A Work Project, presented as part of the requirements for the Award of a Master's degree in Finance from the Nova School of Business and Economics.

FIELD LAB: ANALYSIS OF QUANTITATIVE INVESTMENT STRATEGIES

CONSTRUCTING A MULTI-FACTOR INVESTMENT STRATEGY

OPTIMIZED SECTOR MOMENTUM

LARS BECKONERT

Work project carried out under the supervision of:

Nicholas Hirschey

16-12-2022

Abstract

In the combined part a multi-factor investment strategy is constructed out of four different enhanced single factor strategies using an optimization to maximize the Sharpe ratio of the combined portfolio. In the individual part an optimized sector momentum strategy is constructed that consists of a combination of a long and a market-neutral long/short strategy utilizing a simple regime-switching process with the goal to minimize momentum crashes and achieve robust returns in all market states.

Keywords:

Quantitative Investments, Financial Markets, Factor Investing, Sector Momentum,
Market Neutral, Regime Switching

This work used infrastructure and resources funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013, UID/ECO/00124/2019 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209).

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CONSTRUCTING A MULTI-FACTOR INVESTMENT STRATEGY

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Abstract

This group report combines four individual optimized factor investing strategies based on Value, Quality, Liquidity and Momentum. The portfolio of the four strategies is created based on an in-sample period according to the portfolio optimization by Markowitz (1952). In an out-of-sample period, the performance of the portfolio is evaluated. The optimized portfolio outperforms the equal-weighted strategy in the out-of-sample period but fails to outperform the benchmark index.

Keywords: Quantitative Investing, Multifactor Investing, Portfolio Optimization, Markowitz Optimization, Factor Investing, Value, Liquidity, Quality, Momentum

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Group Part

1. Introduction

The field of factor investing has gained significant attention in recent years as a means of identifying and capturing excess returns in the stock market. This approach to investment management seeks to identify underlying factors that drive stock prices and create investment strategies that capitalize on these factors.

While various factor investing approaches have been developed and studied, there is a growing recognition that these approaches can be combined to create more robust investment strategies. One of the challenges of using a single-factor investing approach is that individual factors can underperform their benchmarks for extended periods of time. For example, value factor indices have significantly underperformed in recent years, and the momentum factor tends to underperform the market significantly following market crashes. By combining multiple factors in portfolio construction, investors can capture the potential benefits of different investment styles and factors, reduce portfolio risk, and improve returns if the individual factors are not highly correlated.

In the individual parts of this work project, four different factor investing approaches are optimized and extended on in-sample data. The Value + Z-Score strategy combines valuation multiples with the Altman Z-Score, an insolvency prediction model, to optimize classic value strategies. The Liquidity strategy aims to improve Amihud's (2002) illiquidity factor by controlling for size. Quality + Value combines a three-dimensional quality factor based on profitability, earnings quality and safety with value metrics to enhance quality-only strategies. The Sector Momentum strategy aims to improve classic momentum strategies by focusing on momentum within sectors and combines a long strategy with a beta-neutral long/short strategy based on the current market state.

The motivation behind the individual strategies, the construction of the strategies and the performance in the in- and out-of-sample period is summarized in Part 2 of this thesis. Part 3 of this paper focuses on the combination of the individual strategies. The weightings of the individual strategies in the combined portfolio are optimized based on an in-sample period and compared with suitable benchmarks. Part 4 presents the results in the in-sample and out-of-sample period to evaluate the suitability of the entire strategy. Part 5 addresses the limitations of the construction and analysis. Finally, the results are summarized in Part 6 of this paper.

We show that the combined portfolio, which is optimized in the in-sample period based on Markowitz (1952), achieves a higher risk-adjusted return than an equal-weighted portfolio in the out-of-sample period. However, in contrast to the in-sample period, the optimized portfolio fails to outperform the equal-weighted and market-weighted S&P500 indexes. In addition, we document that the optimized strategy fails to generate a statistically significant alpha in the out-of-sample period. In conclusion, we find that combining the individual strategies cannot outperform an investment in the index during the out-of-sample period.

2. Individual Strategies

2.1. Value + Z-Score Strategy

2.1.1. Economic Motivation

Value investing, the investing in cheaply valued stocks relative to their fundamentals, remains a popular investment strategy to this day. A body of research in the financial literature over the past decades has found low-priced stocks, according to equity and enterprise multiples, to yield higher returns than high-priced stocks over the long term. While there is little dispute in academia about the fact that value stocks generate higher returns in the long term, there is a fierce debate as to whether these high returns represent a market anomaly or whether they compensate for the additional risk that is merely not captured by the Capital Asset Pricing Model (CAPM). A commonly used explanation by advocates of strong or semi-strong market efficiency is that the value premium compensates for higher distress risk. Consistent with this view, Fama and French (1995) find that high book-to-market stocks exhibit poorer earnings and show deteriorating profitability for five years before ranking. In line with this, Chen and Zhang (1998) find that value stocks are riskier because they are usually distressed firms with high financial leverage and substantial earnings risks.

In contradiction, many studies provide evidence that stocks of companies in financial stress yield lower returns and that safe companies with stable earnings and low financial leverage perform better. Dichev (1998) finds an underperformance of companies in financial distress as measured by the Altman Z-Score (Altman 1968) and Ohlson O-Score (Ohlson 1980). Using other distress indicators, numerous other authors confirm this and argue that this is inconsistent with the conclusion that value compensates for distress risk (Garlappi, Shu and Yan 2008; Campbell, Hilscher and Szilagyi 2008; Avramov et al. 2009). Furthermore, Piotroski (2000), Novy-Marx (2013), and Asness, Frazzini and Pedersen (2019), for example, use various indicators to show that stocks of high-quality firms based on accounting information outperform those of low-quality firms. The results raise the question of whether value strategies can be optimized by filtering out unsafe stocks and investing only in relatively safe value stocks.

A predictor of financial distress and corporate insolvency frequently used in research and practice is the Altman Z-Score (Altman 1968). Initially developed for manufacturing companies, the Z-Score has been further developed in various studies and extended to publicly traded companies in all industries (Z"-Score) (Altman and Hotchkiss 1998). While other, more complex methods have outperformed the Altman Z-Score in insolvency prognosis, recent studies (Altman, et al. 2017) show that it remains well-suited for large, public companies in developed markets. Since the calculation uses versatile metrics suitable to measure the company's financial health, the Z-Score could serve as an additional safety filter and reduce drawdowns during recessions.

For this reason, this analysis investigates whether the Altman Z-Score is a suitable indicator to improve value strategies and achieve outperformance compared to these pure value strategies and the market. Since the score is well suited for large, public companies in developed markets, corresponding strategies for the S&P500 will be tested.

2.1.2. Strategy

Instead of just combining one value indicator and one insolvency risk indicator, an optimization combining several parameters is performed based on in-sample data. To ensure an accurate assessment of the strategy, the optimization is performed over an in-sample period (March 2000 – June 2011) and later evaluated over an out-of-sample period (July 2011 – September 2022). All possible combinations of value indicators (P/B, P/E, P/S, P/CF, EV/EBITDA, and EV/EBIT) are combined with the Z-Score and optimized according to value quantiles (2, 3 ,5 and 10) and Z-Score cut-offs (10%, 20%, 33% or 50%). For the distress risk indicator, the variant of the Z-Score is chosen that is suitable for listed companies in all sectors (Z"-Score) and is calculated as follows:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

Where:

$X_1 = Working\ Capital\ /\ Total\ Assets$

$X_2 = Retained\ Earnings\ /\ Total\ Assets$

$X_3 = EBIT\ /\ Total\ Assets$

$X_4 = Book\ Value\ of\ Equity\ /\ Book\ Value\ of\ Total\ Liabilities$

A long signal is generated when a stock's value component is in the lowest quantile and the Z-Score is above the cut-off in the respective month. The strategies are rebalanced on a monthly basis.

As benchmarks, the stocks from the investment universe are weighted 1) by market capitalization (MW) and 2) equally (EW). In addition, value-only strategies with the same number of value quantiles as the optimized strategy are formed for comparison purposes, which only reflect the pure value ratios without considering the Z-Score. Furthermore, a Z-Score-only portfolio is created with the same cut-offs as in the optimized strategy, using only the Z-Score as a filter criterion without considering value criteria. The strategy with the best risk-adjusted return (by Sharpe ratio) in the in-sample period is evaluated in the out-of-sample period (July 2011 - September 2022). Further details on strategy formation can be found in the individual contribution.

2.1.3. Strategy Results

In the in-sample period, the best risk-adjusted performance is achieved when enterprise multiples are combined with the Z-Score (see individual contribution for a detailed overview). The best strategy in the in-sample period with a Sharpe ratio of 0.998 (see *Table 1*) consists of combining EV/EBITDA with Z-Score using deciles to generate the value signal and setting the Z-Score cut-off to 20%. The strategy of combining EV/EBIT and Z-Score with the same parameters performs similarly well (Sharpe ratio: 0.989). Both strategies also outperform the respective value-only strategies EV/EBITDA (Sharpe ratio: 0.873) and EV/EBIT (Sharpe ratio: 0.866), as well as the Z-Score-only strategy (Sharpe ratio: 0.326) in the in-sample period. The reference portfolios MW (Sharpe ratio: 0.141) and EW (Sharpe ratio: 0.340) are also significantly outperformed. In the out-of-sample period, the optimized strategies EV/EBITDA + Z (Sharpe ratio: 0.430) and EV/EBIT + Z (Sharpe ratio: 0.668) fail to outperform the respective value-only strategies (Sharpe ratio: 0.449 and 0.680), which in turn also perform worse than the market-weighted index (MW; Sharpe ratio: 0.876).

To quantitatively evaluate the strategies, the CAPM, the Fama and French three-factor model (FF3) and the Fama and French five-factor model (FF5) are used. *Table 1* shows the performance statistics and regression results of the FF5 regression for the EV/EBITDA + Z and EV/EBIT + Z strategies. Statistically significant alphas at the 95% significance level are highlighted bold. More detailed results and benchmark statistics can be found in the individual contribution. Both strategies show positive FF5 alphas in the in-sample period and over the whole period, but no significant alphas in the out-of-sample period. To measure the risk-adjusted return relative to a benchmark, the information ratio is calculated. Using the Fama and French market portfolio as a benchmark for the FF5 regression, we can see that both strategies outperform in the in-sample period and over the full period. The EV/EBIT + Z strategy even shows a positive FF5 information ratio over the out-of-sample period.

In order to draw better conclusions regarding the performance of the strategies, the information ratio against the S&P500 (IR SPX) is shown. The ratio is negative for both strategies in the out-of-sample period, which means that a simple investment in the index achieves the better risk-adjusted performance. For each strategy, the information ratio of the strategy versus the respective value-only strategy (IR EV/EBITDA and IR EV/EBIT) is also calculated. Again, both strategies exhibit a negative information ratio in the out-of-sample period, which means that the additional inclusion of the Z-Score would lead to a worse performance in this period.

	EV/EBITDA + Z			**EV/EBIT + Z**		
	In-sample	Out-of-sample	Full sample	In-sample	Out-of-sample	Full sample
Performance Statistics						
Annual return	0.224	0.098	0.16	0.213	0.137	0.175
Annual volatility	0.225	0.227	0.227	0.216	0.205	0.211
Sharpe Ratio	0.998	0.43	0.704	0.989	0.668	0.829
Maximum Drawdown	0.519	0.393	0.519	0.521	0.352	0.521
FF5						
Alpha	**0.0115 (0.000)**	-0.0018 (0.371)	**0.0046 (0.016)**	**0.0105 (0.000)**	0.0016 (0.329)	**0.0061 (0.000)**
Mkt-RF	1.2366 (0.000)	1.2763 (0.000)	1.2200 (0.000)	1.2224 (0.000)	1.1843 (0.000)	1.1586 (0.000)
SMB	0.2037 (0.053)	0.2364 (0.014)	0.2709 (0.000)	0.2145 (0.027)	0.1672 (0.033)	0.2310 (0.000)
HML	0.3273 (0.008)	0.5493 (0.000)	0.4659 (0.000)	0.3067 (0.007)	0.4743 (0.000)	0.4245 (0.000)
RMW	0.4192 (0.003)	0.1511 (0.191)	0.3400 (0.000)	0.5048 (0.000)	0.0902 (0.338)	0.3456 (0.000)
CMA	0.1022 (0.554)	0.2019 (0.131)	0.1293 (0.252)	-0.0038 (0.981)	0.1126 (0.302)	0.0318 (0.749)
R^2 (Adj.)	0.729	0.882	0.795	0.752	0.903	0.815
Information Ratios						
IR CAPM	1.64	-0.25	0.815	1.659	0.149	1.037
IR FF3	1.527	-0.197	0.799	1.555	0.36	1.065
IR FF5	1.204	-0.285	0.545	1.196	0.311	0.82
IR SPX	1.448	-0.462	0.577	1.458	-0.121	0.779
IR EV/EBITDA	0.76	-0.163	0.363			
IR EV/EBIT				0.918	-0.103	0.487

Table 1: Value + Z strategy, performance and associated risk statistics and regression results

Based on the results, it can thus not be concluded that the strategies are superior to the market or a pure value strategy. A detailed analysis, interpretation and discussion of the limitations can be found in the individual contribution.

2.2. Liquidity

2.2.1. Economic Motivation

The liquidity of a stock refers to the speed with which shares can be bought or sold without significantly affecting the stock price or incurring notable transaction costs (Bali, et al. 2013). In academic literature, it is generally acknowledged that less-liquid assets are priced at a discount, while more liquid assets have higher values for the same set of anticipated cash flows.

This discount is influenced by various factors for which investors are willing to pay less. First, it takes longer to trade less-liquid stocks and transaction costs are typically higher. Second, less-liquid stocks may be difficult to sell, especially for larger quantities, resulting in a greater loss if they cannot be sold when desired. Costs of illiquidity can arise from private information regarding the underlying fundamentals and order flows. For this information asymmetry, the uninformed investor must be compensated, as it comes with certain risks (Amihud, Mendelson and Pedersen 2005). Information asymmetry can arise from several components, including ownership structure and can be related to dividend policy. Tsui-Jung, Yi-Pei and Han-Fang (2017) find that firms with higher information asymmetry pay less dividends and have a more concentrated ownership. In addition, the firm's size influences the costs of illiquidity, as it is well established in academia that there is a positive relationship between a firm's size and liquidity. Consequently, the costs of illiquidity can also be partially explained by the risks associated with smaller firms relative to larger firms. Fama and French's (1992) paper is just one example demonstrating that size is a priced risk factor. For holding less-liquid shares, investors require compensation in the form of higher expected returns due to the associated costs.

Therefore, this analysis examines whether illiquidity is a suitable indicator to achieve out-performance of the benchmarks and whether controlling for size helps to improve the impact of this indicator on risk-adjusted return. Further information can be found in the individual part.

2.2.2. Strategy

Combinations of liquidity and size with varying numbers of liquidity quantiles are used to optimize the investment strategy in the in-sample period (February 2000 - May 2011). In the out-of-sample period (June 2011 - September 2022), the optimized strategy is evaluated to test if the results found in the in-sample period are robust. Based on liquidity and size or solely on liquidity, best-in-class, worst-in-class and long-short portfolios are formed. Long-short portfolios are constructed by buying stocks in the best-in-class portfolio and selling stocks in the worst-in-class portfolio.

To measure stock liquidity, Amihud's (2002) illiquidity measure is used. It is defined as the ratio of the average daily absolute return to the average daily dollar trading volume. In other words, this ratio represents the percentage change in price per dollar traded. A high ratio indicates that the month-to-month liquidity of the stock is low. The formula calculates illiquidity as follows:

$$ILLIQ_{iM} = \frac{1}{D_{iM}} \sum_{d=1}^{D_{iM}} \frac{|R_{idM}|}{Dvol_{idM}}$$

Where:

$D_{iM} = Number\ of\ trading\ days\ in\ month\ M\ for\ stock\ i$

$R_{idM} = \ Return\ of\ stock\ i\ on\ day\ d\ in\ month\ M$

$Dvol_{idM} = \ Dollar\ trading\ volume\ of\ stock\ i\ on\ day\ d\ in\ month\ M$

To select the stocks for controlled-size portfolios, the investment universe is divided into four quartiles of equal size, based on the market capitalization of the stocks. The illiquidity factor is then used to rank and allocate stocks into equal-sized quantiles inside each size quartile. The best-in-class (worst-in-class) portfolio is the quantile containing stocks with the highest (lowest) illiquidity factor values from each size quartile. If portfolios are constructed using only the illiquidity factor, the entire investment universe is ranked by the illiquidity factor and quantile sorted as before. To divide the stocks into liquidity quantiles, the 10%, 25%, and 50% cut-off levels are examined for both the portfolios with size control and those without size control. The cut-off levels establish the proportion of stocks allocated to each quantile. Since the illiquidity ratio is calculated every month, portfolios are rebalanced on a monthly basis as well.

The S&P500 is used as the investment universe to build the portfolios. For further information regarding the used data please refer to the individual contribution. The constructed portfolios are compared to each other and to the equal-weighted and market-weighted S&P500 index during the in-sample period in order to find the optimal strategy. The S&P500 is used as the benchmark since the portfolios are constructed based on the stocks in this index. In the in-sample period, the optimal portfolio is selected based on the risk-adjusted return defined by the Sharpe ratio. To evaluate how the selected strategy performs in the out-of-sample period, the same performance measures as during the selection process are used. For the quantitative analysis, the CAPM as well as the FF3 and FF5 are used to analyze and explain the performance of the strategy. More details about the strategy and analysis can be found in the individual contribution.

2.2.3. Strategy Results

In the in-sample period, the 10% cut-off level delivers the best results for the best-in-class and long-short portfolios. Both the best-in-class and long-short portfolios have superior results to the worst-in-class portfolios. Consequently, the focus for the further analysis lays on the performance of portfolios with a 10% cut-off level. *Table 2* shows the results of the portfolios with a 10% cut-off level with and without size control as well as the equal-weighted and market-weighted S&P500 benchmarks for the in-sample period.

	Portfolio	Annual excess return	Annual excess volatility	Sharpe ratio	Max drawdown
	EW S&P500	0.062	0.191	0.323	0.656
	MW S&P500	0.023	0.160	0.141	0.582
Without size control	Worst-in-class	-0.038	0.179	-0.214	0.739
	Best-in-class	0.139	0.300	0.461	0.598
	Long-Short	0.162	0.219	0.739	0.128
With size control	Worst-in-class	-0.026	0.236	-0.110	0.693
	Best-in-class	0.122	0.240	0.509	0.431
	Long-Short	0.106	0.188	0.561	0.098

Table 2: Liquidity strategy in-sample period performance and associated risk statistics

Combining liquidity with size lowers the returns for the best-in-class and long-short portfolios. While the Sharpe ratio decreases for the long-short portfolio, it increases for the best-in-class portfolio by controlling for size. The long-short portfolio without size control exhibits the highest risk-adjusted return in the in-sample period with a Sharpe ratio of 0.74, significantly outperforming both S&P500 benchmarks and other portfolios. The long-short portfolios are also least affected by drawdowns.

Table 3 shows the results of the previously analyzed portfolios in the out-of-sample period. In the out-of-sample period, the results cannot be confirmed as the optimal strategy yields the lowest annual return (-0.035) and Sharpe ratio (-0.258) compared to all other portfolios at the 10% cut-off level and both S&P500 benchmarks. As the chosen portfolio buys stocks with low liquidity (smaller stocks) and sells stocks with high liquidity (larger stocks), the poor performance can be attributed to the fact that large S&P500 companies have performed better than smaller S&P500 companies since 2011 (Morningstar 2020). This is evident from the fact that the best-in-class portfolio performs better than the worst-in-class portfolio under size control. Therefore, the liquidity effect that is not captured by size still has a positive impact on returns. Further information on the economic reasoning can be found in the individual part.

	Portfolio	Annual excess return	Annual excess volatility	Sharpe ratio	Max drawdown
	EW S&P500	0.102	0.161	0.637	0.175
	MW S&P500	0.123	0.143	0.860	0.130
Without size control	Worst-in-class	0.122	0.138	0.882	0.118
	Best-in-class	0.079	0.231	0.344	0.247
	Long-Short	-0.035	0.138	-0.258	0.547
With size control	Worst-in-class	0.109	0.160	0.684	0.163
	Best-in-class	0.117	0.186	0.627	0.187
	Long-Short	0.003	0.081	0.031	0.295

Table 3: Liquidity strategy out-of-sample period performance and associated risk statistics

Table 4 displays the regression statistics for the FF5 regression over the out-of-sample period for a 10% cut-off level. Respective p-values are in parentheses. During the out-of-sample period, the selected strategy achieves a negative abnormal return with a statistically significant monthly alpha of -0.004. The worst-in-class portfolio without size control has a positive statistically significant monthly alpha of 0.002. All other portfolios exhibit insignificant alpha at any of the three standard significance levels (99%, 95%, and 90%). Only the two best-in-class portfolios have higher market beta than the S&P500 benchmark. This indicates that they are more volatile than the equal-weighted S&P500. All other portfolios are less volatile than the S&P500 benchmark. Both worst-in-class portfolios as well as the best-in-class portfolio with size control outperform the S&P500 benchmark as demonstrated by the respective information ratios.

	Portfolio	Alpha	Market	SMB	HML	RMW	CMA	IR	R2 Adj.
	Equal weighted S&P500	0.000 (0.979)	1.011 (0.000)	0.105 (0.001)	0.190 (0.000)	0.077 (0.050)	0.020 (0.653)	-0.008	0.972
Without size control	**Worst-in-class**	0.002 (0.024)	0.935 (0.000)	-0.177 (0.000)	-0.008 (0.765)	0.055 (0.148)	0.050 (0.259)	0.721	0.965
	Best-in-class	-0.002 (0.228)	1.257 (0.000)	0.445 (0.000)	0.510 (0.000)	0.049 (0.644)	0.053 (0.666)	-0.383	0.900
	Long-Short	-0.004 (0.040)	0.324 (0.000)	0.625 (0.000)	0.521 (0.000)	-0.001 (0.996)	0.005 (0.969)	-0.655	0.663
With size control	**Worst-in-class**	0.001 (0.485)	1.009 (0.000)	-0.001 (0.984)	0.128 (0.002)	-0.017 (0.768)	-0.116 (0.081)	0.221	0.941
	Best-in-class	0.001 (0.511)	1.095 (0.000)	0.231 (0.001)	0.251 (0.000)	-0.001 (0.990)	0.058 (0.554)	0.208	0.904
	Long-Short	0.000 (0.919)	0.088 (0.062)	0.234 (0.009)	0.126 (0.106)	0.021 (0.845)	0.175 (0.159)	-0.032	0.187

Table 4: Liquidity strategy out-of-sample period FF5 Regression results

Consequently, it cannot be concluded from the results that the optimized strategy is superior to the market. A detailed analysis of the results as well as a discussion of the limitations can be found in the individual section.

2.3. Quality + Value

2.3.1. Economic Motivation

Quality, unlike size or momentum, has no universally accepted definition and seems to remain the factor with the weakest consensus among the traditional equity factors. Strategies based on quality depend heavily on the author's definition. The rationale behind quality-based investment strategies is to capture the documented excess returns of high-quality stocks over low-quality stocks. Quality factors are solely based on accounting data, which contain ample data that can be combined and therefore make various definitions of the quality factor likely. Feng, Giglio and Xio (2020) show this propagation in a survey of 150 publicly available factors, of which more than half can be directly related to the quality factor. Moreover, academic research about quality investing differs from its practical implementation. While scholars primarily consider quality as a single metric, practitioners define quality as a combination of various metrics (e.g. Asness, Frazzini and Pedersen 2019).

Despite the lack of a distinct definition, quality investing has been ubiquitous in modern finance and is often implemented as a risk-factor combination, though sometimes as a standalone strategy. In practice, investment strategies based on quality are often implemented in combination with other factors such as value and size. Index managers including MSCI, FTSE Russell and S&P have generally included quality as a part of their multi-factor offerings, arguing that the quality factor provides diversification due to its low correlation with the value factor.

Hence, combining quality with value is based on a simple premise: buying high-quality stocks cheaply. An early pioneer in buying high-quality companies at low valuations is

Benjamin Graham. Although Graham is primarily associated with value metrics such as price-book-ratio or price-earnings-ratio, he believes that quality and value go hand in hand (Graham 1949). Greenblatt (2010) follows a similar approach of combining quality and value. He combines the quality metric return on invested capital with the value metric EV/EBIT and only invests in stocks with the highest combined metric. In addition, Novy-Marx (2013) finds that gross profitability is strongly negatively correlated with value, making profitability a valuable hedge to value investors. More specifically, he shows that strategies based on a combined quality and value signal generate higher risk-adjusted returns rather than using the factors alone or running quality and value side-by-side.

Based on the above, this analysis investigates strategies that link quality with value. Herein, the analysis combines the strengths of academic research with the constraints of practitioners. Specifically, quality is considered as multi-faceted rather than described by a single metric. In this analysis, quality is defined as a combination of three dimensions: *profitability*, *safety* and *earnings quality*. Profitability is measured by gross profitability (gross profits-to-assets), safety by long-term debt-to-equity (LTDE) and earnings quality by cashflow accruals (difference between net income and cash flows from investing and operating activities normalized by net operating assets). Gross profitability has been shown to outperform other profitability measures (Novy-Marx 2014). In addition, gross profitability is free from accounting manipulations, as opposed to return ratios. Lepetit et al. (2021) show that LTDE uniquely provides strong downside protection when markets are experiencing turbulence. Hence, LTDE shows typical characteristics of a quality factor. Recent findings about Sloan's (1996) famous accruals have shown that the negative relationship to expected returns has greatly attenuated and is not significant (Richardson and Sloan 2003, Lepetit, et al. 2021). On the other side, cash flow accruals have been shown to generate statistically significant alpha (Lepetit, et al. 2021). In a long-only framework focusing on S&P500 stocks from the beginning of 2000 until September 2022, the three-dimensional quality factor is combined with several value metrics to invest in high-quality stocks at a low valuation. The strategy is expected to deliver above-average risk-adjusted returns as it combines two empirically verified premia: the quality premium and the value premium.

2.3.2. Strategy

To find the ideal strategy, several parameters are optimized. In addition, the entire period is divided into an in-sample period (March 2000 – June 2011) and an out-of-sample period (July 2011 – September 2022) to accurately test the performance of the optimized strategy.

The quality factor consists of three metrics: gross profitability, cash flow accruals and long-term debt-to-equity. The profitability dimension is sorted in ascending order, meaning that firms with high gross profits are considered high-quality firms. The opposite holds for the safety and earnings quality dimensions. Low accruals and low leverage are associated with high quality. As value factors, five different metrics are tested: price-to-book (P/B), price-to-earnings (P/E), price-to-cash flow (P/CF), EV/EBIT and EV/EBITDA. Lower value metrics are associated with a positive value signal. Lastly, the portfolio is optimized by the number of quantiles (3, 5, 8 and 10) for both the quality and value signal.

Each month, each quality metric is converted into ranks, ensuring that the highest rank is allocated to the highest quality company according to this metric. Then, each metric is standardized to obtain a z-score and to put each measure on equal footing. Finally, the combined quality score is the average of the individual z-scores. The investment universe is then divided into quantiles based on the quality factor. Simultaneously, the same number of quantiles based on the value factors are created. With stocks that fall in the highest quantile of both the quality factor and value factor (i.e. show the highest quality and lowest valuations), a long-only portfolio is formed.

Finally, the optimal combined quality and value strategy is selected based on the highest Sharpe ratio in the in-sample period. The performance of the optimized strategy is subsequently tested in the out-of-sample period against benchmarks. As benchmarks, four different portfolios are shown: equal-weighted S&P500 (EW), market-weighted S&P500 (MW), quality-only and value-only, with the same number of quantiles as the combined portfolio. Further information regarding the dimensions and strategy construction can be found in the individual contribution.

2.3.3. Strategy Results

The three-dimensional quality factor performs best in combination with EV/EBIT as value metric in the in-sample period, selecting only stocks that are in the top 12.5% (i.e. eight quantiles) of both the quality and value factor[1]. *Table 5* reports the performances and associated risk statistics of the optimized portfolio and its benchmarks. The best-performing strategy delivers an annual excess return of 20.3% and a Sharpe ratio of 0.91. In addition, the strategy significantly outperforms its benchmarks. The maximum drawdown is also lowest using the combination of quality and value. Hence, combining the quality factor with the value factor (i.e. investing in the intersection of both portfolios) yields significant gains in terms of risk-adjusted returns in the in-sample period, which aligns with the findings of Novy-Marx (2013, 2014) and Greenblatt (2010). On a side note, *Table 20* in the appendix suggests that the combination of the individual dimensions into a composite factor significantly enhances the performance and risk statistics of the quality factor, as demonstrated by the information ratios.

In the out-of-sample period, however, the optimized strategy fails to outperform its benchmarks and shows the worst performance with regard to the Sharpe ratio. The market-weighted portfolio shows the highest Sharpe ratio, followed by the quality-only strategy. In contrast to

[1] For further analyses, the terms best, combined or optimized portfolio/strategy refer to this portfolio (i.e. 3Dim + EV/EBIT with 8 quantiles). Illustrative examples of companies that are in the top 12.5% of both the quality and value factors are Yum! Brands, Allstate, Gap, MetLife, Best Buy, Humana, (Dotdash) Meredith and NCR Corporation, among others.

the in-sample period, combining quality with value does not deliver any benefits. On the contrary, running quality as a stand-alone strategy results in superior risk-adjusted returns.

Strategy	Signal	Quantiles	In-sample (2000/03 - 2011/06)				Out-of-sample (2011/07 - 2022/09)				Full-sample (2000/03 - 2022/09)			
			Exc Ret	Vol	SR	DD	Exc Ret	Vol	SR	DD	Exc Ret	Vol	SR	DD
Quality + Value	3Dim + EV/EBIT	8	0.203	0.224	0.911	0.371	0.100	0.208	0.481	0.289	0.151	0.216	0.697	0.371
Quality-Only	3Dim	8	0.066	0.196	0.336	0.442	0.133	0.155	0.859	0.224	0.099	0.177	0.558	0.442
Value-Only	EV/EBIT	8	0.182	0.217	0.839	0.548	0.136	0.201	0.675	0.358	0.159	0.210	0.758	0.548
Benchmark	EW	-	0.065	0.190	0.340	0.549	0.105	0.161	0.652	0.272	0.085	0.176	0.480	0.559
	MW	-	0.023	0.160	0.141	0.490	0.126	0.143	0.876	0.219	0.073	0.152	0.476	0.490

Table 5: Quality + Value and benchmarks performance and risk statistics

Table 6 exhibits the results of a linear regression aiming to explain the long-only returns of the combined quality and value factor portfolio over the in-sample, out-of-sample and entire period. The Fama and French (2015) five-factor model (FF5) is used, whose explanatory variables are market (Mkt-RF), size (SMB), value (HML), profitability (RMW) and investment (CMA). In the in-sample period, the combined portfolio delivers an alpha of 120 basis points and is statistically significant at any given conventional level. The strategy also shows a statistically significant alpha at the 95% level over the entire period. In the out-of-sample period, however, the optimized portfolio generates a negative alpha, though statistically insignificant. The combined quality and value strategy exhibits strong positive and significant exposure to the market. Lastly, the optimized portfolio outperforms Fama and French's market portfolio in the in-sample and entire period, as demonstrated by the respective information ratios.

Portfolio	Period	Exc Ret	FF5 Regression							
			Alpha	Market	Size	Value	Profitability	Investment	Adj. R^2	IR
3Dim + EV/EBIT	In-sample	0.016	0.012***	1.086***	0.114	0.454***	0.463***	-0.369*	0.585	1.006
			(3.008)	(11.028)	(0.891)	(3.047)	(2.723)	(-1.739)		
	Out-of-sample	0.009	-0.001	1.119***	0.138	0.267**	0.221	0.440**	0.718	-0.125
			(-0.399)	(16.169)	(1.063)	(2.343)	(1.416)	(2.403)		
	Full-sample	0.006	0.005**	1.071***	0.131	0.402***	0.386***	-0.020	0.632	0.475
			(2.108)	(18.572)	(1.440)	(4.314)	(3.588)	(-0.140)		

Table 6: Quality + Value FF5 alphas and factor loadings of the optimized strategy; t-statistics in parentheses.
** p < 0.10, ** p < 0.05, *** p < 0.001*

Table 21 reports the information ratios of the combined, quality-only, value-only and equal-weighted market portfolios to the benchmark S&P500 (IR SPX). In addition, the information ratios of the combined portfolio to both the quality-only and value-only portfolios are shown. All portfolios show positive information ratios in the in-sample and entire period, except for the quality-only portfolio, which exhibits a positive information ratio for all periods. The quality-only portfolio also shows significant alphas for all periods, strongly suggesting the existence of a quality premium. The optimized portfolio thus outperforms the S&P500 only in the in-sample and entire period. Finally, the combined portfolio achieves a risk-adjusted outperformance versus the quality-only in the in-sample and entire period, shown by the positive information ratios (IR 3Dim in *Table 21*). However, during the out-of-sample period, the quality and value portfolio fails to outperform the quality-only portfolio. Note that the full-sample results deliver limited information value as they are strongly biased towards the optimized portfolio in the in-sample period.

The results show that investing in high-quality stocks that are cheap is highly rewarding in the in-sample period, in contrast to investing only in high-quality stocks. However, this investment strategy significantly underperforms the market and quality-only strategies during the out-of-sample period. During this period, value stocks are penalized, while quality stocks are favored, indicating that the general market environment tilts towards growth stocks. Consequently, combining quality with value does not benefit quality-only strategies. Finally, quality as a stand-alone strategy outperforms the equal-weighted benchmark during all periods, suggesting the existence of the quality premium. Further discussions and practical implications can be found in the individual contribution.

2.4. Sector Momentum

2.4.1. Economic Motivation

The momentum factor is a great puzzle in financial research as it has historically achieved substantial abnormal returns although it should not exist according to the weak form of the efficient market hypothesis. The fact that recently outperforming stocks tend to outperform in the short-term future as well, has first been documented by Jegadeesh and Titman (1993). They achieve high excess returns by forming a portfolio that buys the 10% best performing stocks of the previous 12 months and sells the stocks that performed worst over that period. These findings marked the beginning of research in cross-sectional momentum. It has been shown that momentum is robust to other risk factors like market, size, value and liquidity (Asness 1995), and can be found in several geographical regions (Fama and French 2012) and different asset classes (Asness, Moskowitz and Pedersen 2013). The momentum factor is, unlike many other proclaimed factors, still significant if corrected for multiple testing of research factors (Harvey and Liu 2019). Several kinds of momentum factors have been successfully replicated on more recent data (Jensen, Kelly and Pedersen 2021).

The cause of this effect is not entirely clear to this day. Most explanations link the pattern of strong outperformance during the first 12 months after the observation period and underperformance in the following years to a delayed overreaction of market participants (Jegadeesh and Titman 1993; Hong and Stein 1999). Other approaches include varying investor confidence (Daniel, Hirshleifer and Subrahmanyam 1998), gradual information diffusion (Chan, Jegadeesh and Lakonishok 1996), investment behavior of institutions (Gutierrez and Prinsky 2007) or behavioral finance concepts like representativeness and conservatism (Barberis, Shleifer and Vishny 1998) or loss aversion and mental accounting (Grinblatt and Han 2005).

There is evidence that momentum is not only an individual stock phenomenon but can also be found in sectors and industries and that general momentum is often caused by sector momentum. Moskowitz and Grinblatt (1999) find that momentum returns become insignificant when they are controlled for industry momentum and that strategies that are based on industry momentum are more profitable than individual momentum strategies. These two findings are confirmed by Shynkevich (2013) using time-series industry momentum strategies. A successful cross-sectional sector momentum strategy has been tested by J. Wang et al. (2017) using large-cap sector ETFs. Their strategy achieves significant alpha against the Fama and French three-factor model.

Although momentum strategies can achieve high abnormal returns against the market, they occasionally suffer from severe drawdowns. These momentum crashes resulted in losses of about 92% in 1932 or 73% in 2009 for a classic momentum strategy (Daniel and Moskowitz 2016). More generally, these losses happen after the transition from a down market to an up market when the high performance of the rebounding short positions can exceed the returns of the long positions by a multiple (Asem and Tian 2010). The reason for this lies in the time-varying exposure to market risk. Momentum portfolios usually have a positive beta but after down markets their beta can be strongly negative which then leads to high losses during a market rebound (Grundy and Martin 2001). Momentum crashes are probably the biggest flaw of momentum strategies, but fortunately there are means to mitigate these drawdowns. Various approaches have been tested, for example a momentum strategy that is based on residual returns to decrease its time-varying risk factor exposure (Blitz, Huij, and Martens 2011) or scaling the strategy based on realized volatility (Barroso and Santa-Clara 2015), semi-volatility (F. Wang and Yan 2021) or expected return and volatility (Daniel and Moskowitz 2016). All strategies were able to increase the risk-adjusted return of the initial momentum strategy.

The goal of this strategy is to maximize the risk-adjusted returns by achieving high total returns that are typical for momentum strategies, while avoiding large drawdowns from momentum crashes to keep the volatility on a low level. The investment universe is comprised of eleven ETFs that each track the performance of the stocks from one sector of the S&P500 index. They are chosen for several reasons. We have seen that momentum can be exceptionally strong within sectors and industries. To make use of this, there is no need to invest in individual stocks. The advantage is that all the ETFs are highly liquid, inexpensive to trade and easy to borrow. This makes the strategy much easier to implement in practice, reduces the explicit and implicit trading costs and severely lowers short-sale constraints. It has been shown that these factors can diminish the success of individual stock momentum strategies (Lesmond, Schill, and Zhou

2004), so in this way, we can avoid these issues. As a market proxy and benchmark, the SPDR S&P500 ETF Trust (SPY) is used because it is the market-weighted investment alternative of the underlying assets to the sector ETFs and replicates the performance of a broad US equity index.

2.4.2. Strategy Construction

The strategy is constructed step-by-step over an in-sample period from January 2000 until May 2011. After each step, the results are evaluated and based on this, the next step in the process is decided on. In the first step, various cross-sectional sector momentum strategies are formed. The portfolio invests in the assets with the highest returns during the observation period and, if applicable, short sells those with the lowest returns. The strategies differ by the following parameters: the start of the observation period (in months before today), the end of the observation period (in months before today), the number of assets the strategy buys and short sells and the type of the strategy. Consequently, each strategy is defined and named by its parameter values like this: (start, end, positions, type). The strategy called (12, 1, 2, long/short) for example, has an observation period that starts 12 months before today and ends one month before today, takes a long position in the two assets with the highest returns in the observation period and a short position in the two assets with the lowest returns. All possible combinations are formed from the following parameter inputs: start ∈ {1, 3, 6, 12}, end ∈ {0, 1}, positions ∈ {1, 2, 3}, type ∈ {long, long/short}. This yields a total of 42 strategies. The portfolios are equal-weighted; long positions sum to one and short positions sum to minus one. The weights are calculated at the end of each month after close of the last business day and all trades are made at open of the following business day. The holding period is always one month. *Table 7* shows performance statistics of selected strategies that achieved the best or worst result in at least one metric. Overall, the long strategies have outperformed the long/short strategies. The highest returns and Sharpe ratios are achieved by long strategies with longer observation periods, whereas the lowest volatility and drawdown come from a short-term long/short strategy. The results are in line with the previous findings that sector momentum profits mainly come from their long positions (Moskowitz and Grinblatt 1999) and that the short positions of momentum portfolios can lead to large drawdowns (Daniel and Moskowitz 2016).

Start	End	Positions	Type	Return	Volatility	Sharpe ratio	Drawdown
3	0	3	long/short	-1.07%	12.60%	-0.2642	-29.99%
3	1	1	long/short	-12.31%	28.46%	-0.5034	-79.80%
3	1	3	long/short	-5.07%	14.10%	-0.5130	-45.36%
6	0	1	long/short	-0.39%	28.58%	-0.0904	-60.04%
6	1	2	long	10.16%	15.91%	0.4856	-39.06%

Table 7: Sector Momentum, excerpt of performance statistics. The best (worst) result is highlighted in green (red). The whole table can be found in the individual contribution.

To mitigate the drawdowns and to improve the performance of the long/short strategies, they are optimized in the second step of the process to decrease their market risk exposure. Specifically, the optimization aims to maximize the portfolio signal value, which is the weighted average return over the observation period of the assets, with the constraints that the estimated market beta of the portfolio is zero, and long (short) positions sum to one (minus one). The market beta of each asset for the following month is estimated by calculating the beta with the SPY over the observation period, using daily returns. This optimization is carried out for each month over the in-sample period for all strategies with at least two positions. The optimization improves about half of the strategies. The best results are achieved by strategies with a three months lookback. *Table 8* compares the performance of the non-optimized and optimized version of the (3, 0, 3, long/short) strategy. It almost halves its drawdown and is now by far the most stable strategy out of all tested so far. This, and its low correlation with the market (-0.25) and other long strategies (around 0), creates the possibility to improve the risk-adjusted returns of the long strategies by combining them with this long/short strategy.

			Non-optimized				Optimized			
Start	End	Positions	Return	Volatility	Sharpe ratio	Drawdown	Return	Volatility	Sharpe ratio	Drawdown
3	0	3	-1.07%	12.60%	-0.2642	-29.99%	3.91%	11.06%	0.1400	-16.72%

Table 8: Sector Momentum, comparison between optimized and non-optimized version for the best long/short strategy. Comparisons for all long/short strategies can be found in the individual contribution.

In the final step, long strategies are combined with the optimized long/short strategy. A simple regime-switching process that invests in the long/short strategy if the market return over the three months observation period is negative and in the long strategy otherwise, defines the combined strategy. The best performing strategy is the combination of the (6, 1, 2, long) strategy and the (3, 0, 3, long/short) strategy. It achieves a Sharpe ratio of 0.89 over the in-sample period and substantially outperforms the market, as can be seen in *Figure 1*. Its correlation to the market is only 0.19.

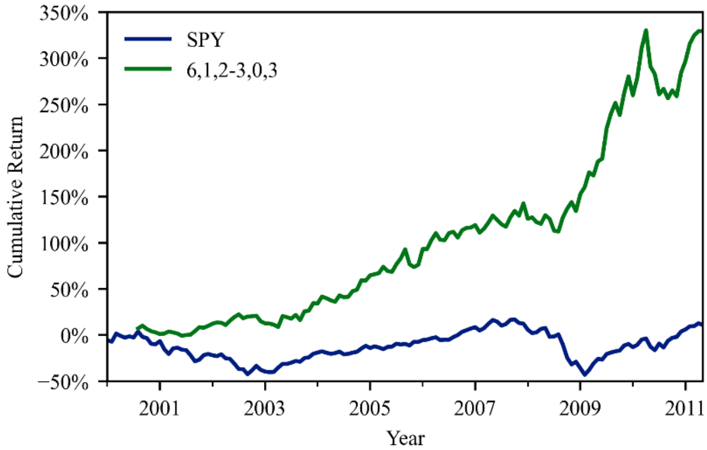

Figure 1: Sector Momentum, cumulative returns of the combined strategy and the market over the in-sample period (2000:01 – 2011:05).

The out-of-sample period starts in June 2011 and ends in September 2022. The strategy yields lower returns and is outperformed by the market on a risk-adjusted basis, although it has slightly lower volatility and drawdown (see *Table 9*). The correlation to the market increased from 0.19 to 0.31. To better understand which risk factors drive the performance of the strategy, a Fama and French (2015) five-factor model and a Carhart (1997) four-factor model are used to analyze the strategy excess returns. Only the market factor has a significant coefficient (0.37) out-of-sample. While the strategy achieved significant alpha in-sample and over the full period, it does not do so out-of-sample (see *Table 22*). The four-factor model is able to add some explanatory power compared to the five-factor model, but the results are very similar.

	Return	Volatility	Sharpe ratio	Draw-down
Strategy				
In-sample	14.40%	13.25%	0.8926	-17.13%
Out-of-sample	10.04%	15.06%	0.6279	-21.30%
Full period	11.93%	14.23%	0.7313	-21.30%
Market				
In-sample	0.89%	16.59%	-0.0905	-51.30%
Out-of-sample	12.12%	15.19%	0.7584	-22.90%
Full period	6.32%	15.95%	0.2975	-51.30%

Table 9: Sector Momentum, performance statistics of the combined strategy and the market over all periods.

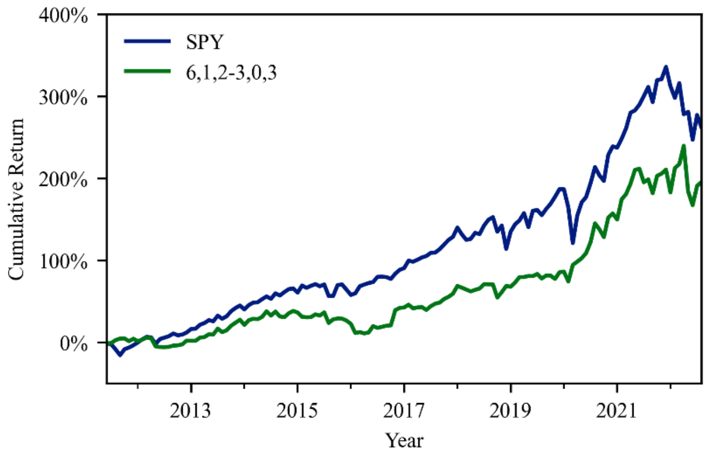

Figure 2: Sector Momentum, cumulative returns of the combined strategy and the market over the out-of-sample period (2011:06 – 2022:09).

The momentum factor is significant in-sample and over the full period, but not out of sample (see *Table 23*). *Figure 2* shows the cumulative returns of the strategy and market out-of-sample. Although the increased correlation is visible and the strategy cannot keep up with the performance of the market, there are some positive aspects. The strategy provides downside protection in 2020 like it did in-sample during the dotcom bust or the financial crisis. The different benchmark results over the two periods do not result from a performance crash of the strategy. Its returns are relatively stable, but the market shows different characteristics over the periods. While its returns are flat in-sample it performs unusually strong out-of-sample. A possible conclusion is that the strategy is more defensive compared to the market but provides solid protection from market stress. In a tenacious bull market, however, it can fall short of the returns the market provides. A more detailed conclusion and discussion about the limitations about this strategy can be found in the individual part.

3. Combined Strategy

Single-factor strategies are created to represent the performance of stocks with specific characteristics that have shown risk-adjusted outperformance in the long term. However, these factors can also underperform market-weighted indexes for extended periods of time. Value factor indices, for instance, have significantly underperformed their benchmarks over the past decade (Asness 2022) and the momentum factor tends to underperform the market significantly after market crashes (Daniel and Moskowitz 2016).

The advantage of using multiple factors in portfolio construction is that it allows to capture the potential benefits of different investment styles and factors, and it can help to reduce portfolio risk and improve returns. Consequently, multi-factor strategies are widely applied in practice. Blackrock counts more than 25 fund providers that offer multi-factor strategies (Blackrock 2022).

Combining the individual strategies aims to create a portfolio that yields a higher risk-adjusted return than each of the individual strategies. For this purpose, we use the portfolio optimization approach according to Markowitz (1952).

Markowitz' Portfolio Theory is a mathematical framework for constructing a diversified investment portfolio that aims to maximize expected return while minimizing risk. The theory is based on the idea that the relationship between risk and return is linear, and that investors can choose a portfolio that offers the optimal trade-off between these two factors. The expected return of a portfolio is calculated as the weighted sum of the returns of the individual assets in the portfolio. The portfolio's risk is defined as the standard deviation of the portfolio. The efficient frontier is a concept from portfolio theory that refers to the set of all portfolios that provide the highest possible expected return for a given level of risk, in other words that offers the best trade-off between risk and return. The tangency portfolio is a specific portfolio that lies on the efficient frontier and is the optimal portfolio because it yields the highest risk-adjusted return as measured by the Sharpe ratio. The optimization problem is defined by the following formula.

$$\arg\max_{\mathbf{t}} \frac{\mathbf{t}'\boldsymbol{\mu}^e}{\mathbf{t}'\boldsymbol{\Omega}\mathbf{t}}, \text{s.t.} \sum_{i=1}^{n} t_i = 1, t_i \in [0,1],$$

where:

$\boldsymbol{t} = Vector\ of\ portolio\ weigths,$

$\boldsymbol{\mu}^e = Vector\ of\ asset\ excess\ returns,$

$\boldsymbol{\Omega} = Covariance\ matrix\ of\ assets$

$n = Number\ of\ assets$

For the Markowitz optimization, the best-performing strategies in-sample from the individual optimizations are employed. In the following, for the Value + Z-Score strategy, the combination of EV/EBITDA and Z-Score with value deciles and Z-Score cut-off at 20% is used accordingly. For the Liquidity component, the long/short strategy without size control is used. The Quality + Value component consists of the combination of the defined quality factor with EV/EBIT and eight quantiles each. For the Sector Momentum component, the combination of the (6, 1, 2, long) strategy and the (3, 0, 3, long/short) strategy is employed.

To obtain the efficient frontier, 100,000 weighting combinations of the strategies are simulated for the in-sample period (August 2000 - June 2011). The best combination of strategies (tangency portfolio) according to the in-sample data is subsequently evaluated on out-of-sample data (July 2011 – September 2022). An in-sample/out-of-sample split is necessary to assess the combined strategy appropriately since the optimization is based on past data. To evaluate the suitability of a portfolio optimization, the strategy must be tested on new data on which no optimization has been performed.

The performance statistics of the tangency portfolios are compared to the individual strategies, an equal-weighted portfolio that invests 25% in each of the strategies and the equal-weighted and market-weighted S&P500.

4. Results

4.1. In-Sample Performance

Before combining the individual strategies, their return performances are briefly analyzed within the in-sample period. *Figure 3* shows the cumulative returns for each individual strategy in the in-sample period.

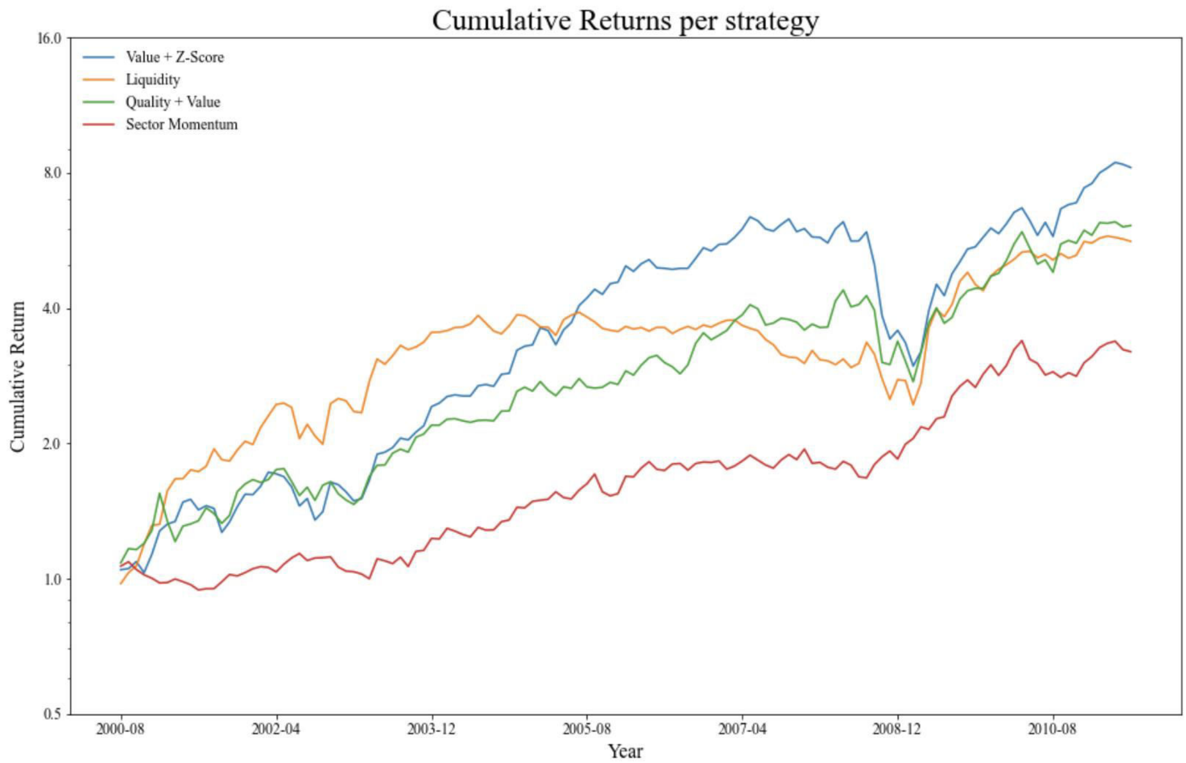

Figure 3: Cumulative returns of the individual strategies

As shown in the plot, the returns of each strategy vary strongly over time. While the Liquidity strategy shows the highest total return at the beginning of the in-sample period, Value + Z-Score and Quality + Value show a strong increase in the further course. Whereas the three strategies plummet during the financial crisis in 2008/2009, the Sector Momentum strategy performs very well in this phase, providing strong downside protection. During the in-sample period, the Value + Z-Score strategy generates the highest cumulative return, followed by the Quality + Value, Liquidity and Sector Momentum strategies.

Table 10 displays the correlation matrix among the individual strategies in the in-sample period. The table shows that the Value + Z-Score strategy and the Quality + Value strategy exhibit the highest correlation. The high correlation can be explained by the fact that both strategies have a value component in their selection criteria. The Sector Momentum strategy exhibits its low correlations to all other individual strategies and shows even a negative correlation to the Liquidity strategy. The low correlation of the Sector Momentum strategy with the other strategies is expected to offer diversification benefits to the combined portfolio.

	Value + Z-Score	Liquidity	Quality + Value	Sector Momentum
Value + Z-Score	1.000			
Liquidity	0.640	1.000		
Quality + Value	0.755	0.453	1.000	
Sector Momentum	0.197	-0.033	0.089	1.000

Table 10: Correlation matrix of the individual strategies

Figure 4 shows 100,000 portfolios compiled from different weightings of the individual strategies. The annual excess return is shown on the y-axis, while the x-axis shows the annual excess volatility. The black line in the plot marks the efficiency frontier. All combinations of the individual strategies below this line are considered inefficient, as there is always a portfolio with a higher excess return given the same excess volatility. The minimum standard deviation portfolio shows the combination of the individual strategies that generates the lowest annual excess volatility in the in-sample period and is located on the efficient frontier. The tangency portfolio is the optimal combination of the individual strategies that maximizes the Sharpe ratio during the in-sample period and therefore lies on the efficient frontier. The Value + Z-Score strategy is the only portfolio of the individual strategies that lies on the efficient frontier. This can be explained by the fact that the Value + Z-Score portfolio achieves the highest annual excess return of all individual strategies. In addition, no combination of the four individual strategies can achieve a higher annual excess return. All other individual strategies place below the efficient frontier, which means that for each portfolio, there is a combination of the individual strategies that delivers a higher excess return given the same annual excess volatility. The Sector Momentum strategy has a much lower annual excess volatility compared to the other individual strategies, but on the other hand, also shows lower excess returns. The comparison of the individual strategies shows that none of them is superior to any other in terms of both annual excess volatility and annual excess return.

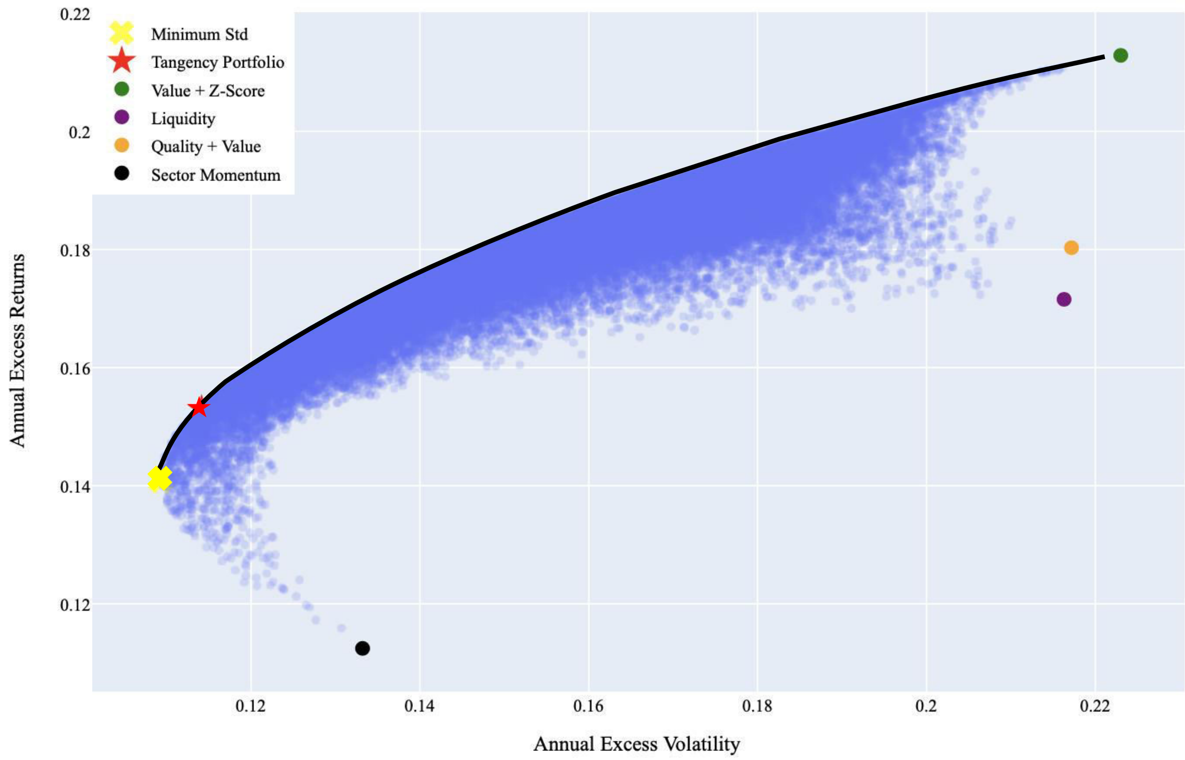

Figure 4: Efficient frontier

The weights of the individual strategies calculated with Markowitz' mathematical framework to determine the tangency portfolio are shown in *Table 11*. As shown, the portfolio optimizing the Sharpe ratio invests 5.98% in the Value + Z-Score strategy, 22.82% in the Liquidity strategy, 16.81% in the Quality + Value strategy and 54.39% in the Sector Momentum strategy. As previously indicated, the high proportion of the Sector Momentum strategy can be explained by the low correlation to the other strategies while the other strategies have higher correlations between each other. Value + Z-Score provides the highest annual excess return, but also shows a high correlation to all other individual strategies, resulting in a low weighting of this strategy within the tangency portfolio.

	Value + Z-Score	**Liquidity**	**Quality + Value**	**Sector Momentum**
Tangency weights	5.98%	22.82%	16.81%	54.39%

Table 11: Tangency portfolio weights

Table 12 shows the performances and associated risk statistics of the tangency portfolio in the in-sample period. The results are compared to the equal-weighted portfolio, the S&P500 benchmarks and the individual strategies. The tangency portfolio achieves an annual excess return of 15.3% with an annual excess volatility of 0.114, resulting in a Sharpe ratio of 1.340. In terms of risk adjusted returns, the tangency portfolio outperforms the equal-weighted portfolio, the S&P500 benchmarks and the individual strategies. As the individual strategies all have higher Sharpe ratios than the S&P500 benchmarks and the tangency portfolio is an optimized combination of those individual strategies that aims to maximize the risk-adjusted return, the results are no surprise. Through the diversification of the risk by investing in different individual strategies, the risk-adjusted return increases for the tangency and equal-weighted portfolio compared to the individual strategies. Investing in the tangency portfolio also results in a lower maximum drawdown in the in-sample period compared to the equal-weighted portfolio, the individual strategies and the S&P500 benchmarks.

Portfolio	**Annual excess return**	**Annual excess volatility**	**Sharpe ratio**	**Max Drawdown**
EW S&P500	0.058	0.191	0.304	0.666
MW S&P500	0.017	0.159	0.110	0.574
Tangency	0.153	0.114	1.340	0.130
Equal-weighted	0.179	0.149	1.205	0.287
Value + Z-Score	0.213	0.223	0.955	0.534
Liquidity	0.172	0.216	0.793	0.377
Quality + Value	0.180	0.217	0.830	0.375
Sector Momentum	0.112	0.133	0.844	0.172

Table 12: Combined strategy in-sample period performance and associated risk statistics

Table 13 shows the results of the Fama and French five-factor model regression for the tangency portfolio and equal-weighted portfolio in the in-sample period. Both the tangency portfolio and the equal-weighted portfolio have a monthly alpha of 0.009 over the in-sample period, both significantly different from zero at the 99% significance level. The market beta of the tangency and equal-weighted portfolio are both significantly different from zero at the 99% significance level, indicating that both portfolios are less volatile than the market as their beta is less than one. The adjusted R^2 values show that the returns of the equal-weighted portfolio are better explained by the regression than the returns of the tangency portfolio. The information ratio (IR) relates the alpha of the portfolio to the tracking error against the FF5 portfolio. The information ratio of the equal-weighted portfolio with the FF5 portfolio is higher than that of the tangency portfolio, indicating that the equal-weighted portfolio has a lower tracking error in the in-sample period. In addition, the information ratio against the market-weighted S&P500 (MW S&P IR) is calculated in *Table 13* and is also higher for the equal-weighted portfolio than for the tangency portfolio in the in-sample period. *Table 17* and *Table 18* in the appendix show the regressions results for the Fama and French three-factor model and the CAPM.

Portfolio	Alpha	Market	SMB	HML	RMW	CMA	R^2 Adj.	IR	MW S&P IR
Tangency	0.009	0.444	0.210	0.184	0.005	0.241	0.558	1.411	1.580
	(0.000)	(0.000)	(0.008)	(0.027)	(0.960)	(0.037)			
Equal-weighted	0.009	0.715	0.348	0.277	0.124	0.154	0.768	1.560	1.699
	(0.000)	(0.000)	(0.000)	(0.000)	(0.162)	(0.158)			

Table 13: Combined strategy in-sample period FF5 regression results

4.2. Out-Of-Sample Performance

This section analyzes the performance of the tangency portfolio in the out-of-sample period. In particular, we compare the performance of the optimized portfolio to the equal-weighted and market-weighted benchmarks and an equal-weighted combination of the individual strategies.

Table 14 reports the performances and associated risk statistics of the tangency portfolio, its benchmarks and the individual strategies. The tangency portfolio generates an annual excess return of 7.3% and an annualized volatility of 0.119 resulting in a Sharpe ratio of 0.612. Consequently, the optimized portfolio confirms its outperformance to the equal-weighted portfolio, which delivers a Sharpe ratio of 0.491. In addition, the maximum drawdown is significantly lower than investing equal weights in the four individual strategies. Comparing the performances of the individual strategies between the in-sample and out-of-sample period, all individual strategies perform significantly worse in the out-of-sample period. While the Value + Z-Score portfolio shows the best risk-adjusted return statistics among the individual strategies in the in-sample period, the Sector Momentum portfolio outperforms the single strategies in the out-of-sample period. Liquidity performs poorly, documenting a negative Sharpe ratio of -0.251 compared to a Sharpe ratio of 0.793 in the in-sample period. As previously mentioned in the Liquidity section, the underperformance of Liquidity in the out-of-sample period can primarily be explained through the performance of the short position in the strategy. The performance of the strategies is visualized in *Figure 5*. While all individual strategies, except for Liquidity, generate higher total returns than the tangency and equal-weighted portfolio, only Sector Momentum outperforms both portfolios in risk-adjusted terms. In addition, investing solely in the Sector Momentum portfolio reduces the maximum drawdown compared to the equal-weighted portfolio.

Portfolio	**Annual excess return**	**Annual excess volatility**	**Sharpe ratio**	**Max Drawdown**
EW S&P500	0.105	0.161	0.652	0.142
MW S&P500	0.126	0.144	0.876	0.112
Tangency	0.073	0.119	0.612	0.166
Equal-weighted	0.071	0.144	0.491	0.254
Value + Z-Score	0.098	0.228	0.430	0.395
Liquidity	-0.347	0.138	-0.251	0.523
Quality + Value	0.100	0.208	0.481	0.319
Sector Momentum	0.096	0.150	0.640	0.214

Table 14: Combined strategy of-sample period performance and associated risk statistics

Considering the weights of the individual strategies within the tangency portfolio (shown in *Table 11*), the outperformance of the tangency portfolio compared to the equal-weighted portfolio is mainly based on two findings: First, slightly more than 50% is invested into the Sector Momentum portfolio, which ranks best among the individual strategies on a risk-adjusted basis and thus boosts the Sharpe ratio. Second, the optimized portfolio invests roughly 23% in the Liquidity portfolio, which is slightly less than the 25% in the equal-weighted portfolio. Consequently, the tangency portfolio shows a smaller exposure to the poor performance of the Liquidity portfolio.

While the optimized portfolio maintains its outperformance to the equal-weighted portfolio in the out-of-sample period, it fails to do so compared to the market-weighted and equal-weighted market portfolios. Both portfolios show a significantly higher Sharpe ratio of 0.876 and 0.652, respectively. In addition, none of the individual strategies outperform the market benchmarks. Overall, the market-weighted portfolio performs best, both regarding the risk-adjusted return and maximum drawdown, with the latter amounting to 11.2%.

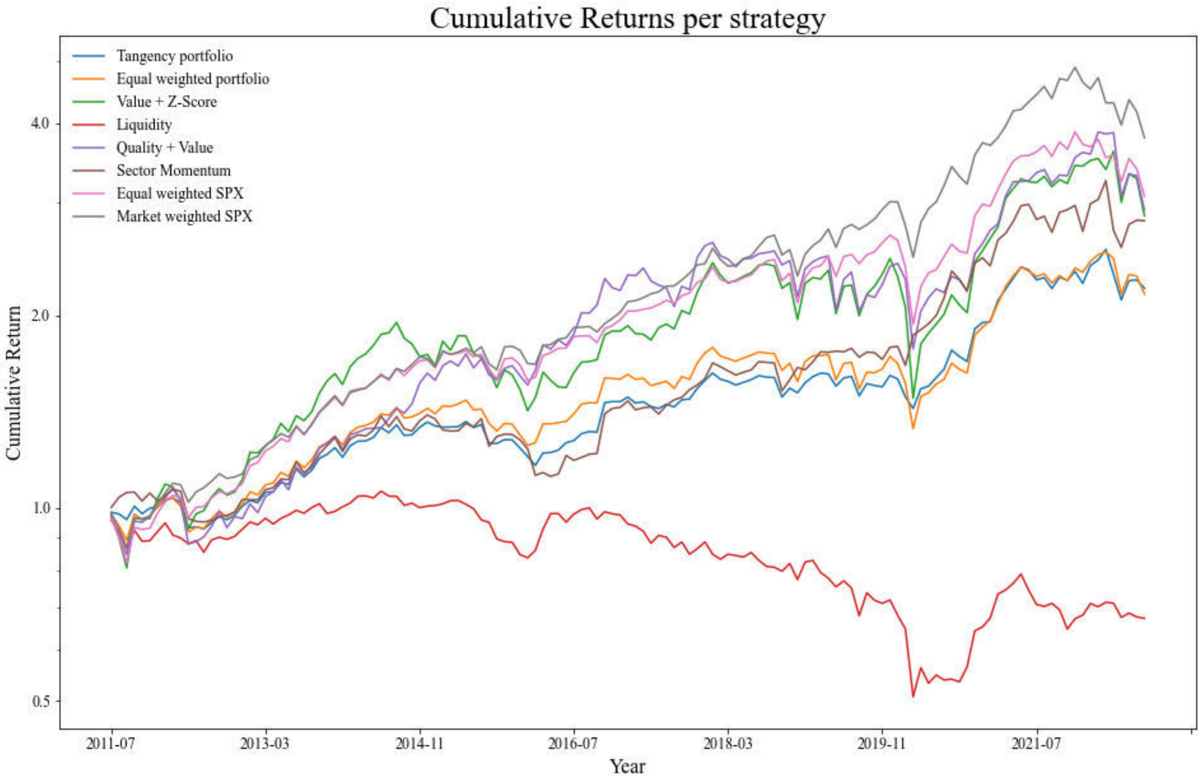

Figure 5: Combined strategy and individual strategies cumulative returns in the out-of-sample period

Table 15 exhibits the results of a linear regression aiming to explain the returns of the tangency portfolio in the out-of-sample period. In addition, the regression results of the equal-weighted portfolio are shown. We use the Fama and French (2015) five-factor model, whose explanatory variables are market (Mkt-RF), size (SMB), value (HML), profitability (RMW) and investment (CMA). The tangency portfolio delivers a monthly alpha of 0.001, whereas the equal-weighted portfolio shows a negative monthly alpha of -0.001. In contrast to the in-sample period, however, both alphas are statistically insignificant. As shown in the individual parts of this work project, all portfolios exhibit positive and significant exposure to the market, which also holds for the tangency and equal-weighted portfolio. The latter, however, has a higher exposure to the market as the Quality + Value and Value + Z-Score portfolios, which both show market betas greater than one, receive higher weights than in the tangency portfolio. With regards to the tangency portfolio, only the size factor provides a significant exposure at the 90%

confidence level mainly driven by the significant size factors within the Liquidity and Value + Z-Score portfolios. The tangency portfolio has a slightly positive information ratio relative to the FF5 Portfolio (IR), while the information ratio relative to the market-weighted S&P500 (MW S&P IR) is close to zero.

Portfolio	Alpha	Market	SMB	HML	RMW	CMA	R2 Adj.	IR	MW S&P IR
Tangency	0.001 (0.514)	0.539 (0.000)	0.192 (0.051)	0.088 (0.300)	0.058 (0.626)	0.206 (0.134)	0.543	0.208	0.041
Equal-weighted	-0.001 (0.683)	0.773 (0.000)	0.255 (0.000)	0.283 (0.000)	0.097 (0.250)	0.220 (0.025)	0.843	-0.130	-0.341

Table 15: Combined strategy out-of-sample period FF5 regression results

The equal-weighted portfolio exhibits positive and significant exposure to the value factor, investing a higher fraction into portfolios that show positive correlation to value (Liquidity, Value + Z-Score and Quality + Value), as opposed to the tangency portfolio. In addition, the equal-weighted portfolio loads positively on the investment factor. Lastly, the size factor shows positive exposure to the equal-weighted portfolio and is statistically significant at any given conventional level. Consequently, the Fama and French five-factor model has a higher explanatory power regarding the equal-weighted portfolio, capturing the value and size factors of the Value + Z-Score, Quality + Value and Liquidity portfolios.

The tangency and equal-weighted portfolios generate statistically significant alphas over the entire period, as shown in *Table 16*. In addition, the equal-weighted portfolio shows for all Fama and French factors statistically significant exposures at any given conventional level. On the other side, the tangency portfolio shows positive significant exposures to all factors except for profitability, which is mainly included in the Value + Z-Score and Quality + Value portfolios. Furthermore, the higher statistical significance of the value factor in the equal-weighted portfolio results from the larger weights in the Value + Z-Score and Quality + Value portfolios. Both portfolios significantly outperform the market over the entire period, as demonstrated by the information ratios. These findings, however, deliver limited information value as they are strongly biased towards the optimized portfolio, which significantly outperforms its benchmarks during the in-sample period.

Portfolio	Alpha	Market	SMB	HML	RMW	CMA	R2 Adj.	IR	MW S&P IR
Tangency	0.005 (0.001)	0.493 (0.000)	0.237 (0.000)	0.120 (0.041)	0.093 (0.160)	0.237 (0.007)	0.547	0.761	0.819
Equal weighted	0.004 (0.001)	0.733 (0.000)	0.345 (0.000)	0.272 (0.000)	0.154 (0.006)	0.200 (0.007)	0.797	0.760	0.728

Table 16: Combined strategy entire period FF5 regression results of the combined strategy

Finally, the out-of-sample results show that the tangency portfolio holds its outperformance to the equal-weighted portfolio, mainly due to its high exposure to the Sector Momentum strategy. In addition, the tangency portfolio is less volatile, but fails to outperform both the market-weighted and equal-weighted market portfolios in risk-adjusted terms.

5. Limitations

Limitations of the development and analysis of the strategy can be categorized in two different types. First, there are limitations in the construction process of the strategy that can lead to the implementation of a sub-optimal strategy. Second, limitations in the strategy analysis can distort the results and give an inaccurate impression of the returns that would have been achieved if the strategy had been implemented in practice.

The first issue is that the strategy design severely depends on the in-sample period. A strategy that aims to achieve consistent returns in the long run must be based on data that is representative of the future market environment. Most strategies perform very differently over different market states. Therefore, the in-sample period should include stable as well as more turbulent market phases, to an extent that can also be expected in the future. Although the in-sample period we have used features stressful periods like the dotcom crash and the global financial crisis, as well as a stable period between 2003 and 2008, it is characterized by a weak market with low returns and large drawdowns. Thus, strategies that are successful in-sample are likely to be defensive strategies with moderate correlation to the market and therefore have a high weight in the tangency portfolio. If the market behaves differently out-of-sample and achieves higher returns, the tangency portfolio is likely to underperform the market.

The second problem is overfitting the strategy to the in-sample data. The more precisely a strategy is optimized to the market environment, the less likely it is that the strategy will yield robust returns out-of-sample. Each individual strategy has been created by selecting the best strategy out of many combinations from multiple parameters. The tangency portfolio has then been constructed using mathematical optimization over the sample to find the ideal solution for the existing data. However, this approach is not always very robust and DeMiguel, Garlappi and Uppal (2009) show that mean-variance optimized strategies do not consistently outperform equal-weighted strategies. Together with a low representativeness of the in-sample period, the future returns of the strategy can be very unstable and lower than expected.

Finally, backtests can never guarantee the future performance of any strategy. Even if the strategy is based on solid economic reasoning and the strategy construction procedure does not underly any biases from the in-sample data, the developed strategy could have been found by other investors as well. Consequently, the strategy can become overcrowded, which diminishes its returns and might even eradicate all of its future alpha. In the worst case, it leads to other market participants anticipating future trades of this strategy and exploiting this knowledge against us.

The first limitation of the performance analysis is very similar to the problem of the representativeness of the in-sample period, only that it is the representativeness of the out-of-sample data in this case. If the market environment during the analyzed period is unique, the analysis results can be inaccurate and substantially differ from those of future periods. The out-of-sample period stands out in the sense, that it features unusually high market returns coupled with relatively low volatility. This development is due to a long-lasting bull market that began in

2012 and has only been interrupted temporarily in 2020, before it continued until 2022. This market environment favors more risky and high-beta growth stocks, while more defensive strategies underperform.

The analysis is further limited as it only considers gross returns without taking into account explicit and implicit trading costs. Explicit costs include brokerage fees that depend on the number and size of trades, as well as lending fees for borrowed securities, that can be especially high for illiquid stocks. Additionally, we assumed that observed historical prices could be traded by us. This ignores any bid/ask spread and the market impact of our trades that would result in worse realized prices than the observed quotes. Consequently, the presented results are upward biased compared to those that would have been achieved if the strategy had been implemented in reality.

6. Conclusion

In this paper, four optimized individual factor investing strategies, covering value, liquidity, quality and momentum premiums, were combined to form a single multi-factor strategy. In an in-sample period, the tangency portfolio was formed from the four strategies according to Markowitz' portfolio optimization. The performance analysis in the out-of-sample period revealed mainly two things. The outperformance of the tangency portfolio against the equal-weighted combination of the four individual strategies shows that our combination approach added value to the individual strategies. On the other hand, it was outperformed by the market benchmarks.

One weakness of the Markowitz optimization procedure is that it relies on static estimates of returns and covariances. Especially the Liquidity strategy but also the other individual strategies display substantial differences in their returns between in- and out-of-sample period. This suggests the conclusion that our combination approach misallocates weights because the parameters it is based on are not valid in the out-of-sample period. However, the tangency portfolio overweights the Sector Momentum strategy that performed best out-of-sample and underweights all other strategies although they achieved higher risk-adjusted returns in-sample. Thus, the combination process achieves a good result and is not to blame for underperforming the benchmark. Another explanation for that is the nature of the individual strategies and the different market environments in the two periods. The two market crashes during the in-sample period led to an outperformance of low-risk stocks and low-beta strategies. This also influenced the individual strategies as their construction was based on their in-sample performance.

The out-of-sample period, however, is characterized by exceptionally high risk-adjusted returns of the market, fueled by policies of zero interest rates that pushed growth stocks to unprecedented valuations. Our strategies are tilted toward more stable value stocks or have generally a low correlation to the market and are therefore not able to keep up with the returns of the market.

Recent macroeconomic events, however, indicate a changing market environment compared to the out-of-sample period. In 2022, the US equity market experienced a substantial drawdown (-13% YTD). Consequently, the hedge-like characteristics of the Sector Momentum portfolio bear significant potential. In addition, rising interest rates may change investors' behavior toward value stocks, boosting risk-adjusted returns of the Value + Z-Score and Quality + Value portfolios. Lastly, large-cap US stocks have significantly underperformed this year. In particular, "mega-cap" tech stocks have contributed a substantial part to this underperformance (S&P Global 2022). Accordingly, the Liquidity strategy may recover from its downward performance by investing in smaller S&P500 stocks and shorting larger S&P500 stocks, thereby delivering benefits to the tangency portfolio. Therefore, it will be interesting to see how the strategy will perform against the market in the future.

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FIELD LAB: ANALYSIS OF QUANTITATIVE INVESTMENT STRATEGIES

OPTIMIZED SECTOR MOMENTUM

LARS BECKONERT

Work project carried out under the supervision of:

Nicholas Hirschey

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Abstract

This work project documents the construction of a sector momentum strategy over an in-sample period and analyzes its performance out-of-sample. The strategy is constructed through a filtering, optimization and combination process and results in a combination of a long-only and a long/short sector momentum strategy that uses a simple market regime indicator to achieve stable returns in all market states. The out-of-sample analysis shows that the strategy is less volatile but yields lower risk-adjusted returns than the market. Its good performance during periods of stress and its low correlation with the market make it appealing as a hedging strategy.

Keywords:

Quantitative Investments, Financial Markets, Factor Investing, Sector Momentum,

Market Neutral, Regime Switching

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1. Introduction

The momentum anomaly is a thoroughly researched yet not entirely understood phenomenon. The fact that investment strategies that buy stocks with relatively high past performance and sell stocks with relatively low past performance historically outperformed buy-and-hold strategies is a major puzzle in the asset pricing research field. There are several approaches to explain the cause of this phenomenon, often using structural or behavioral issues of markets and their participants. A unified theory that is able to explain all of its characteristics, however, is yet to be found. The persistence of the momentum premium, even after the publication of its existence, is also noteworthy and means either that there is a limit to arbitrage it or that the cause of the anomaly dominates informed investors. Abnormal momentum returns have also been found in portfolios that consist of stocks of a specific industry and there is evidence that industry-specific momentum explains aggregate market momentum. Although momentum strategies have achieved substantial abnormal returns in the past, they experience periods of large drawdowns that diminish the overall returns of the strategy. These drawdowns usually happen during phases of market recovery after an extensive market decline. However, the causes of these performance drops are well documented and several approaches to mitigate their impact have been studied.

In this work project, a strategy is developed and analyzed that builds upon these findings to feature the high abnormal momentum returns we have seen in the past while avoiding the undesirable drawdowns that classic momentum strategies have. The strategy will be constructed step-by-step using an in-sample period from January 2000 until May 2011 to evaluate different types of momentum strategies. The investment universe comprises eleven ETFs replicating the returns of large-cap stocks in the U.S. In the first step, multiple versions of classic momentum strategies are tested. They include different observation periods between one and twelve months, different numbers of assets and are either long-only or long-short strategies. In the second step, the long/short strategies are optimized to have as little exposure to market risk as possible. Finally, the best of the optimized long/short strategy is combined with each of the two best long strategies in a simple regime-switching model that invests in the long/short strategy in times of market stress and in the long strategy otherwise. The strategy substantially outperforms the market in the in-sample period and achieves significant alpha over different asset pricing models. In the out-of-sample period, however, it fails to achieve any of this. Although the volatility of its returns is still lower than the market's, its return cannot keep up with the overall market.

The following parts of this work project are structured as follows. Section 2 gives an overview of the most critical findings from academic research regarding different aspects of the momentum anomaly. It discusses the discovery and the major characteristics of the momentum factor and evaluates several economic and behavioral approaches to explain the existence of this anomaly. Subsequently, the special traits of momentum patterns within sectors and industries and the differences to individual stock momentum are highlighted. After that, the major weakness of momentum strategies, the momentum crashes, are examined and several approaches to mitigate these drawdowns are explained. The third section deals with strategy construction and analysis. At first, the motivation to develop a strategy like this is outlined, the used data is described and then the construction of the strategy is explained. The performance of the strategy out-of-sample is analyzed and the limitations of the strategy and the analysis are discussed in the last subsection. Section 4 concludes the analysis and gives some interpretation of the results.

2. Literature Review

2.1. Evidence of the Momentum Factor

The first evidence of time-series momentum patterns in stock returns was presented by Jegadeesh (1990). In his analysis of monthly U.S. stock returns from 1934 to 1987, he finds statistically significant negative first-order serial correlation and positive higher-order serial correlation, with the 12-month serial correlation being the strongest. Jegadeesh and Titman (1993) form portfolios based on the 1, 2, 3 and 4 quarters previous returns and a similar set of holding periods from 1965 to 1989. Additionally, they form portfolios with a one-week lag between the formation and holding periods to avoid the short-term negative return serial correlation. They achieve a monthly return of 1.49% for the strategy that buys the top and sells the bottom decile stocks using a 12 months formation period, a three months holding period and a one-week lag. For almost all the zero-cost strategies, the monthly returns are statistically significantly positive. Furthermore, they show that the positive momentum returns turn negative around twelve months after the formation period. Their results document the first evidence of cross-sectional momentum patterns. Asness (1995) confirms the existence of the momentum anomaly using a zero-cost portfolio with a 12 months observation period excluding the most recent month. He shows that the momentum returns are robust to market, size, value and liquidity factors, different exchanges, and different sample periods. He concludes that the momentum factor is necessary to explain the cross-section of stock returns. Fama and French (2012) find strong momentum returns in North America, Europe and Asia Pacific, especially for small-sized firms. They show that a four-factor model that includes a momentum factor (Carhart 1997) adds explanatory power to their three-factor model (Fama and French 1992). Asness, Moskowitz, and Pedersen (2013) show that momentum returns can also be found in currencies, bonds and commodities. Harvey and Liu (2019) correct factor results to multiple testing issues but still cannot reject the statistical significance of the momentum factor. In a replication study, Jensen, Kelly, and Pedersen (2021) find statistically significant alpha for all tested momentum factors.

2.2. Economic and Behavioral Explanations

Jegadeesh and Titman (1993) give two possible explanations regarding their findings. The observed momentum patterns could be attributed to investors buying past winners and selling past losers, temporarily moving prices from their fair value. Alternatively, they suggest that market participants could underreact to short-term and overreact to long-term firm-specific information. Chan, Jegadeesh, and Lakonishok (1996) come to a similar conclusion that momentum profits stem from the market gradually responding to new information. They find that after a year, the returns of momentum stocks are very similar to the market average. This observation makes them reject a risk-based explanation for the momentum profitability. Daniel, Hirshleifer, and Subrahmanyam (1998) attribute the short-term momentum and the long-term reversal patterns to biased self-attribution of investment outcomes that leads to shifting confidence levels of investors. Barberis, Shleifer, and Vishny (1998) link the findings about return continuation to behavioral finance concepts like representativeness and conservatism. They also argue that arbitrage is limited by noise trader risk, i.e., even if asset prices deviate substantially from their fundamental value, arbitrageurs face the risk of a continuing deviation in the short term. Hong and Stein (1999) use a model with two different types of investors to show that momentum traders try to profit from market underreactions and cause an overreaction in the long run. Another explanatory approach that uses behavioral finance comes from Grinblatt and Han (2005), who use the prospect theory and mental accounting to explain the momentum effect by the stocks' aggregate cost basis. Additionally, they find evidence that the momentum returns of a stock are linked to its aggregate unrealized capital gains. Gutierrez and Prinsky (2007) compare two different types of momentum: one based on the relative return compared to other stocks and one based on firm-specific abnormal returns. They find that, corresponding to previous research, relative-return momentum reverses after a year, but abnormal-return momentum continues to persist for about five years. They conclude that relative-return momentum can be attributed to overreaction and abnormal-return momentum to underreaction and find evidence that these characteristics relate to the investment behavior of institutions that buy relative-return winners but not abnormal-return winners.

2.3. Sector Momentum

Moskowitz and Grinblatt (1999) form 20 value-weighted industry portfolios based on Standard Industrial Classification and compare them to individual stock returns from 1963 to 1995. They find that a large part of the return of individual stock momentum strategies can be explained by industry momentum and most of their returns become statistically insignificant when controlled for industry momentum. Strategies that are based on industries' past returns are more profitable than individual stock momentum strategies and are robust to size, value, and individual stock momentum factors. Contrary to individual momentum strategies, their profitability is mainly driven by the long positions and the momentum effect is strongest over a one-month horizon. Pan, Liano, and Huang (2004) decompose returns from industry momentum portfolios based on abnormal returns over the market return. They find that industry momentum returns can mainly be attributed to own-autocovariances of industry returns rather than to cross-autocorrelation or cross-sectional differences in mean returns. Shynkevich (2013) compares time-series momentum strategies based on industry and sector returns to those based on aggregate market returns. He shows that strategies based on industry and sector returns are more successful and that market price continuation patterns mainly result from industry momentum. The effects are especially strong in the 1990s but weaken during the 2000s; a possible explanation for this phenomenon is the emergence of sector ETFs that lead to higher market efficiency and a higher correlation between sectors. J. Wang et al. (2017) conduct a cross-sectional momentum strategy using ETFs that each replicate one sector of the S&P 500 index. For their strategy with a six months observation and holding period, they achieve a monthly return of 0.89%, which is robust to the Fama-French three-factor model.

2.4. Momentum Crashes

Grundy and Martin (2001) show that momentum strategies have time-varying factor exposures. If the portfolio formation period lies in a down market, the winning stocks usually have a low market beta and the losing stocks have a high beta. Thus, the winner-minus-loser momentum portfolio has a negative beta during and after a down market. During up markets, the portfolio beta is positive when the portfolio goes long in high-beta and short in low-beta stocks. It follows that while momentum strategies can perform during up and down markets, they result in negative returns after a transition from an up (down) to a down (up) market (Asem and Tian 2010). More specifically, the momentum portfolio underperforms if the formation period lies in a different market state than the realized portfolio. Daniel and Moskowitz (2016) examine the returns of a U.S. equity momentum portfolio from 1927 to 2013 and highlight the patterns of the worst drawdowns during this period, the so-called momentum crashes. In 1932, the portfolio experienced a crash of -91.59% over two months and in 2009, it had a return of -73.42% in three months. They find that these drawdowns can be attributed to the strong outperformance of the loser portfolio against the winner portfolio during sharp market rebounds that followed market crashes. Furthermore, the time-varying market exposure of the momentum portfolio is confirmed and identified as a contributing factor to these momentum crashes.

2.5. Enhanced Momentum Strategies

The findings about momentum crashes have led to various adaptations of the classic winner minus loser momentum strategy. Blitz, Huij, and Martens (2011) are able to reduce the time-varying exposure to Fama-French risk factors by implementing a momentum portfolio that is based on the residual returns over the Fama-French three-factor model during the observation period instead of total stock returns. Their portfolio earns higher and more consistent risk-adjusted returns compared to the classic momentum portfolio. Barroso and Santa-Clara (2015) use a strategy that scales the portfolio to match a fixed volatility based on its realized six months daily return volatility. This method leads to improvements in Sharpe ratio, kurtosis, skew and drawdown. The improvement is strongest in crash periods but is also apparent in months without crashes and is consistent for different geographic regions. Daniel and Moskowitz (2016) build upon these findings and develop a dynamically scaled strategy that uses forecasts for the conditional expected return and volatility of the momentum portfolio for each period. They achieve a Sharpe ratio about twice as large as that of the classic momentum strategy. F. Wang and Yan (2021) show that strategies scaled by semi-volatility can achieve better results for several factor strategies. Hanauer and Windmüller (2023) test constant volatility-scaled, constant semi-volatility-scaled and dynamic-scaled momentum strategies from 1930 to 2017 in the U.S. market and from 1990 to 2017 in 48 international markets. They were able to roughly double the Sharpe ratio and decrease the maximum drawdown of the standard momentum strategy with each of the strategy enhancements.

3. Strategy

3.1. Motivation

Research has shown that momentum strategies have provided substantial abnormal returns in the past. Even after the initial findings had been published, the results have been confirmed over more recent time periods. Although classic momentum strategies are associated with occasional large drawdowns, several adaptations with the goal to minimize these drawdowns have already been documented and showed promising results. There is evidence that momentum is especially strong within sectors and industries and the existence of highly liquid sector ETFs make it easy to implement a strategy that is cost- and tax-efficient and always provides a decent amount of diversification. Therefore, the goal is to develop a sector momentum strategy optimized to avoid momentum crashes.

3.2. Data

The investment universe comprises the 11 Select Sector SPDR ETFs, administrated by State Street Bank and Trust Company. These ETFs seek to replicate the total return of each sector of the S&P 500 Index (SPX). Each stock of the SPX is allocated to exactly one of the ETFs and the weightings mirror the proportional market capitalizations of each sector in the SPX, capped at 25% of the total portfolio (ALPS Holdings 2022). The daily prices (Open, High, Low, Close, Adjusted Close) for each ETF are obtained from Yahoo Finance over the period starting at the beginning of 2000 until September 30th, 2022. The adjusted close reflects all future distributions that have been made, such that the price return of the adjusted close over a period equals the total return from holding the ETF over this period. Open prices have been adjusted using the daily adjustment factor to enable return calculations based on open prices (see *Equation 1* for the used formula). The sector classification is based on the Global Industry Classification Standard and due to revisions of this standard over time, the Communication Services (XLC) and the Real Estate (XLRE) ETFs have been added later to the investment universe. Additionally, to the sector ETFs the strategy invests in, similar daily prices of the SPDR S&P 500 ETF Trust (SPY) over the same period is gathered. This data serves as an investable proxy of the value-weighted market return of our investment universe. It will later be used as a return benchmark to the strategy and an indicator of the current market state. Descriptive statistics of the ETF data can be found in *Table 1*. For the factor analysis of the strategy returns, the monthly Fama and French (2015) five-factor and Carhart (1997) Momentum factor returns are obtained from the data library of Kenneth R. French (French 2022).

3.3. Construction

The investment strategy is not constructed ex-ante but rather tested and optimized over an in-sample period. The dataset is therefore split in the middle into an in-sample period from January 2000 until May 2011 and an out-of-sample period from June 2011 until September 2022, which will only be used to analyze the final strategy. The first step of the strategy construction is to backtest and compare various simple sector cross-sectional momentum strategies. Each strategy is defined by the observation period of the return calculation, the number of assets it invests in, and if it is a long or long/short strategy. The start and end of the observation period are both described by the number of months before today and the signal is calculated at the end of each month. The names of the strategies follow the convention (start, end, positions, type). The strategy called (12, 1, 2, long/short), for example, has an observation period that starts 12 months before today and ends one month before today, has a long position in the two assets with the highest returns in the observation period and a short position in the two assets with the lowest returns. The weights are split equally between the positions and long positions sum to 1 while short positions sum to -1. For each signal, the holding period is always one month, so the whole portfolio is rebalanced each month. Both buy and sell trades are always made at open of the business day following the signal calculation. We test strategies from all the combinations out of the following range of strategy parameters: start $\in$ {1, 3, 6, 12}, end $\in$ {0, 1}, positions $\in$ {1, 2, 3}, type $\in$ {long, long/short}. *Table 2* shows the performance statistics of all 42 tested strategies. The long strategies generally perform better than the long/short strategies, with an average annual return of 4.80% against -0.78%. This confirms the previous findings that sector momentum profits mainly come from their long positions (Moskowitz and Grinblatt 1999) and that their returns can suffer from reversals in the short positions (Daniel and Moskowitz 2016). We cannot confirm a strong one-month momentum effect and strategies with a 12 months observation period have the highest returns with an average of 5.14% (from which the long strategies yield 6.98% on average). Over all strategies, no substantial differences result from skipping the last month of the observation period or the number of long positions. The most successful strategy is the (6, 1, 2, long) strategy, with a Sharpe ratio of 0.49, followed by (12, 0, 2, long) with 0.37. The best long/short strategy is the (12, 0, 1, long/short) with a Sharpe ratio of 0.24. It is one of only three long/short strategies that achieve a positive Sharpe ratio. Interestingly, there is no difference in the average drawdown between long and long/short strategies, but the lowest drawdown and volatility can be found in the (3, 0, 3, long/short) strategy, while the highest drawdown is produced by the (3, 1, 1, long/short) strategy.

As seen in the literature, long/short momentum strategies can experience severe drawdowns if observation period and holding period lie in different market regimes. This risk comes from the time-varying exposure to market risk. Therefore, one approach to improve the performance of the long/short strategies is to control their market exposure, i.e., make the portfolio neutral to market risk. For each long/short strategy we calculate the market exposure (or market beta) of the assets with daily closing prices over the observation period, using *Equation 2*. It is assumed that the market beta in the following month will be equal to that in the observation period. This is, of course not always true, because momentum strategies suffer from their time-varying market exposure, but as long as the exposure does not change too quickly, estimated and realized market beta should not diverge too much, especially for strategies with shorter observation periods. Based on this relationship, the portfolio beta for the following month is calculated and the asset weights are adjusted such that the resulting beta equals zero. The adjustments underlie two constraints, long (short) positions must still sum to 1 (-1), and each asset must have a weight between -1 and 1. This leads to two problems. For portfolios with only one long and short position, there might not be a portfolio that fulfills these constraints and has an estimated beta of zero. Portfolios with two or three long and short positions might have an infinite number of valid weight combinations. Therefore, the problem is solved using an optimization that maximizes the portfolio signal value (which is the weighted average of the asset returns over the observation period) while holding the estimated portfolio beta equal to zero and considering the previously defined constraints as well. The resulting optimization problem is described by *Equation 3*. This optimization is carried out each month over the in-sample period for all strategies with at least two long and short positions to ensure that valid portfolio weights exist. *Table 3* compares performance statistics of the non-optimized and optimized strategies. The results are mixed but promising. While the strategies with a one-month observation period performed worse in the optimized version, the strategies with three months of lookback showed significant improvements. The (3, 0, 3, long/short) strategy is now the best in all analyzed metrics and almost halved its maximum drawdown to only 17%. While its return of about 4% is far behind those of the better long strategies, its low volatility and drawdown might allow it to combine the high returns of a long strategy with the stability of this long/short strategy.

To get an idea if there are some obvious weaknesses in the long strategies that could be improved, the returns of the two best long strategies, namely (6, 1, 2, long) and (12, 0, 2, long), are compared to the return of the market (SPY) over the in-sample period (see *Figure 1*). The strategies usually move in the same direction as the market, which is confirmed by their correlation coefficients. Both have a correlation with the market of about 0.78 (see *Table 4*). Most importantly, the two periods in which the strategies had the largest drawdowns coincide with market crashes. Between 2001 and 2003, all portfolios lost about 30% and roughly 40% during the year 2008. Comparing the returns of the (3, 0, 3, long/short) strategy with the market, we see that the long/short strategy is not at all affected by market downturns (see *Figure 2*). It even tends to have positive returns during these periods. Its most severe drawdown happened from 2009 to 2011, when the market recovered from the financial crisis. It seems like the momentum crash risk is not entirely avoided but its negative correlation of -0.25 with the market makes it look like a good alternative to a long momentum strategy in times of crisis (for months where SPY return is negative, the correlation is -0.41). In the last step of the strategy construction, each long strategy is combined with the long/short strategy. The long strategies yield good returns most of the time and the long/short strategy can shield from losses in times of market stress. The idea is to switch between the two strategies depending on the current market state. To do this, we need an indicator that signals us if we are in an up- or down-state. Because, on average, we give up gains every time we switch from the long to the long/short strategy, it must be precise enough to roughly catch the market cycles correctly. On the other hand, it must be general enough and not too specific to the market development during the in-sample period to also work in the future. Therefore, the market return over the observation period of the long/short strategy is used as the indicator. If it is negative, we interpret this as a sign of a down-market and will invest in the long/short strategy in the following month. If it is positive, we stick to the long strategy. *Table 5* shows simple performance statistics of the two different combinations. The (6, 1, 2 – 3, 0, 3) combination is the strongest in all four metrics and yields a significantly higher return than the original long strategy while being almost as stable as the long/short strategy. It barely loses any money between 2001 and 2003 and is only slightly affected by the financial crisis (see *Figure 3*). Based on these results, we choose it as our final strategy and will analyze its performance in the out-of-sample period in the next section.

3.4. Out-Of-Sample Results

The out-of-sample period starts in June 2011 and ends in September 2022. We will also make comparisons to the in-sample period that begins in August 2000 (the start is the strategy's first return). The strategy does not perform as good as in the in-sample period. It only achieves a Sharpe ratio of 0.63 due to lower returns and slightly higher volatility. Its highest drawdown is -21%, which is also a bit higher than that in the in-sample period (see *Table 6*). The SPY outperforms our strategy in the out-of-sample period in absolute and risk-adjusted returns, although its volatility is slightly higher (see *Table 7*). Generally, the returns of the strategy are more closely aligned to the market than in the in-sample period. Their correlation has risen from 0.19 to about 0.31 and the regression results show similar outcomes. To understand which risk factors drive the returns of the strategy, we conduct two regression analyses. First, we use the Fama and French (2015) five-factor model that uses the market (Mkt-RF), size (SMB), value (HML), profitability (RMW) and investment (CMA) factors to explain the excess returns of the strategy (see *Table 8*). While over the in-sample period, none of the factors had a statistically significant coefficient different from zero, out-of-sample, the strategy has a significant market exposure of roughly 0.37. The strategy does not produce a significant alpha over the model in the out-of-sample period and the information ratio has approximately halved to 0.41. Overall, the model does not have much explanatory power (adjusted R^2: 9.79%). Therefore, we do another regression with the Carhart (1997) four-factor model (see *Table 9*). This includes a momentum (MOM) factor and thus could be more appropriate to explain the strategy returns. Although it adds explanatory power to the model and slightly increases R^2, it is not a significant factor out-of-sample. Again, only the market factor has a significant coefficient (0.40). Looking at the cumulative returns over the out-of-sample period in *Figure 4*, we see again that our strategy is now much closer to the market than in the in-sample period. While it is very stable during the market turbulence in 2020, it experiences a larger drawdown than the market in the second half of 2015 and is overall unable to keep up with the strong performance of the market during this period.

3.5. Limitations

The construction and the implementation of the strategy have several limitations that divert our hypothetical backtesting results from the real results we would have achieved if we had implemented the strategy in practice. First, our strategy depends on the characteristics of the in-sample period. The strategy might be different if we had chosen different periods for construction and testing. We filtered and optimized many strategies based on the in-sample data. This can lead to an overfitting problem. Second, our trade prices are assumed to be the observed quotes at market open. This is very simplified and does not consider the bid-ask spread at that moment and the market impact that our additional order would have had. However, the assets we are trading are partly chosen because of their high liquidity, so the impact is not expected to be large here. The same applies to trading costs that are also not considered. Lesmond, Schill, and Zhou (2004) show that trading costs can completely eliminate the abnormal returns of momentum strategies due to the trading of high-cost securities. In our case, all the assets are very inexpensive to trade and easily shortable. Due to our low amount of assets, we generally have fewer trades than individual stock strategies, which also decreases our expense ratio. Therefore, the impact of trading costs is not expected to be substantial for this strategy.

4. Conclusion

While the strategy significantly outperformed the market and achieved positive alpha over both asset pricing models, it failed to achieve any of this in the out-of-sample period. This is common for strategies constructed through filtering and optimization methods in an in-sample period. The typical reason for the underperformance that follows is that the strategy has been overfit to the market development in the construction period. Regarding our strategy, some aspects support the notion that the strategy has been overfit, and some speak against it. During the strategy construction, we tested 42 simple momentum combinations, 14 optimized long/short strategies and two combined strategies. That makes a total of 58 tested strategies. The more strategies have been tested, the more likely it is that the best strategy was overfit to the data. The number of tested strategies could support the conclusion of overfitting. On the other hand, we tried to keep the strategy as general as possible. The in-sample period contains both market crashes and stable periods, the portfolio optimization and market state indication are held very simple and based on short-term rolling historical data. Another explanation for the large change in the difference between the strategy and market returns between the two periods is the substantial increase of the market returns. While our strategy has relatively stable returns over the whole period, the market, which was flat over the in-sample period, achieved very high returns out-of-sample. These facts do not support the existence of an overfitting problem. The strategy can be characterized as a defensive strategy that is able to hedge against market drawdowns in bad times but does not produce as high returns in bull markets. The in-sample period was more influenced by large market drawdowns in which our strategy flourished. In the out-of-sample period, the market had unusually high returns that beat our strategy. The regression results strengthen this explanation, finding a significant positive alpha over the full period, but not in the out-of-sample period. Another possible explanation is that the increasing popularity of sector ETFs has made this market more efficient and decreased the size of the momentum anomaly (Shynkevich 2013). In 2022 the U.S. equity market experienced a substantial drawdown (about -13% YTD) which could be the start of a longer-term bear market. It will be interesting to see how the strategy will perform against the market in the future, in a period that might have more market fluctuations than the out-of-sample period. Finally, the hedge-like characteristics of this strategy give it a lot of potential in a portfolio with other assets or strategies that have a higher correlation with the market.

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Appendix – Combined Part

Portfolio	Period	Alpha	Market	SMB	HML	R2 Adj.	IR	MW S&P IR
Tangency	In-sample	0.010 (0.000)	0.419 (0.000)	0.213 (0.007)	0.330 0.000	0.549	1.523	1.580
	Out of sample	0.002 (0.390)	0.525 (0.000)	0.145 (0.095)	0.205 (0.001)	0.540	0.268	0.041
	Entire period	0.006 (0.000)	0.455 (0.000)	0.199 (0.001)	0.278 (0.000)	0.532	0.926	0.819
Equal weighted	In-sample	0.011 (0.000)	0.657 (0.000)	0.313 (0.000)	0.449 (0.000)	0.760	1.779	1.699
	Out of sample	0.000 (0.935)	0.761 0.000	0.190 (0.003)	0.418 (0.000)	0.836	-0.025	-0.341
	Entire period	0.006 (0.000)	0.689 (0.000)	0.284 (0.000)	0.447 (0.000)	0.783	0.992	0.728

Table 1:Combined strategy FF3 regression results

Portfolio	Period	Alpha	Market	R2 Adj.	IR	MW S&P IR
Tangency	In-sample	0.012 (0.000)	0.450 (0.000)	0.426	1.680	1.580
	Out of sample	0.001 (0.565)	0.558 (0.000)	0.498	0.177	0.041
	Entire period	0.007 (0.000)	0.489 (0.000)	0.443	0.945	0.819
Equal weighted	In-sample	0.014 (0.000)	0.705 (0.000)	0.618	1.849	1.699
	Out of sample	-0.001 (0.618)	0.808 (0.000)	0.716	-0.153	-0.341
	Entire period	0.007 (0.000)	0.738 (0.000)	0.639	0.920	0.728

Table 2: Combined strategy CAPM regression results

Portfolio	Annual excess return	Annual excess volatility	Sharpe ratio	Max Drawdown
EW S&P 500	0.082	0.176	0.464	0.656
MW S&P 500	0.072	0.153	0.470	0.582
Tangency	0.112	0.117	0.953	0.166
Equal weighted	0.123	0.147	0.835	0.287
Value + Z-Score	0.153	0.226	0.678	0.534
Liquidity	0.062	0.183	0.338	0.523
Quality + Value	0.139	0.213	0.652	0.375
Sector Momentum	0.104	0.142	0.733	0.214

Table 3: Combined strategy entire period performance and associated risk statistics

	Annualized Excess Return			Information Ratio		
	2000/03 - 2011-06	2011/07 - 2022/09	2000/03 - 2022/09	2000/03 - 2011-06	2011/07 - 2022/09	2000/03 - 2022/09
GPA	0.076	0.106	0.091	0.497	-0.111	0.217
LTDE	0.014	0.108	0.059	0.675	0.078	0.325
Acc	0.068	0.139	0.103	0.802	0.520	0.626
3Dim	**0.066**	**0.133**	**0.099**	**0.867**	**0.547**	**0.675**

Table 4: Quality factor and its dimensions annualized excess returns and information ratios

			FF5 Regression								Comparison IRs		
Portfolio	**Period**	**Exc Ret**	**Alpha**	**Market**	**Size**	**Value**	**Profitability**	**Investment**	**Adj. R^2**	**IR**	**IR SPX**	**IR 3Dim**	**IR EV/EBIT**
3Dim + EV/EBIT	In-sample	0.016	0.012***	1.086***	0.114	0.454***	0.463***	-0.369*	0.585	1.006	1.149	0.948	0.408
			(3.008)	(11.028)	(0.891)	(3.047)	(2.723)	(-1.739)					
	Out-of-sample	0.009	-0.001	1.119***	0.138	0.267**	0.221	0.440**	0.718	-0.125	-0.239	-0.330	-0.177
			(-0.399)	(16.169)	(1.063)	(2.343)	(1.416)	(2.403)					
	Full-sample	0.006	0.005**	1.071***	0.131	0.402***	0.386***	-0.020	0.632	0.475	0.542	0.442	0.157
			(2.108)	(18.572)	(1.440)	(4.314)	(3.588)	(-0.140)					
3Dim	In-sample	0.006	0.005***	1.103***	0.115*	0.043	0.022	0.046	0.878	0.910	0.605		
			(2.720)	(23.491)	(1.877)	(0.612)	(0.269)	(0.454)					
	Out-of-sample	0.011	0.002*	0.971***	0.102**	-0.022	0.198***	0.023	0.926	0.595	0.090		
			(1.899)	(36.659)	(2.044)	(-0.492)	(3.311)	(0.070)					
	Full-sample	0.004	0.003***	0.003***	0.095**	0.005	0.044	0.059	0.891	0.707	0.344		
			(3.135)	(40.683)	(2.336)	(0.117)	(0.909)	(0.064)					
EV/EBIT	In-sample	0.015	0.009***	1.265***	0.196**	0.303***	0.509***	-0.041	0.789	1.054	1.309		
			(3.150)	(0.000)	(2.200)	(2.936)	(4.316)	(-0.281)					
	Out-of-sample	0.011	0.002	1.173***	0.172**	0.467***	0.139*	0.058	0.917	0.406	-0.136		
			(1.297)	(32.104)	(2.508)	(7.761)	(0.094)	(0.600)					
	Full-sample	0.007	0.005**	1.178***	0.203**	0.426***	0.332***	-0.013	0.841	0.750	0.688		
			(3.323)	(32.025)	(3.501)	(7.170)	(4.838)	(-0.137)					
EW	In-sample	0.006	0.003**	1.143***	0.047	0.241***	0.123**	0.138*	0.935	0.682	0.699		
			(2.038)	(34.440)	(1.098)	(4.795)	(2.137)	(1.929)					
	Out-of-sample	0.009	0.000	1.010***	0.110***	0.187***	0.086**	0.018	0.972	0.057	-0.602		
			(0.183)	(59.466)	(3.434)	(6.678)	(2.235)	(0.402)					
	Full-sample	0.004	0.001*	1.073***	0.067**	0.229***	0.085**	0.086*	0.946	0.395	0.127		
			(1.751)	(59.581)	(2.348)	(7.888)	(2.533)	(1.925)					

Table 5: Quality + Value and benchmarks FF5 regression results

	In-sample	**Out-of-sample**	**Full period**
Start	2000:08	2011:06	2000:08
End	2011:05	2022:09	2022:09
Observations	130	136	266
Alpha	**0.0096**	0.0048	**0.0070**
P-Value	0.0102	0.1923	0.0068
Information Ratio	0.8905	0.4140	0.6203
Adjusted R^2	0.0325	0.0979	0.0730
Mkt-RF	0.1740	**0.3684**	**0.2862**
P-Value	0.0692	0.0001	0.0000
SMB	-0.0572	0.0197	0.0090
P-Value	0.6714	0.9091	0.9306
HML	-0.0398	-0.1961	-0.1378
P-Value	0.7801	0.1944	0.1764
RMW	-0.1109	0.0182	0.0452
P-Value	0.4956	0.9300	0.6946
CMA	0.2617	0.2153	0.2397
P-Value	0.1911	0.3718	0.1182

Table 6: Sector Momentum, Fama and French five-factor regression results.
Coefficients that are statistically significant on a 5% significance level are bold.

	In-sample	Out-of-sample	Full period
Start	2000:08	2011:06	2000:08
End	2011:05	2022:09	2022:09
Observations	130	136	266
Alpha	**0.0094**	0.0044	**0.0071**
P-Value	0.0059	0.2301	0.0037
Information Ratio	0.8939	0.3795	0.6371
Adjusted R^2	0.0726	0.1150	0.1030
Mkt-RF	**0.2843**	**0.3976**	**0.3332**
P-Value	0.0006	0.0000	0.0000
SMB	-0.0311	0.0272	0.0103
P-Value	0.8108	0.8581	0.9161
HML	0.0308	-0.0361	0.0010
P-Value	0.7612	0.7653	0.9892
MOM	**0.1576**	0.1862	**0.1746**
P-Value	0.0107	0.1285	0.0014

Table 7: Sector Momentum, Carhart four-factor regression results.
Coefficients that are statistically significant on a 5% significance level are bold.

Appendix – Individual Part

Ticker	Sector	First Price	Months	Annual Return
XLB	Materials	2000-01-03	272	7.02 %
XLC	Communication Services	2018-06-19	51	2.93 %
XLE	Energy	2000-01-03	272	7.45 %
XLF	Financial	2000-01-03	272	4.45 %
XLI	Industrial	2000-01-03	272	7.08 %
XLK	Technology	2000-01-03	272	5.19 %
XLP	Consumer Staples	2000-01-03	272	7.67 %
XLRE	Real Estate	2015-10-08	83	8.37 %
XLU	Utilities	2000-01-03	272	7.97 %
XLV	Healthcare	2000-01-03	272	7.89 %
XLY	Consumer Discretionary	2000-01-03	272	8.62 %
SPY	/	2000-01-03	272	6.32 %

Table 8: Descriptive statistics of ETF dataset.

Start	End	Positions	Type	Return	Volatility	Sharpe ratio	Drawdown
1	0	1	long	3.70%	23.14%	0.0553	-59.52%
1	0	1	long/short	0.96%	26.42%	-0.0530	-66.48%
1	0	2	long	0.58%	19.69%	-0.0896	-62.56%
1	0	2	long/short	-4.35%	18.43%	-0.3581	-56.82%
1	0	3	long	3.50%	17.46%	0.0622	-51.38%
1	0	3	long/short	-0.06%	13.65%	-0.1751	-40.45%
3	0	1	long	-0.29%	20.45%	-0.1257	-55.22%
3	0	1	long/short	-6.90%	26.83%	-0.3372	-70.47%
3	0	2	long	1.75%	16.86%	-0.0343	-46.31%
3	0	2	long/short	-5.51%	17.74%	-0.4323	-53.25%
3	0	3	long	4.12%	15.72%	0.1105	-43.63%
3	0	3	long/short	-1.07%	12.60%	-0.2642	-29.99%
3	1	1	long	-3.08%	20.34%	-0.2605	-65.85%
3	1	1	long/short	-12.31%	28.46%	-0.5034	-79.80%
3	1	2	long	2.14%	16.38%	-0.0122	-43.47%
3	1	2	long/short	-5.48%	17.48%	-0.4372	-46.61%
3	1	3	long	3.03%	15.19%	0.0446	-44.47%
3	1	3	long/short	-5.07%	14.10%	-0.5130	-45.36%
6	0	1	long	7.21%	19.63%	0.2481	-48.50%
6	0	1	long/short	-0.39%	28.58%	-0.0904	-60.04%
6	0	2	long	6.92%	16.78%	0.2721	-44.50%
6	0	2	long/short	0.08%	17.80%	-0.1198	-41.67%
6	0	3	long	5.15%	16.10%	0.1758	-46.93%
6	0	3	long/short	-1.11%	15.07%	-0.2193	-40.97%
6	1	1	long	8.00%	19.92%	0.2822	-47.82%
6	1	1	long/short	2.23%	27.37%	-0.0009	-47.33%
6	1	2	long	10.16%	15.91%	0.4856	-39.06%
6	1	2	long/short	2.16%	18.75%	-0.0047	-34.46%
6	1	3	long	6.00%	15.67%	0.2334	-41.08%
6	1	3	long/short	0.66%	15.41%	-0.1013	-35.95%
12	0	1	long	8.05%	20.08%	0.2920	-47.36%
12	0	1	long/short	8.71%	27.36%	0.2386	-47.82%
12	0	2	long	8.32%	16.55%	0.3703	-39.97%
12	0	2	long/short	3.71%	18.38%	0.0884	-37.69%
12	0	3	long	5.80%	15.69%	0.2324	-39.39%
12	0	3	long/short	-0.13%	15.16%	-0.1420	-32.03%
12	1	1	long	7.57%	20.46%	0.2638	-47.36%
12	1	1	long/short	5.28%	28.08%	0.1126	-45.37%
12	1	2	long	6.17%	17.46%	0.2305	-44.65%
12	1	2	long/short	1.91%	18.38%	-0.0080	-33.50%
12	1	3	long	5.96%	15.89%	0.2397	-40.90%
12	1	3	long/short	0.37%	14.73%	-0.1128	-32.62%

Table 9: Performance of the simple momentum strategies over the in-sample period (2000:01 - 2011:05). Return and Volatility are annualized, the best (worst) result for each metric is highlighted in green (red).

			Non-optimized				Optimized			
Start	**End**	**Positions**	**Return**	**Volatility**	**Sharpe ratio**	**Drawdown**	**Return**	**Volatility**	**Sharpe ratio**	**Drawdown**
1	0	2	-4.35%	18.43%	-0.3581	-56.82%	-6.66%	15.71%	-0.5646	-60.51%
1	0	3	-0.06%	13.65%	-0.1751	-40.45%	-1.17%	14.05%	-0.2476	-53.04%
3	0	2	-5.51%	17.74%	-0.4323	-53.25%	0.85%	13.53%	-0.1073	-36.40%
3	0	3	-1.07%	12.60%	-0.2642	-29.99%	3.91%	11.06%	0.1400	-16.72%
3	1	2	-5.48%	17.48%	-0.4372	-46.61%	0.66%	16.45%	-0.0996	-36.30%
3	1	3	-5.07%	14.10%	-0.5130	-45.36%	-0.74%	14.12%	-0.2132	-35.99%
6	0	2	0.08%	17.80%	-0.1198	-41.67%	-0.05%	16.34%	-0.1387	-30.00%
6	0	3	-1.11%	15.07%	-0.2193	-40.97%	1.28%	13.41%	-0.0711	-27.83%
6	1	2	2.16%	18.75%	-0.0047	-34.46%	2.81%	16.86%	0.0324	-39.34%
6	1	3	0.66%	15.41%	-0.1013	-35.95%	2.05%	13.92%	-0.0151	-24.81%
12	0	2	3.71%	18.38%	0.0884	-37.69%	1.21%	16.79%	-0.0495	-50.83%
12	0	3	-0.13%	15.16%	-0.1420	-32.03%	-4.00%	13.05%	-0.4552	-41.01%
12	1	2	1.91%	18.38%	-0.0080	-33.50%	1.03%	17.25%	-0.0586	-40.47%
12	1	3	0.37%	14.73%	-0.1128	-32.62%	0.77%	12.94%	-0.0977	-33.50%

Table 10: Comparison of performance statistics between non-optimized and optimized long/short strategies over the in-sample period (2000:01 - 2011:05). Return and Volatility are annualized, the best (worst) result for each metric is highlighted in green (red).

	SPY	(3,0,3,long/short)	(6,1,2,long)	(12,0,2,long)
SPY	1.0000			
(3,0,3,long/short)	-0.2492	1.0000		
(6,1,2,long)	0.7754	-0.0312	1.0000	
(12,0,2,long)	0.7812	-0.0203	0.8624	1.0000

Table 11: Correlations of momentum strategies and SPY over the in-sample period (2001:02 - 2011:05).

	Return	Volatility	Sharpe ratio	Drawdown
(6,1,2-3,0,3)	14.40%	13.25%	0.8926	-17.13%
(12,0,2-3,0,3)	12.55%	12.95%	0.7921	-18.41%

Table 12: Performance statistics of long and long/short strategy combinations over the in-sample period (2000:01 - 2011:05).

	Return	Volatility	Sharpe ratio	Drawdown
In-sample	14.40%	13.25%	0.8926	-17.13%
Out-of-sample	10.04%	15.06%	0.6279	-21.30%
Full sample	11.93%	14.23%	0.7313	-21.30%

Table 13: Performance statistics of final strategy over different samples.

	Return	Volatility	Sharpe ratio	Drawdown
In-sample	0.89%	16.59%	-0.0905	-51.30%
Out-of-sample	12.12%	15.19%	0.7584	-22.90%
Full sample	6.32%	15.95%	0.2975	-51.30%

Table 14: Performance statistics of SPY over different samples.

	In-sample	Out-of-sample	Full period
Start	2000:08	2011:06	2000:08
End	2011:05	2022:09	2022:09
Observations	130	136	266
Alpha	**0.1147**	0.0579	**0.0841**
P-Value	0.0102	0.1923	0.0068
Information Ratio	0.8905	0.4140	0.6203
Adjusted R^2	0.0325	0.0979	0.0730
Mkt-RF	0.1740	**0.3684**	**0.2862**
P-Value	0.0692	0.0001	0.0000
SMB	-0.0572	0.0197	0.0090
P-Value	0.6714	0.9091	0.9306
HML	-0.0398	-0.1961	-0.1378
P-Value	0.7801	0.1944	0.1764
RMW	-0.1109	0.0182	0.0452
P-Value	0.4956	0.9300	0.6946
CMA	0.2617	0.2153	0.2397
P-Value	0.1911	0.3718	0.1182

Table 15: Fama-French five-factor regression results.
Coefficients that are statistically significant on a 5% significance level are bold.

	In-sample	Out-of-sample	Full period
Start	2000:08	2011:06	2000:08
End	2011:05	2022:09	2022:09
Observations	130	136	266
Alpha	**0.1132**	0.0528	**0.0852**
P-Value	0.0059	0.2301	0.0037
Information Ratio	0.8939	0.3795	0.6371
Adjusted R^2	0.0726	0.1150	0.1030
Mkt-RF	**0.2843**	**0.3976**	**0.3332**
P-Value	0.0006	0.0000	0.0000
SMB	-0.0311	0.0272	0.0103
P-Value	0.8108	0.8581	0.9161
HML	0.0308	-0.0361	0.0010
P-Value	0.7612	0.7653	0.9892
MOM	**0.1576**	0.1862	**0.1746**
P-Value	0.0107	0.1285	0.0014

Table 16: Carhart four-factor regression results.
Coefficients that are statistically significant on a 5% significance level are bold.

Equation 1: Open price adjustment

$$O_t^A = O_t * \frac{C_t^A}{C_t}$$

where:

$O_t^A = Adjusted\ Open\ at\ time\ t,$

$O_t = Open\ at\ time\ t,$

$C_t^A = Adjusted\ Close\ at\ time\ t,$

$C_t = Close\ at\ time\ t$

Equation 2: Market Beta Calculation

$$\beta_i = Cov(r_i, r_m)/Var(r_m)$$

where:

$\beta_i = Market\ beta\ of\ asset\ i\ over\ the\ observation\ period,$

$r_i = Returns\ of\ asset\ i\ over\ the\ observation\ period,$

$r_m = Return\ of\ the\ market\ over\ the\ observation\ period$

Equation 3: Description of the optimization problem that maximizes the portfolio signal value while holding the estimated portfolio beta equal to zero.

$$arg\,\max_x x^T * s \text{ , subject to:}$$

$$x_i \in [-1, 1],$$

$$\sum_{i=1}^{n} \max(0, x_i) = 1,$$

$$\sum_{i=1}^{n} \min(0, x_i) = -1,$$

$$x^T * \beta = 0,$$

where:

$x = Asset\ weights,$

$s = Asset\ signal\ values,$

$\beta = Estimated\ asset\ betas$

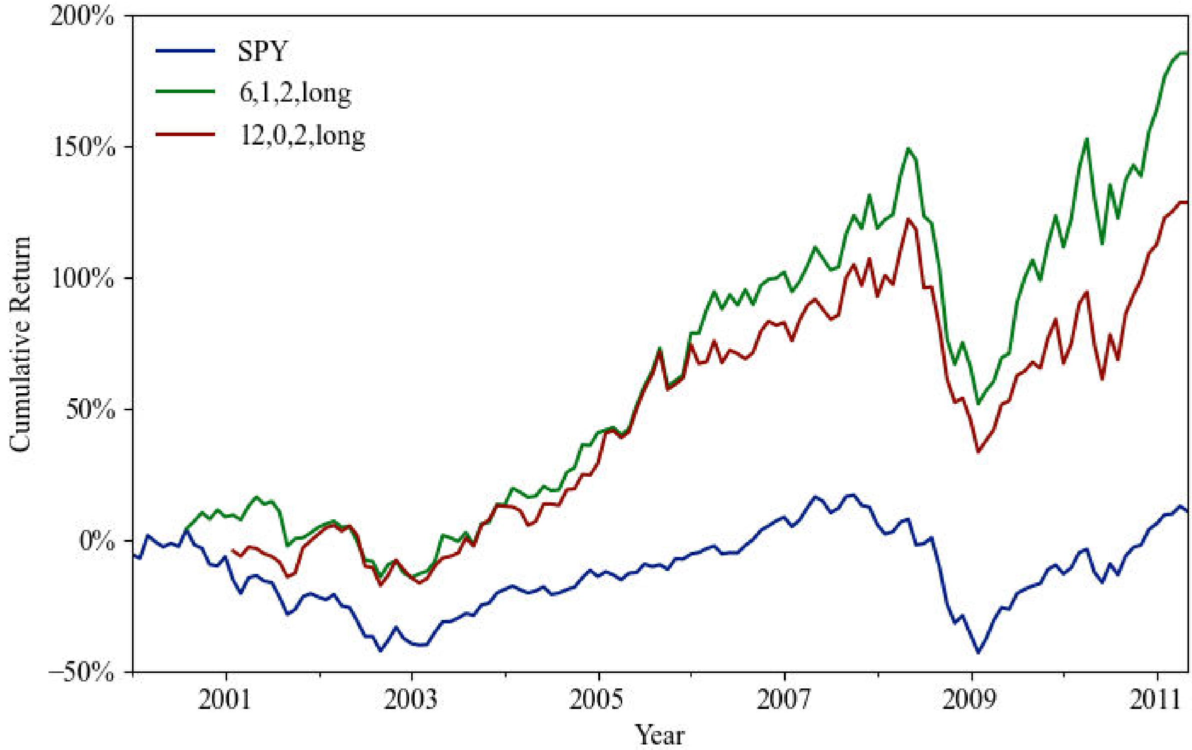

Figure 1: Cumulative returns of selected long momentum strategies and SPY over the in-sample period (2000:01 - 2011:05).

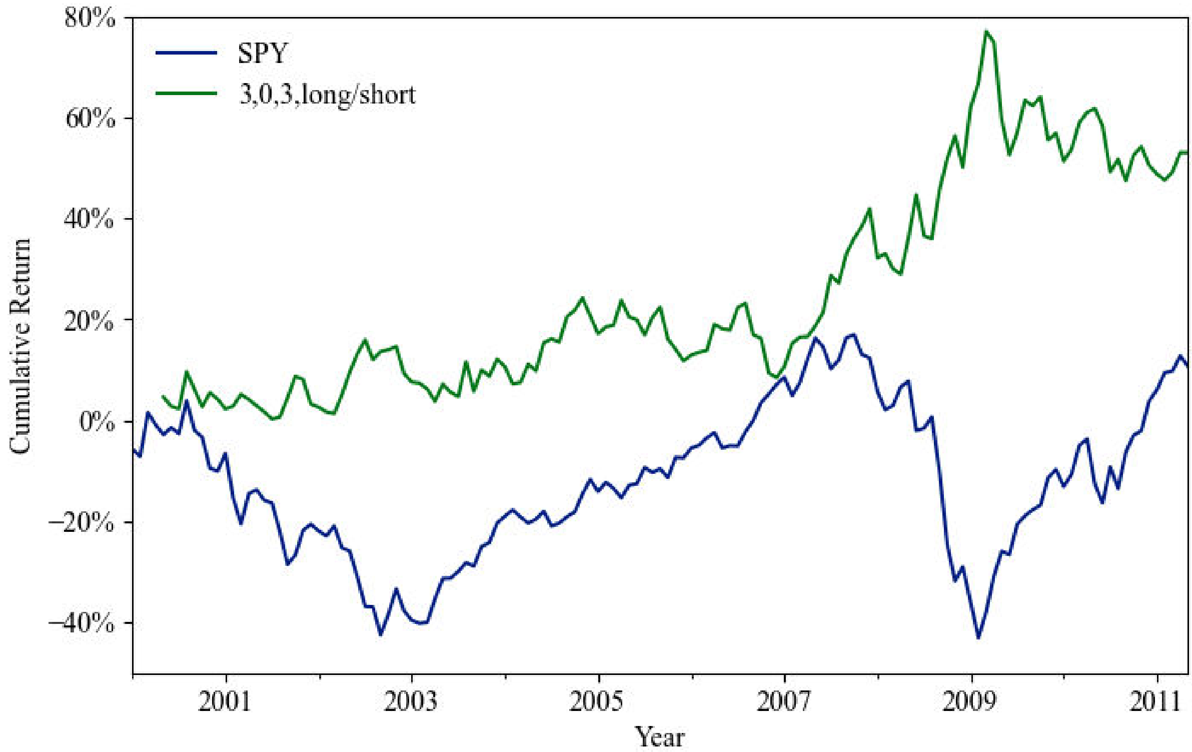

Figure 2: Cumulative returns of long/short strategy and SPY over the in-sample period (2000:01 - 2011:05).

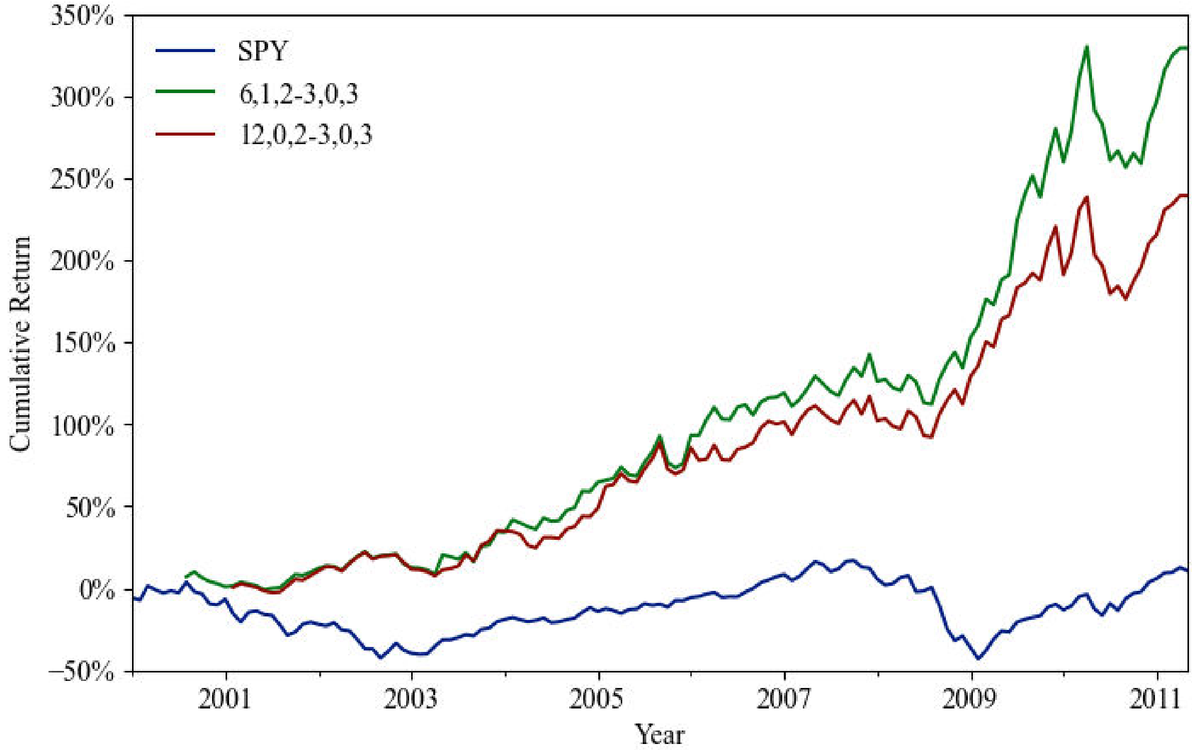

Figure 3: Cumulative returns of long-long/short combinations and SPY over the in-sample period (2000:01 - 2011:05).

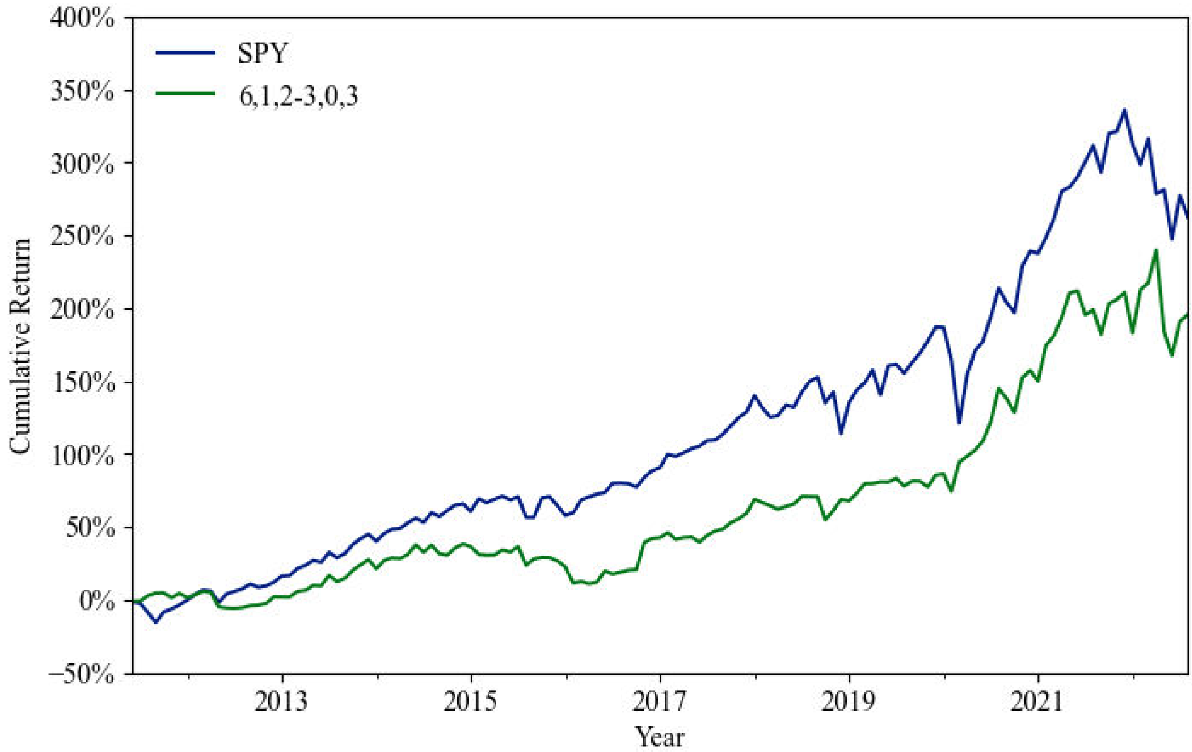

Figure 4: Cumulative returns of the strategy and SPY over the out-of-sample period (2011:06 – 2022:09).