000384

Wang, K. Q., & Xu, J. (2015). Market volatility and momentum. *Journal of Empirical Finance, 30*, 79–91. https://doi.org/10.1016/j.jempfin.2014.11.009

APPENDIX A Miscellaneous Tables and Figures

Figure 6: Momentum crash 2016, alternative formation date (31st of December 2015).



Note: Daily returns of each portfolio following an alternative formation date of 31st of February 2015 up to 30th of December 2016. Portfolios are value-weighted; weights based on the market capitalization on the formation date. Each tick on the x-axis represents one month.

Table 3: Best and worst monthly returns.

		1st	2nd	3rd	4th	5th
Winners	Best (%)	26.3	22.3	22.1	18.7	18.3
		(Apr. 2020)	(Aug. 2020)	(Oct. 2022)	(Jan. 2019)	(Jun. 2020)
	Worst (%)	-21.1	-18.4	-16.5	-15.2	-14.8
		(Apr. 2022)	(Jun. 2022)	(Oct. 2018)	(Jan. 2016)	(Mar. 2020)
Losers	Best (%)	39.1	33.0	25.3	15.2	14.2
		(Nov. 2020)	(Apr. 2020)	(Jan. 2019)	(Feb. 2016)	(Aug. 2022)
	Worst (%)	-24.6	-20.7	-20.1	-18.4	-16.0
		(Mar. 2020)	(Sep. 2015)	(Apr. 2022)	(May 2019)	(Nov. 2018)
WML	Best (%)	22.9	22.8	18.7	17.7	14.7
		(Jul. 2020)	(Oct. 2022)	(Jul. 2015)	(Nov. 2018)	(Aug. 2020)
	Worst (%)	-26.8	-21.3	-17.4	-12.0	-11.5
		(Nov. 2020)	(Sep. 2019)	(Apr. 2015)	(Feb. 2015)	(Feb. 2017)

Note: Table of the best and worse single month returns based on the trailing 12-month performance formations. In parenthesis is the actual month that each percentage return accompanies.

APPENDIX B Equal-Weighted Momentum Portfolios

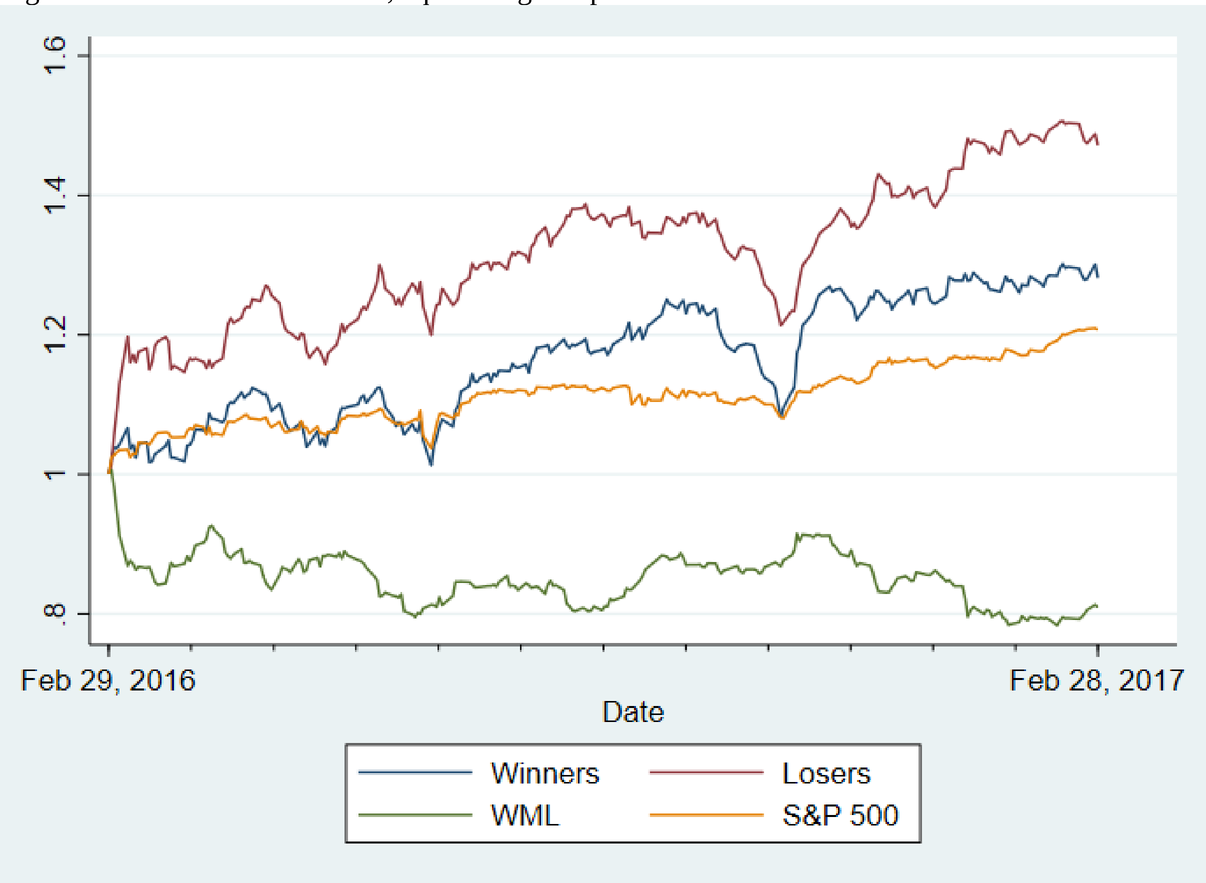
Table 4: Momentum performance during 2014-2022, equal weighted.

		Holding Period				
Portfolio		1 Month	3 Months	6 Months	12 Months	24 Months
Winners	Mean (%)	1.06	0.803*	0.715**	0.791***	1.19***
	T-Stat.	(1.22)	(1.64)	(2.12)	(2.70)	(6.58)
	Standard deviation (%)	8.47	4.72	3.20	2.69	1.54
	Maximum (%)	28.9	17.4	9.43	9.08	4.65
	Minimum (%)	-23.0	-10.5	-5.54	-3.70	-1.42
	Difference with the value-weighted portfolio	-0.527	-0.799**	-0.752***	-0.753***	-0.471***
	T-Stat.	(-1.12)	(-2.32)	(-3.50)	(-7.30)	(-4.89)
	Beta	-0.927	-0.123	-0.365	-0.0700	-0.436
	Sharpe Ratio	0.117	0.157	0.204	0.270	0.727
Losers	Mean	0.106	0.423	0.537	1.01**	1.79***
	T-Stat.	(0.0922)	(0.557)	(0.890)	(1.99)	(6.25)
	Standard deviation (%)	11.2	7.33	5.73	4.66	2.43
	Maximum (%)	37.0	27.3	16.5	14.3	6.55
	Minimum (%)	-24.2	-15.2	-9.98	-7.29	-2.00
	Difference with the value-weighted portfolio	0.796	0.682**	0.492**	0.0929	0.559***
	T-Stat.	(1.37)	(1.91)	(1.91)	(0.406)	(3.693)
	Beta	-0.217	-0.193	-0.0477	-0.143	-0.0341
	Sharpe Ratio	0.00334	0.0490	0.0830	0.203	0.706

WML	Mean	0.956*	0.379	0.118	-0.219	-0.594***
	T-Stat.	(1.46)	(0.951)	(0.543)	(-0.891)	(-3.53)
	Standard Deviation (%)	6.39	3.84	3.11	2.26	1.42
	Maximum (%)	14.1	8.08	7.47	5.67	1.28
	Minimum (%)	-15.7	-9.97	-7.47	-5.22	-3.89
	Difference with the value-weighted portfolio	-1.32**	-1.48***	-1.24***	-0.846***	-1.03***
	T-Stat.	(-1.98)	(-3.43)	(-4.00)	(-3.53)	(-6.13)
	Beta	0.125	-0.177	0.00558	0.0727	-0.00949
	Sharpe Ratio	0.139	0.0819	0.0374	-0.126	-0.469

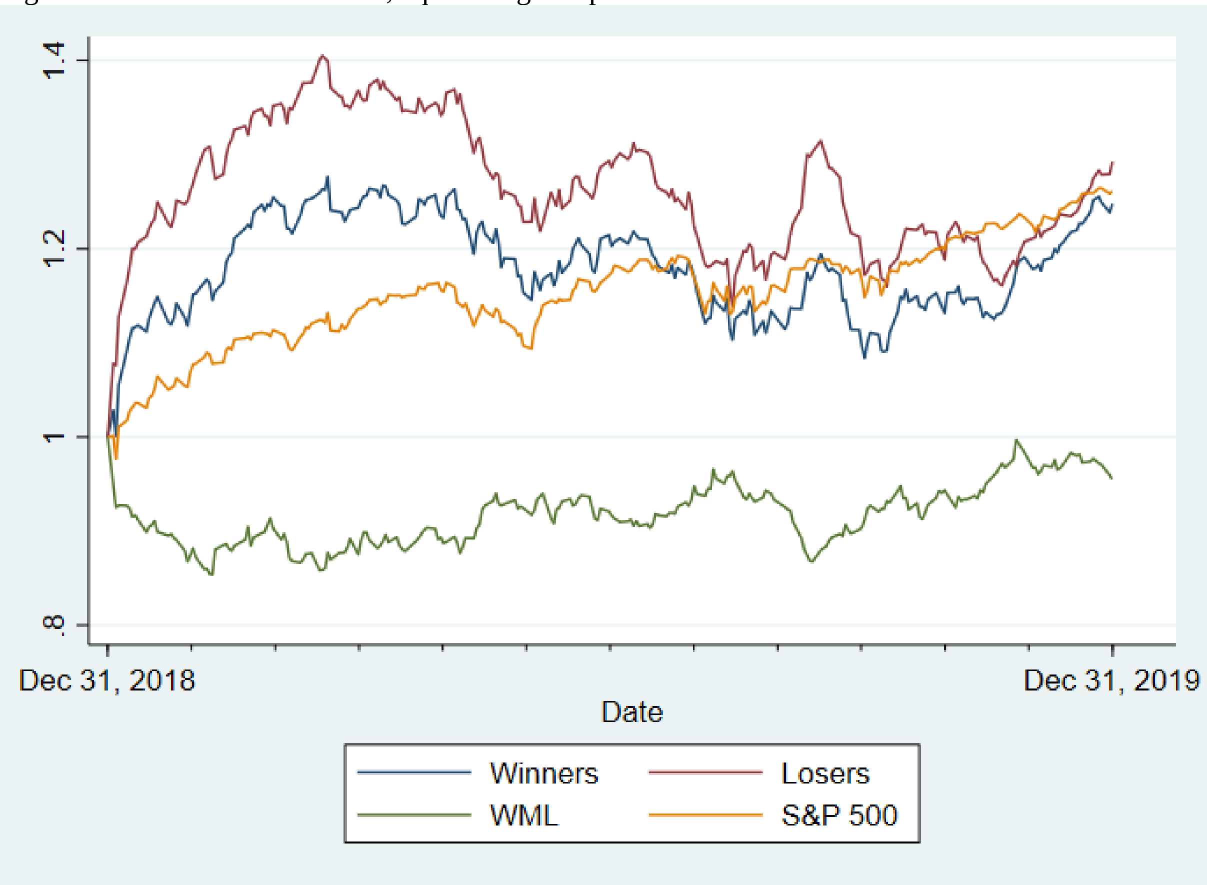
Note: This table includes the average monthly returns, standard deviations, maximum/minimums, difference in returns with the value-weighted portfolios, CAPM betas, and Sharpe Ratios of equal-weighted momentum portfolios for various holding periods after a formation period consisting of the previous 12-1 months prior to the formation date. All values in three significant figures. Data sourced from the CRSP. Stars indicate significance levels (one-sided) based on the T-statistics directly below (* $p<0.10$, ** $p<0.05$, *** $p<0.01$).

Figure 7: Momentum crash 2016, equal-weighted portfolios.



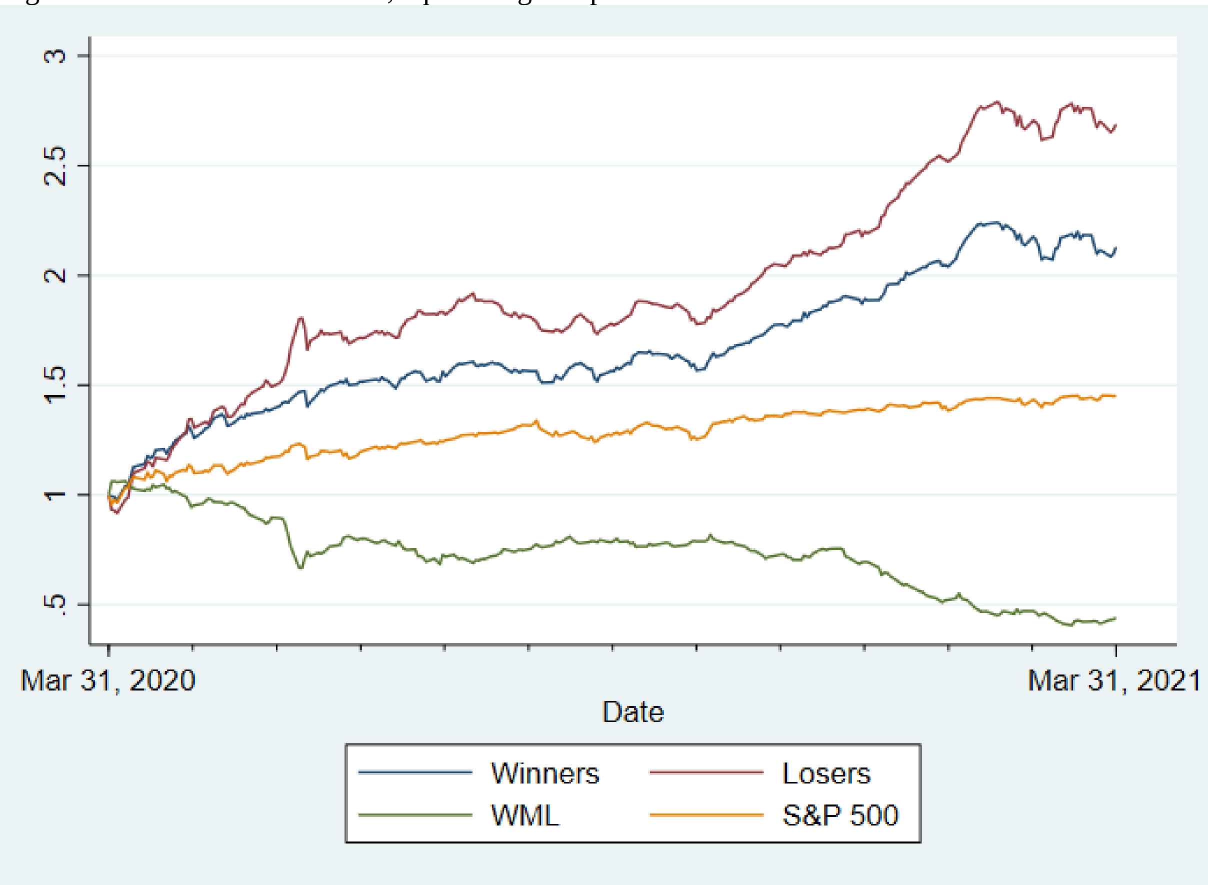
Note: Daily equal-weighted/average returns of each portfolio following a formation date of 29th of February, 2016 up to 28th of February, 2017.Each tick on the x-axis represents one month.

Figure 8: Momentum crash 2018, equal-weighted portfolios.



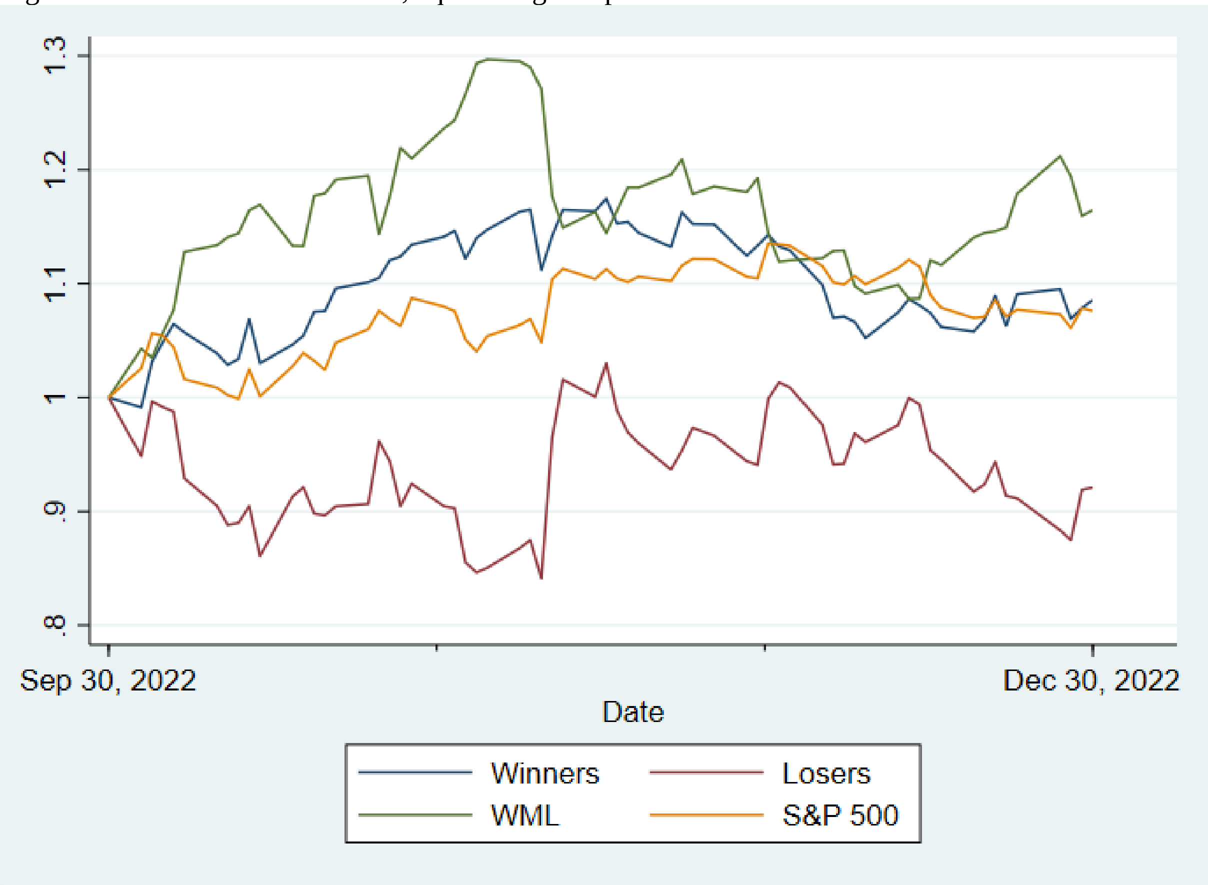
Note: Daily equal-weighted/returns of each portfolio following a formation date of 31st of December, 2018 up to 31st of December, 2019. Each tick on the x-axis represents one month.

Figure 9: Momentum crash 2020, equal-weighted portfolios.



Note: Daily equal-weighted/returns of each portfolio following a formation date of 31st of March, 2020 up to 31st of March, 2021. Each tick on the x-axis represents 1 month.

Figure 10: Momentum crash 2022, equal-weighted portfolios.



Note: Daily equal-weighted/returns of each portfolio following a formation date of 30th of September, 2022 up to 30th of December, 2022. Each tick on the x-axis represents 1 month.