Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	16-01-2022 09:00	**Termin:**	202210
Sluttdato:	01-07-2022 12:00	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202210||10936||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

Navn:	Bendik Heder og Martin Braathen

Informasjon fra deltaker

Tittel *:	Cross-sectional Momentum in the Norwegian Stock Market
Navn på veileder *:	Alessandro Graniero

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	241
Andre medlemmer i gruppen:	

BI Norwegian Business School

Master Thesis

GRA19703

Cross-sectional Momentum in the Norwegian Stock Market

By Bendik Torp and

Martin Braathen

Hand-in date: 01.07.2022

Campus: BI Oslo

Supervisor: Alessandro Graniero

Programme: Master of Science in Finance

Abstract

We document significant "cross-sectional momentum" profitability in the Norwegian stock market from Q1 1995 to Q2 2022. The past winners portfolio is identified as the main driver of the cross-sectional momentum returns over the full sample. On the other hand, the past loser portfolio provides a negative return contribution on average on the corresponding sample. Further, we investigate the performance of cross-sectional momentum strategies during three volatile market events. We find that the majority of the strategy returns generated through each of the tested sub-samples is attributable to the past winners portfolio. However, the past losers portfolio consistently yields a strong hedge against the most abrupt market declines. On the flip side, the past loser portfolio accounts for the majority of losses in the wake of each crisis due to its excessive loadings on the market compared to the past winners portfolio. The relapse of the strategy returns is however not considerable enough to be categorised as a "momentum crash".

Acknowledgements

We want to express our gratitude to our supervisor, Associate Professor Alessandro Graniero of the Department of Finance at BI Norwegian Business School, for his valuable guidance and advice along the way. His feedback has allowed us to improve both our qualitative and quantitative work.

Contents

1 Introduction

Since the inception of the financial markets, the competition among fund managers to achieve abnormal returns has always been present. Several theories and hypotheses have been developed to understand the markets and further enable the investors to construct strategies that beat the market. However, due to the markets dynamic nature, few strategies seem to generate consistent and sustainable results in the long run.

In this context, we would like to investigate one of the most widely documented trading strategies, namely the cross-sectional momentum strategy and its performance under volatile market conditions in the Norwegian stock market. Cross-sectional momentum is an asset pricing anomaly based on the notion of price continuation. In its most fundamental sense, momentum is a bet that assets which have previously generated superior (inferior) returns relative to their cross-section will continue to do so in the subsequent months.

Previous literature documents the cross-sectional momentum strategies' efficacy in generating abnormal returns in international markets. Despite its ability to generate positive returns on average, momentum strategies seem to be subject to infrequent strings of negative returns. Momentum crashes have historically originated from "panic states", i.e., market declines embossed by high volatility - and are contemporaneous with market rebounds (Daniel & Moskowitz, 2016). In order to address and extend the analysis on the problem stated by Daniel & Moskowitz, we delimit our research to first: Constructing a cross-sectional momentum strategy accordingly to the methods applied by Jegadeesh and Titman to either confirm or debunk the existence of momentum anomalies in the Norwegian stock market (Jegadeesh & Titman, 1993). We further separate the sample into three specific market events that encompass the complete cycle of a market crash. Two of these market events are categorised as "classic" market-wide declines, namely the financial crisis of 2008 and the covid-pandemic market crash of 2020. In addition, an assessment of the momentum strategy's performance during the oil price plunge of 2014 is conducted to examine the trading strategy's response to macroeconomic shocks. The aim of the assessment is to identify the drivers of momentum returns in both normal and volatile market conditions. To achieve the set of objectives outlined above, the scope of the analysis is directed toward answering the following questions:

- Are the empirical findings suggestive of significant momentum anomalies in the Norwegian stock market?

  With the following sub-questions:

  1. Do we observe any presence of momentum crashes in the Norwegian stock market, comparable with the findings of Daniel and Moskowitz (2016)?

2. Are there any recurring patterns in the selected market events suggesting that the driver of momentum returns are attributable to the long portfolio, short portfolio, and/or time-varying market exposures?

2 Literature review

2.1 Preface

The scope of this section is directed towards presenting the most notable previous findings on cross-sectional momentum performance. In the first subsection, we present some of the most cited literary works on the topic. The research uncovers that momentum anomalies exist across different asset classes and geographical areas. However, recent research reveals that the performance of momentum strategies is fragile to extreme market volatilities (market crashes), which is covered in the subsequent subsection.

2.2 Validity of cross-sectional momentum returns

Jegadeesh and Titman present one of the first papers that documents the concept and performance of cross-sectional momentum strategies and is arguably perceived as one of the cornerstones within this particular field of research (Jegadeesh & Titman, 1993). The study examines the profitability of buying past winners and selling past losers on a sample of stocks from the New York Stock Exchange and American Stock Exchange, ranging from 1965 to 1989. Winners and losers are identified by ranking the past 1 to 12 month returns across all assets and further arranging them into decile portfolios. The winner portfolio consists of the top 10% performers, and conversely, the bottom 10% performing assets form the loser portfolio. The long and short positions in the winner and loser portfolios are then held for the next 1 to 12 months. The aggregated returns of all portfolios for each date in time constitute the strategy returns.

The authors document that the proposed strategy yields significant abnormal returns over 3- to 12-month holding periods. However, the returns generated over 3- to 12-month holding periods dissipate if the investor continues to hold them for the following two years. The most profitable momentum strategy documented is the 12-month formation period and 3-month holding period, in which the authors report a statistically significant (t-stat 4.28) monthly average return of 1.31% without utilising adjustments for short-term reversals and 1.41% monthly average return when using a one-week gap between the formation- and transaction date. In addition, the authors find statistically significant returns in 31 out of 32 constructed portfolios, thus amplifying the statistical validity of the relative strength portfolio returns. Some argue that the profitability of these strategies was due to either additional risk loading or data-snooping. However, Jegadeesh and Titman provided additional research on the significance of momentum by extending their sample data and reported that the significant performance of cross-sectional momentum also persisted during the 1990s, consequently refuting the claim that the cross-sectional momentum profitability stems from data-snooping bias (Jegadeesh & Titman, 2001).

Conrad and Kaul further documents the robustness of the cross-sectional momentum strategy by running the same trading strategies on the same assets as Jegadeesh and Titman, though extending the sample from 1926 to 1989 (Conrad & Kaul, 1998). However, the authors decided to alter the stock weights within each portfolio relative to their performance instead of equal weightings. Intuitively, that means that each portfolio should be able to capture price continuation effects to a more considerable extent than that of equal weightings, given that the notion of momentum effects holds in reality. The authors report 30 statistically significant momentum strategies of the 55 strategies tested. The momentum strategies are also proven to produce significant returns when tested on other asset classes, such as industry portfolios (Moskowitz & Grinblatt, 1999). However, their results do reveal that the profitability of cross-sectional momentum originates from industry-wide momentum. i.e., the momentum strategies applied to stocks are significantly less profitable when the data is adjusted for industry momentum.

It is essential to address that the abovementioned findings originate from U.S data samples. Thus, it is crucial to address whether these anomalies are a product of a more elaborate data snooping process. Rouwenhorst investigates if similar anomalies exist outside the U.S and find support for medium-term price continuation in international equity markets, using a sample consisting of 2190 stocks from 12 European countries. Nevertheless, there is a notable return correlation between the international- and U.S-strategies, which suggests that the profitability of momentum strategies stems from exposure to common factors (Rouwenhorst, 1998).

2.3 Cross-sectional momentum performance amid market crashes

The articles mentioned in the former subsection present credible evidence on the profitability of cross-sectional momentum strategies. However, According to Daniel & Moskowitz (2016), the strong risk-adjusted returns generated by momentum strategies are subject to occasional "crashes" (Daniel & Moskowitz, 2016).

The authors run the cross-sectional momentum strategies on a U.S equity sample from 1927 to 2013 and find that the two worst performing months for the momentum strategy occurred amid the great depression. More specifically, the two consecutive months, July and August of 1932. The reported return over this period was 232% for the past loser portfolio and 32% for the past winner portfolio, thus delivering a sizeable loss as the momentum strategy shorts the past loser portfolio. Evidence shows that momentum crashes are just as likely in recent times and highlights the strategy return amid the financial crisis. Over three months (March to May 2009), the past loser portfolio returned 163%, while the past winner decile only gained a negligible return of 8%.

In investigating the potential impact and predictability of the strategy crashes, the authors attempt to locate the source of these crashes using conditional risk measures. The research suggests that the momentum portfolio's changing betas over time partly explains the negative strategy returns. The momentum strategy goes long in stocks with return realisations above its peers and takes short positions in stocks with underperforming realisations. When the formation period spans over a market crash, there is a chance that the strategy will form the past loser portfolio on stocks that fell in tandem with the market decline, i.e., the past loser portfolio loads on high beta stocks. On the other hand, the winner portfolio is formed on more defensive stocks with lower betas (Grundy & Martin, 2001). Empirical evidence shows that the past loser decile's betas can rise above 3, while the winner decile betas can fall below 0.5 (Daniel & Moskowitz, 2016). An abrupt market recovery may thus impose significant losses due to surging returns for the high beta stocks.

On average, trading strategies based on the price continuation anomaly appears to be both statistically- and economically sound across several equity markets and different asset classes, consistent with the literature presented in the former subsection. However, the authors find that the negative momentum returns during market crashes and subsequent rebounds are attributable to the past loser portfolios. This is explained by the fact that in bear market states, the down-market betas are low for the loser decile and very large in up-market states. The past winner decile portfolios do, however, not share the same features, consequently resulting in an asymmetric winner and loser exposure to the market during times of high market volatility (Daniel & Moskowitz, 2016).

3 Theory

3.1 Momentum

Academic literature distinguishes between two distinct types of explanations for the sources of momentum profitability: 1) Risk-based explanations and 2) Behavioural explanations. First, risk-based explanations utilise economic theory and traditional models such as the CAPM and the multiple Fama French models to demonstrate why and how momentum strategies can be profitable. On the other hand, behavioural explanations entail the irrational behaviour of different market players, also known as behavioural bias. However, the main scope of this thesis is delimited to risk-based explanations for momentum profitability.

3.1.1 Risk-based explanations

Momentum effects are not necessarily indicating irrationality (Johnson, 2002). Instead, the author finds evidence of a strong correlation between past realised returns and current expected returns. When exposure to growth rate risk and prices correlate in the same direction, a positive correlation between expected returns and changes in growth rates should also be observed. This leads to large positive movements in prices, increasing the probability of positive shocks in growth rates resulting in higher expected end-of-period returns.

Another risk-based explanation for profitability in momentum strategy returns is the approximated cross-sectional dispersion in mean returns (Conrad & Kaul, 1998). The authors extrapolated that cross-sectional dispersion in mean returns yields the most profitable results when utilising a medium horizon for the strategy. Their analysis was executed on the entire NYSE/AMEX sample from 1926 to 1989.

Time-varying factors are also identified as a potential source of momentum profits (Zhang, 2004). This implies that market betas might not be time-invariant as previously assumed in the capital asset pricing model. The initial problem of market betas is their unobservable nature. However, this could be resolved by regressing time-series portfolio returns on market returns. Suppose market betas are used to make inferences about the future returns (or asset values) in a portfolio. In that case, we effectively assume that the parameter estimation of betas on a given sample is representative for all future periods, hence the term time-invariance. If such a statement were to hold, it is a prerequisite that asset returns are stationary, which is commonly recognised as untrue in practice.

The notion of time-variability in beta parameters effectively argues that momentum crashes are potentially due to unfavourable market exposure. This is because the increasing (or decreasing) deviation of betas in the past winner and past loser portfolios in the post-formation period provides a non-zero market exposure. E.g., a net negative market exposure will be favourable when markets suffer but can, on the other hand, cause severe losses under rapidly appreciating markets.

4 Data

4.1 Variable description & sample selection

The data used in this thesis can be separated into three distinct asset classes:

- Equity (stocks)
- Equity index (strategy benchmark)
- Risk-free asset

Where the vast majority of the data falls in the first category, stocks. Historical monthly price data on all actively listed stocks on the Oslo Bors Exchange as of 31.03.2022 were gathered from Datastream and stored in Excel. The data span ranges from 31.12.1994 to 31.03.2022, corresponding to 329 monthly price observations on 194 individual stocks. The complete list of stocks included in the analysis can be found in the appendix. Further, 328 price observations on the OSEBX equity index were recorded, serving as the strategy benchmark. Finally, 327 return observations on the 1-month NIBOR are gathered and used as a proxy for the risk-free rate. The data for all asset classes were made available through BIs Eikon license, which gives data access to Datastream. The license was approved by the library department of Handelshøyskolen BI.

The data set was further prepared by removing four stocks with an insufficient number of observations. In total, 190 stocks are carried over for further use in the analysis. Because 190 is divisible by 10, we can now construct ten symmetric portfolios with respect to the number of constituents in each portfolio. Also, note that companies that have been de-listed from Oslo Bors Exchange within the range of the sample are omitted from the analysis. We acknowledge that this limits the number of companies with price data available throughout the full sample. Consequently, the cross-sectional momentum strategy performance at the beginning of the sample period may contain some bias due to the limited investment universe. Finally, the price series of all underlying stocks are indexed by date to ensure equal length before importing the dataset to Python.

5 Methodology

The research conducted throughout this thesis can, in a simplified manner, be compressed into three main components:

- Trading strategy construction
- The average strategy performance over the full sample
- Strategy performance analyses under volatile market conditions

This section describes the methodological approach to our research, which will be ordered according to the components mentioned above. Initially, a brief description of each subsection will be provided before we outline a more detailed explanation of the step-wise process further down within each respective subsection.

The first subsection outlines the general structure of the strategy and the different modifications that investors can apply to the cross-sectional momentum strategy. The following section describes the thought process behind which statistics were found most helpful when evaluating the general performance of the strategy. Finally, we present the chosen approach for analysing the strategy performance during market crashes and a description of the calculated metrics.

5.1 Trading strategy construction

The cross-sectional momentum strategy is built on the notion that assets that have previously outperformed their peers will continue to outperform in the subsequent period(s). Conversely, under-performing assets will continue to provide returns inferior to their peers in the next period(s). Thus, the cross-sectional momentum strategy seeks to exploit the concept of price continuation (or price trends) by taking long positions in previous winners and short positions in previous losers. We identify previous winners and losers based on their returns over the past 1 to 4 quarters, known as the formation period denoted as J-months. Similarly, we consider holding periods ranging from 1 to 4 quarters, denoted as K-months. In total, 16 cross-sectional momentum strategies will be considered in our analysis as it is allowed for to have asymmetric formation- and holding periods. The cross-sectional momentum theory can be expressed mathematically as:

$$E(r_{it} - \overline{r}_t | r_{it-1} - \overline{r}_{t-1} > 0) > 0$$

$$E(r_{it} - \overline{r}_t | r_{it-1} - \overline{r}_{t-1} < 0) < 0$$

Where r_{it} is the return of asset i at time t, and $\overline{r}_{it}$ denotes the cross-sectional average of returns for the corresponding period.

In identifying previous winners and losers, the strategy requires return series ranging across the different assets within the available investment universe. For this purpose, we start by computing a simple return series for each asset.

$$R_t = \frac{P_t}{P_{t-1}} - 1$$

Next, we convert the simple return to log returns due to their convenient statistical properties using the following formula:

$$r_t = log(R_t + 1)$$

We further compound the returns of each asset into a cumulative return index, consequently enabling us to compute returns at any horizon.

Based on the chosen formation and holding period, all assets will be ranked in ascending order subject to their returns in the past *J-Months*, and further allocated with equal weights to decile portfolios. The first portfolio contains the weakest performers while the tenth portfolio contains the strongest performers, denoted *Losers* and *Winners* respectively. In each month, the strategy buys the winner portfolio and sells the loser portfolio, holding this position for *K months.* A gap month is also used between the formation date and execution date to avoid short-term reversal effects. We also consider overlapping holding periods, which means that in any given month *t*, the strategies may hold a series of different portfolios, which were initiated in both the current month and the previous *K-1 months.* As each month passes by, the strategy closes out the position taken in *t-K*, and further rebalance the entire portfolio to maintain equal weights. Intuitively, that means the investor can hold up to *K* active winner and loser portfolios, where *K-1* of these portfolios are carried over from the previous month(s), and the last portfolio is the one initiated at time *t*. By allowing for overlapping holding periods, the strategy may be "re-applied" each month, which in theory amplifies the credibility of the strategy as it is being used more frequently over the sample period. Also, note that the constituents in each active portfolio may differ as the mix of winners and losers may change from month to month, even though it is somewhat contradictory to momentum theory as it violates the concept of price continuation. However, it is evident that winners do not necessarily remain winners in perpetuity. In fact, assets that have experienced strong price continuation for a 12-month period tend to face price reversals the following 24 months (Moskowitz, Ooi, & Pedersen, 2012). Nevertheless, they may still be perceived as winners if their peers perform relatively worse.

5.2 The average strategy performance over the full sample

The 1-month NIBOR is used as a proxy for the risk-free rate and is subtracted from the OSEBX return series to obtain excess monthly benchmark returns. The excess monthly return on the cross-sectional momentum strategy is further defined as:

$$WML_t^{(J,K),e} = (r_{t,W} - Rf) - (r_{t,L} - Rf)$$

Where $r_{t,W}$, $r_{t,L}$, and Rf denotes return on the winner portfolio, loser portfolio and the risk-free asset, respectively. The ordinary least square method is used to regress the respective strategy returns on the excess market returns to investigate the cross-sectional momentum strategy's proclaimed ability to generate abnormal returns.

$$WML_t^{(J,K),e} = \alpha + \beta_{M,t} Mkt_t^e + \epsilon_t$$

After the excess return series for all unique variations of the momentum strategy (J, K) are regressed on excess market return, we assess the strategies' ability to generate abnormal returns by investigating the α (regression constant) for each strategy regression, and further select a handful of strategies with the most statistically significant properties, evaluated by:

$$T - statistic = \frac{m - \mu}{s/\sqrt{n}}$$

Where m is the computed mean from the sample, μ is the hypothetical mean (or value) we want to test against, and the denominator is the standard deviation of the mean. To assess whether the strategies generate abnormal returns or not, we compute the following t-statistic:

$$T - statistic = \frac{\alpha}{STD(\alpha)}$$

And evaluate the following expression: $\alpha > 0$. The statistical interpretation of the constant term is essential in this regard. It reveals the mean value of the dependent variable (strategy return series) when the tested feature-variable (benchmark return) is equal to zero. I.e., the alpha value indicates the mean return of the strategies in excess of benchmark returns.

The cumulative returns of the selected strategies are then plotted against the cumulative benchmark return for illustrative purposes. Finally, we produce a table reporting descriptive statistics on the selected strategies.

5.3 Strategy performance analyses under volatile market conditions

This section presents the methods used to identify the main contributors to the strategy returns during market crashes. We start by breaking the $WML^{(J,K)}$ return series into its main components. More specifically, we will analyse the performance of the long- and short portfolios over each market crash sub-sample and highlight which portfolio(s) contribute to the success or failure of the strategy under volatile market conditions.

The cross-sectional momentum strategy's performance will be evaluated in three non-overlapping periods: The financial crisis of 2008, the oil price plunge period of 2014, and finally, the covid-pandemic in 2020. Because each market crash differs in length and magnitude, the sub-sample around each market crash will be defined so that it encompasses the complete cycle of a traditional market crash event. Thus, each sub-sample contains the prolonged period of rising stock markets (bull market) before the crash, the period of abrupt and dramatic price declines, and finally, the market rebound. For each period, we report the statistics on both the long- and short portfolios and the full strategy and benchmark returns.

At last, we investigate if the strategies' success or failure stems from time-varying market beta exposures. A rolling regression is used to uncover any presence of time-varying betas:

$$WML_t^{(J,K),e} = \alpha + \beta_{M,t} Mkt_t^e + \epsilon_t$$

The model is based on a traditional linear regression but allows the data set to change over time, where the length of the data is defined by a fixed "window". Intuitively, for each point in time, the ordinary least square regression runs on the past n observations defined by the "window-size" and stores the beta values retrieved by the regression. This procedure is repeated for each point in time $t \to T$, where the sample window shifts proportionally. The window includes 50 observations (monthly), which coincides with the notion that beta values are more reliable when constructed (and applied to) on a rather short frame of historical data (4-5 years).

For the plots and tables presented in section 7, two distinct computational methods are applied to find the simple mean returns and the cumulative returns. The simple mean return of the strategy is presented by subtracting the loser portfolio's simple mean return from the winner portfolio's simple mean return. The strategy combinations inherit different levels of volatility through the sample period. Hence, monthly returns corrected for volatility drag are also presented to show comparable results across each strategy combination. These are computed with the following formula:

$$Monthly\, geometric\, return \;\approx\; Monthly\, arithmetic\, return \;-\; \frac{\sigma^2}{2}$$

Lastly, when computing the cumulative returns, the following approach is utilised. The cumulative excess returns on each long, short, and WML portfolio is computed independently from one another. I.e., the results reflect a situation in which the hypothetical investor buys and hold one of the portfolios (either the WML, Winner, or Loser portfolio). Due to the effect of compounding, we have that $WML \neq R_W - R_L$, where WML, R_W, and R_L denote the cumulative returns of the strategy, winner portfolio, and loser portfolio, respectively.

6 Trading strategy results

In the first subsection, we briefly document the average performance of cross-sectional momentum in Norway over the whole sample. Each of the following subsections thereafter covers the performance of the strategies under three specific market events and addresses whether the strategy's performance under these market conditions is attributable to the long portfolio, short portfolio and/or time-varying market exposures. Any significant abnormal returns generated by the strategy would violate the weakest form of efficiency according to the market efficiency theory introduced by Eugene Fama in 1970.

6.1 Is there momentum in the Norwegian stock market?

The empirical findings are retrieved by applying the constructed cross-sectional momentum strategy to the Norwegian stock market on a sample ranging from 1995 to the end of Q1 2022. The purpose of this subsection is to document the presence of cross-sectional momentum profitability in the Norwegian stock market and further identify to what extent the findings are consistent with previous literature on the topic.

Cross-sectional momentum returns (%)

J,K	Portfolio	3	6	9	12
3	WML	1.14	0.96	0.81	0.58
3	Winners	1.35	1.50	1.45	1.31
3	Losers	0.21	0.53	0.64	0.73
6	WML	1.36	1.08	0.86	0.59
6	Winners	1.68	1.56	1.47	1.32
6	Losers	0.32	0.48	0.61	0.73
9	WML	1.18	1.03	0.77	0.50
9	Winners	1.75	1.57	1.40	1.26
9	Losers	0.57	0.54	0.63	0.76
12	WML	0.99	0.68	0.43	0.17
12	Winners	1.63	1.37	1.15	1.03
12	Losers	0.64	0.68	0.71	0.86

Table 1: Mean monthly excess returns on all strategy combinations

Table 1 reports the monthly excess return on all cross-sectional momentum strategies, as well as the performance of each the long and short portfolio, using a look-back period J ranging from 3 to 12 months along the row-axis, and holding each portfolio for 3 to 12 months which is mapped along the column-axis. A gap month between the formation- and holding period is used to avoid short-term reversal effects. The stocks in the winner and loser decile portfolios are equally weighted. Note that the monthly returns are reported regardless of the type of transaction, i.e., positive monthly returns on the loser portfolio will negatively contribute to strategy returns due to short positions.

The results of the analysis evidently suggest that the Norwegian stock market is a suitable playing field for cross-sectional momentum strategies. However, the monthly excess returns presented in table 1 exhibit a rather clear but yet, interesting pattern. Regardless of the look-back period, the WML strategy returns are clearly negatively correlated with the number of holding periods. This is attributable to how each of the strategy constituents moves, namely the past winner and past loser portfolios. First and foremost, the past winner portfolio yields more significant monthly returns than the past loser portfolio, consistent with traditional momentum theory. However, the two portfolios seem to have opposing signs on the correlation coefficient with respect to the number of holding periods. I.e., the past winner portfolio experiences the most substantial returns when the holding period is low. Conversely, the past loser portfolio yields the highest returns when the assets are held for a longer duration. If this pattern continues in subsequent months, the past winner and past loser portfolio returns converge before the latter starts yielding higher returns than the former, ultimately resulting in negative strategy returns. However, testing for holding periods exceeding 12 months goes beyond the scope of our analysis, but if this recognised trend sustains in the subsequent months, the empirical findings would suggest that the strategy faces price-reversals for holding periods exceeding 12 months, comparable with Moskowitz, Ooi, and Pedersen (2012b).

Another intriguing finding is that all the constructed past losers portfolios across every look-back- and holding period yield positive returns on average, i.e., adversely affecting the WML return series. Thus, the findings on past losers portfolio returns in the Norwegian stock market seem to oppose the empirical findings on past loser returns in other markets. As a reference, the return contribution from long- and short portfolios to the momentum portfolio is roughly found to be equally weighted when tested on US equities from 1927-2013 (Asness, Frazzini, Israel, & Moskowitz, 2014).

We acknowledge that the difference between our empirical findings and the findings presented in previous literature may originate from the data set used in the analysis. Firstly, the strategy is limited to taking long/short positions on a rather small sample of 190 stocks, which is a significantly smaller investment universe than the U.S stock market. Secondly, the data set omits companies previously de-listed from the Oslo Bors stock exchange. One can therefore reasonably argue that the absolute worst performing stocks may have been de-listed due to the event of bankruptcy. Consequently, the strategy might be unable to exploit some of the most extensive shorting opportunities occurring within the 1995-2022 interval.

Alpha's generated from the strategy (%)

J,K	3	6	9	12
3	1.27 (3.02)	1.12 (3.19)	0.97 (2.91)	0.70 (2.32)
6	1.56 (3.46)	1.27 (2.95)	1.03 (2.59)	0.75 (2.01)
9	1.41 (2.76)	1.23 (2.67)	0.95 (2.17)	0.65 (1.59)
12	1.21 (2.28)	0.88 (1.75)	0.60 (1.26)	0.33 (0.72)

Table 2: strategy returns in excess of risk-free rate and benchmark returns

The reported monthly α coefficients with corresponding t-statistics in parenthesis are computed by regressing all J, K combinations of the WML monthly excess return series on the monthly market excess return.

Table 2 documents the presence of cross-sectional momentum anomalies in the Norwegian stock market. In fact, 12 out of the 16 strategies yield significant alphas when tested on a 5% significance level. As expected, the magnitude of alpha-returns and their statistical significance decreases in the number of holding periods (and look-back periods), which is comparable to the properties of monthly excess returns exhibited in table 1. For the purpose of structure and clarity, a selection of 3 strategies will be subject to further analysis for the remainder of this thesis, rather than proceeding with all 16 strategies. This is considered justifiable as all of the strategies fundamentally share similar properties. The three strategies are selected on the basis of alpha-size and statistical significance of the alpha, and are depicted in Figure 1:

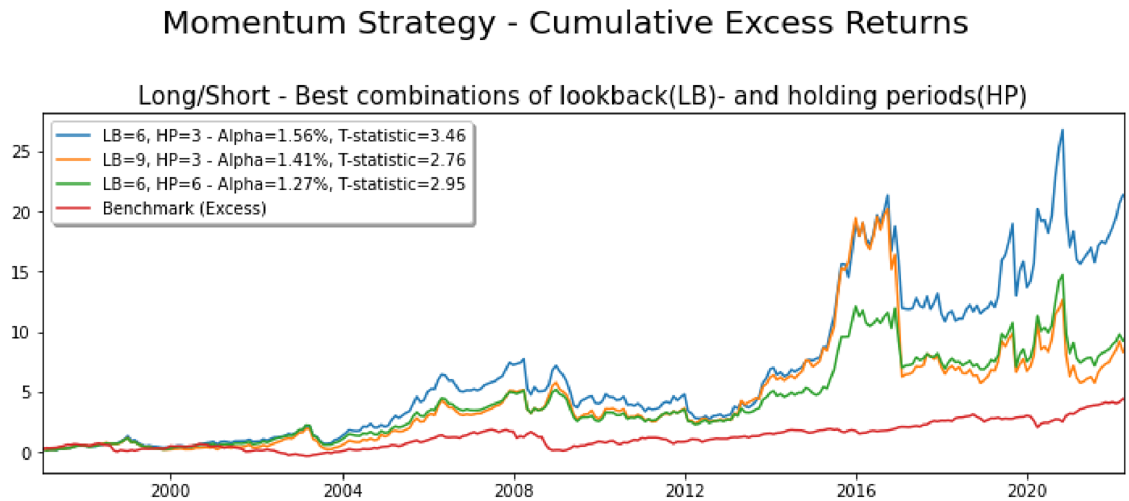

Figure 1: Momentum Strategy - Cumulative Excess Returns

Figure 1 depicts the cumulative strategy returns across the entire sample. The computation follows a simple compounding framework but subtracts one after the return is computed, effectively indexing the return series at zero. Thus, a value of one along the y-axis corresponds to a 100 per cent return.

At first glance, it is evident that the selected strategies outperform the benchmark with substantial margin. Interestingly, one can observe that all three strategies steadily outperform the benchmark with comparable variation in the standard deviation of returns. However, the return series breaks away from this pattern on three occasions: At the end of 2008, 2014-2017, and 2019-2021. However, this will be the subject of discussion in subsections 7.2-7.4 and is thus disregarded for now. Table 3 provides some statistical measures that serve helpful when analysing the differences in properties between the strategy- and benchmark returns.

All three strategies yield sizable monthly excess returns relative to the benchmark but at the cost of more considerable variation in returns from month to month, as revealed by the standard deviation. Nonetheless, the additional risk incurred by the momentum investor is proven to be worthwhile as they benefit from a better risk-reward relationship, exhibited by the Sharpe Ratio. The table also uncovers a rather interesting difference between momentum- and benchmark returns, namely that all alpha coefficients exceed the excess returns. This can be explained by the fact that all beta coefficients are (statistically significant) negative, i.e., the strategy ultimately has a negative market exposure whilst yielding positive abnormal returns. This coincides with some of the abrupt return movements depicted in figure 1. Intuitively, in a simple CAPM regression setting, this means that the strategy return is the largest at the y-axis intercept, which occurs when the benchmark return equals zero. Additionally, the negative beta values implies that the average strategy returns in excess of the risk-free rate declines as the benchmark return increases. The alpha (y-intercept) will therefore mark the highest return the strategy generates, because we have a negative slope coefficient, which is consistent with the

Descriptive statistics

Top three strategy combinations	6_3	9_3	6_6	Market
Excess return (%)	1.36	1.18	1.08	0.67
Excess return - corrected for volatility drag (%)	1.04	0.77	0.78	0.50
Standard deviation (%)	7.99	9.06	7.65	5.75
Alpha (%)	1.56	1.41	1.27	0.00
T-statistic (alpha)	3.46	2.76	2.95	0.00
Beta	-0.30	-0.35	-0.29	1.00
Sharpe ratio	0.17	0.13	0.14	0.12
Annualised sharpe ratio	0.59	0.45	0.49	0.41
Skewness	-0.50	-0.67	-0.63	-1.07
Kurtosis	4.45	5.78	4.93	3.42

Table 3: Key statistical metrics on selected strategies

The reported statistics are computed on a monthly basis unless the metric(s) explicitly states otherwise. Excess returns (excess of rf), alphas, and betas are retrieved using a traditional CAPM regression framework. Standard deviation documents the standard deviation in monthly excess returns on each strategy, as well as the benchmark excess return series.

findings of Daniel and Moskowitz (2016) over the "full-period". Note that the beta coefficients imply that the strategies "on average" negatively load on the market. However, it is not given that each strategy consistently has a negative market exposure. Figure 1 instead suggests that the negative coefficients are, in fact, a result of a handful of substantial negative spikes in beta values, clustered by time.

Moreover, the distribution of all strategy returns and the benchmark return is negatively skewed. The mass of the return distribution is located to the right of the mean. Intuitively, negative skewness suggests that the (rational) investors are willing to invest in assets with a high probability of positive expected returns while contemporaneously being exposed to the negligible risk of incurring extreme losses. The shape of a negatively skewed distribution resembles a reversed lottery effect. When observing some of the immense draw-down periods of the strategies, it is expected that the strategies' negative skewness should exceed that of the negative market skewness. However, this is not the case. This is because the strategy does not only stumble across occasional extreme losses but also has periods yielding paramount positive returns, effectively counterweighing the shape of the distribution.

6.2 Strategy performance during: The financial crisis of 2008

This subsection presents three cross-sectional momentum strategy performances during the renowned financial crisis. The sub-sample is delimited from 01.01.2007 to 31.12.2009, effectively capturing parts of the bull market in advance of the OSEBX crash, the steep decline, and the most aggressive market rebound following the crash. Firstly, the cumulative return on the long-, short-, and strategy portfolio is presented and compared to the cumulative benchmark return. This should provide a general understanding of the performance of each momentum strategy compared to the market and further enables us to analyse if the success or failure of the strategy is attributable to any of the strategy portfolio constituents. Further, a more analytical approach is undertaken to substantiate the findings, namely investigating time-varying beta parameters in both long- and short portfolios.

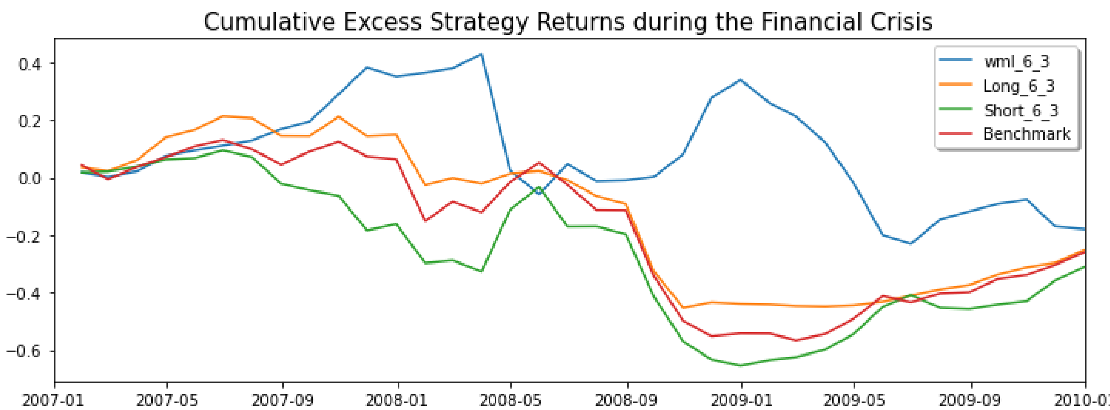

Figure 2: Portfolio constituents cumulative excess return

Figure 2 depicts the cumulative excess return for the long-, short-, and WML portfolios and the benchmark excess return using look-back- and holding period of 6 months and 3 months, respectively. The 9/3- and 6/6 strategy plots exhibit similar visuals and are therefore placed in the appendix.

Daniel and Moskowitz argues about the robustness of momentum strategies across multiple periods, different markets and a broad range of asset classes (Daniel, Hirshleifer, & Subrahmanyam, 1998). However, momentum strategies' efficiency in generating strong positive returns is punctuated with occasional crashes. We have formulated our hypothesis accordingly: Do we observe any presence of momentum crashes in the Norwegian stock market, comparable with the findings of Daniel and Moskowitz (2016)? Interestingly, all three cross-sectional momentum strategies outperformed the broad Norwegian market during the financial crisis, as reported in table 4. The strategy yields rather contrarian results compared to the Norwegian stock market through the financial crisis. As shown in Figure 2, the momentum strategy thrives during the most dramatic market decline but faces a reversal in the wake of the financial crisis.

The financial crisis	6_3	9_3	6_6	Market
WML Excess Return (%)	-0.17	0.15	-0.33	-0.39
WML Excess Return - Corrected for volatility drag (%)	-0.53	-0.22	-0.63	-0.81
WML Cumulative Excess Return (%)	-17.96	-7.91	-20.69	-26.02
Winners Excess Return (%)	-0.55	-0.59	-0.76	n/a
Winners Cumulative Excess Return (%)	-25.21	-24.62	-29.74	n/a
Losers Excess Return (%)	-0.37	-0.74	-0.43	n/a
Losers Cumulative Excess Return (%)	-31.07	-39.83	-31.48	n/a

Table 4: Monthly and cumulative excess returns

The table documents the performance of each strategy through the period 01.01.2007 to 31.12.2009. The excess returns reports the monthly mean return in excess of the risk-free rate, and is calculated using the same series of returns as used for constructing the cumulative return index.

Table 4 documents the momentum strategies' ability to frequently identify past losers and enter short positions accordingly. The results suggest that the price continuation phenomenon is present for the past loser stocks in the Norwegian stock market during high market volatility. However, past losers also seem to rebound more aggressively during the market rebound (01.01.2009 to 01.05.2009). On the other hand, past winners yield returns inferior to both the past loser portfolio and the market. I.e., the results substantiate the notion that both size and variability in beta parameters may partly explain momentum crashes during market rebounds, consistent with Grundy and Martin (2001b). To investigate this further, we perform a rolling regression with a fixed window size of 50 monthly return observations on both the past winners and past losers portfolios, depicted in Figure 3.

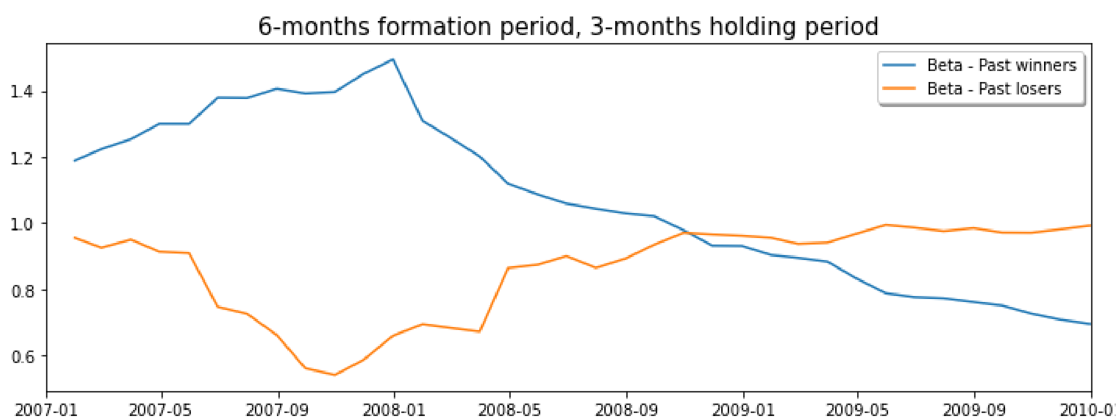

Figure 3: Time-varying betas during the financial crisis

Figure 3 plots the beta values computed by running rolling regressions on both the long (past winners) and short portfolio (past losers). Both portfolios are formed using a formation period of 6 months, holding period of 3 months, as well as a gap month between the formation period and the start of the holding period. The 9/3- and 6/6 strategy plots exhibits similar visuals, and is therefore placed in the appendix.

Firstly, we recognise some variability in beta parameters for both the long and short portfolios. There is also a considerable difference in beta size between the past winners and past losers portfolios. Pre-2008, the strategy loads its long positions on high beta stocks, which is intuitive considering that the benchmark, where its constituents define the investment universe, yielded a positive return. However, after January 2008, the long portfolio became incrementally more defensive as each month passed by due to the ”minor” market correction starting at that exact date. The strategy has a lagged response to stock returns and will thus reshape the long (and short) positions accordingly each month after January of 2008. In practical terms, some market draw-down in returns before a crisis may improve momentum profits during market crashes, as it will have more time to reshape its long and short position.

The most notable result from the rolling regression is that the beta-curves of the past winners and losers invert in the wake of the financial crisis. This is because the formation period now spans over the market crash. The momentum portfolio will consequently take long positions in stocks that were more robust during the crash (low beta) and, conversely, short positions in the stocks that fell the most during the crash (high beta). The results presented in Figure 2 suggest that the shorted stocks rebounded more rapidly than low beta stocks. The downfall of the momentum strategy during market rebounds is therefore arguably attributable to the defensive lagged response to the market crash, consistent with the results of Grundy and Martin (2001b).

6.3 Strategy performance during: The oil price plunge period of 2014-2017

In this subsection, we present the analysis on cross-sectional momentum performance from January 2014 to January 2017. Unlike the financial crisis and the covid-pandemic, this period is not characterised by a precipitous decline in the broad market index. On the other hand, the defined sub-sample spans over a time frame in which some specific sectors experienced significant declines in market prices due to the sharp drop in oil prices, where oversupply exerted downward price pressure on the commodity famously produced by Norway. Moreover, because momentum strategies trade stocks using a trend-identification pattern, we find it particularly interesting to investigate how well or poor the strategy performs when macroeconomic shocks heavily burden parts of the investment universe.

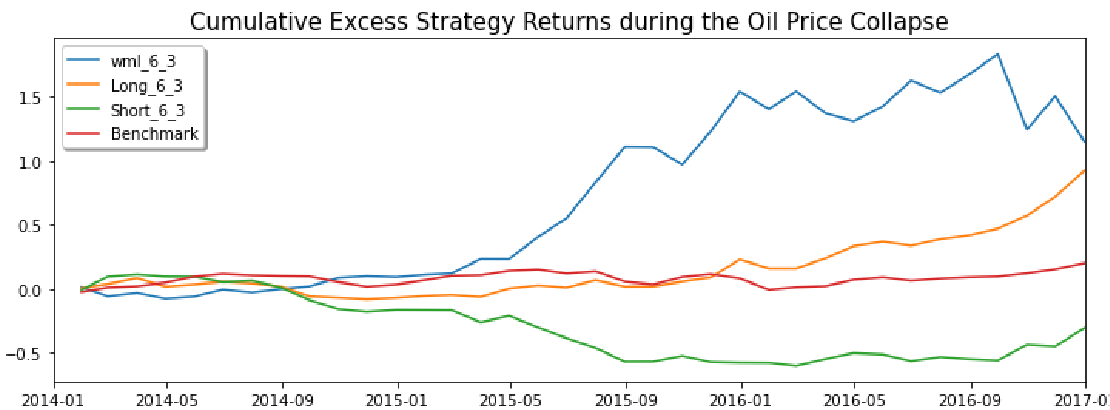

Figure 4: Portfolio constituents cumulative excess return

Figure 4 depicts the cumulative excess return for the long-, short-, and WML portfolio as well as the benchmark excess return using look-back- and holding period of 6 months and 3 months, respectively. The 9/3- and 6/6 strategy plots exhibits similar visuals, and is therefore placed in the appendix.

The oil plunge	6_3	9_3	6_6	Market
WML Excess Return (%)	2.49	1.99	1.84	0.56
WML Excess Return - Corrected for volatility drag (%)	2.14	1.50	1.52	0.51
WML Cumulative Excess Return (%)	115.09	69.71	72.58	20.01
Winners Excess Return (%)	1.94	2.10	1.69	n/a
Winners Cumulative Excess Return (%)	92.38	104.49	75.57	n/a
Losers Excess Return (%)	-0.55	0.11	-0.14	n/a
Losers Cumulative Excess Return (%)	-30.67	-16.08	-17.69	n/a

Table 5: Monthly and cumulative excess returns during the oil crisis

The table documents the performance of each strategy through the period 01.01.2014 to 01.01.2017. The excess returns reports the monthly mean return in excess of the risk-free rate, and is calculated using the same series of returns as used for constructing the cumulative return index.

From Figure 4, we do not recognise any presence of a "momentum crash" between 2014 and 2017. In fact, the results are suggestive of the contrary. All the selected momentum strategies yield substantially higher cumulative returns than the relevant benchmark, as exhibited in Table 5. However, the results indicate that the main driver of the momentum returns stems from the past winners portfolio, which interestingly opposes the findings under the financial crisis. This is partly explained by the fact that the market characteristics of the oil price plunge differs from other traditional market crashes. Most importantly, it is not defined as a crisis period comparable to the financial crisis, and comparisons should therefore be made with caution. Figure 4 displays a discernible event, namely that the strategy under-performed the benchmark up until the fourth quarter of 2014 and later outperformed the benchmark in the subsequent months. The reversal point of performance is mainly due to the realised returns obtained on the short positions. To identify the underlying sources of return, we further deconstruct the past loser portfolio. We present its constituents list in table 6 and find that the strategy aggressively shorts stocks in the energy- and offshore sector following the steep decline in oil prices.

Most frequent stocks in the loser portfolio	Frequency
Norwegian Energy Company	93 %
Seabird Exploration	93 %
InterOil Exploration & Production	86 %
Odfjell Drilling	71 %
Siem Offshore	71 %

Table 6: Shorting frequency from August 2014 to September 2015

Most frequently shorted stocks identified by counting how many times each specific stock have been assigned to the bottom decile portfolio.

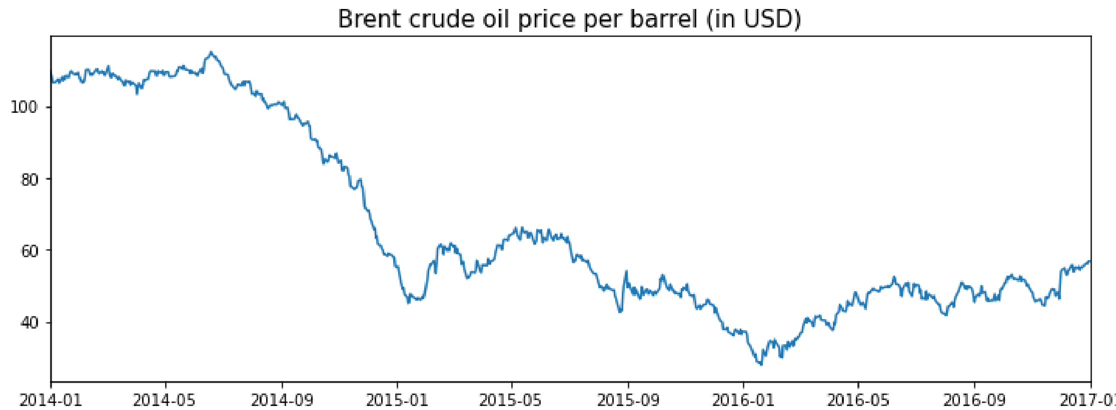

Figure 5: Historical oil price during the oil price plunge

The presented strategy accounts for overlapping observations, which means it can effectively hold up to k number of WML portfolios each month. I.e., the 6/3 strategy holds three equally weighted WML portfolios at all times and realises the returns on the oldest portfolio while contemporaneously entering a new portfolio based on the return data available in the look-back period. Consequently, in the months following the steep decline in oil prices depicted in Figure 5, the strategy gradually started taking short positions in stocks adversely affected by the deteriorated oil price. I.e., macroeconomic shocks to the Norwegian stock market may be favourable for momentum strategies because they can take both long- and short positions. However, the strategy's performance will heavily rely on the longevity of each market shock compared to the responsiveness of the momentum strategy. In other words, the performance is contingent on whether the momentum strategy is sufficiently responsive to capitalise on the identified price trend, where the strategy responsiveness is dictated by the chosen number of lookback and holding periods.

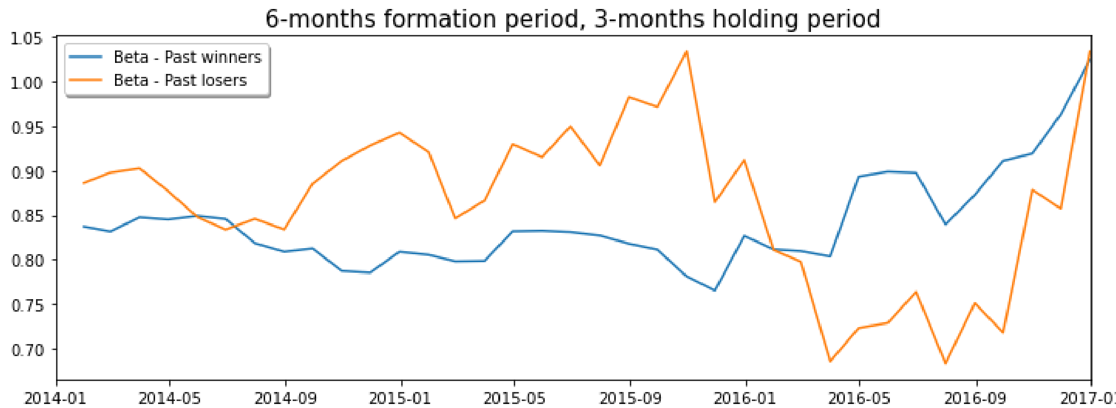

Figure 6: Time-varying betas during the oil price plunge

Figure 6 plots the beta values computed by running rolling regressions on both the long (past winners)- and short portfolio (past losers). Both portfolios are formed using a formation period of 6 months, holding period of 3 months, as well as a gap month between the formation period and the start of the holding period. The 9/3- and 6/6 strategy plots exhibits similar visuals, and is therefore placed in the appendix.

A closer examination of the variability in beta parameters helps explain the strategy's drawback from its peak in the fourth quarter of 2016. As shown in Figure 6, the deviation in betas between the short- and long positions declines through the fourth quarter of 2016. This means that the strategy's net exposure to the market converges towards zero due to the rapidly increasing beta on the past losers portfolio. This happens simultaneously as the market appreciates. I.e., the results imply that the active short portfolios rebound more rapidly than the active long portfolios, ultimately generating negative momentum profits.

6.4 Strategy performance during: The covid-pandemic market crash

The final market event examined in this thesis is the market crash caused by the covid-pandemic. We delimit the time frame to January 2019 - January 2022. The analyses presented in this subsection examine how well momentum strategies maneuver through market crashes and rebound that are more concentrated in time, compared to, e.g. the financial crisis.

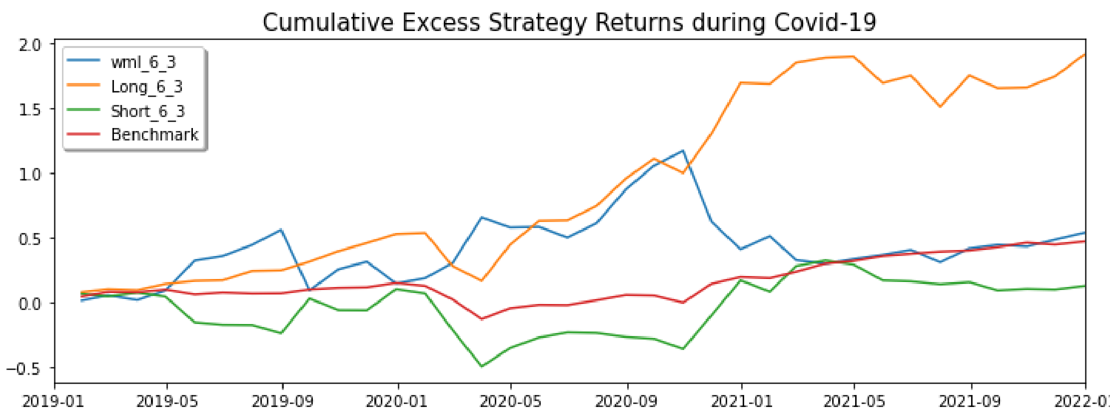

Figure 7: Portfolio constituents cumulative excess return

Figure 7 depicts the cumulative excess return for the long-, short-, and WML portfolio as well as the benchmark excess return using a look-back- and holding period of 6 months and 3 months, respectively. The 9/3- and 6/6 strategy plots exhibits similar visuals, and is therefore placed in the appendix.

The Covid-19 Pandemic	6_3	9_3	6_6	Market
WML Excess Return (%)	1.84	1.60	1.37	1.19
WML Excess Return - Corrected for volatility drag (%)	1.22	0.76	0.69	1.07
WML Cumulative Excess Return (%)	53.71	29.53	26.22	46.98
Winners Excess Return (%)	3.30	3.13	2.97	n/a
Winners Cumulative Excess Return (%)	191.35	177.14	162.32	n/a
Losers Excess Return (%)	1.46	1.53	1.60	n/a
Losers Cumulative Excess Return (%)	12.57	5.20	16.91	n/a

Table 7: Monthly and cumulative excess returns during the Covid-pandemic market crash

The table documents the performance of each strategy through the period 01.01.2019 to 01.01.2022. The excess returns reports the monthly mean return in excess of the risk-free rate, and is calculated using the same series of returns as used for constructing the cumulative return index.

The table above shows that only one of the selected strategies outperformed the benchmark in terms of cumulative returns, namely the 6/3 strategy. The main differentiating factor among the three strategies is the magnitude of returns concentrated in specific periods. This, in turn, affects the cumulative return across the full sample, which explains why all the strategies display very similar patterns but on different scales. For that reason, the 9/3 and 6/6 plots are placed in the appendix, and we focus on the patterns observed in the 6/3 strategy.

The empirical findings suggest that momentum returns' main driver is the long portfolio for all strategies tested across the full sub-sample, which opposes the findings under the financial crisis. However, we identify some similarities when observing the cumulative strategy returns relative to the benchmark when comparing the two market crashes. The past loser portfolio consistently provides a favorable hedge when the broader market declines. However, the flip-side is that the past loser portfolios tend to rebound more than the past winners portfolio when the market rebounds. We do not find this dynamic significant enough to cause a "momentum crash", but it seemingly tends to wipe out the returns accumulated during the most volatile periods. We further substantiate this finding by examining the variation in beta parameters between the long- and short portfolios, exhibited in Figure 8.

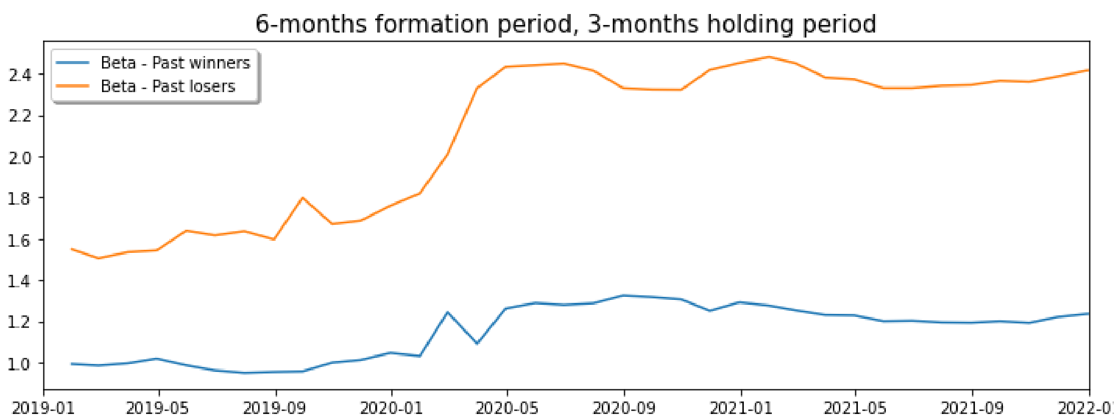

Figure 8: Time-varying betas during the covid-19 pandemic

Figure 8 plots the beta values computed by running rolling regressions on both the long (past winners) and short portfolio (past losers). Both portfolios are formed using a formation period of 6 months, holding period of 3 months, as well as a gap month between the formation period and the start of the holding period. The 9/3- and 6/6 strategy plots exhibits similar visuals, and is therefore placed in the appendix.

We identify that the variability in beta parameters was more stable during the full covid-pandemic sample than in the two formerly analysed market events, except for the rather violent spike in beta values as the market crash occurred. The identified beta values suggest that the momentum strategy consistently had considerable negative net market exposure. This finding, bundled up with the fact that the strategy successfully manages to identify and short under-performing stocks, creates a robust hedge against the abrupt market decline starting mid-March of 2020. However, because the past losers portfolio also sustains its high beta values in the wake of the market crash, the findings again suggest that the past losers portfolio rebounds excessively relative to the past winners portfolio.

We notice that the beta levels of the past loser portfolio before the covid-pandemic market crash is significantly higher than that of the financial crisis of 2008. This is arguably partly explained by the computational methods used to calculate the beta parameters. The rolling regression utilises a rolling window of 50 monthly observations. This is roughly the equivalent of 4-5 years of historical data. This means that the computed beta levels in 2019 will in fact be formed on the returns of the past loser portfolio all the way back to late 2014 - early 2015. We therefore argue that the difference in beta levels at the beginning of each market crash sub-sample stems from the differences in market volatility in the preceding 4 to 5 years. We find it probable that during periods of higher market volatility, there is an increased chance that some stocks will exhibit bigger return deviations relative to the benchmark. Consequently, there will be more stocks with higher beta values available in the investment universe. By computing the volatility on a simple return series of the market 50 months before each market crash, we find that the market volatility 50 months before the covid market crash is roughly 22% higher than the market volatility 50 months before the financial crisis. We do however not have sufficient evidence to infer that this single-handily explains the rather big differences in beta levels when comparing the past loser portfolio in the financial crisis and covid-pandemic market crash.

7 Conclusive remarks

We construct 16 cross-sectional momentum portfolios consistent with Jegadeesh and Titman (1993), and find that trading on price continuation patterns in the Norwegian stock market from 01.01.1995 to 31.03.2022 yields significant abnormal returns across 12 different combinations of look-back- and holding periods. The results suggest that the past winners portfolio drives the cross-sectional momentum returns whilst the past losers portfolio provides a negative return contribution on average over the full sample. Furthermore, the results consistently show that going long the past winners portfolio yields bigger returns with shorter holding periods. Conversely, the return associated with shorting past losers increases with longer holding periods.

We do not find sufficient evidence to conclude that cross-sectional momentum strategies crash during volatile market conditions. The three emphasised strategies (6/3, 9/3, and 6/6) outperform the market in all sub-samples except the covid market crash, where 6/3 is the only superior strategy. We find that the long positions in the past winners portfolio are the primary driver of returns in the tested sub-samples (except the financial crisis), consistent with the findings over the full sample. Apart from that, the results of the conducted analyses suggest that the strategy yields somewhat contrarian results amid these market events, and we identify some recurring patterns. After testing for three specific volatile market events, we find that when the market (or parts of the market) declines, the shorted past losers portfolio works as a strong hedge against market losses. On the other hand, the short positions also account for the severe strategy losses occurring in the wake of each crisis. When the market rebounds, the past losers portfolio exhibits excessive loadings on the market compared to the past winners portfolio.

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Appendix 1 - Summary statistics and performance of momentum strategies

Descriptive statistics

Top six strategy combinations	6_3	9_3	6_6	3_3	9_6	12_3	Market
Excess return	1.36 %	1.18 %	1.08 %	1.14 %	1.03 %	0.99 %	0.69 %
Standard deviation	7.99 %	9.06 %	7.65 %	7.37 %	8.16 %	9.23 %	5.75 %
Alpha	1.56 %	1.41 %	1.27 %	1.27 %	1.23 %	1.21 %	0.00 %
T-statistic (alpha)	3.46	2.76	2.95	3.02	2.67	2.28	0.00 %
Beta	-0.30	-0.35	-0.29	-0.19	-0.30	-0.35	1.00
Sharpe ratio	0.17	0.13	0.14	0.15	0.13	0.11	0.12
Annualised sharpe ratio	0.59	0.45	0.49	0.54	0.44	0.37	0.41
Skewness	-0.50	-0.67	-0.63	-2.05	-0.69	-1.32	-1.07
Kurtosis	4.45	5.78	4.93	16.76	5.59	10.64	3.42

Table 8: **Key statistical metrics on selected strategies**

Strategy	alpha	tstat	pvalue	MOMR, WML	MOMR, winners	MOMR, losers
3_3	0.0127	3.0171	0.0028	0.0114	0.0161	0.0047
3_6	0.0112	3.1911	0.0016	0.0096	0.0150	0.0053
3_9	0.0097	2.9096	0.0039	0.0081	0.0145	0.0064
3_12	0.0070	2.3225	0.0209	0.0058	0.0131	0.0073
6_3	0.0156	3.4599	0.0006	0.0136	0.0168	0.0032
6_6	0.0127	2.9492	0.0034	0.0108	0.0156	0.0048
6_9	0.0103	2.5928	0.0100	0.0086	0.0147	0.0061
6_12	0.0075	2.0053	0.0458	0.0059	0.0132	0.0073
9_3	0.0141	2.7574	0.0062	0.0118	0.0175	0.0057
9_6	0.0123	2.6666	0.0081	0.0103	0.0157	0.0054
9_9	0.0095	2.1693	0.0308	0.0077	0.0140	0.0063
9_12	0.0065	1.5905	0.1128	0.0050	0.0126	0.0076
12_3	0.0121	2.2778	0.0235	0.0099	0.0163	0.0064
12_6	0.0088	1.7451	0.0820	0.0068	0.0137	0.0068
12_9	0.0060	1.2612	0.2083	0.0043	0.0115	0.0071
12_12	0.0033	0.7211	0.4714	0.0017	0.0103	0.0086

Table 9: **Momentum strategies - Performance (MOMR equals raw monthly returns, not excess returns)**

2020 BULKERS	DOF	MERCELL HOLDING	SAGA PURE
ABG SUNDAL COLLIER HOLDING	EIDESVIK OFFSHORE	MOWI	SALMAR
ADEVINTA	ELECTROMAG.GEOSVS.	MPC CONTAINER SHIPS	SALMON EVOLUTION
AF GRUPPEN 'A'	ELKEM	MULTICONSULT	SALMONES CAMANCHAC GDR
AKASTOR	ELLIPTIC LABORATORIES	NAPATECH	SAS
AKER	ELOPAK	NAVAMEDIC	SATS
AKER BIOMARINE	ENDUR	NEKKAR	SBANKEN
AKER BP	ENSURGE MICROPOWER	NEL	SCANA
AKER CARBON CAPTURE	ENTRA	NEXT BIOMETRICS GROUP	SCATEC
AKER HORIZONS	EQUINOR	NORBIT	SCHIBSTED A
AKER SOLUTIONS	EUROPRIS	NORDIC NANOVECT	SCHIBSTED B
AKVA GROUP	FJORDKRAFT HOLDING	NORDIC SEMICONDUCTOR	SEABIRD EXPLORATION
AMERICAN SHIPPING	FLEX LNG	NORSK HYDRO	SEADRILL
AQUALISBRAEMAR LOC	FRONTLINE	NORSKE SKOG	SELF STORAGE GROUP
ARCHER	FROY	NORTHERN DRILLING	SELVAAG BOLIG
ARCTICZYMES TECHNOLOGIES	GAMING INNOVATION GROUP	NORTHERN OCEAN	SHELF DRILLING
ARENDALS FOSSEKOMPANI	GC RIEBER SHIPPING	NORWAY ROYAL SALMON	SIEM OFFSHORE
ARRIBATEC GROUP	GENTIAN DIAGNOSTICS	NORWEGIAN AIR SHUTTLE	SMARTCRAFT
ASETEK	GJENSIDIGE FORSIKRING	NORWEGIAN ENERGY CO.	SOLSTAD OFFSHORE
ATEA	GOLDEN OCEAN GROUP	NRC GROUP	SPAREBANK 1 SR-BANK
ATLANTIC SAPPHIRE (OSL)	GOODTECH	NTS	STOLT-NIELSEN
AUSTEVOLL SEAFOOD	GRIEG SEAFOOD	OCEANTEAM	STOREBRAND
AUTOSTORE HOLDINGS	GYLDENDAL	ODFJELL A	STRONGPOINT
AVANCE GAS	HAFNIA	ODFJELL B	SUBSEA 7
AWILCO DRILLING	HAVILA SHIPPING	ODFJELL DRILLING	TARGOVAX
AXACTOR	HAVYARD GROUP	OKEA	TECHSTEP
B2HOLDING	HEXAGON COMPOSITES	OKEANIS ECO TANKERS	TELENOR
BAKKAFROST	HOFSETH BIOCARE	OLAV THON EIEP.	TGS
BELSHIPS	IDEX BIOMETRICS	ORKLA	TIETOEVRY
BERGENBIO	INSR	OTELLO CORPORATION	TOMRA SYSTEMS
BEWI	INTEROIL EXP.&. PRDN.	PANORO ENERGY	TREASURE ASA
BONHEUR	ITERA	PARETO BANK	ULTIMOVACS
BORGESTAD 'A'	JINHUI SHIPPING AND TRANSPORTATION	PCI BIOTECH HOLDING	VEIDEKKE
BORR DRILLING	KAHOOT!	PETROLIA E&P HOLDINGS	VISTIN PHARMA
BORREGAARD	KID	PEXIP HOLDING	VOLUE
BOUVET	KITRON	PGS	VOSS VEKSEL- OG LANDMANDSBANK
BW ENERGY	KLAVENESS COMBINATION CARRIERS	PHOTOCURE	VOW
BW LPG	KMC PROPERTIES	POLARIS MEDIA	WALLENIUS WILHELMSEN
BW OFFSHORE	KOMPLETT	POLIGHT	WEBSTEP
BYGGMA	KOMPLETT BANK	PROSAFE	WILH WILHELMSEN HOLDING B
CADELER	KONGSBERG AUTV.HOLDING	PROTECTOR FORSIKRING	WILHS.WILHELMSEN HDG.'A'
CARASENT	KONGSBERG GRUPPEN	Q-FREE	WILSON
CLOUDBERRY CLEAN ENERGY	LEROY SEAFOOD GROUP	QUESTERRE ENERGY	XXL
CONTEXTVISION	LINK MOBILITY GROUP HOLDING	RAK PETROLEUM	YARA INTERNATIONAL
CRAYON GROUP HOLDING	MAGNORA	RANA GRUBER	ZALARIS
DLT	MAGSEIS FAIRFIELD	REACH SUBSEA	
DNB BANK	MEDI-STIM	REC SILICON	
DNO	MELTWATER	S D STANDARD ETC	

Table 10: **List of all stocks**

Appendix 2 - Performance plots of all strategy combinations (WML, Winner and Loser portfolio)

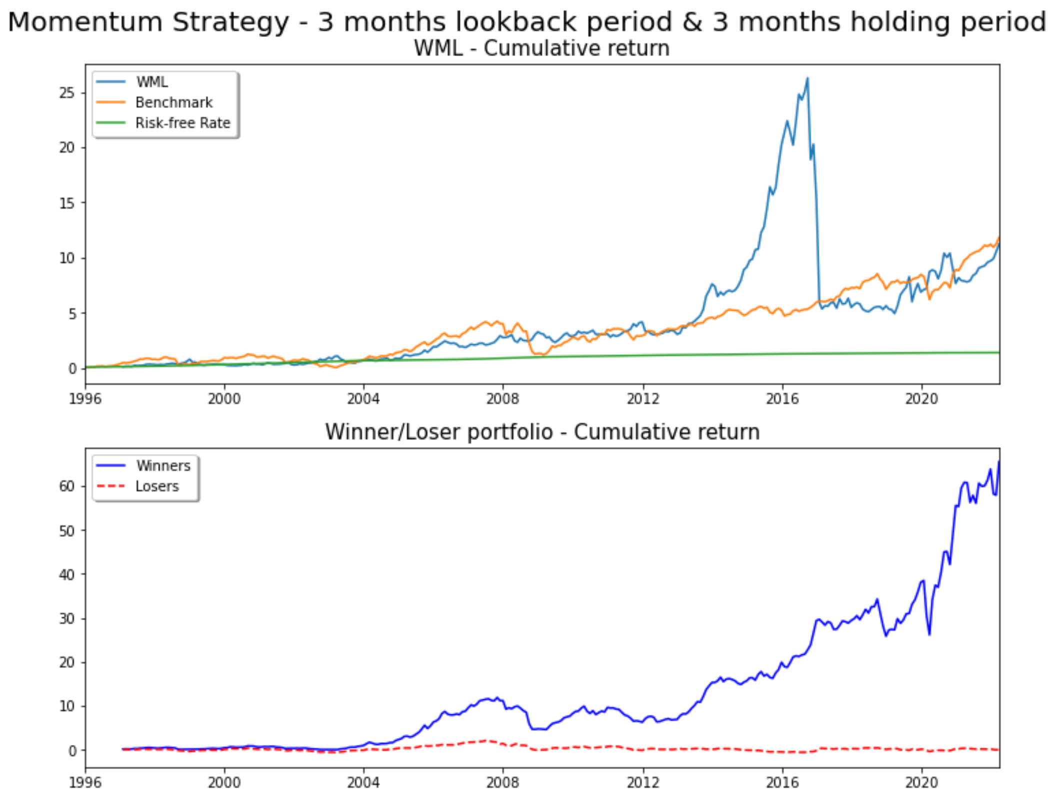

Figure 9: Momentum strategy 3/3

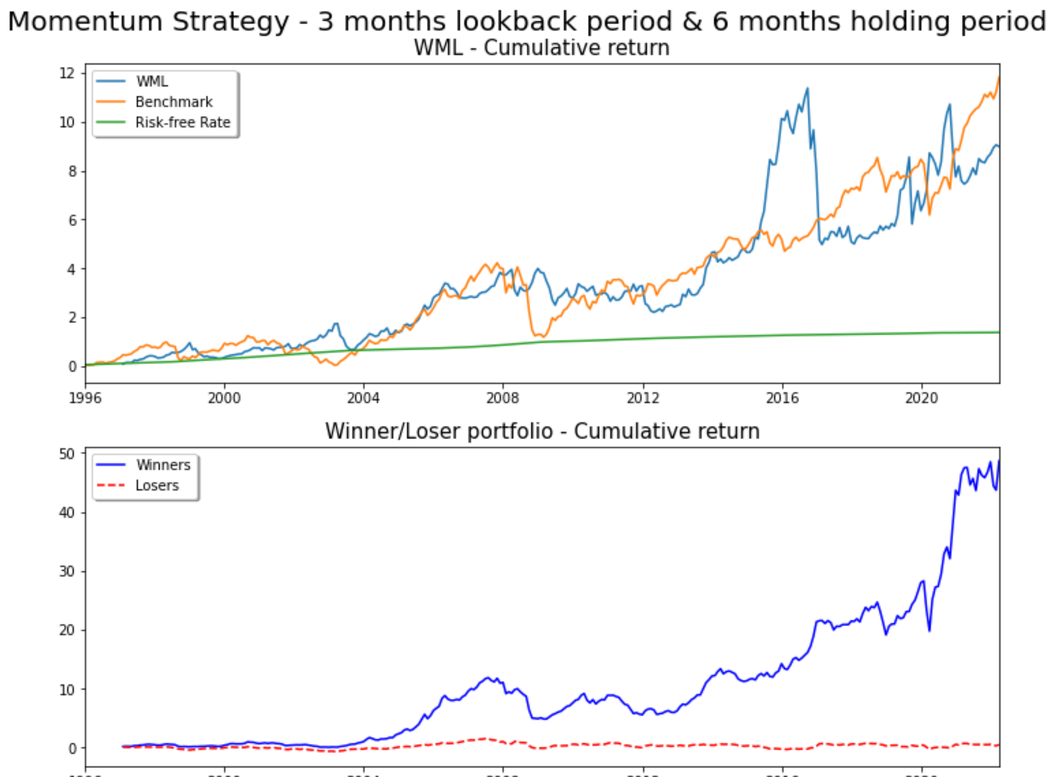

Figure 10: Momentum strategy 3/6

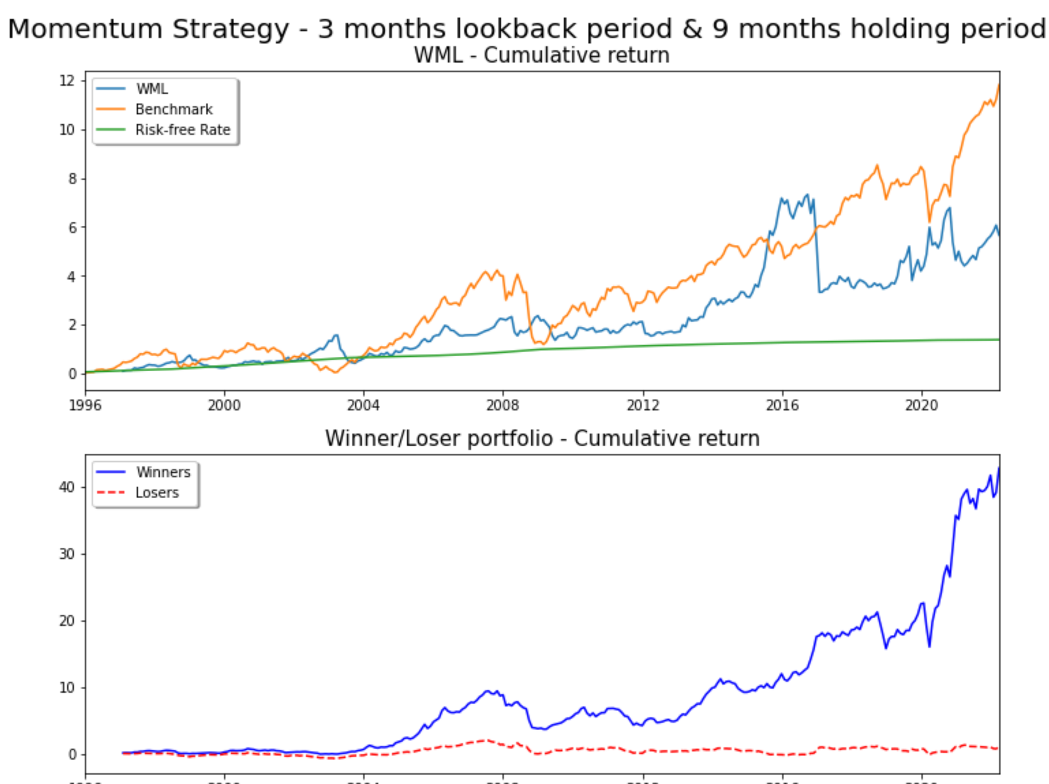

Figure 11: Momentum strategy 3/9

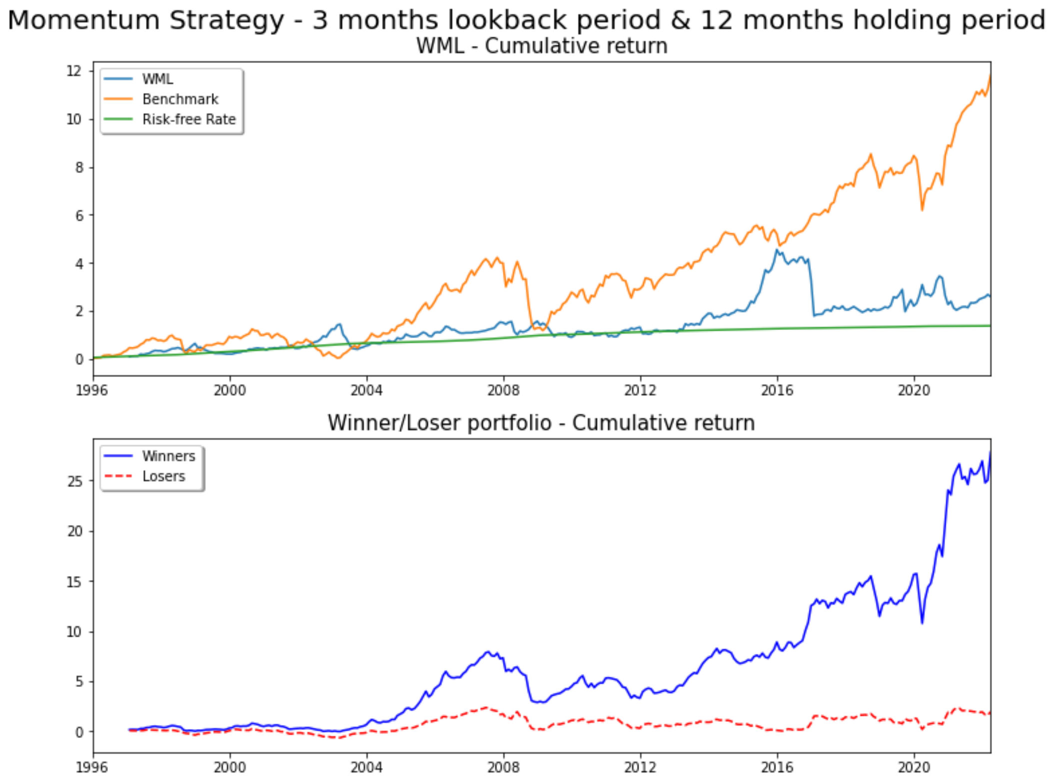

Figure 12: Momentum strategy 3/12

Figure 13: Momentum strategy 6/3

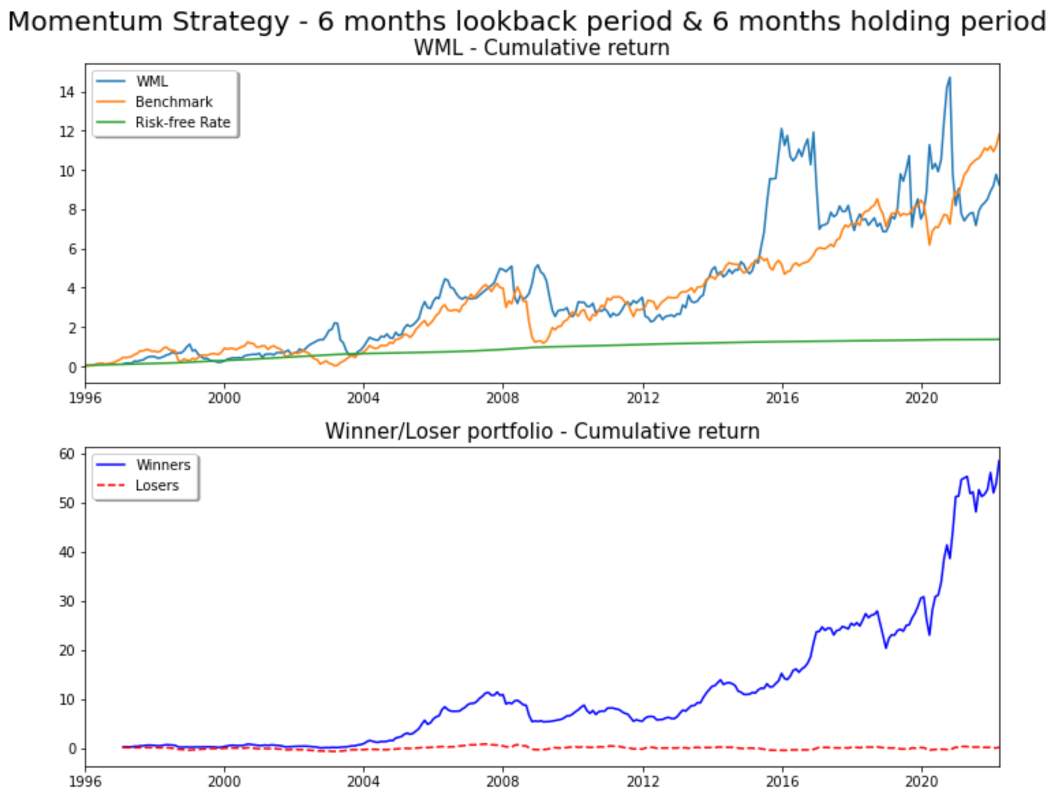

Figure 14: Momentum strategy 6/6

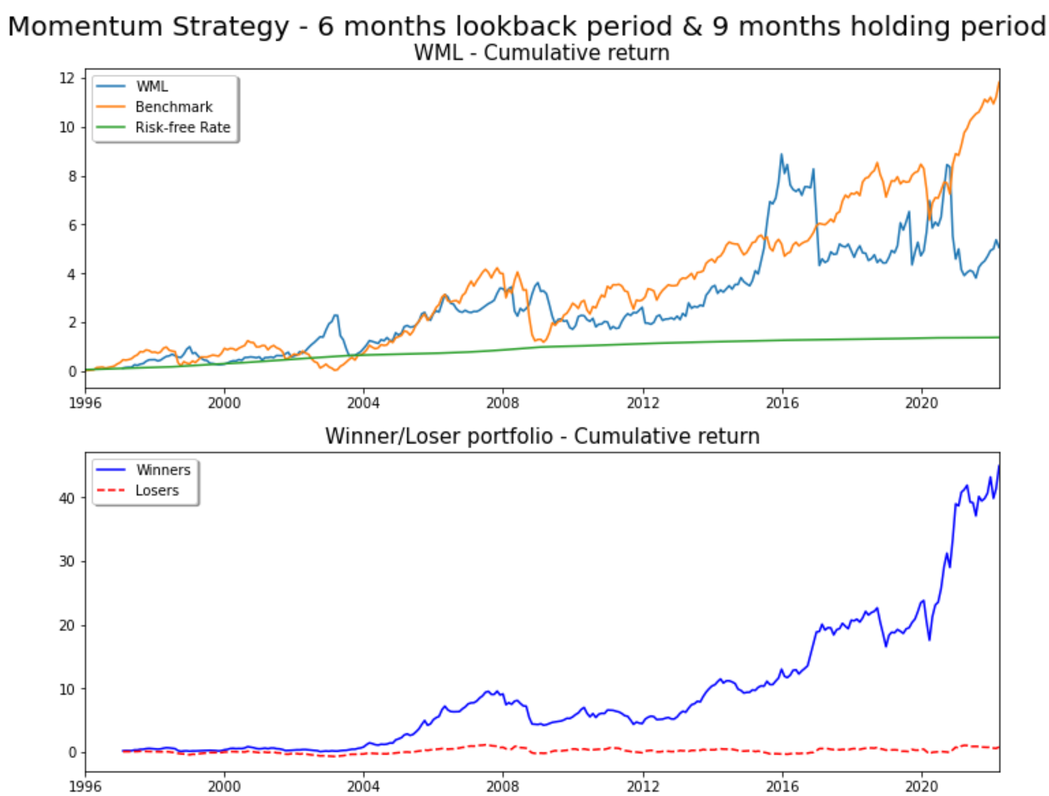

Figure 15: Momentum strategy 6/9

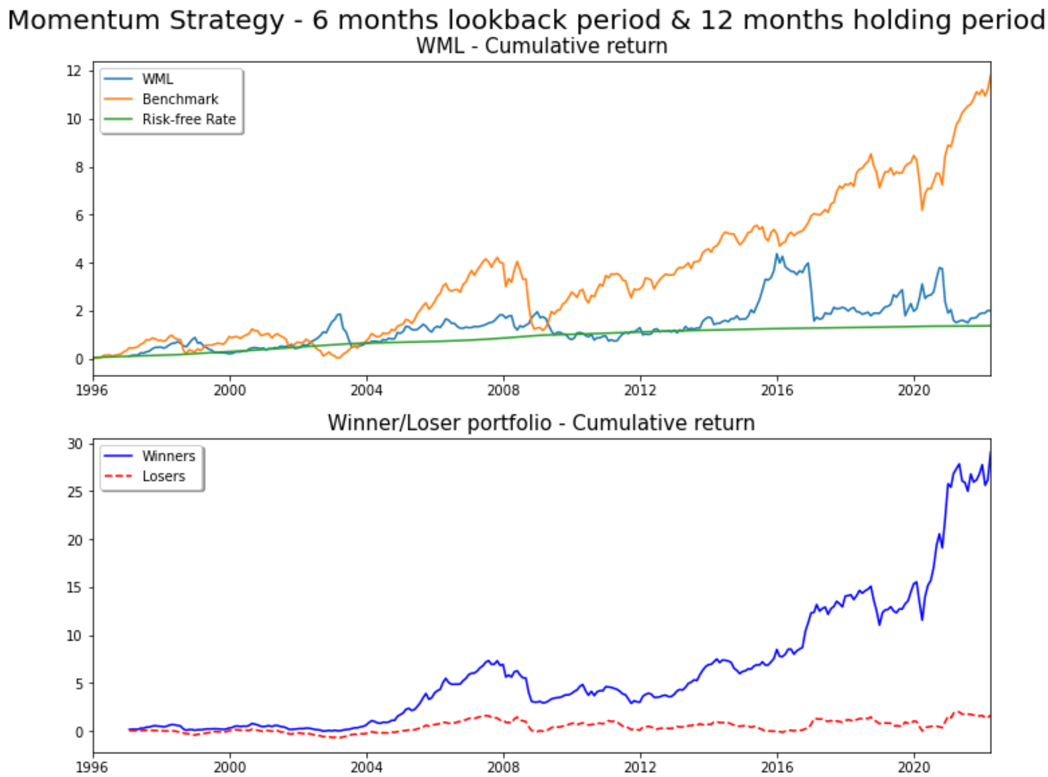

Figure 16: Momentum strategy 6/12

Figure 17: Momentum strategy 9/3

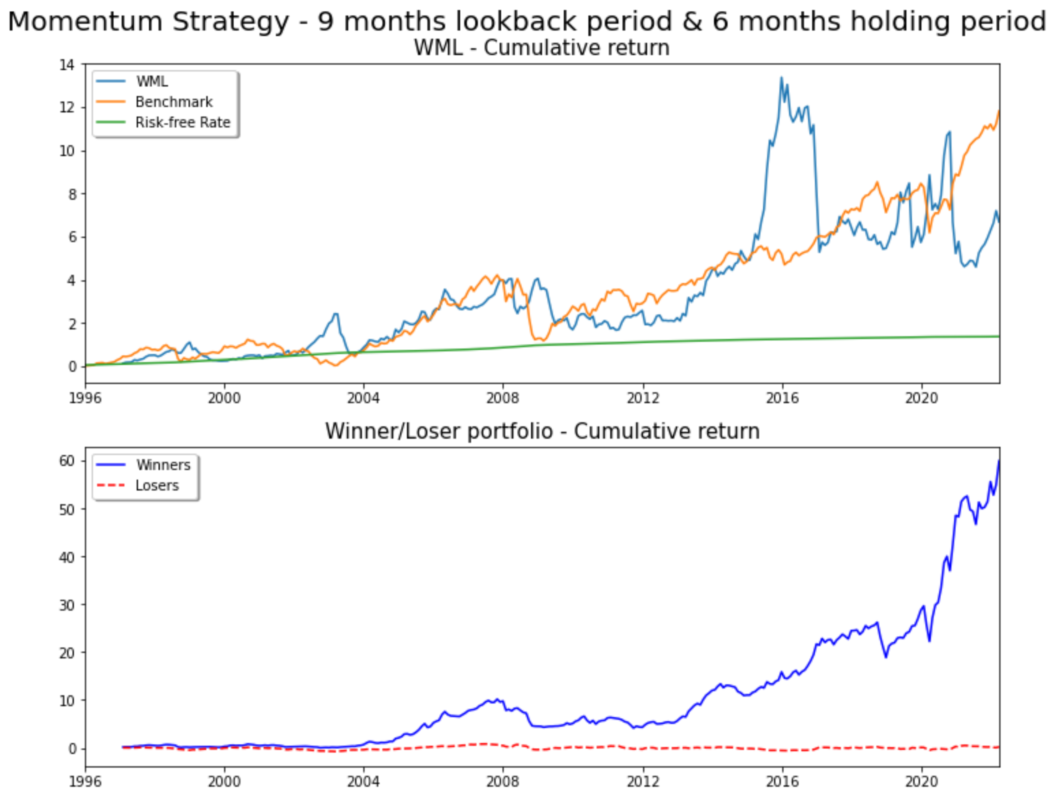

Figure 18: Momentum strategy 9/6

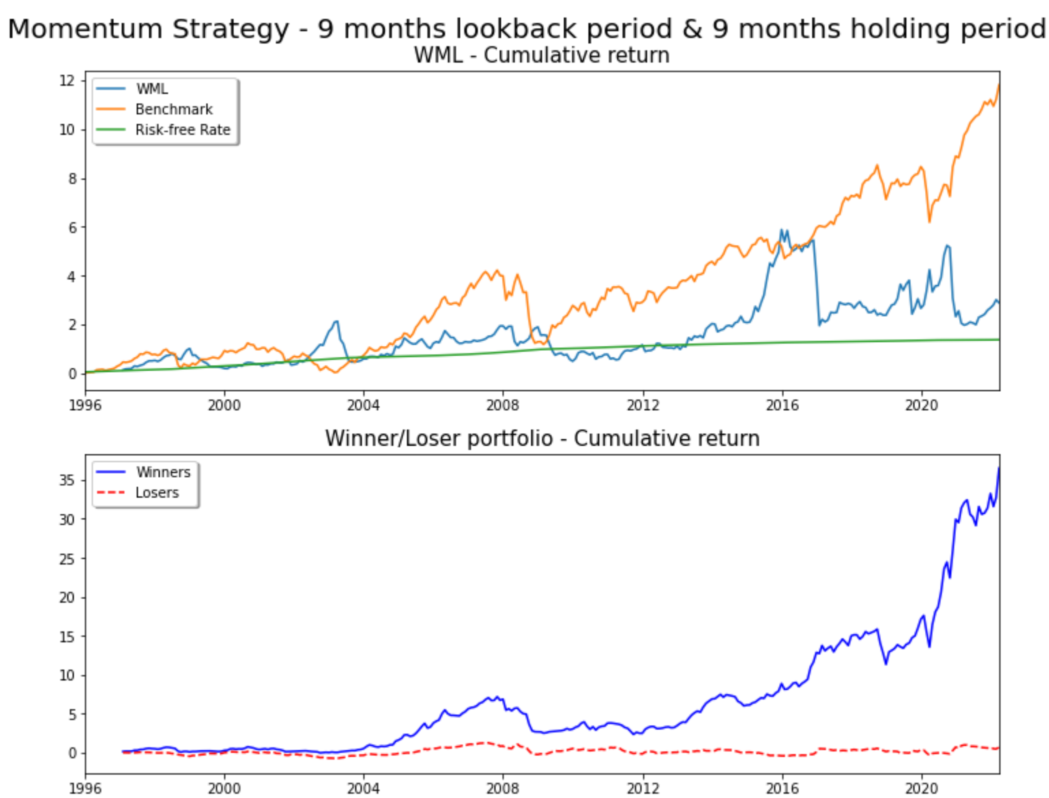

Figure 19: Momentum strategy 9/9

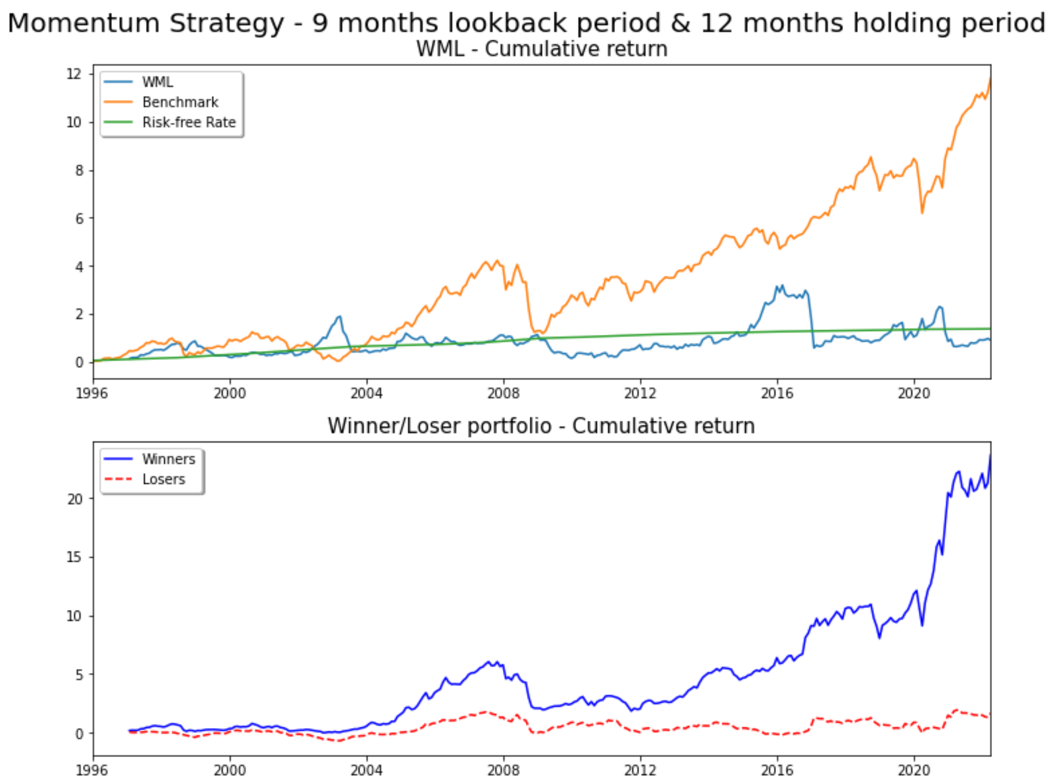

Figure 20: Momentum strategy 9/12

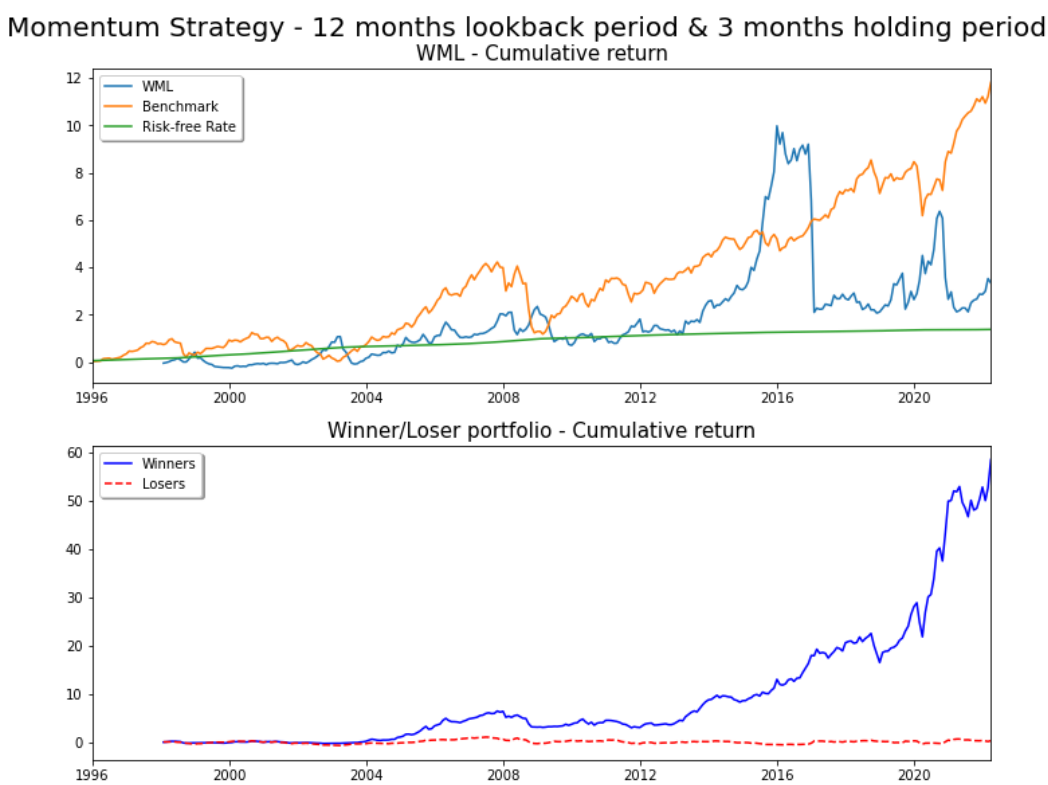

Figure 21: Momentum strategy 12/3

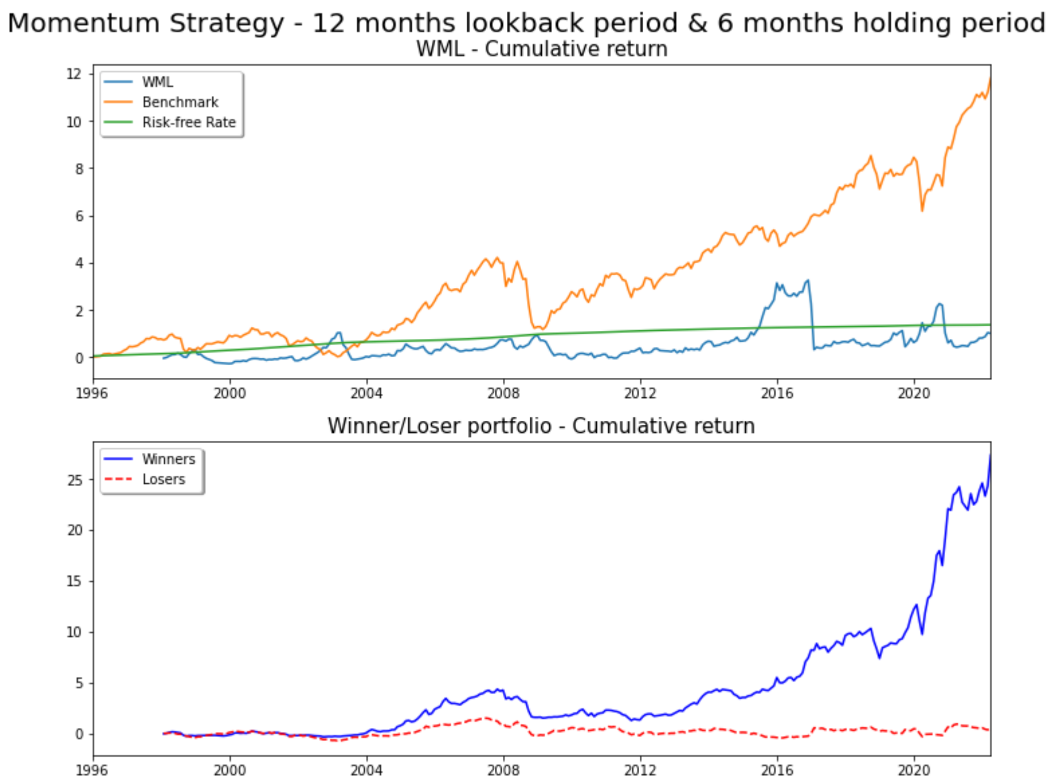

Figure 22: Momentum strategy 12/6

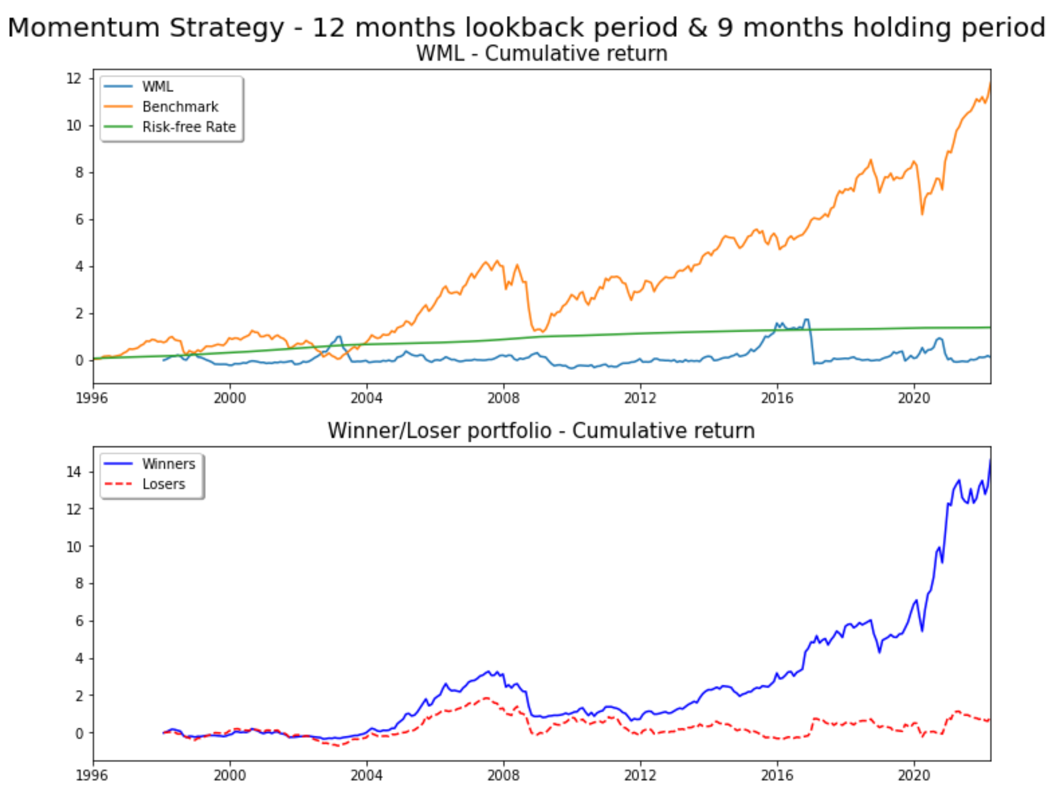

Figure 23: Momentum strategy 12/9

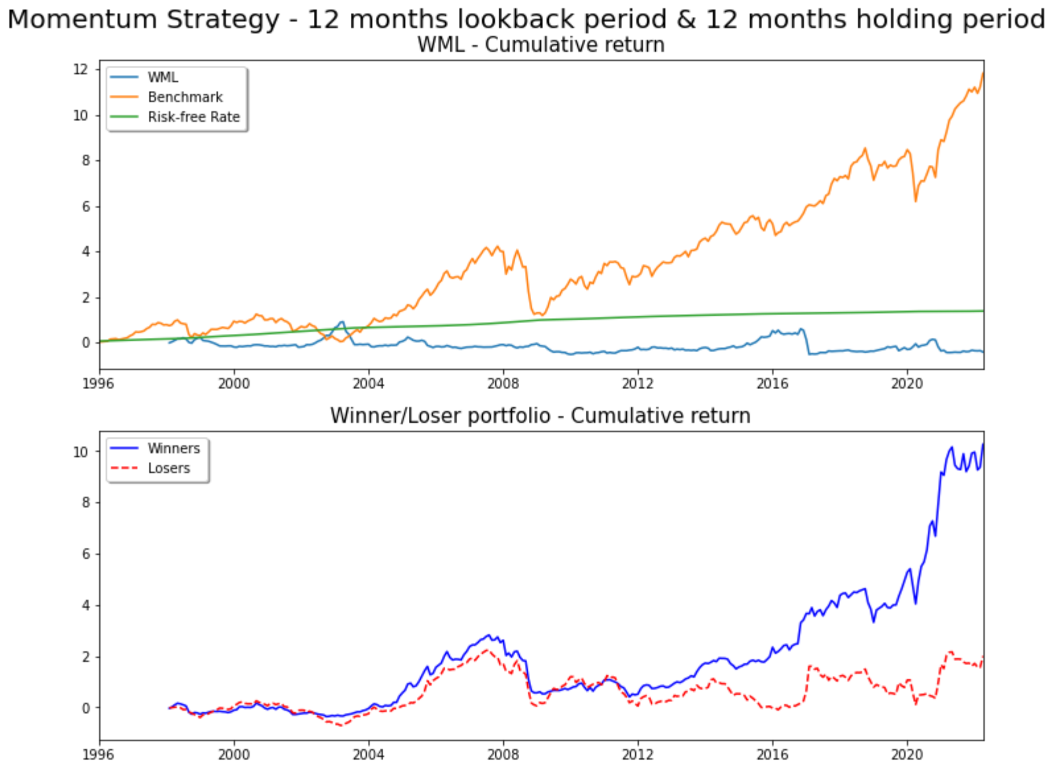

Figure 24: Momentum strategy 12/12

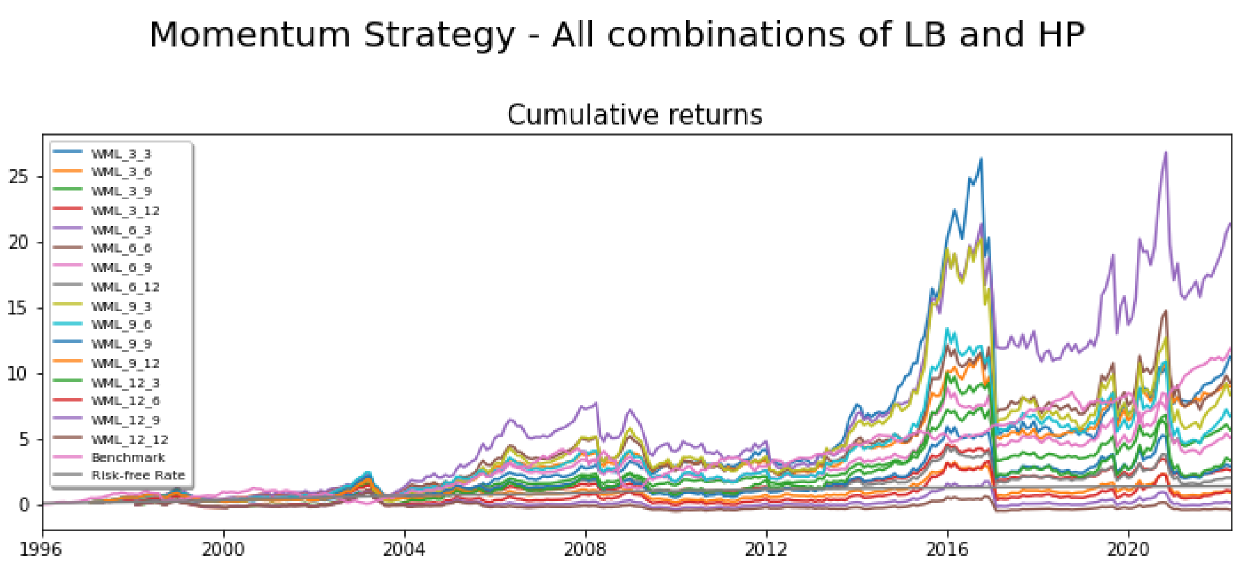

Figure 25: Momentum strategy - All combinations

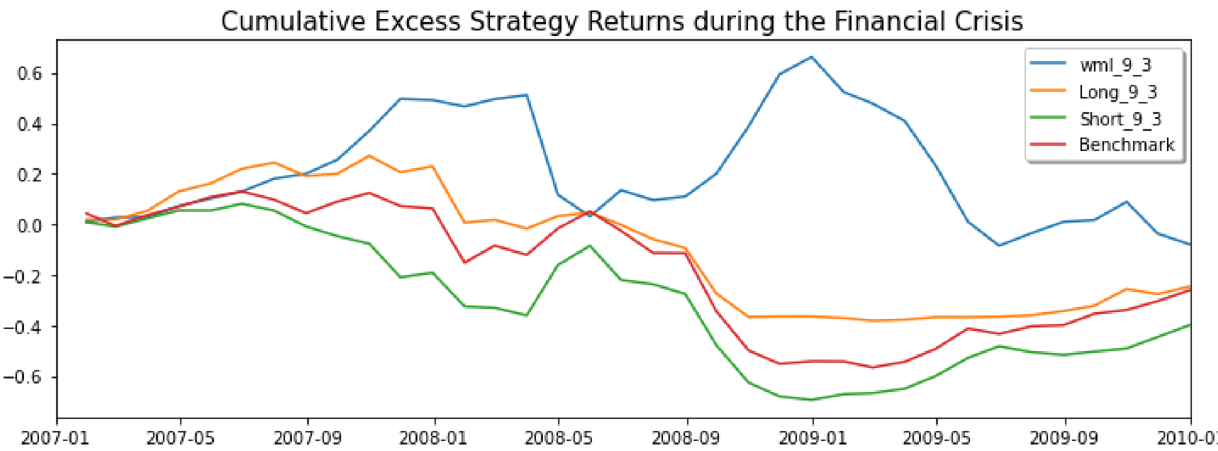

Figure 26: The financial crisis - Strategy 9/3

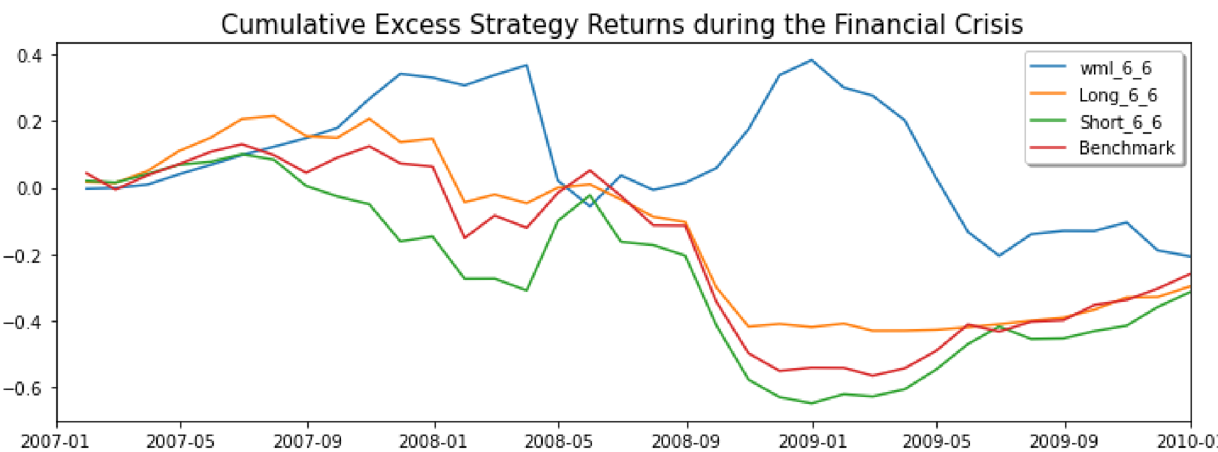

Figure 27: The financial crisis - Strategy 6/6

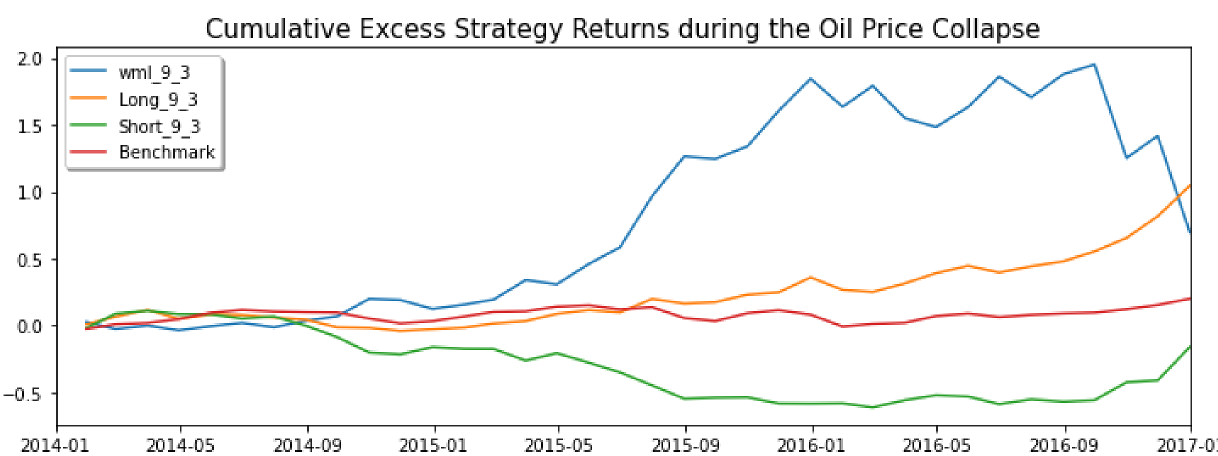

Figure 28: The oil price plunge - Strategy 9/3

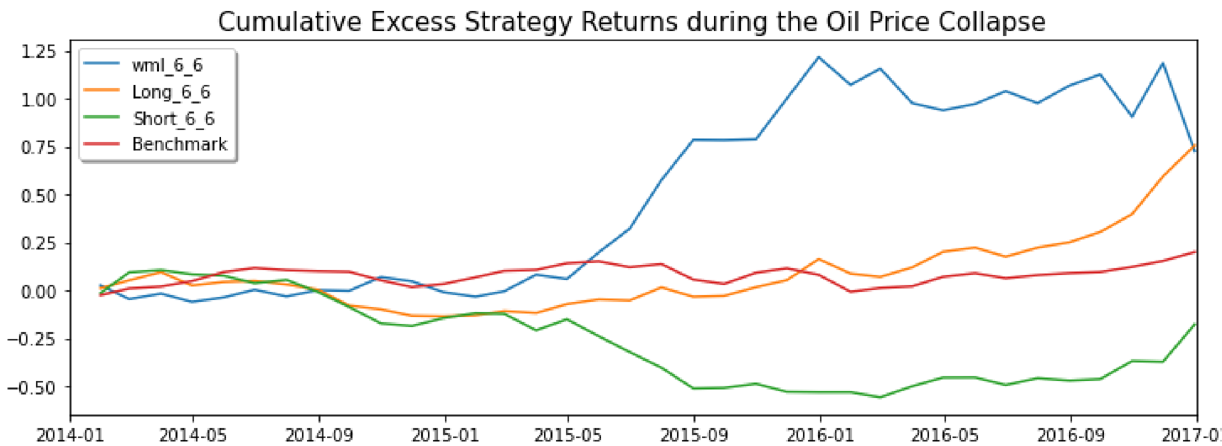

Figure 29: The oil price plunge - Strategy 6/6

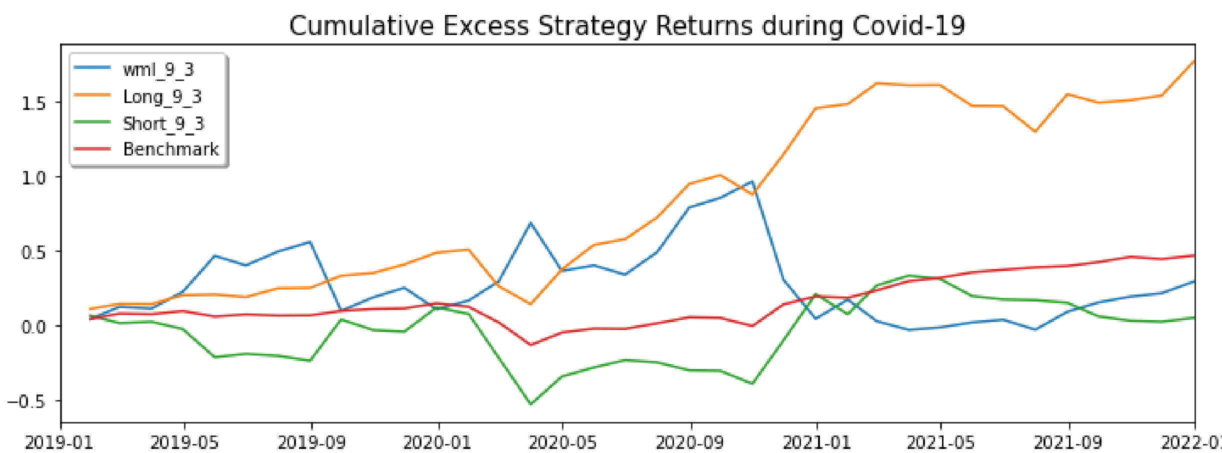

Figure 30: The Covid-19 pandemic - Strategy 9/3

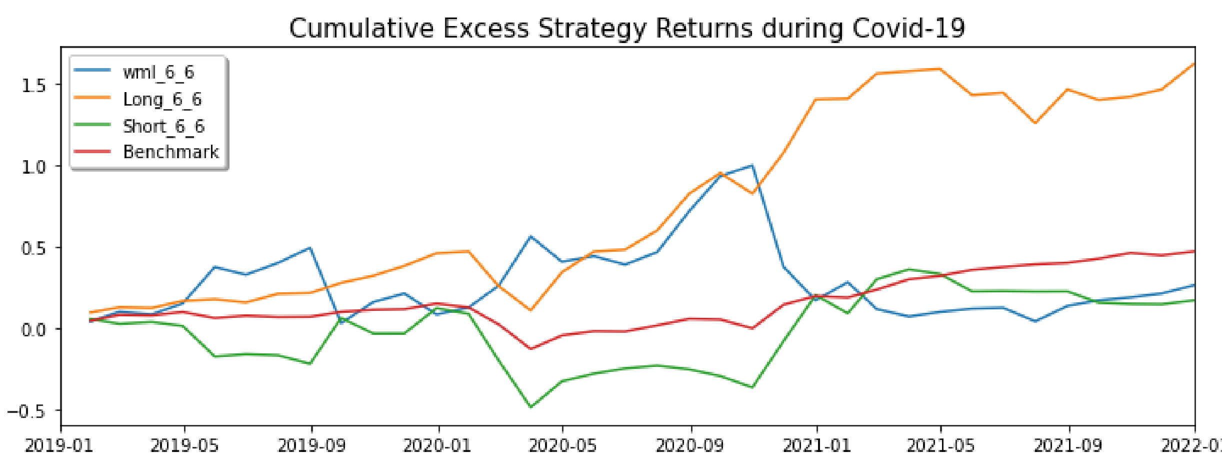

Figure 31: The Covid-19 pandemic - Strategy 6/6