Chasing the Winners: Investigating the Performance of Momentum Strategies

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Abstract

Momentum strategies are receiving increasing attention in the field of finance due to their potential to generate superior returns. Momentum investing is based on the premise that assets that have exhibited strong performance in the recent past are likely to continue to perform well in the near future. This thesis explores the different momentum strategies in diverse markets and asset classes, such as the US equity market utilizing industry portfolios, multi-asset funds, and developed countries. Our study involves a comprehensive analysis of various momentum strategies, including relative momentum and absolute momentum, as well as more recently extended strategies such as dual and triple momentum. In this study, we investigated the optimal parameters for various momentum trading strategies. Our findings suggest that there is no single set of optimal parameters for past price performance and the number of chosen best/worst performing assets that is universally applicable across all datasets and strategies. The study examines momentum strategies using three distinct datasets. The long-only dual momentum strategy has been identified as the optimal approach for the dataset of US industry portfolios, exhibiting a statistically significant Sharpe ratio. The multi-asset fund dataset reveals that the optimal strategy is the triple momentum strategy, which presents the highest statistically significant Sharpe ratio. Similarly, the dataset of developed countries presents the triple momentum strategy as the optimal strategy with the highest Sharpe ratio and the highest statistically significant alpha values from both the Capital Asset Pricing Model and the Fama-French-Carhart Four-Factor Model. Overall, the study highlights the importance of considering various performance and risk measures to determine the optimal momentum strategy.

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Chapter 1

Introduction

Momentum investing has gained substantial attention in recent years as investors search for ways to generate excess returns and outperform the market. This investment strategy is based on the assumption that assets with strong recent performance are likely to continue to perform well in the near future, also known as the momentum effect. Momentum investing has become a popular area of finance research, resulting in the development of numerous momentum strategies that have been extensively tested across diverse asset classes and markets to evaluate their performance and profitability.

The concept of momentum investment strategies was first introduced in a seminal work by Jegadeesh and Titman (1993). Specifically, they proposed the relative momentum strategy, also known as the "cross-sectional" momentum strategy, which paved the way for numerous scholars to conduct research that confirmed the profitability of this strategy across various markets and asset classes (Blitz & Van Vliet, 2008; Asness, Moskowitz, & Pedersen, 2013). Subsequently, the absolute momentum strategy, also known as the "time-series" momentum strategy, was introduced as a new momentum strategy by Moskowitz, Ooi, and Pedersen (2012). This investment strategy is centered around the directional movement of an asset's price over a historical period, in contrast to relative momentum, which compares the performance of an asset to other assets. This serves as the basis for determining whether an asset exhibits positive or negative momentum. The essence of the absolute momentum strategy is to allocate investments in favor of stocks that exhibit positive momentum while selling assets with negative momentum. The validity of this strategy was corroborated by Antonacci (2013) and supported by numerous studies that documented the superior performance of the absolute momentum strategy across different markets and asset classes, including Clare, Seaton, Smith, and Thomas (2014), Moss, Clare, Thomas, and Seaton (2015), and Clare, Seaton, Smith, and Thomas (2017).

Recently, new momentum strategies have emerged. Antonacci (2017) and Lim, Wang, and Yao (2018) introduced the dual momentum strategy, an extension of the absolute momentum strategy with elements from the relative momentum strategy, namely the choice of the best/worst performing asset to include in a portfolio. Both studies reported superior performance of the dual momentum strategy compared to the standalone relative and absolute momentum strategies. Furthermore, Singh, Walia, Jain, and Garg (2022) recently proposed a fourth strategy, the triple momentum strategy, which represents an extension of the dual momentum strategy by incorporating a screening process aimed at mitigating potential "momentum crashes". To clarify, the triple momentum strategy incorporates the absolute and relative momentum strategies, along with a trend-following strategy that helps avoid potentially risky assets.

While previous studies have examined the profitability of individual momentum strategies, few have compared the performance of multiple strategies across different asset classes and markets. Based on our current understanding of the literature, there appears to be a scarcity of research exploring the full range of momentum strategies across US industry portfolios, multi-asset funds, and developed country portfolios. Additionally, our investigation centers on a novel momentum strategy, the triple momentum strategy, which has yet to receive adequate scholarly attention. In light of these gaps in the literature, our study seeks to contribute to the existing body of knowledge by conducting a thorough analysis of momentum strategies in diverse financial contexts.

Specifically, our study aims to identify the best-performing momentum strategies across various datasets and contribute to the existing literature on momentum strategies. We will focus on four momentum investment strategies: the relative momentum strategy, the absolute momentum strategy, the dual momentum strategy, and the triple momentum strategy. The study analyzes the performance of these momentum strategies across three datasets, including 40 US industry portfolios, 8 funds spanning various markets and asset classes, and 19 developed countries.

Momentum strategies offer investors the flexibility to implement either long-short or long-only strategies, except for the relative momentum strategy, which can only be implemented as a long-short strategy. In a long-short strategy, investors buy assets with positive momentum while simultaneously short-selling those with negative momentum. In contrast, a long-only strategy focuses solely on buying assets with positive momentum. All momentum strategies require choosing a specific lookback period, which is the time period used to analyze past price data and determine asset momentum. Moreover, many of the momentum strategies invest in the best/worst-performing assets. Our study aims to determine whether long-short or long-only is optimal, the optimal number of best/worst-performing assets to choose, and the optimal length of the lookback period.

Our empirical results are presented in two parts. Firstly, we report on strategies by varying two key parameters: the time period used to evaluate the performance of the assets (lookback period) and the number of the best/worst assets included in the relative, dual, and triple momentum strategies. Secondly, our empirical results reveal the optimal strategy for each of the aforementioned datasets.

The empirical findings of the study indicate that for the industry dataset, the optimal lookback period for all strategies, except for the absolute momentum strategies, is 12 months based on the Sharpe ratio. The long-short version of the absolute momentum strategy achieves the highest risk-adjusted returns with a lookback period of 6, while the long-only version achieves optimal performance with a lookback period of 8 or 12. Moreover, the optimal number of best/worst assets to include in the strategy is 3 for the long-short dual momentum strategy, 5 for the long-only dual momentum strategy, 3 or 10 for the relative momentum strategy, and lastly, 3 or 5 for the triple momentum strategy. In contrast, for the country dataset, the optimal number of best/worst assets to include in the strategy is dependent on the specific momentum strategy employed. Most of the strategies produce the highest risk-adjusted returns with a number of best/worst performing assets of 5, while the long-only dual momentum strategy performs best with a number of 3, as evaluated using the Sharpe ratio.

The empirical results suggest that different strategies are optimal across the different datasets utilized. For the industry dataset, the long-only dual momentum strategy is deemed the optimal strategy with the highest statistically significant Sharpe ratio, outperforming the naive benchmark. The multi-asset fund dataset reveals the optimal strategy to be the triple momentum strategy yielding the highest statistically significant Sharpe ratio. Similarly, the country-level dataset emphasizes the triple momentum strategy as the optimal strategy based on the Sharpe ratio and the alpha values obtained from both the Capital Asset Pricing Model and the Fama-French-Carhart Four-Factor model. Overall, the study highlights the importance of considering various performance measures to determine the optimal momentum strategy. The study's outcomes suggest that the triple momentum strategy shows potential for further exploration in the field of momentum strategies. As a result, these findings offer valuable contributions to the existing literature on momentum strategies and provide insights into the profitability and suitability of various strategies across diverse markets and asset categories.

The remaining thesis is structured as follows: Chapter 2 provides a comprehensive overview of the existing literature on the topic of interest, establishing a strong theoretical foundation for the study. In Chapter 3, a detailed description of the data sources and the data collection process is provided. Chapter 4 describes the methodology and statistical procedures used to analyze the data, while Chapter 5 presents the key findings of the study with relevant tables and statistical measures. The implications and limitations of the results are discussed in Chapter 6, along with a comparison to the existing literature. Finally, Chapter 7 summarizes the main findings and implications of the study.

Chapter 2

Literature Review

Academic literature extensively studied momentum strategies after the first approach to relative momentum was proposed by Jegadeesh and Titman (1993). Momentum investing strategies are based on the principle that stocks that have exhibited strong performance in the past are likely to continue doing so in the future. As a result, momentum strategies have gained popularity among researchers in recent years, leading to the emergence of different types of momentum strategies, including relative momentum, absolute momentum, dual momentum, and triple momentum. In this chapter, we will provide an overview of each type of momentum strategy and its performance in various financial markets.

In their seminal work, Jegadeesh and Titman (1993) examined the relative momentum strategy, also known as cross-sectional momentum strategy, which involves comparing the performance of a stock to other stocks in the same market or sector. This approach is termed a "cross-sectional" strategy, as investors rank stocks based on their past returns and select a portfolio of assets to buy or sell based on these rankings. The purpose of relative momentum is to identify assets that are likely to continue outperforming or underperforming their peers in the future, thereby providing an investment advantage.

Momentum strategies are based on the principle that past performance can provide insight into future performance. As such, Grinblatt and Moskowitz (2004) argued that past returns could provide information about expected returns. Their study aimed to investigate the relationship between relative momentum returns and macroeconomic risk on a global scale. Their analysis revealed that winner consistency played a crucial role. Investors who consistently achieved high returns over several months were more likely to continue doing so in the future and outperform those who achieved a high return in just a few lucky months.

Asness et al. (2013) confirmed the findings of Jegadeesh and Titman (1993) in their paper and extended their research by incorporating diverse markets and asset classes. The study analyzed the performance of relative momentum and value strategies across individual stocks in the United States, the United Kingdom, continental Europe, and Japan, as well as country equity index futures, government bonds, currencies, and commodity futures. The authors concluded that these strategies were robust and profitable across all the considered asset classes.

The efficiency of the relative momentum strategy was challenged with the introduction of the absolute momentum strategy. As Moskowitz et al. (2012) explained, the absolute momentum strategy involved taking long (buy) positions in assets that had positive returns and short (sell) positions in assets that had negative returns over a specified period, such as the past 12 months. This approach was also termed time series momentum, as it focused on the momentum of an asset's returns over time rather than relative to other assets. The authors found that this strategy generated significant profits across a range of asset classes, including equity indexes, currencies, commodities, and bond futures, and was robust to various market conditions. In their study, Moskowitz et al. (2012) discovered that the 12-month past returns of each asset were a positive indicator of its future returns. They further noted that the profitability of the 12-month absolute momentum strategy was not limited to a particular asset or group of assets, but rather extended to all assets examined in their study.

As an alternative approach to Moskowitz et al. (2012) long-short absolute momentum, Antonacci (2013) introduced the concept of long-only absolute momentum, a strategy that exclusively assumed long positions based on past performance and avoided short-selling. The strategy was implemented as a long-only approach in order to capture upward price trends, simplify implementation, and enhance interpretability of the results. The author conducted a comparative study of long-only absolute momentum with the long-short absolute momentum strategy. Results of the study indicated that the long-only absolute momentum strategy outperformed the long-short strategy when adjusted for risk while also experiencing less significant declines during market downturns. The findings of Antonacci (2013) were also recently confirmed by Zambrano and Rizzolo (2022).

Numerous studies have evaluated the effectiveness of absolute momentum strategies across diverse markets and asset classes. Among the literature, the work of Clare et al. (2014) is notable as it demonstrated that trend-following strategies generated favorable risk-adjusted returns for individual commodity futures. Another study by Moss et al. (2015) presented findings that combining momentum and trend-following approaches yielded advantages for a real estate investment trust (REIT) portfolio. Additionally, Clare et al. (2017) contributed to this discourse by demonstrating that the absolute momentum strategy produced favorable outcomes in international equity markets.

In recent years, Antonacci (2017) introduced an ad-hoc strategy known as "dual momentum", which serves as an alternative to the more traditional absolute and relative momentum strategies. The author's goal was to minimize downside risk by first identifying assets with positive momentum that was already exhibiting an uptrend and then selecting the best-performing assets among them. Fundamentally, this strategy was designed as a long-only approach. In his study, Antonacci (2017) showed that the dual momentum approach performed considerably well across different asset classes and market conditions, such as equities, credit risk, real estate, and economic stress. The author reported that the long-only dual momentum strategy outperformed the relative and absolute momentum strategies, as well as the buy-and-hold strategy. Although Antonacci (2017) reported positive results for the dual momentum strategy, there was disagreement among academics regarding its implementation.

An alternative implementation of dual momentum was introduced by Lim et al. (2018) to address the absolute momentum strategy's requirement to hold positions across all publicly traded assets. This approach involves taking a short position in the assets with the worst negative momentum returns and a long position in the assets with the best positive momentum returns. Their findings confirmed the superior performance of the dual momentum strategy and documented improved profitability compared to absolute momentum. This aligns with the results reported by Antonacci (2017).

Recently, Singh et al. (2022) proposed the "triple momentum" strategy framework, building on the work of Daniel and Moskowitz (2016), Lim et al. (2018) and Antonacci (2017). The triple momentum strategy adds a new screening process called "macro momentum", which takes into account current macroeconomic trends before deciding on investment positions. This screening process is designed to avoid "momentum crashes", which are sudden and severe reversals in asset prices that can occur when there is a significant shift in market conditions. The authors emphasized the importance of risk management in momentum strategies and showed that the triple momentum strategy framework generated substantial increases in average monthly momentum payoffs, as well as significant improvements in higher-order moments and downside risk. However, it is important to note that this study was conducted only in the Indian market.

The momentum effect is a well-researched phenomenon in finance, yet the reasons for its persistence remain unclear. To address this issue, scholars including Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), Hong and Stein (1999), and Frazzini (2006) have put forth several behavioral explanations. One such explanation was anchoring, which referred to the tendency of investors to rely too heavily on a particular piece of information, including the price at which they initially acquired a stock, when making subsequent decisions about that stock. This could lead to an initial underreaction to new information, causing investors to be slow in responding to changes in the stock's value. Another explanation was herding behavior, which described the tendency of investors to follow the actions of others in the market rather than make independent decisions. This behavior could lead investors to buy overvalued stocks, creating a self-reinforcing cycle where buying causes more buying, pushing prices beyond their fundamental value.

Lastly, the disposition effect can explain the momentum effect as it leads to a systematic bias in the behavior of investors. Specifically, the tendency to hold onto losing investments and sell winning investments too early can lead to a situation where the demand for winning stocks exceeds that for losing stocks. This, in turn, can cause the prices of winning stocks to continue to rise as investors continue to buy them, while the prices of losing stocks may stagnate or even decline further due to the lack of demand. As a result, the momentum effect may arise as a consequence of the disposition effect, as investors continue to buy winning stocks and sell losing stocks, causing the prices of winning stocks to continue to rise and those of losing stocks to continue to decline. In conclusion, while the momentum effect remained an important area of study in finance, it was clear that its underlying causes were complex and multifaceted. As the scholars showed, behavioral biases and tendencies were likely to play a significant role in driving momentum.

The momentum effect has been widely studied in financial literature, with the majority of research utilizing a relative momentum approach for selecting securities in portfolio formation. Nevertheless, recent studies have shown that absolute momentum strategies are superior to relative momentum strategies. Moreover, Antonacci (2017) and Lim et al. (2018) suggested that the dual momentum approach generated superior results compared to standalone momentum strategies and that dual momentum strategies outperformed time-series momentum strategies. Finally, Singh et al. (2022) had proposed a novel strategy that they claim performed better than relative, absolute, and dual momentum strategies, namely the triple momentum strategy. However, given that this triple momentum strategy had only recently been published, no other studies had yet verified its validity. In conclusion, it can be argued that the momentum effect is very well known; there are many variants of momentum strategies, but only a few papers have compared and contrasted different momentum strategies systematically, including different datasets to test their robustness.

Chapter 3

Data Collection

3.1 Description of data

The investigation of momentum strategies in this analysis involves the utilization of three distinct datasets. These datasets include US industry data, multi-asset fund data, and country-level data. This approach was employed to provide a comprehensive representation of the various momentum strategies across diverse markets and asset classes. The use of multiple datasets allowed for more robust analysis, providing a more accurate understanding of the performance of the momentum strategies under investigation. It is important to note that the selection of these datasets is based on their relevance to the research question and the availability of data.

3.1.1 US Industries

This study aims to investigate the profitability of various momentum strategies by gathering monthly data from 48 value-weighted industry portfolios sourced from the Kenneth French data library. Due to the absence of complete observations, the study eliminates eight of these industries from the analysis. The study uses monthly data to counteract the potential overestimation of momentum profitability due to false serial correlation associated with asynchronous trading and the bid-ask spread, which can occur when using daily data (Pan, Liano, & Huang, 2004). The use of monthly data is following the standard of momentum investment research. The monthly returns of stocks listed on the NYSE, AMEX, and NASDAQ are categorized into industry portfolios based on their four-digit SIC code as of the end of June of year t, and the returns are then computed from July of t to June of t+1 (French, 2023). The sample period selected for this study spans 1151 months, from January 1st, 1927, to December 31st, 2022, and is intended to provide a comprehensive evaluation of the profitability of momentum strategies over a prolonged duration.

To evaluate the performance of the various momentum strategies, the study integrates additional data from the Kenneth French Data Library, including information on the US risk-free rate, US market rate return, and Fama-French factors, namely SMB (Small minus big), HML (High minus low), and the Carhart factor MOM (Momentum factor). These supplementary datasets are incorporated into the analysis to examine the profitability of various momentum strategies. The incorporation of these datasets further provides a nuanced understanding of the factors that may impact the performance of the different momentum strategies.

Table 1 presents the descriptive statistics of the industry portfolios. The statistics comprise various parameters such as the mean return, the standard deviation of returns, minimum and maximum returns, kurtosis, skewness, and the Sharpe ratio. Additionally, the table includes alpha and beta estimates from the Capital Asset Pricing Model (CAPM). The study tests for the normality of the data using the Shapiro-Wilk test. The null hypothesis is that the data are normally distributed. The table reports the Shapiro-Wilk test statistics (nStats). Asterisk indicates that the null hypothesis is rejected at the 5% level. The acronyms of the industry portfolios are sourced from Fama and French (1997). While the acronyms are mostly self-explanatory, comprehensive definitions of these indices can be found on Kenneth French's website.

Table 1:
The table presents descriptive statistics of monthly industry data sourced from the Kenneth French data library. The industry portfolios are categorized based on their four-digit SIC code as of the end of June of year t, and the monthly stock returns of stocks listed on the NYSE, AMEX, and NASDAQ are computed from July of t to June of t+1. The data covers the period from January 1927 to November 2022. The table includes various parameters, such as the mean return, the standard deviation of return, minimum and maximum returns, kurtosis, skewness, the Sharpe ratio, and CAPM alpha and beta. The coefficient of excess kurtosis is reported. The Shapiro-Wilk test statistic (nStat) is used to test for normality, with an asterisk indicating statistical significance at the 5% level. The mean return, the standard deviation of return, the Sharpe ratio, and the alpha are all annualized, and the values of the mean return, the standard deviation of return, and the minimum and maximum returns are all in percentages.

	Mean	St.Dev	Min	Max	Kurt	Skew	Sharpe	Alpha	Beta	nStat
Agric	11.74	25.92	-36.45	91.34	20.16	1.52	0.33	1.24	0.91	0.90^{*}
Food	11.65	16.51	-27.87	32.63	5.65	0.04	0.51	2.69	0.72	0.94^{*}
Beer	14.20	24.50	-29.19	87.61	22.63	1.75	0.45	3.58	0.92	0.87^{*}
Smoke	13.52	20.25	-24.93	33.04	2.99	-0.00	0.51	5.29	0.63	0.97
Toys	11.34	34.35	-43.34	140.45	35.99	2.65	0.24	-1.61	1.21	0.86^{*}
Fun	14.85	32.19	-44.28	69.57	9.26	0.63	0.36	0.26	1.42	0.90^{*}
Books	11.01	26.49	-34.81	54.75	5.47	0.54	0.29	-1.17	1.12	0.93^{*}
Hshld	11.20	20.01	-34.97	58.33	12.48	0.36	0.40	0.87	0.89	0.91^{*}
Clths	11.24	21.52	-30.85	41.40	4.05	0.25	0.37	1.30	0.84	0.96^{*}
MedEq	13.46	21.51	-25.97	30.28	1.91	-0.17	0.48	3.46	0.85	0.98^{*}
Drugs	13.23	19.69	-35.47	39.50	7.19	0.22	0.51	3.41	0.82	0.93^{*}
Chems	12.38	21.95	-33.30	46.60	6.02	0.27	0.42	0.79	1.04	0.94^{*}
Txtls	11.11	27.10	-35.96	58.93	9.05	0.78	0.29	-1.32	1.15	0.91^{*}
BldMt	12.00	24.09	-31.81	42.41	5.63	0.28	0.36	-0.60	1.17	0.93^{*}
Cnstr	12.85	32.42	-38.04	67.40	6.94	0.83	0.30	-1.19	1.35	0.92^{*}
Steel	11.42	29.87	-32.91	80.84	11.39	1.15	0.27	-2.77	1.37	0.91^{*}
Mach	12.89	25.16	-33.35	52.08	6.66	0.39	0.38	-0.31	1.24	0.93^{*}
ElcEq	13.96	26.46	-34.53	59.58	7.92	0.52	0.41	0.41	1.29	0.93^{*}
Autos	13.79	28.84	-36.42	81.88	12.22	1.23	0.37	0.31	1.28	0.89^{*}
Aero	16.87	31.99	-40.40	72.37	7.90	0.85	0.43	3.20	1.30	0.91^{*}
Ships	12.06	27.94	-34.42	63.37	6.44	0.67	0.32	-0.52	1.17	0.94^{*}
Mines	12.34	25.45	-34.75	46.10	3.12	0.03	0.36	1.20	0.99	0.97^{*}
Coal	13.27	38.22	-40.72	125.43	19.10	1.88	0.26	-0.23	1.28	0.88^{*}
Oil	12.67	22.34	-34.68	39.08	4.27	0.26	0.42	2.29	0.89	0.95^{*}
Util	10.54	19.02	-33.05	43.46	7.78	0.05	0.39	1.19	0.77	0.91^{*}
Telcm	9.92	16.10	-21.56	28.17	2.79	-0.05	0.42	1.34	0.67	0.97^{*}
BusSv	12.74	25.31	-40.28	56.83	8.25	0.46	0.38	1.95	0.94	0.91^{*}
Comps	14.30	25.14	-34.75	54.04	4.45	0.10	0.44	2.19	1.11	0.96^{*}
Chips	14.75	29.74	-42.15	62.78	5.67	0.37	0.39	0.76	1.34	0.94^{*}
LabEq	13.75	23.37	-33.22	25.42	1.89	-0.26	0.45	2.62	0.99	0.98^{*}
Boxes	12.76	21.15	-29.24	43.19	5.29	0.12	0.45	1.93	0.95	0.95^{*}
Trans	11.01	24.60	-34.61	65.40	12.63	1.00	0.32	-1.35	1.14	0.90^{*}
Whlsl	10.50	25.06	-43.85	57.64	12.06	0.65	0.29	-1.44	1.09	0.88^{*}
Rtail	12.49	20.73	-30.41	43.51	5.54	0.04	0.45	1.52	0.97	0.94^{*}
Meals	12.90	22.52	-31.61	30.65	2.78	-0.36	0.43	2.09	0.95	0.96^{*}
Banks	13.86	24.37	-34.00	41.79	4.75	-0.02	0.44	2.24	1.05	0.93^{*}
Insur	12.95	25.58	-45.76	75.11	16.79	1.04	0.38	0.88	1.10	0.87^{*}
RlEst	9.89	33.30	-52.54	66.02	7.60	0.75	0.20	-3.68	1.29	0.90^{*}
Fin	13.27	26.55	-39.47	66.79	8.78	0.46	0.38	-0.36	1.30	0.92^{*}
Other	8.78	25.31	-33.56	45.30	3.74	-0.00	0.22	-2.88	1.05	0.96^{*}

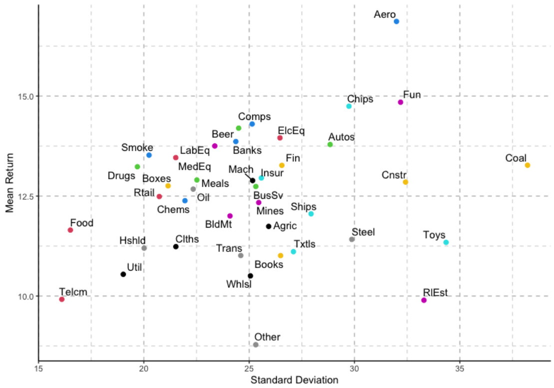

Figure 1: Relationship between US industry returns and standard deviation

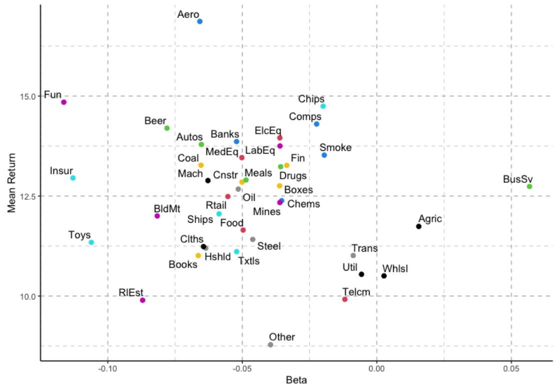

Figure 2: Relationship between US industry returns and market beta

Figures 1 and 2 illustrate the relationship between the average monthly returns of different industry sectors and their corresponding risk levels, with the risk being measured by standard deviation and beta. It is important to note that while standard deviation captures the overall risk of an investment, including both systematic and unsystematic risk, beta only measures the systematic risk, or the degree of correlation between the stock or portfolio and the market. Each data point within the plot corresponds to a distinct sector, and its placement therein is determined by its mean return and risk. Notably, sectors located in the upper right quadrant of the plot, such as Aero (denoting the aerospace and defense industry), are characterized by high average returns and high risk. Conversely, sectors situated in the lower left quadrant, such as Telcm (denoting the telecommunications industry), exhibit lower average returns and lower risk.

3.1.2 Multi-Asset Funds

To broaden the scope of our research on momentum strategies, we expand our analysis to include fund data from a diverse range of markets, such as developed and emerging markets, as well as various asset classes like US bonds and REITs. Specifically, we employ a total of eight funds as proxies to represent the markets and asset classes under investigation. These funds include the Vanguard 500 Index Fund (VFINX), the Fidelity Value Fund (FDVLX), the Vanguard European Stock Index Fund (VEURX), the Vanguard Pacific Stock Index Fund (VPACX), the Fidelity Emerging Markets (FEMKX), the Fidelity Intermediate Government Income Fund (FSTGX), the PIMCO Long-Term U.S. Government Fund (PFGAX), the Vanguard Real Estate Index Fund (VGSIX), and the Fidelity Real Estate Investment Portfolio (FRESX). Each fund is carefully selected based on its ability to provide a comprehensive representation of the relevant market or asset class.

Our fund selection process predominantly focuses on Vanguard and Fidelity funds, owing to their established reputations for reliability and performance. The information on the eight distinct funds is presented in Table 2. The monthly adjusted closed price for the selected funds is obtained from Yahoo Finance and spans the period from January 1st, 1991, to December 31st, 2022. Utilizing the same methodology as the industry dataset, we calculate the simple return as $P_t = \frac{P_t - P_{(t-1)}}{P_t}$. The Fama-French factors, which comprise the market factor, risk-free rate of return, SMB, HML, and MOM, are consistent with the industry data and are also utilized for the multi-asset data. This gives a total of 370 observations.

Table 2:
Information about selected funds. Each fund was carefully selected based on its ability to provide a comprehensive representation of the relevant market or asset class. All funds are denoted in US dollars.

Ticker	Fund	Sector
VFINX	Vanguard 500 Index Fund	Large US Stocks
FDVLX	Fidelity Value Fund	Mid-cap US stocks
VEURX	Vanguard European Stock Index Fund	European Stocks
VPACX	Vanguard Pacific Stock Index Fund	Pacific Stocks
FEMKX	Fidelity Emerging Markets	Emerging Markets
FSTGX	Fidelity Intermediate Government Income Fund	Intermediate US bonds
PFGAX	Long-Term U.S. Government Fund	Long-term US bonds
FRESX	Fidelity Real Estate Investment Portfolio	REIT

The descriptive statistics of the fund portfolios are presented in Table 3. These statistics encompass several parameters, including the mean return, the standard deviation of returns, the minimum and maximum returns, kurtosis, skewness, and the Sharpe ratio. Furthermore, the table reports alpha and beta estimates from the CAPM as well as nStats statistics derived from the Shapiro-Wilk test to test the normality of the data. The data is found to be non-normally distributed, as the null hypothesis of normality is rejected for all values at a significance level of 5%. The acronyms of the fund portfolios are summarized in Table 2.

Table 3:
The monthly prices are sourced from Yahoo Finance, and simple monthly returns are calculated. The returns cover a period from January 1992 to December 2022. The table reports the coefficient of excess kurtosis for each fund. Additionally, CAPM alpha and beta estimates, as well as nStats statistics derived from the Shapiro-Wilk test to test the normality of the data, are included. The asterisk indicates statistical significance at the 5% level. The mean return, the standard deviation of return, the Sharpe ratio, and the alpha are all annualized. The values of the mean return, standard deviation of return, and the minimum and maximum returns are all in percentages.

	Mean	St.Dev	Min	Max	Kurt	Skew	Sharpe	Alpha	Beta	nStat
VFINX	7.84	15.17	-20.99	11.18	2.05	-0.96	0.37	-2.32	0.97	0.95^*
FDVLX	7.80	21.45	-38.83	21.57	7.04	-1.51	0.26	-3.13	1.07	0.89^*
VEURX	4.70	18.06	-29.91	13.69	3.72	-1.10	0.14	-5.41	0.97	0.94^*
VPACX	0.96	17.90	-23.49	14.29	1.02	-0.49	-0.07	-7.69	0.79	0.99^*
FEMKX	0.78	25.50	-51.94	16.85	10.77	-2.12	-0.06	-10.92	1.16	0.87^*
FSTGX	3.66	3.15	-3.02	2.98	1.01	-0.33	0.46	1.60	-0.02	0.98^*
PFGAX	3.06	16.97	-42.07	44.97	33.36	0.08	0.05	1.75	-0.11	0.74^*
FRESX	6.67	21.76	-56.01	24.34	19.92	-2.62	0.20	-2.41	0.84	0.82^*

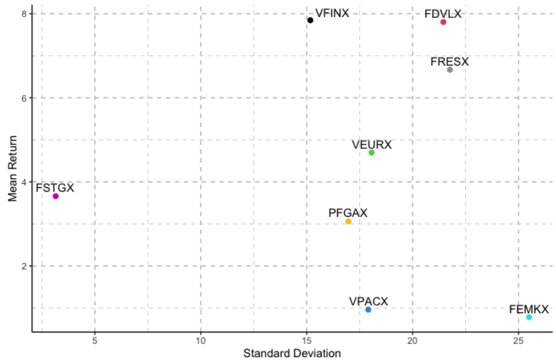

Figure 3: Relationship between fund returns and standard deviation

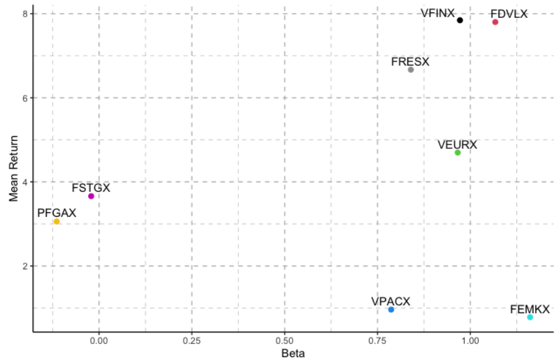

Figure 4: Relationship between fund returns and market beta

Figure 3 and Figure 4 exhibit the relationship between the average monthly fund returns and risk, wherein risk is measured through the standard deviation and market beta. Each data point within the plot corresponds to a distinct sector, and its placement therein is determined by its mean return and risk. Notably, sectors located in the upper right quadrant of the plot, such as FDVLX, are characterized by high average returns and high risk. Conversely, sectors situated in the lower left quadrant, such as FSTGX, exhibit lower average returns and lower risk.

3.1.3 Developed Countries

In this study, we expand our analysis beyond industry and fund data and incorporate return data at the country level. This additional data allows us to examine the performance of the various momentum strategies across different geographical locations. We gather data from the Kenneth French website, which provides data for 21 developed countries. Due to insufficient data on two countries, Ireland and Malaysia, a decision was made to exclude them from the analysis. As a result, a subset of 19 countries is selected for the study. The countries included are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Italy, Japan, the Netherlands, New Zealand, Norway, Singapore, Spain, Sweden, Switzerland, and the UK.

The data used in our analysis focuses on monthly observations spanning from November 1990 to December 2022, with information sourced from Morgan Stanley Capital International for the period between 1990 to 2006 and Bloomberg for the years 2007 to the present. This data provides us with 386 observations, allowing us to analyze the performance of momentum strategies over a lengthy period. In conjunction with the country-level dataset, we acquire supplementary data from the Kenneth French website on developed market factors, encompassing the developed market risk-free rate, developed market rate, and Fama-French-Carhart (FFC) developed factors, namely developed SMB, developed HML, and developed MOM factors.

The descriptive statistics for the country portfolios are showcased in Table 4. The parameters included in these statistics consist of the mean return, the standard deviation of returns, the minimum and maximum returns, kurtosis, skewness, and the Sharpe ratio. The table also includes estimates of alpha and beta from the CAPM. The Shapiro-Wilk test statistic (nStat) is used to test for normality, with an asterisk indicating statistical significance at the 5% level.

Table 4:
This table presents the descriptive statistics for 19 different countries. The data cover a period from January 1990 to December 2022. Monthly returns are sourced from the Kenneth French website. The table displays the alpha and beta values of the CAPM. Kurtosis is the coefficient of excess kurtosis. The Shapiro-Wilk test statistic (nStat) is used to test for normality, with an asterisk indicating statistical significance at the 5% level. The mean return, the standard deviation of return, the Sharpe ratio, and the alpha are all annualized, and the values of the mean return, the standard deviation of the return, and the minimum and maximum returns are displayed in percentages.

	Mean	St.Dev	Min	Max	Kurt	Skew	Sharpe	Alpha	Beta	nStat
Australia	11.00	20.77	-27.68	17.10	2.16	-0.59	0.42	1.48	1.14	0.97^*
Austria	7.52	21.88	-34.25	23.65	3.45	-0.64	0.24	-1.55	1.06	0.96^*
Belgium	8.58	18.28	-29.53	21.31	3.39	-0.66	0.34	0.28	0.94	0.96^*
Canada	10.07	18.77	-26.94	21.71	2.93	-0.67	0.41	1.05	1.05	0.96^*
Denmark	11.95	18.85	-25.69	18.10	1.66	-0.55	0.51	3.50	0.97	0.98^*
Finland	13.56	27.63	-28.99	30.83	1.49	0.14	0.41	2.89	1.32	0.98^*
France	9.89	19.59	-22.23	21.12	1.04	-0.31	0.38	0.32	1.14	0.99^*
Germany	8.69	20.57	-23.30	21.99	1.35	-0.40	0.31	-1.05	1.17	0.98^*
HongKong	11.92	23.75	-28.60	32.18	3.02	0.29	0.40	3.43	0.97	0.96^*
Italy	7.52	23.90	-22.88	24.00	0.65	0.07	0.22	-2.21	1.17	0.99
Japan	3.90	18.39	-15.88	17.93	0.66	0.23	0.08	-3.82	0.85	0.99^*
Nethrlnd	11.15	19.11	-26.38	19.17	2.04	-0.64	0.46	1.77	1.11	0.97^*
NewZland	9.84	20.75	-18.98	15.17	0.41	-0.32	0.36	1.40	0.96	0.99^*
Norway	10.37	24.77	-30.95	22.33	1.98	-0.59	0.32	-0.16	1.30	0.97^*
Singapor	9.40	22.73	-28.31	29.61	3.71	0.07	0.31	0.19	1.09	0.94^*
Spain	8.53	22.12	-22.78	25.87	1.35	-0.03	0.28	-1.06	1.15	0.99^*
Sweden	12.48	23.92	-27.66	25.22	1.15	-0.20	0.42	1.68	1.34	0.99^*
Swtzrlnd	10.96	15.50	-14.72	13.21	0.54	-0.44	0.56	3.50	0.81	0.99^*
UK	7.75	16.60	-20.46	16.38	1.64	-0.36	0.32	-0.72	0.97	0.98^*

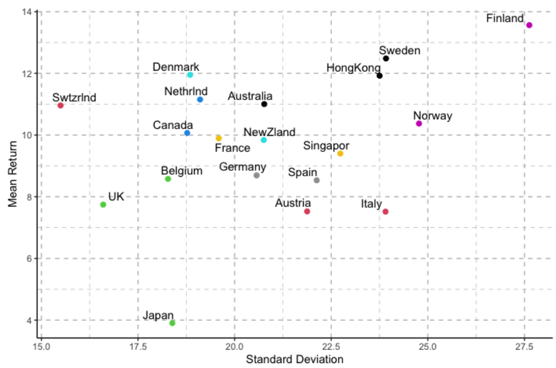

Figure 5: Relationship between country returns and standard deviation

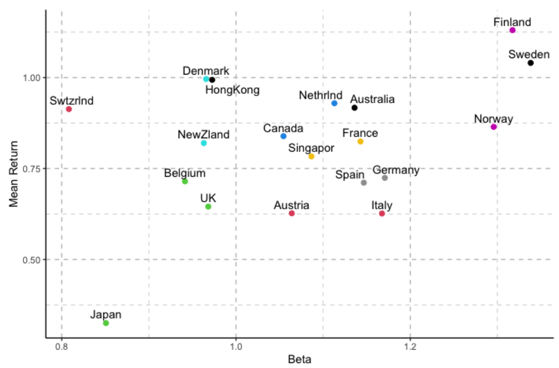

Figure 6: Relationship between country returns and market beta

Figure 5 and Figure 6 exhibit the relationship between the average monthly country returns and risk, wherein risk is measured through the standard deviation and market beta. Each data point within the plot corresponds to a distinct sector, and its placement therein is determined by its mean return and risk. Notably, sectors located in the upper right quadrant of the plot, such as Finland, are characterized by high average returns and high risk. Conversely, sectors situated in the lower left quadrant, such as Japan, exhibit lower average returns and lower risk.

Chapter 4

Methodology

4.1 Portfolio Theory

Portfolio theory is a fundamental concept in finance that seeks to maximize investment returns while minimizing risk. It is based on the principle of diversification, which suggests that by spreading investments across a variety of assets with different risk and return characteristics, investors can reduce the overall risk of their portfolio (Bodie, Drew, Basu, Kane, & Marcus, 2013).

4.1.1 Naive Strategy

In portfolio theory, a naive strategy is a simplistic approach to portfolio construction that assigns equal weights to all N assets in a portfolio, without considering the risk, returns, and covariance between assets. This approach is based on the assumption that each asset has an equal probability of performing well, and thus, an equal amount of money is invested in each security, regardless of its characteristics. Although this strategy does account for diversification, it naively assumes that optimal diversification is an equally weighted portfolio. The Modern Portfolio Theory (MPT) suggests that the 1/N rule is optimal only when all assets have the same mean return, the same variance, and the same correlations. However, this approach is considered suboptimal in general as it fails to capture the potential benefits of further diversification and may expose the investor to concentration risk, which can have adverse effects on portfolio performance (DeMiguel, Garlappi, & Uppal, 2009). In our study, the naive strategy is used as a benchmark to compare against the momentum strategies. By comparing the performance of the momentum strategy to the naive strategy, one can evaluate whether the momentum strategy adds value by providing higher returns or reducing risk compared to the simple, naive approach of equally weighting all assets.

4.1.2 Modern Portfolio Theory

Modern Portfolio Theory (MPT), introduced by Markowitz (1952) in his seminal work "Portfolio Selection", is widely used by investors to construct portfolios that optimize expected returns for a given level of risk or minimize risk for a given level of expected return. MPT provides a quantitative framework for portfolio management and is a crucial tool for balancing risk and return. MPT assumes that the mean returns and variance-covariance matrix of assets are known, but the theoretical implementation of the theory using historical data and assuming stable correlations among assets are not fundamental assumptions of the theory itself. MPT has influenced the development of other theories, such as the capital asset pricing model, which explains the relationship between expected returns and systematic risk (Bodie et al., 2013). The purpose of discussing MPT here is to provide a foundation for understanding the CAPM, which will be elaborated upon in the following section.

4.2 Asset Pricing Theory

Asset pricing theory is a fundamental framework used to understand the determinants of asset prices. It seeks to explain how financial assets, such as stocks and bonds, are priced in the market. This theory incorporates factors such as risk, return expectations, market efficiency, and investor behavior to provide insights into the valuation and pricing of various financial instruments. By analyzing the relationship between these factors, asset pricing theory plays a crucial role in guiding investment decisions and assessing the fair value of assets in financial markets Bodie et al. (2013). Asset pricing theories include the Capital Asset Pricing Model, Fama-French Three-Factor Model and Fama-French-Carhart Four-Factor Model.

4.2.1 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM), a prominent model in modern financial economics, serves as a cornerstone for understanding the relationship between an asset's risk and expected return. To facilitate a proper interpretation of the empirical results presented in the following section, it is essential to provide background information on the CAPM. This model published in articles by Sharpe (1964), Lintner (1975), and Mossin (1966) provides a precise theoretical prediction of the expected relationship between risk and reward. The CAPM, based on MPT, is useful in determining the required rate of return on an investment given its risk profile, as it implies that the expected return on an asset is proportional to its beta, or systematic risk (Bodie et al., 2013). The regression for estimating the CAPM is given as

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i(R_{MKT,t} - R_{f,t}) + \epsilon_{i,t}. \tag{4.1}$$

The CAPM regression equation describes the relationship between the return on an asset i at time t ($R_{i,t}$), the risk-free rate at time t ($R_{f,t}$), and the excess return of the market ($R_{MKT,t} - R_{f,t}$). The intercept term α_i captures the excess return of the asset that cannot be explained by the market, while the slope coefficient β_i measures the sensitivity of the asset's return to the market return. The market risk premium ($R_{M,t} - R_{f,t}$) is the difference between the expected return of the market portfolio and the risk-free rate $R_{f,t}$, and the residual term $\epsilon_{i,t}$ represents the idiosyncratic or company-specific risk of the asset.

The CAPM introduces the concept of beta (β), which measures the sensitivity of a security's return to changes in the market return. A security with a beta of 1 has the same volatility as the market, while a security with a beta greater than 1 is more volatile than the market, and vice versa. The formula for the beta is depicted in equation 4.2

$$\beta_i = \frac{cov(R_i, R_M)}{var(R_M)} \tag{4.2}$$

where $cov(R_i, R_M)$ represents the covariance between the returns of asset i and the market returns, while $var(R_M)$ represents the variance of the market returns. By dividing the covariance by the variance, we obtain a measure of the relative volatility of asset i compared to the market.

The objective of our study is to use the CAPM to investigate the intercept estimate for the regression, which is known as Jensen's alpha (α). This estimate reveals whether asset i (Momentum strategy) outperformed or underperformed the market, given its level of market risk. According to the CAPM, security is mispriced if its alpha is statistically significantly different from zero. In our study, a positive alpha would indicate that the momentum strategies are outperforming the market, while a negative alpha would suggest that the momentum strategies are underperforming the market (Ruppert, 2004).

4.2.2 Fama-French Three Factor Model

In 1993, Fama and French proposed the Fama-French 3-Factor Model (FF3) as an alternative approach to the CAPM to explain asset returns more effectively and address some of the anomalies associated with CAPM. The 3-factor model introduces two additional risk proxies: HML (high minus low), which represents the excess return of a high book-to-market ratio stock portfolio compared to a low book-to-market ratio stock portfolio, and SMB (small minus big), which represents the excess return of a small stock portfolio compared to a large stock portfolio. This model attempts to capture the empirical evidence that small firms tend to outperform large firms and that firms with high book-to-market ratios tend to outperform those with low book-to-market ratios (Fama & French, 1993). The regression for the

Fama-French 3-Factor Model is expressed as follows

$$\begin{aligned} R_{i,t} - R_{f,t} = &\alpha_i + \beta_{i,MKT}(R_{MKT,t} - R_{f,t}) \\ &+ \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \epsilon_{i,t}, \end{aligned} \tag{4.3}$$

where $R_{i,t}$ is the return of asset i at time t, $R_{f,t}$ is the risk-free rate at time t, and $R_{MKT,t}$ is the return of the market at time t. α_i is the expected excess return of asset i that is not explained by the four factors, and $\beta_{i,MKT}$, $\beta_{i,SMB}$, and $\beta_{i,HML}$ represent the sensitivities of asset i's return to the market, size, and value, respectively. SMB_t and HML_t are the values of the size and value factors at time t, and $\epsilon_{i,t}$ represents the idiosyncratic risk of asset i, which is the portion of the asset's return that cannot be explained by the three factors.

The FF3 has become a widely accepted model in finance and is often used by investors and academics to explain the returns of portfolios or individual stocks. For this study, the description of the three-factor model is employed as a preliminary framework to examine the Fama-French-Carhart four-factor model.

4.2.3 Fama-French-Carhart Four Factor Model

The Fama-French-Carhart four-factor model (FFC) is used in finance to explain the returns of a portfolio or security beyond market risk, incorporating additional factors beyond the CAPM. The first set of factors includes the three factors developed in the study by Fama and French (1993): the MKT factor, which represents the excess return on the US equity market; the SMB factor, designed to capture the risk associated with small stocks relative to large stocks; and the HML factor, which captures the premium on high book-to-market value stocks relative to low book-to-market value stocks. The fourth risk factor is the momentum factor (MOM) proposed by Carhart. In summary, the four risk factors used in the model are MKT, SMB, HML, and MOM.

The size factor measures the tendency of smaller firms to outperform larger firms, while the value factor reflects the tendency of stocks with lower prices relative to their fundamentals to generate higher returns. Additionally, the momentum factor captures the tendency of stocks that have recently outperformed or underperformed to continue their performance in the short run. The incorporation of these factors into the four-factor model provides a more comprehensive understanding of the sources of risk and return in a portfolio and enables a more precise estimation of alpha for various investment strategies. The regression for the four-factor model is given by

$$
\begin{aligned}
R_{i,t} - R_{f,t} = &\alpha_i + \beta_{i,MKT}(R_{MKT,t} - R_{f,t}) \\
&+ \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,MOM} MOM_t + \epsilon_{i,t},
\end{aligned} \tag{4.4}
$$

where $R_{i,t}$ is the return of asset i at time t, $R_{f,t}$ is the risk-free rate at time t, and $R_{MKT,t}$ is the return of the market at time t. α_i is the expected excess return of asset i that is not explained by the four factors, and $\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$, and $\beta_{i,MOM}$ represent the sensitivities of asset i's return to the market, size, value, and momentum factors, respectively. SMB_t, HML_t, and MOM_t are the values of the size, value, and momentum factors at time t, and $\epsilon_{i,t}$ represents the idiosyncratic risk of asset i, which is the portion of the asset's return that cannot be explained by the four factors. The purpose of our study is to utilize the FFC to examine the alpha (α) intercept estimate for the regression. Similar to the approach adopted for the CAPM, our analysis concentrates exclusively on this metric and refrains from providing any remarks on the beta coefficients. Following the Fama-French-Carhart (FFC) paradigm, the higher the value of α, the better the performance (Ruppert, 2004).

4.3 Performance measures

Performance measures play an important role in evaluating investment portfolios. They provide valuable insights into the risk-adjusted returns and the ability of portfolio managers to generate excess returns. These measures help gauge the profitability of investment strategies, and compare the performance of different portfolios. Some performance measures includes the Sharpe ratio and Jensen's alpha.

4.3.1 Sharpe Ratio

The Sharpe ratio is a financial metric introduced by Sharpe (1966) that is widely used to assess the risk-adjusted performance of an investment or portfolio. It is calculated as the expected return minus the risk-free rate of return, divided by the standard deviation of returns for the investment. The Sharpe ratio serves as a measure of how much an investor earns in return for each unit of risk taken. A higher Sharpe ratio indicates a better risk-adjusted return, as it represents a higher excess return per unit of risk. Conversely, a lower Sharpe ratio suggests a lower return per unit of risk and may not be as attractive to investors. The formula for the Sharpe ratio is given by

$$
S = \frac{E(R_p) - R_f}{\sigma_p}, \tag{4.5}
$$

where $E(R_p)$ is the expected return of the investment or portfolio. R_f is the risk-free rate of return and σ_p is the standard deviation of the investment's or portfolio's returns.

Our research involves conducting hypothesis testing to evaluate the statistical significance of the Sharpe ratio. We conduct a two-sided test to evaluate whether the Sharpe ratio of the momentum strategy is the same as that of the naive benchmark strategy. The null hypothesis is thus that the Sharpe ratio of the momentum strategies equals the Sharpe ratio of the naive benchmark, depicted as

$$H_0 : SR_{MOM} = SR_N$$

where SR_{MOM} and SR_N denote the Sharpe ratio of momentum strategy and naive strategy, respectively. We utilize the Jobson and Korkie (1981) test, corrected by Memmel (2003), to conduct a hypothesis test assessing the statistical significance of the Sharpe ratio. The test is formulated as follows

$$z = \frac{SR_{MOM} - SR_N}{\sqrt{\frac{1}{T}[2(1-\rho) + \frac{1}{2}(SR_{MOM}^2 + SR_N^2 - 2\rho^2 SR_{MOM} SR_N)]}}$$

where SR_{MOM} and SR_N represent the estimated Sharpe ratios for the momentum and naive strategies, respectively, while ρ denotes the estimated correlation coefficient between the returns of these strategies, over a sample period of T months. If the null hypothesis is true, then z follows an asymptotic standard normal distribution. When the p-value of the test is below the pre-specified significance level of 0.05, we reject the null hypothesis, which suggests that there is sufficient evidence to conclude that the Sharpe ratio of the momentum strategy is statistically significantly distinct from that of the benchmark strategy.

Furthermore, the Sharpe ratio is used as an evaluation measure to identify the strategies that generate the highest risk-adjusted returns. According to Bodie et al. (2013), the Sharpe ratio is a more appropriate performance measure when evaluating individual portfolios against each other. It should be emphasized that the performance measure selected plays a crucial role in determining the optimal strategy. The Sharpe ratio is a performance measure that takes into account total risk, whereas the CAPM and FFC alphas are performance measures that only consider systematic risk.

4.3.2 Alphas

Jensen's alpha is a widely used measure of a portfolio's performance relative to its expected return under the CAPM and FFC. The alpha represents the abnormal return of a portfolio, or the portion of the return that cannot be explained by its exposure to the market or other risk factors. In the CAPM, the alpha is the intercept of the regression line between the portfolio's excess return and the market's excess return. A positive alpha suggests that the portfolio outperformed the market after adjusting for its risk, while a negative alpha suggests the opposite. Similarly, in the FFC, the alpha is the intercept of the regression line between the portfolio's excess return and the factors (market risk, size risk, value risk, and momentum). The FFC allows for a more nuanced analysis of a portfolio's performance by taking into account other risk factors beyond market risk. By using Jensen's alpha, investors can evaluate whether a portfolio has generated excess returns that are not explained by systematic risks and determine the skill of the portfolio manager in generating alpha (Bodie et al., 2013).

This thesis involves conducting hypothesis testing to evaluate the statistical significance of alpha from the CAPM and FFC. We conduct a two-sided test to evaluate whether the alpha of the momentum strategy is the same as the alpha of the naive benchmark strategy. The null hypothesis is thus that the alpha of the momentum strategies equals the alpha of the naive benchmark, depicted as

$$H_0 : \alpha_{MOM} = \alpha_N$$

where α_{MOM} and α_N denote the alpha values of the momentum strategy and the naive strategy, respectively. The test of the null hypothesis is performed using the following test statistics

$$z = \frac{\alpha_{MOM} - \alpha_N}{\sqrt{\frac{1}{T}(\sigma_{MOM}^2 - 2\rho\sigma_{MOM}\sigma_N + \sigma_N^2)}},$$

where α_{MOM}, α_N and ρ are estimated alpha values and correlation coefficients of the residuals of the linear regression ϵ_{MOM} and ϵ_N over a sample period T. Under the null hypothesis, the test is asymptotically distributed as a standard normal, meaning that it follows a normal distribution with a mean of zero and a standard deviation of one. The p-value is a crucial tool for assessing the statistical significance of alpha values. A significance level of 0.05 is commonly used to determine whether to reject the null hypothesis. If the p-value is below this threshold, the null hypothesis is rejected. In the context of momentum strategies versus naive strategies, if the null hypothesis is rejected, it implies that the alpha values derived from these two strategies are statistically significantly different.

4.4 Risk measures

Utilizing risk measures enables us to evaluate the risk of momentum trading strategies. For instance, metrics such as standard deviation, maximum drawdown, value at risk, and conditional value at risk can assist in estimating the expected level of volatility, downside risk, and maximum loss that may be incurred by the specific strategy over a specified time period.

4.4.1 Standard Deviation

Standard deviation is a commonly used risk measure that quantifies the amount of variability or dispersion in a dataset. It is used to measure the risk of an asset or portfolio by estimating the degree of fluctuations in its returns. A higher standard deviation indicates higher volatility and, thus, higher risk. The standard deviation is a popular risk measure due to its ease of calculation, interpretability, and ability to distinguish between high- and low-risk investments. Furthermore, it is often used in combination with other risk measures, such as value at risk (VaR), which will be discussed in more detail in a later subsection, to provide a more comprehensive understanding of the risk profile of an investment or portfolio.

The standard deviation is expressed as

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{n-1}}, \tag{4.6}$$

where σ represents the sample standard deviation, N is the total number of observations, x_i represents each individual observation, $\bar{x}$ represents the sample mean, and n is the sample size. The sample standard deviation is a measure of how much the observations in a sample vary from the sample mean. The formula calculates the square root of the average squared deviation of each observation from the sample mean divided by the degrees of freedom, which is the sample size minus one. The use of the degrees of freedom in the denominator allows the sample standard deviation to be an unbiased estimator of the population standard deviation (Brooks, 2019).

4.4.2 Maximum Drawdown

Maximum drawdown (MDD) is a popular risk measure and refers to the largest percentage decline from the peak value of an investment to its subsequent lowest point, over a specific period of time T. It represents the maximum value of the drawdowns observed during the specific observation period and serves as an essential measure of the risk associated with using a particular trading system. MDD is often used in combination with other risk metrics, such as standard deviation and beta, to get a more comprehensive understanding of the risk profile of an investment (Di Lorenzo, 2013).

Mathematically, MDD at time T is given by the following equation

$$MDD(T) = \max_{\tau \in (0,T)} \left[\max_{t \in (0,\tau)} (X(t) - X(\tau)) \right] \tag{4.7}$$

where $\max_{\tau \in (0,T)}$ selects the time τ between 0 and T that maximizes the expression in the outer brackets, $\max_{t \in (0,\tau)}$ selects the time t between 0 and τ that maximizes the expression in the inner brackets, $X(t)$ represents the value of the asset at time t, and $X(\tau)$ represents the value of the asset at time τ.

4.4.3 Value at Risk

Value at risk (VaR) is a commonly used approach for assessing financial risk and is often compared to other measures such as volatility (standard deviation), maximum drawdown, and expected shortfall (CVaR). It provides an estimate of the potential financial losses that may occur due to fluctuations in market prices. Specifically, VaR is defined as the expected monetary loss that can be incurred over a predetermined period of time with a predetermined level of confidence. There are several ways to compute VaR. One approach to computing VaR involves sorting the returns of a portfolio and selecting the appropriate quantile from the empirical distribution of ordered returns. This non-parametric approach does not rely on any specific distribution for returns and is commonly known as historical simulation.

In this method, a sample of historical returns is collected and ranked, and the fifth percentile of the empirical distribution is taken as the VaR at the 95% confidence level. This approach is relatively easy to calculate and can potentially capture the fat tails of actual distributions of losses. However, the historical simulation VaR technique only uses one data point and disregards all other information in the distribution of points that are both less and more extreme. This is a disadvantage compared to the extreme value theory approach, which considers all data points defined as being in the tail of the distribution (Brooks, 2019).

The VaR is used to estimate the potential loss of an investment portfolio over a specified time horizon with a given level of confidence. Suppose X is a profit and loss distribution where losses are negative and profits are positive. The VaR at level $\alpha \in (0, 1)$ is the smallest value y such that the probability that $Y := -X$ does not exceed y is at least $1 - \alpha$.

Mathematically VaR can be calculated using the following equation

$$\mathrm{VaR}_\alpha(X) = -\inf\{x \in \mathbb{R} : F_X(x) > \alpha\} = F_Y^{-1}(1 - \alpha) \tag{4.8}$$

where F_X and F_Y are the cumulative distribution functions of X and Y, respectively.

4.4.4 Conditional Value At Risk

Conditional Value at Risk (CVaR), also referred to as Expected Shortfall (ES) or Expected Tail Loss (ETL), is a widely utilized risk metric that estimates the potential loss in the tail of a probability distribution beyond a given confidence level, over a specified time horizon. In contrast to traditional methods such as VaR, CVaR provides a more comprehensive assessment of risk by incorporating the severity of potential losses in the tail of the distribution. As such, CVaR is particularly useful for estimating the expected loss under the assumption of encountering worst-case scenarios. This allows for a more nuanced and realistic evaluation of the risk associated with such scenarios, making it a valuable tool for investors and businesses seeking to manage risk (Bodie et al., 2013).

At a given probability level, denoted by p, the CVaR corresponds to the negative value of the expected return for instances when the return falls below its $c = 1 - p$ quantile. In the case of a well-established set of returns with sufficient historical data, the per-period CVaR can be approximated by calculating the negative value of the sample mean of all returns below the specified quantile. This method is occasionally referred to as "historical CVaR", as it is a retrospective analysis of the distribution of returns.

Mathematically, CVaR can be expressed as

$$\mathrm{CVaR}_{\alpha}(X) = -\frac{1}{\alpha}\left(\mathrm{E}\left[X\mathbf{1}_{\{X \le x_\alpha\}}\right] + x_\alpha(\alpha - P[X \le x_\alpha])\right) \tag{4.9}$$

where $x_\alpha = \inf x \in \mathbb{R} : P(X \le x) \ge \alpha$ is the lower α-quantile, and $1_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{else} \end{cases}$ is the indicator function.

4.5 Momentum Strategies

4.5.1 Lookback Period and Asset Selection

Momentum investment strategies rely on identifying securities with strong past performance and assuming that they will continue to perform well in the future. The lookback period (K), or the formation period over which past performance is evaluated, is an important component of momentum investment strategies. Some momentum strategies select a number of best and worst-performing assets (N) to include in the strategy. In this study, we intend to investigate the impact of varying the lookback period K and the number of best/worst assets N on the performance of momentum investment strategies, taking into consideration the size of the dataset. Specifically, we aim to explore the optimal lookback period and the number of best/worst assets to include for different dataset sizes to identify the most effective approach when implementing momentum strategies in different markets and asset classes.

In line with previous literature, we adopt a range of lookback periods (K) in our analysis of the industry dataset, including 6, 8, 10, and 12 months. The selection of these specific time frames is informed by prior research by Jegadeesh and Titman (1993), Singh et al. (2022), Antonacci (2013), and Clare et al. (2014). Additionally, we employ a variety of the number of best/worst assets to include (N) in our analysis, including 3, 5, and 10. This decision aligns with previous studies, as documented by Moss et al. (2015) and Jegadeesh and Titman (1993). It is important to highlight that absolute momentum strategies do not necessitate the use of N and, as such, are not influenced by the selection of a specific N.

Regarding the fund and country datasets, a 12-month lookback period has been employed for calculating the momentum strategies, following the recommendation put forth by Jegadeesh and Titman (1993). Given the restricted size of the fund dataset, a number of best/worst assets of N=3 has been used. Meanwhile, for the country dataset a number of best/worst assets is set to N=3 and N=5, following prior research by Moss et al. (2015) and in consideration of the dataset's size.

4.5.2 Relative Momentum

To evaluate the performance of relative momentum strategies, the present study follows the methodology of Jegadeesh and Titman (1993). The strategy's initial step involves calculating momentum returns by aggregating the returns of a specified lookback period (K). Next, the stocks are ranked based on their returns in the lookback period, and the N best/worst performing assets are selected for inclusion in the portfolio. The top-performing assets comprise the stocks with the highest return in the recent past (best) while the bottom-performing assets include the stocks with the lowest return in the recent past (worst). The relative momentum strategy is a long-short investment strategy that involves taking a long position in stocks in the top-performing assets (best) and a short position in the bottom-performing assets (worst). Consequently, the basic idea of relative momentum is to identify assets or securities that have performed well compared to their peers or benchmark index over a certain time frame and buy them, while selling or avoiding those that have performed poorly.

$$\text{Strategy} = \begin{cases} \text{Buy N best performers} \\ \text{Sell N worst performers} \end{cases}$$

4.5.3 Absolute Momentum

Absolute momentum is a trading strategy that, like all other momentum strategies, first considers an asset's excess return over a given lookback period. This strategy then involves buying assets with a positive return over the formation period (K) (i.e., assets with positive momentum return) and selling assets with a negative return over the same period (i.e., those with negative momentum return) (Moskowitz et al., 2012). Unlike relative momentum, which compares the performance of one asset to another, absolute momentum does not require the selection of a fixed number of best/worst-performing assets.

In contrast to strategies that require an investor to select the N best or worst performing assets (i.e. relative momentum), the absolute momentum approach involves a binary decision where an asset is considered to have positive momentum or not, thus eliminating the need for such selection. This approach focuses on individual asset performance rather than the performance of one asset compared to another. This strategy can be implemented as both a long-short strategy, as previously explained, and as a long-only strategy. The long-only absolute momentum strategy works in the same way as the traditional absolute long-short momentum strategy, expect that this approach, as described by Antonacci (2013), involves investing only in assets with positive momentum over a certain time frame, without short-selling any assets.

Both the absolute long-short and the absolute long-only momentum strategies involve testing for different lookback periods. This is based on the findings of previous research that suggest varying the lookback period can have a significant impact on the performance of the strategy. In certain circumstances, the absolute momentum strategy may encounter situations where the observed returns over a specific lookback period demonstrate exclusively positive or negative momentum. When only positive absolute momentum is present, investors focus solely on positive momentum. Conversely, when positive momentum is absent, investors resort to short-selling (Moskowitz et al., 2012).

$$\text{Strategy} = \begin{cases} \text{Buy assets with positive momentum} \\ \text{Sell short assets with negative momentum} \end{cases}$$

4.5.4 Dual Momentum

This study implements the dual momentum strategy, following the methodological approach proposed by Antonacci (2017) and Lim et al. (2018). The authors' implementation of the strategies exhibits a notable discrepancy, with the former employing a long-only approach, and the latter utilizing a long-short approach. As such, we have devised and constructed both a long-only and a long-short implementation of the strategy. In the dual momentum strategy, the process involves first sorting returns based on the lookback period returns (i.e., momentum returns). Then one selects the N best assets out of the positive momentum returns and the N worst-performing assets out of the negative momentum returns. The long-short approach then involves investing in the N best positive momentum assets and short-selling the N worst negative momentum assets, while the long-only approach only invests in the N best positive momentum assets. Antonacci (2017) proposed a long-only dual momentum strategy that bears market risk when it makes sense, whereas (Lim et al., 2018) introduced the long-short version of the strategy.

Table 5: Dual momentum trading grid

	Absolute Momentum > 0	Absolute Momentum < 0
Relative Momentum N Best	Buy	
Relative Momentum N Worst		Sell

4.5.5 Triple Momentum

This study examines the triple momentum strategy proposed by Singh et al. (2022), which extends the dual momentum approach by including an additional screening process referred to as "macro momentum". However, the validity and scientific justification of this strategy may be questionable, as it can be viewed as an ad-hoc approach. In essence, the strategy compares the lagged 24-month market return with the lagged 1-month market return monthly and, based on this analysis, takes both long and short positions, long-only positions, or short positions. The lagged 24-month market return is defined as the return of the market over the preceding 24-month period. The lagged 1-month market return is defined as the return of the market over the most recently completed month. This additional macro momentum screening aims to enhance the performance of the dual momentum strategy by taking into account the broader macroeconomic environment in which the assets are traded.

Table 6:
"Macro momentum" is used as a collective term for the 24-month and 1-month market returns. When the 24-month return is greater than the 1-month return, it is defined as a positive macro momentum, and when the 1-month return is greater than the 24-month return, it is defined as a negative macro momentum. Therefore, "Macro momentum $>$ 0" refers to the condition where the 24-month return is greater than the 1-month return, and "Macro momentum $<$ 0" refers to the condition where the 1-month return is greater than the 24-month return. In the table, "Macro momentum (+/-)" refers to the condition where one of the returns is positive and the other is negative. 24-month and 1-month returns refer to market returns, not to be confused with momentum returns.

Position	Condition 1	Condition 2
Long/Short	Macro momentum $>$ 0	24-month return $>$ 1-month return
Long Only	Macro momentum (+/-)	24-month return $>$ 1-month return
Short Only	Macro momentum $<$ 0	24-month return $<$ 1-month return

Chapter 5

Empirical Results

5.1 Analysis

5.1.1 US Industry Analysis

In this section, we present the findings of our investigation into various momentum strategies using the industry dataset. As a result of the large size of the dataset, we can evaluate various momentum strategies using different lookback periods (K) and the number of best/worst assets to include in the strategies (N). By doing so, we can evaluate the optimal values of N and K for these strategies. It is worth noting that absolute momentum strategies do not involve N in their estimations. Therefore, we will solely display the optimal K for these strategies. Lastly, we will identify the optimal strategy based on our findings from the industry dataset. The study conducts hypothesis tests for the Sharpe ratio and Alpha (both CAPM and FFC) to assess the statistical significance of the results. Specifically, the tests compare the different momentum strategies against the equal-weighted (naive) benchmark strategy.

Table 7 reports the performance of absolute, long-only, and long-short, momentum strategies with different K-month lookback periods (6, 8, 10, and 12 months), using different performance measures including the Sharpe ratio and alpha from CAPM and FFC. The Sharpe ratio is a key metric in evaluating the performance of these strategies, as it is particularly effective in comparing the performance of individual strategies. The table includes four specific risk measures, namely the standard deviation, MDD, VaR, and CVaR.

In Panel A, which shows the long-short absolute momentum strategy, the highest Sharpe ratio for this strategy is 0.50 for a K of 6 months. The Sharpe ratio of the naive benchmark strategy is 0.45, reported in Panel C, indicating that the long-short absolute momentum strategy seemingly outperforms the naive benchmark strategy, however, we cannot reject the null hypothesis. The alpha coefficient from the CAPM model has its highest statistically significant value at K=8. The FFC model's alpha coefficients are statistically significant and positive for K=6, 8, and 12, with K=6 being the highest among the examined lookback periods. Based on the assessment of the risk measure, the results presented in the table indicate that the minimum value of the MDD is recorded at 57.55 when the parameter K equals 12. The values of VaR and CVaR have the lowest values at K=6. Additionally, the analysis reveals that the standard deviation is lowest when K equals 6. Thus, based on the evaluation of the risk measures, it can be inferred that there is no singular optimal parameter value of K that exhibits a lower level of risk than the others. The performance measures also exhibit variations, with the optimal parameter K identified as 6 months when evaluating based on the Sharpe ratio and the alpha from the FFC model, whereas K=8 months is found to be optimal when utilizing the CAPM model for evaluation.

In Panel B, illustrating the long-only absolute momentum strategy, the statistically significant highest Sharpe ratio of 0.57 is observed when employing a lookback period (K) of 8 or 12 months. These Sharpe ratios exceed the Sharpe ratio of the naive benchmark strategy and have p-values lower than 5%; therefore, we have evidence that the long-only absolute momentum strategy outperforms the naive benchmark. Moreover, the results indicate that the alpha coefficients derived from the CAPM show the highest positive statistically significant value at K=8 months. None of the alpha FFC values are larger than the benchmark. An examination of the risk measures reveals that the lowest MDD of 66.75 is attained at K=8. The values of VaR and CVaR are the lowest when K equals 8. These findings indicate that the optimal parameter K varies depending on the performance measure utilized. Specifically, the Sharpe ratio finds the optimal lookback period when K equals 8 or 12. On the other hand, the alpha measure identifies K equals 8 for CAPM as the optimal value, while the risk measures exhibit lower values at K=8.

These empirical findings indicate that the long-only absolute momentum strategy outperforms the long-short absolute momentum strategy in terms of risk-adjusted returns, as measured by the Sharpe ratio, for all K lookback periods. However, the long-short absolute momentum strategy exhibits the highest alpha value between the two. The long-short strategy generates a substantial-high alpha because the beta of this strategy is low. Hence, the long-short strategy has a very small systematic risk. Therefore, the optimal strategy choice is dependent on the performance metric. Observing the risk measures, the long-short absolute momentum strategy shows the lowest MDD and the lowest VaR and CVaR parameters. Compared to the naive benchmark strategy, the long-short absolute momentum strategy outperforms the naive benchmark strategy on every risk and performance measure. The long-only absolute momentum strategy generates better risk-adjusted returns than the naive benchmark strategy when comparing almost all measures.

Table 7: Performance statistics of absolute momentum, both long-short and long-only strategies, were obtained from US industry data. The table displays statistics for each strategy with lookback periods K of 6, 8, 10, and 12 months and includes performance measures for the Sharpe ratio and two alphas (CAPM and FFC). The p-values of the alphas and Sharpe ratios are reported in brackets. The table also includes the risk measures of MDD, VaR, and CVaR. The statistics are all annualized, except for MDD, VaR, and CVaR, as these measures are not dependent on the frequency of the data. The values, except for the Sharpe ratio, are quoted in percentages

Panel A: Long-short absolute momentum

	K Months			
	6	8	10	12
Mean return	7.04	6.89	6.04	7.14
Standard deviation	14.08	14.66	15.01	15.41
Sharpe ratio	0.50	0.47	0.40	0.46
	(0.37)	(0.44)	(0.61)	(0.45)
α_{CAPM}	8.04	8.13	6.14	7.76
	(0.00)	(0.00)	(0.00)	(0.00)
α_{FFC}	3.19	2.10	-0.29	1.06
	(0.00)	(0.00)	(0.00)	(0.00)
Max drawdown	68.98	78.20	61.26	57.55
VaR (5%)	-5.42	-6.03	-5.47	-5.82
CVaR (5%)	-9.21	-9.84	-9.50	-9.91

Panel B: Long-only absolute momentum

	K Months			
	6	8	10	12
Mean Return	12.87	13.32	12.33	13.32
Standard Deviation	18.27	17.67	18.24	17.88
Sharpe ratio	0.53	0.57	0.50	0.57
	(0.04)	(0.01)	(0.10)	(0.00)
α_{CAPM}	2.89	3.68	2.27	3.49
	(0.00)	(0.00)	(0.00)	(0.00)
α_{FFC}	0.43	0.38	-0.60	0.55
	(0.00)	(0.00)	(0.00)	(0.20)
Max drawdown	81.33	66.75	83.05	67.33
VaR (5%)	-7.70	-6.94	-7.27	-7.23
CVaR (5%)	-12.01	-11.32	-12.12	-11.35

Panel C: Naive benchmark strategy

Mean return	12.23
Standard deviation	20.22
Sharpe ratio	0.45
α_{CAPM}	0.72
α_{FFC}	0.62
Max drawdown	85.12
VaR (5%)	-8.32
CVaR (5%)	-13.00

Table 8 reports the performance statistics of the four momentum strategies, including relative momentum, dual momentum (both long-short and long-only), and triple momentum strategies, with different lookback periods (K) and the number of best/worst assets (N).

In Panel A, presenting the outcomes of the relative momentum strategy, noteworthy findings emerge regarding the optimal parameter combinations that yield the highest Sharpe ratios. Specifically, the analysis reveals that the strategy attains its most favorable performance, as measured by the Sharpe ratio, at two distinct sets of parameters: K=12 and N=3 or 5. Notably, both combinations produce identical Sharpe ratios of 0.62, indicating comparable levels of risk-adjusted returns. There are indications that the relative momentum strategy outperforms the naive benchmark strategy with these combinations, but we fail to reject the null hypothesis at the 5% level. We observe that when K increases, the performance generally improves for all values of N. Focusing on the best K, we can see that K=12 generally outperform the other values of K in terms of the Sharpe ratio for all values of N. Increasing the N parameter generally leads to higher Sharpe ratios for K equal 6, 8, and 10, however, the combinations of K=12 and N=3 or N=10 outperforms other combinations concerning both Sharpe ratios. N=3 and K=12 is the optimal combination in terms of the alpha values, with the highest positive statistically significant values. Hence, we can infer that this combination is optimal for implementing a relative momentum strategy using the industry dataset. In Panel A, the risk measures MDD, VaR, and CVaR for the relative momentum strategy are provided. It is discernible from the table that MDD exhibits a declining trend with increasing N. Similar behavior is displayed by the VaR, CVaR, and standard deviation parameters, implying that increasing the value of N leads to a reduction in risk for the relative momentum strategy. When N equals 5 and 10, the MDD, VaR, and CVaR are lower than those of the naive benchmark strategy.

Panel B, which shows the long-short dual momentum strategy, reveals that the best performance is achieved with a combination of K=12 and N=3, which has a Sharpe ratio of 0.57. This Sharpe ratio is higher than the Sharpe ratio of the naive benchmark strategy, and thus there are indications that the long-short dual momentum strategy outperforms the benchmark, but we cannot reject the null hypothesis. All alpha CAPM values are positive and statistically significantly different from the benchmark, with the combination of N=3 and K=12 exhibiting the highest alpha CAPM value of 15.56. Similarly, the alphas from the FFC model are all statistically significant, and the highest alpha is achieved for N=3 and K=8. Upon evaluating the risk measures, it is observed that the combination of N=10 and K=12 exhibits the lowest MDD of 64.72 for the long-short dual momentum strategy. This value is lower than the naive benchmark. Additionally, the lowest VaR and CVaR are observed when N=10 and K=6. For the long-short dual momentum strategy, we generally observe a trend of lower downside risk, as reflected by the MDD, as K increases.

In Panel C, depicting the outcomes of the long-only dual momentum strategy, our analysis reveals that the highest Sharpe ratio of 0.69, with statistical significance, is achieved when K=12 and N=5. This optimal combination of parameters indicates the most favorable risk-adjusted return among the tested variations of N and K. Additionally, the Sharpe ratios for every combination of the long-only dual momentum strategy is higher than the naive benchmarks Sharpe ratio. The alpha values obtained from the application of the CAPM and FFC models exhibit their highest statistically significant positive value when considering the parameter combination of K=12 and N=3. By analyzing the risk measures, a discernible pattern emerges, indicating a decrease in downside risk as the lookback period is extended to 12 months for all values of N. Notably, the combination of K=12 and N=5 demonstrates the lowest MDD value. This finding suggests that a longer lookback period, coupled with a larger number of best-performing assets, can potentially mitigate the downside risk associated with the momentum strategy under consideration. Upon examination of the value at risk parameters, evidence suggests a decrease in VaR values when N=10. The CVaR has its lowest value observed at N=10. These findings indicate that a larger number of best assets included (N) contributes to a reduction in the estimated downside risk.

In Panel D, we examine the performance of the triple momentum strategy across different values of N and K parameters. Evaluating based on the Sharpe ratio gives the two optimal combinations, K=12, and N=3 or N=5 with an equal Sharpe ratio of 0.52. These findings suggest that the triple momentum strategy exhibits enhanced performance when employing a 12 months lookback period and selecting either three or five best-performing assets. These Sharpe ratios appear to be higher than the benchmark, but we cannot reject the null hypothesis at the 5% level. When evaluating based on the alpha values of the CAPM and FFC models, the highest statistically significant value is found with the combination of N=3 and K=12. In general, the results reveal that when evaluating the performance of the triple momentum strategy, it seemingly outperforms the benchmark strategy. The MDD values for the triple momentum strategy are consistently lower than those of the benchmark, with the lowest value found when K equals 12 and N equals 3. When N equals 10, the VaR and CVaR reaches its lowest levels, which are also lower than those of the benchmark strategies.

Table 8:

Performance statistics of relative, dual (both long-short and long-only), and triple momentum strategies using US industry data. The table reports the returns of the momentum strategies with different lookback periods (K) and ranks (N). Performance measures such as standard deviation, Sharpe ratio, and alpha from CAPM and FFC are also reported. CAPM and FFC stand for the Capital Asset Pricing Model and the Fama-French-Carhart Model, respectively. The p-values of the CAPM and FFC alphas and the Sharpe ratio are reported in brackets. The table also includes the risk measures of MDD, VaR, and CVaR. The statistics are all annualized, except for MDD, VaR, and CVaR, as these measures are not dependent on the frequency of the data. The values, except for the Sharpe ratio, are quoted in percentages

Panel A: Relative momentum

N	Top 3				Top 5				Top 10			
K	6	8	10	12	6	8	10	12	6	8	10	12
Mean return	8.31	9.55	9.91	14.00	7.77	8.90	9.74	11.37	5.88	6.50	7.66	8.72
Standard dev	21.73	21.81	22.19	22.60	17.63	17.99	18.14	18.87	13.40	13.35	13.60	13.96
Sharpe ratio	0.38	0.44	0.45	0.62	0.44	0.49	0.54	0.60	0.44	0.49	0.56	0.62
	(0.66)	(0.52)	(0.50)	(0.13)	(0.51)	(0.38)	(0.28)	(0.16)	(0.52)	(0.40)	(0.23)	(0.13)
α_{CAPM}	9.80	11.04	11.05	15.05	9.06	10.27	10.72	12.52	7.31	7.57	8.67	9.74
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α_{FFC}	1.22	1.70	0.55	4.64	1.52	1.55	1.20	3.05	1.28	0.77	1.12	2.13
	(0.00)	(0.00)	(0.62)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.00)	(0.00)
Max drawdown	85.50	88.00	86.99	71.83	73.46	78.74	68.48	68.66	69.36	52.88	50.59	53.65
VaR (5%)	-8.86	-9.30	-8.93	-9.04	-7.32	-7.78	-7.61	-7.86	-5.46	-5.47	-5.79	-5.63
CVaR (5%)	-13.50	-14.24	-13.86	-13.49	-11.67	-12.14	-11.82	-11.96	-9.18	-8.86	-9.07	-9.07

Panel B:Long-short dual momentum

N	Top 3				Top 5				Top 10			
K	6	8	10	12	6	8	10	12	6	8	10	12
Mean return	11.40	12.64	11.36	14.67	10.63	11.23	10.89	12.52	8.89	9.38	9.23	10.36
Standard dev	24.19	24.40	24.67	25.53	21.00	21.68	21.84	22.62	18.19	18.86	19.12	19.65
Sharpe ratio	0.47	0.52	0.46	0.57	0.51	0.52	0.50	0.55	0.49	0.50	0.48	0.53
	(0.44)	(0.33)	(0.46)	(0.20)	(0.35)	(0.33)	(0.36)	(0.24)	(0.39)	(0.37)	(0.40)	(0.30)
α_{CAPM}	13.01	14.39	11.80	15.56	12.04	12.99	11.25	13.44	10.48	10.95	9.61	11.26
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α_{FFC}	3.50	3.80	-0.27	3.34	3.60	2.81	0.06	1.79	3.14	2.18	-0.06	1.17
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Max drawdown	91.54	86.16	87.36	67.85	85.62	88.43	74.22	69.28	84.26	82.60	65.86	64.72
VaR (5%)	-9.35	-10.08	-9.44	-9.94	-8.68	-8.90	-9.05	-9.13	-6.90	-7.46	-7.34	-7.61
CVaR (5%)	-14.96	-15.48	-15.45	-15.95	-13.47	-14.11	-14.01	-14.65	-12.22	-12.50	-12.48	-12.90

Panel C: Long-only dual momentum

N	Top 3				Top 5				Top 10			
K	6	8	10	12	6	8	10	12	6	8	10	12
Mean return	16.62	17.94	17.58	19.46	15.85	17.09	16.99	18.33	14.71	15.69	15.33	16.53
Standard dev	23.56	23.04	23.87	24.27	21.62	21.33	22.17	22.06	19.82	19.52	20.26	19.95
Sharpe ratio	0.57	0.64	0.60	0.67	0.58	0.65	0.62	0.69	0.58	0.64	0.60	0.67
	(0.04)	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
α_{CAPM}	5.88	7.47	6.68	8.63	5.28	6.77	6.20	7.70	4.40	5.63	4.78	6.23
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α_{FFC}	0.75	1.72	0.71	2.51	0.68	1.26	0.77	2.05	0.62	0.85	0.28	1.48
	(0.25)	(0.00)	(0.44)	(0.00)	(0.53)	(0.00)	(0.08)	(0.00)	(0.99)	(0.00)	(0.00)	(0.00)
Max drawdown	89.19	78.36	88.33	74.51	85.10	73.28	85.59	69.81	83.97	71.77	86.34	71.12
VaR (5%)	-9.66	-8.89	-10.11	-9.76	-8.83	-8.61	-9.25	-8.85	-8.50	-7.33	-8.37	-8.34
CVaR (5%)	-15.00	-14.40	-15.08	-15.19	-14.05	-13.72	-14.53	-13.89	-13.05	-12.57	-13.53	-12.68

Panel D: Triple momentum

N	Top 3				Top 5				Top 10			
K	6	8	10	12	6	8	10	12	6	8	10	12
Mean return	9.03	9.44	9.26	11.40	8.27	8.50	9.02	10.43	7.26	7.38	8.15	9.04
Standard dev	21.64	21.56	21.89	22.00	19.69	19.78	20.11	20.06	17.79	17.84	18.05	17.99
Sharpe ratio	0.42	0.44	0.42	0.52	0.42	0.43	0.45	0.52	0.41	0.41	0.45	0.50
	(0.58)	(0.52)	(0.57)	(0.30)	(0.57)	(0.55)	(0.49)	(0.29)	(0.61)	(0.59)	(0.48)	(0.33)
α_{CAPM}	7.86	8.50	7.80	9.96	7.07	7.54	7.51	9.09	6.17	6.34	6.61	7.74
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α_{FFC}	4.58	4.49	2.84	4.99	4.08	3.40	2.91	4.22	3.68	2.86	2.75	3.61
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Max drawdown	77.83	77.79	82.72	63.26	74.54	79.90	82.54	68.09	73.69	75.80	77.55	66.98
VaR (5%)	-8.43	-8.26	-8.85	-8.68	-7.62	-7.77	-8.08	-7.93	-6.97	-7.19	-7.10	-7.30
CVaR (5%)	-13.21	-13.19	-13.27	-13.09	-12.54	-12.45	-12.42	-12.22	-11.65	-11.38	-11.06	-10.93

In the context of industry data, our findings reveal a general trend of improved Sharpe ratios with increasing values of K across most momentum strategies, except for the absolute momentum strategies. Moreover, our results demonstrate that the selection of different values for N influences the observed outcomes of the performance measures. Specifically, for the relative momentum strategies, the highest levels of performance, as evidenced by the highest Sharpe ratios, are achieved when N is set at either 3 or 10. Likewise, for the triple momentum strategy, the most favorable performance levels are observed when N takes values of 3 or 5. The long-only dual momentum strategy exhibits its highest performance when N is set to 5, while the long-short dual momentum strategy achieves its optimal performance with N=3. The risk reported by the MDD, VaR, and CVaR indicates a general trend of lower risk when increasing N to 10.

The empirical findings indicate that the relative, dual, and triple momentum strategies exhibit optimal risk-adjusted returns when a 12-month lookback period (K) is employed. However, the absolute momentum strategies deviate from this pattern, as the long-short version achieves higher risk-adjusted returns, as measured by the Sharpe ratio, with a 6-month lookback period, while the long-only version achieves optimal results with either an 8- or 12-month lookback period. Moreover, the alpha coefficients derived from the CAPM and FFC models support the aforementioned results. The relative, dual, and triple momentum strategies yield their highest alpha values at a lookback period of 12 months. In contrast, the absolute momentum strategies exhibit different outcomes, with alpha CAPM reaching its peak at an 8-month lookback period for both strategies, while alpha FFc performs best with a 6-month lookback period. Evaluating based on risk, the results indicate that there is no consistent value for parameter K that uniformly minimizes overall risk.

When using industry data, our analysis indicates that the long-only dual momentum strategy yields the highest statistically significant Sharpe ratio of 0.69, surpassing the relative momentum strategy, the long-only absolute momentum strategy, the long-short dual momentum strategy, the triple momentum strategy and the long-short absolute momentum strategy. These results provide evidence that all of the momentum strategies outperform the naive benchmark, however, not all are less than 5% and thus we cannot reject the null hypothesis. There is therefore indication that momentum strategies can possess superior risk-adjusted performance and can offer the potential for generating higher returns relative to a simple buy-and-hold approach. In conclusion, based on the Sharpe ratio, the long-only dual momentum strategy has the best performance.

The identification of an optimal strategy is dependent on the performance measure utilized. Evaluation based on the alpha derived from the CAPM model indicates that the long-short dual momentum strategy attains the highest statistically significant positive value and is therefore identified as the optimal strategy under this model. Conversely, evaluation based on the FFC model reveals that the triple momentum strategy exhibits the highest statistically significant alpha and is hence identified as the optimal strategy. The risk measures indicate that the relative momentum strategy achieves the lowest MMD and the lowest CVaR. The long-short absolute momentum strategy, however, exhibits the lowest VaR.

Appendix A1 presents the cumulative returns for each momentum strategy using the industry dataset. Figure A1.1 displays the cumulative returns of the relative momentum strategy for different values of N and K. The cumulative returns for the absolute momentum strategies (long-short and long-only) with varying K values are shown in Figure A1.2 and Figure A1.3, respectively. The cumulative returns for the dual momentum strategy (long-short and long-only) with varying N and K values are presented in Figure A1.4 and Figure A1.5, respectively. Finally, Figure A1.6 illustrates the cumulative returns of the triple momentum strategy with varying N and K. The cumulative returns of the naive benchmark strategy are depicted in Figure A1.7.

5.1.2 Multi-Asset Fund Analysis

In this section, we present the results of our investigation into various momentum strategies utilizing the multi-asset fund dataset. Due to the limited size of the dataset, altering the values of N and K was impractical, and as such, we opted to exclude that analysis from this dataset. Therefore, we utilized K=12 and N=3 to compare the performance of the momentum strategies in this dataset. Our analysis of this dataset will consequently only focus on determining the best-performing strategy. Similar to the other datasets, we primarily relied on the Sharpe ratio as the performance measure. Hypothesis tests are conducted for the Sharpe ratio and Alpha (both CAPM and FFC) to assess the statistical significance of the results. Specifically, the tests compare the different momentum strategies against the equal-weighted (naive) benchmark strategy.

Table 9 presents the results of our investigation into the performance of various momentum strategies applied to fund data. Panel A of the table reports the performance and risk statistics of relative, long-short absolute, and long-only absolute momentum strategies. Among these strategies, the relative momentum strategy exhibits the highest Sharpe ratio, denoted as 0.50. There are statistically significant differences between the Sharpe ratios of the momentum strategies and the Sharpe ratio of the naive benchmark strategy. Alpha from all three momentum strategies (relative, absolute, and long-only absolute) is statistically significantly different from the alpha of the naive strategy. Among these three strategies, the relative momentum strategy generates the highest alpha under both models. Upon analyzing the risk measures of the three strategies, it is observed that the long-only absolute momentum strategy exhibits the lowest level of risk. Specifically, it achieves the lowest MDD of 31.34, as well as the lowest values for VaR and CVaR, at -4.09 percent and -6.89 percent, respectively.

In Panel B, the performance and risk statistics of the long-short dual, long-only dual, and triple momentum strategies are presented. Evaluating based on the Sharpe ratio, the triple momentum strategy is identified as the optimal strategy among the three, with the highest Sharpe ratio. The Sharpe ratio of all strategies is found to be statistically significantly different from the Sharpe ratio of the naive benchmark. Furthermore, all three strategies yield statistically significant positive alphas when evaluated using the CAPM and FFC models. Notably, the long-short dual momentum strategy produces the highest alpha under both models. Upon examining the risk metrics, it is observed that the long-only dual momentum strategy demonstrates the least amount of risk, as evidenced by its minimum MMD value of 27.38 and the lowest VaR and CVaR values of -5.26 percent and -7.61 percent, respectively. However, it is worth noting that the long-only dual momentum strategy displays a negative Sharpe ratio, which implies that the investment's returns are not adequately compensating for the volatility or riskiness of the investment.

Table 9:
Performance statistics of various momentum strategies applied to fund data. The table reports the returns of relative, absolute, dual, and triple momentum strategies, along with performance measures such as standard deviation, the Sharpe ratio, and alpha from CAPM and FFC. CAPM and FFC stand for the Capital Asset Pricing Model and the Fama-French-Carhart Model, respectively. The fund data is sorted either by sign, rank, or both based on their past 12-month returns. The p-values of the CAPM and FFC alphas and Sharpe ratios are reported in brackets. The table also includes the risk measures of MDD, VaR, and CVaR. The statistics are all annualized, except for MDD, VaR, and CVaR, as these measures are not dependent on the frequency of the data. The values, except for the Sharpe ratio, are quoted in percentages.

Panel A: Relative, long-short absolute and long-only absolute momentum strategies

	Relative Momentum	Long-short Absolute Momentum	Long-only Absolute momentum
Mean return	8.08	6.50	5.76
Standard deviation	16.25	16.52	9.68
Sharpe ratio	0.50	0.39	-0.21
	(0.00)	(0.00)	(0.04)
α_{CAPM}	10.47	9.48	2.40
	(0.00)	(0.00)	(0.00)
α_{FFC}	6.98	6.46	1.17
	(0.00)	(0.00)	(0.00)
Max drawdown	51.84	70.24	31.34
VaR (5%)	-6.23	-6.22	-4.09
CVaR (5%)	-8.70	-8.49	-6.89

Panel B:Long-short dual, long-only dual, and triple momentum strategies

	Long-short Dual Momentum	Long-only Dual Momentum	Triple Momentum
Mean return	8.61	7.69	7.48
Standard deviation	19.43	11.56	14.74
Sharpe ratio	0.44	-0.04	0.51
	(0.00)	(0.01)	(0.00)
α_{CAPM}	11.63	4.01	7.90
	(0.00)	(0.00)	(0.00)
α_{FFC}	7.82	2.28	6.19
	(0.00)	(0.00)	(0.00)
Max drawdown	71.59	27.38	36.37
VaR (5%)	-7.20	-5.26	-5.27
CVaR (5%)	-10.29	-7.61	-8.60

Panel C: Benchmark strategy

	Naive Strategy
Mean return	4.16
Standard deviation	13.08
Sharpe ratio	-0.49
α_{CAPM}	-1.69
α_{FFC}	-1.75
Max drawdown	59.29
VaR (5%)	-6.51
CVaR (5%)	-9.83

The results reported in Table 9 reveal that, among the momentum strategies examined using the fund dataset, the triple momentum strategy yields the highest statistically significant Sharpe ratio of 0.51, followed by the relative momentum strategy with a Sharpe ratio of 0.50. All Sharpe ratios exceed the Sharpe ratio of the benchmark strategy. In terms of alpha from both models, the long-short dual momentum strategy demonstrates the strongest performance. All alpha values from both models are higher than the alpha values of the naive benchmark strategy. The choice of the optimal strategy depends on the performance measure used. Based on the risk measures, the long-only strategies (dual and absolute) produced the lowest risk out of the strategies. The long-only absolute momentum strategy displays the lowest VaR and CVaR, while the long-only dual momentum strategy produces the lowest MDD. Out of the two momentum strategies deemed the best performers by the Sharpe ratio and alphas, namely the triple momentum strategy and the long-short dual momentum strategy, respectively, it is the former that exhibits the lower level of risk, notably lower than the benchmark strategy. Based on these findings, it can be concluded that the triple momentum strategy demonstrates better performance than other momentum strategies when assessing individual strategy performance.

Appendix A2 presents the cumulative returns for each momentum strategy using the multi-asset fund dataset. The cumulative returns of the momentum strategies are depicted in Figure A2.1. The naive benchmarks' cumulative returns are presented in Figure A2.2.

5.1.3 Developed Country Analysis

This section presents the results of our investigation into various momentum strategies using the country-level dataset. Due to the dataset's size, we only varied the number of best/worst assets (N) to include in the strategies and concentrated on N=3 and N=5 in our analysis. For this analysis, we utilize the K=12-month lookback period. To maintain consistency, we mainly utilize the Sharpe ratio as the primary performance measure for evaluating individual strategy performance. We perform hypothesis testing for the Sharpe ratio and Alpha (both CAPM and FFC) to assess the statistical significance of the results. Specifically, the tests compare the different momentum strategies against the equal-weighted (naive) benchmark strategy.

Table 10 summarizes the performance statistics of various momentum strategies applied to country-level data. The table is divided into two panels: In Panel A, we present the outcomes of three momentum strategies: relative momentum with N=3 and N=5, long-short absolute momentum, and long-only absolute momentum. The naive benchmark strategy is also included in Panel A. Note that the N parameter is not relevant for the absolute momentum approach and is thus not included in the table. Panel B reports the results of long-short dual, long-only dual, and triple momentum strategies divided into N=3 and N=5, denotes “Top 3” and “Top 5”, respectively.

Initially, we examine the optimal number of best/worst assets N and find that when N=5 the Sharpe ratio is highest across almost all strategies, except for long-only dual momentum strategy, which has the highest Sharpe ratio when N=3. Moreover, upon evaluating the strategies using alpha derived from the CAPM model, it is evident that the alpha values attain statistical significance and reach their highest levels when N=3 for almost all strategies, except for the relative momentum strategy, which exhibits its highest alpha CAPM value at N=5. For most strategies, the FFC-derived alpha values are highest when N is set to 5. This evidence suggests that the optimal N to include in the strategies depends on the performance measure used and the strategy utilized. Upon examining the risk measures, we do not discern any trends that would identify a single optimal N that minimizes the level of risk.

Panel A presents the performance and risk statistics of the naive benchmark strategy, as well as the relative, long-short absolute, and long-only absolute momentum strategies. For the relative momentum strategy, the results are further categorized into “Top 3” (N=3) and “Top 5” (N=5). The naive benchmark strategy outperforms all strategies in Panel A with a Sharpe ratio of 0.44. We cannot reject the null hypothesis for any of the strategies, and thus they are not statistically significantly different from the benchmark and, thus, do not work with country data when evaluating them based on the Sharpe ratio. The alpha CAPM coefficients demonstrate a positive and statistically significant relationship across all strategies. Notably, the long-short absolute momentum strategy yields the highest alpha CAPM coefficient of 4.74, denoting superior performance relative to the benchmark of 0.48. All strategies produce negative alpha FFC coefficients, suggesting that the investment strategies analyzed in this panel generated risk-adjusted returns that were below those predicted by the FFC model.

An examination of the risk measures in Panel A reveals that the relative and long-only absolute momentum strategies exhibit lower MDD than the benchmark. These findings suggest that the relative and long-only absolute momentum strategies may provide more favorable risk profiles than the benchmark, as they demonstrate a lower degree of potential losses from their peak values. Furthermore, an assessment of the value-at-risk parameters reveals that all investment strategies in this panel exhibit VaR and CVaR values that are lower than those of the naive benchmark. Specifically, the VaR and CVaR parameters of the investment strategies are found to be at their lowest for the relative momentum strategy at N=5. These results suggest that the investment strategies in this panel may offer improved risk management benefits, as they demonstrate a lower likelihood of incurring losses beyond the specified VaR or CVaR thresholds when compared to the naive benchmark.

Panel B reports the long-short dual, long-only dual, and triple momentum strategies, categorized into N=“Top 3” and N=“Top 5”. Both the long-only dual and triple momentum strategies outperform the benchmark. Among the two strategies, the triple momentum strategy achieves the highest Sharpe ratio at N=5. That the long-short dual momentum strategy's reported Sharpe ratios are below the benchmark's level. Moreover, we fail to reject the null hypothesis that the strategies in Panel B are not statistically significantly different from the Sharpe ratio of the naive benchmark. Upon evaluating the alpha coefficient from the CAPM and FFC, we observe that all values are positive and statistically significant, exceeding those of the benchmark. Specifically, the triple momentum strategy shows the highest alpha CAPM value of 6.80 and FFC value at 4.41, higher than the other alpha coefficients reported. These results indicate that the triple momentum strategy was able to generate risk-adjusted returns that surpassed those predicted by the model. All alpha FFC values, including the benchmark, demonstrate negative values, except for the triple momentum strategy. The triple momentum strategy yielded positive and statistically significant alpha coefficients. Evaluating the risk measures, we observe MDD values below the benchmark for long-only dual momentum and triple momentum, with the former exhibiting the lowest values. In terms of value at risk, the long-short dual at, the long-only dual, and triple momentum strategies exhibit lower VaR and CVaR values than the benchmark.

Table 10:
Performance statistics of various momentum strategies applied to country data. The table reports the returns of relative, long-short absolute, long-only absolute, long-short dual, long-only dual, and triple momentum strategies, as well as the naive benchmark strategy. "Mom" is used as an abbreviation for momentum. Specifically, the abbreviation "Abs Mom" denotes the long-short absolute momentum strategy, while "Dual Mom" refers to the long-short dual momentum strategy. Additionally, "Long Abs Mom" and "Long Dual Mom" denote the long-only absolute and long-only dual momentum strategy. The table report performance measures such as standard deviation, Sharpe ratio, and alpha from CAPM and FFC. CAPM and FFC stand for the Capital Asset Pricing Model and the Fama-French-Carhart Model, respectively. The country data is sorted either by sign, rank, or both based on their past 12-month returns. The ranking-based strategies are predicated on selecting the 3 or 5 best/worst-performing countries. The p-values of the CAPM and FFC alphas and Sharpe ratios are reported in brackets. The table also includes the risk measures of MDD, VaR, and CVaR. The statistics are all annualized, except for MDD, VaR, and CVaR, as these measures are not dependent on the frequency of the data. The values, except for the Sharpe ratio, are quoted in percentages..

Panel A: Naive Benchmark Strategy + relative, long-short absolute and long-only absolute momentum strategies

	Naive	Relative Mom		Abs Mom	Long Abs Mom
N	-	Top 3	Top 5	-	-
Mean return	9.93	1.17	1.82	3.94	8.59
Standard deviation	17.39	15.22	11.60	14.91	15.41
Sharpe ratio	0.44	0.08	0.16	0.26	0.41
		(0.91)	(0.85)	(0.75)	(0.62)
α_{CAPM}	0.48	2.30	2.52	4.74	0.86
		(0.00)	(0.00)	(0.00)	(0.00)
α_{FFC}	-0.40	-2.95	-1.46	-0.59	-2.02
		(0.00)	(0.00)	(0.39)	(0.00)
Max drawdown	59.30	46.47	38.37	69.48	42.77
VaR (5%)	-8.41	-7.06	-5.25	-6.93	-6.14
CVaR (5%)	-11.61	-9.51	-6.70	-9.56	-10.64

Panel B: Dual, long-only dual and triple Momentum strategies

	Dual Mom		Long Dual Mom		Triple Mom	
N	Top 3	Top 5	Top 3	Top 5	Top 3	Top 5
Mean return	3.92	4.19	10.74	9.92	7.95	8.02
Standard deviation	19.84	17.79	17.49	16.85	17.24	16.15
Sharpe ratio	0.20	0.24	0.49	0.46	0.46	0.50
	(0.82)	(0.78)	(0.35)	(0.45)	(0.47)	(0.41)
α_{CAPM}	5.17	5.11	2.84	1.91	6.80	6.76
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α_{FFC}	-2.85	-1.92	-0.79	-1.45	3.77	4.41
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Max drawdown	73.25	72.37	40.49	43.32	51.50	53.81
VaR(5%)	-9.24	-7.84	-7.35	-7.06	-7.59	-6.33
CVaR (5%)	-12.24	-10.87	-10.73	-10.83	-10.91	-9.89

In the context of the country-level data, we observe that almost all strategies produce a higher Sharpe ratio when N=5, except for the long-only dual momentum strategy. However, it is noteworthy that the alpha CAPM values are superior for N=3, except for the relative momentum strategy. Regarding the alpha of the FFC model, most strategies, except for the long-only dual momentum strategy, have the highest alpha FFC value of N=5. Furthermore, no clear trends were observed in the risk measure of MDD; however, the VaR and CVaR are lower for N=5 compared to N=3, with an exception for the long-only dual having a lower CVaR for N=3.

Overall, for the country data, the best momentum strategy appears to be the triple momentum strategy. However, it is worth noting that this Sharpe ratio is not statistically significantly different from the naive strategy. Nevertheless, the triple momentum strategy demonstrates the highest positive and statistically significant alpha value according to both the CAPM and FFC models. The strategy that overall produces the lowest risk appears to be the relative momentum strategy at N=5. However, the triple momentum strategy achieves lower risk parameters compared to the naive benchmark strategy.

Appendix A3 presents the cumulative returns for each momentum strategy using the country-level dataset. The relative momentum strategies cumulative returns are depicted for N=3 and N=5 in Figure A3.1. Figure A3.2 and Figure A3.3 display the cumulative returns of the long-short and long-only absolute momentum, respectively. The cumulative returns of the long-short and the long-only dual momentum strategies are shown in Figure A3.4 and Figure A3.5, respectively, with varying N of 3 and 5. Figure A3.6 displays the cumulative returns of the triple momentum strategy with varying N. Lastly, the naive benchmark strategy's cumulative returns are shown in Figure A3.7.

5.2 Overview of Findings

Based on the empirical results presented, the optimal lookback period (K) and the number of best/worst assets (N) to include in the strategy vary depending on the performance and risk measures being considered, as well as on the dataset being analyzed. The results thus suggest that there are no unique optimal values of K and N across the different datasets.

The industry dataset presents a range of optimal parameter values for K and N, which are dependent on the chosen performance and risk measures as well as the employed strategy. For most of the strategies, a lookback period of 12 month is optimal, evaluating based on the Sharpe ratio. Moreover, the long-short absolute momentum performs best with K=6 when evaluated based on the Sharpe ratio. Lastly, the long-only absolute momentum displays its highest statistically significant Sharpe ratio for K equals 8 or 12, yielding identical Sharpe ratios. The long-short dual momentum strategy demonstrates optimal performance when the parameters N equals

3 and 12 are employed, as determined through the evaluation of the Sharpe ratio. In contrast, the long-only dual momentum strategy achieves optimal performance when N=5. Notably, the relative momentum strategy achieves its highest Sharpe ratios when N equals 3 or 10 are employed, exhibiting identical values in both cases. Similarly, the triple momentum strategy demonstrates its highest Sharpe ratios for N=3, as well as N=5 with identical values in both instances.

The alpha derived from the CAPM model is highest with the combination of N=3 and K=12 for the relative, dual (long-short and long-only), and triple momentum strategies. For the long-short absolute and long-only absolute momentum strategies, the models have the highest CAPM alpha values at K=8. For alpha derived from the FFC model, K=12 and N=3 are optimal for relative, long-only dual, and triple momentum strategies, while N=3 and K=8 are optimal for long-short dual momentum. The highest statistically significant alpha FFC values for long-short absolute and long-only absolute momentum are at K=6 for both strategies. The long-only absolute momentum seemingly has a higher alpha FFC value when K=12, but this value is not statistically significant. In conclusion, when evaluating based on the alpha coefficients from the CAPM and FFC models, no K and N consistently outperform. When it comes to the risk measures, no combination is reported to consistently minimize the risk, however, as N increases, the risk decreases in most cases.

For the country data, it is evident that N=5 yields the highest Sharpe ratios for almost all strategies, except for the long-only dual momentum, with the highest Sharpe ratio at N=3. Additionally, the alpha derived from the CAPM performs best with N=3 in nearly all strategies, while the FFC exhibits the highest values when N=5 for most strategies. The risk measure of MDD does not indicate a single optimal N, but VaR suggests that N=5 is the optimal parameter for all strategies, while CVaR shows the lowest values at N=5 for most strategies. In conclusion, there is no consistent optimal parameter N that outperforms all strategies and datasets. Nevertheless, most measures do indicate improved performance when N=5 is utilized.

Empirical results show that different performance measures yield different optimal strategies within each of the datasets. The industry dataset displays a diversity of optimal strategies that are contingent upon the selected performance and risk measures. The long-only dual momentum strategy yields the highest statistical Sharpe ratio, outperforming the naive benchmark. However, evaluating the optimal strategy based on the alpha from the CAPM model reports the long-short dual momentum strategy as the most favorable. Evaluating based on the FFC model presents the triple momentum strategy as the optimal strategy. The results of the risk measures differ, as the relative momentum strategy has the lowest MDD and CVaR. The lowest VaR is observed for the long-short absolute momentum strategy.

Similar to the previously mentioned dataset, the multi-asset fund dataset reveals a range of optimal strategies that depend on the chosen performance and risk metrics. Specifically, the triple momentum strategy presents the highest statistically significant Sharpe ratio, surpassing the benchmark's negative Sharpe ratio. Meanwhile, the alpha derived from the CAPM model attains its peak statistically significant value with the long-short dual momentum strategy, which also yields the highest statistically significant alpha FFC value. Therefore, evaluating the strategies based on alpha aligns with the performance of the long-short dual momentum strategy. Concerning the risk measure of MDD, the long-only dual momentum strategy obtains the lowest MDD value. In contrast, the long-only absolute momentum strategy demonstrates the lowest VaR and CVaR values.

The country-level dataset exhibits a higher degree of consistency in determining the optimal strategies across various performance and risk measures compared to the other two datasets. The triple momentum strategy displays the highest Sharpe ratio out of every strategy, which is higher than the benchmark's Sharpe ratio. However, the null hypothesis cannot be rejected, and thus, the outperformance of the triple momentum strategy over the benchmark is not statistically significant. Nevertheless, the alpha values obtained from both the CAPM and FFC models exhibit their highest statistically significant values for the triple momentum strategy, providing evidence that it surpasses the benchmark and the other strategies. Consequently, based on the performance measures, the triple momentum strategy can be deemed the optimal strategy for this dataset. In terms of risk evaluation, the relative momentum strategy emerges as the least risky strategy with the lowest MDD, VaR, and CVaR.

A comprehensive examination of the results suggests that a single optimal strategy does not exist that would perform uniformly well across all datasets. However, for K=12, there are indications that all momentum strategies outperform the naive benchmark, but we cannot always reject the null hypothesis of equal performance. The choice of the best strategy depends on the performance measure. When the Sharpe ratio is used, long-only strategies are typically the best. When alpha is used, long-short strategies are typically the best, as they provide very low systematic risk.

Chapter 6

Discussion and Interpretation

Based on the empirical results, the findings suggest that there are no optimal parameter combinations that work with every strategy across each data set. However, there is some evidence in the industry dataset that the optimal lookback period for most of the momentum strategies is K=12. This finding is consistent with research by Jegadeesh and Titman (1993), Moss et al. (2015), Singh et al. (2022), and Moskowitz et al. (2012). It is important to note that this observation does not apply to the long-short absolute momentum strategy, which has optimal parameters K of 6. The cumulative returns displayed in Appendix A1 reinforce these findings, revealing a discernible pattern of greater cumulative returns when K=12 for the relative, dual (both long-short and long-only), and triple momentum strategies. Conversely, we observe greater cumulative returns for the long-short absolute momentum strategy when K=6. For the long-only absolute momentum, we observe almost identical cumulative returns for K=8 and K=12, consistent with the identical Sharpe ratios for the strategies at these values of K. No single N parameter is found that consistently produces a larger Sharpe ratio across every strategy, however, from the cumulative returns in Appendix A1, the returns are larger for N=3 across every strategy.

The analysis of the country dataset reveal a trend towards an optimal value of N when evaluating it based on the Sharpe ratio. N=5 generates a greater Sharpe ratio for almost all strategies, except for the long-only dual momentum strategy. When evaluating based on alpha, more varied results are evident. N=3 is identified as the optimal according to the alpha CAPM for almost all strategies, except for the relative. The alpha FFC values, however, are greater for N=5 for almost all strategies except for the long-only dual momentum. These observations are corroborated by the cumulative returns presented in the figures in Appendix A3. The cumulative returns show greater returns when N=5 for almost all strategies except for the long-only dual momentum, which shows almost identical values until 2020. This phenomenon suggests that the evaluation of the optimal N for the long-only dual momentum strategy may be challenging due to the closely matched Sharpe ratios. Alternatively, utilizing alpha as a performance measure proves to be more effective for this strategy, as both alpha values demonstrate higher values when N=3, consistent with the cumulative returns.

The latter portion of our findings centers on the determination of the optimal momentum strategy for each dataset and finds that the results differ across the various datasets. Nevertheless, it is worth mentioning that the same optimal strategy was identified for two of the three datasets. This lack of consistency in the optimal strategies can be seen as a noteworthy limitation of our study, as it reveals a discrepancy in the applicability of momentum strategies in different settings.

Our empirical findings for the industry dataset are consistent with previous literature by Antonacci (2017), which documents the superior returns of the long-only dual momentum strategy. The author states that "A dual momentum approach bears market risk when it makes the most sense". This indicates that the long-only dual momentum strategy was able to mitigate market risk by dynamically allocating assets based on the momentum signals using absolute momentum while simultaneously capitalizing on regime persistence and exploiting both relative strength and absolute momentum to enhance expected returns. This leads to improved performance compared to other momentum strategies and the naive benchmark. The outperformance of the long-only dual momentum strategy supports its viability as a profitable investment approach in the industry context.

The long-only dual momentum strategy is an extension of the absolute momentum strategy, indicating that our finding is also consistent with previous research by Lim et al. (2018) and (Clare et al., 2017) which documents strong evidence of absolute momentum in US equities. This could be due to the specific characteristics of the US stock market, where individual stocks tend to exhibit persistent trends over long periods, making it easier to identify stocks with strong positive momentum over the long term and hold them for an extended period. In this context, the long-only dual momentum strategy may be more suitable for equity portfolios, as it allows for exposure to positive momentum while limiting downside risk. Short-selling can be risky and may not always be feasible for all investors, which is why a long-only strategy could be preferred. Additionally, the long-only dual momentum strategy has the highest Sharpe ratio, which measures the risk-adjusted return of an investment, as it offers a favorable risk-reward relationship. By only taking long positions in assets that exhibit positive momentum, investors can potentially earn higher returns while avoiding the downside risks associated with short selling.

In contrast to the fund and country datasets, the industry dataset spans a considerably longer time period. Momentum strategies are often sensitive to market changes and may perform differently in different time periods (Fama & French, 2012). The industry dataset covers a much longer period, from 1927 to 2022, compared to the country and fund datasets, which cover the period from the 1990s to 2022. The longer time period may capture different market conditions and economic cycles, which may affect the performance of momentum strategies. This can be a reason why the long-only dual momentum strategy was better able to capture the overall market trend and adjust to changes in market conditions. Furthermore, with a larger dataset, there is a higher likelihood of identifying and capitalizing on sustained positive momentum trends and relative strength among assets. This longer-term perspective allows for smoother and more accurate identification of assets with stronger performance compared to their peers over extended periods. The restricted time frame of the country and fund datasets compared to the industry dataset may represent a limitation in the scope of our research.

The triple momentum strategy was deemed the optimal strategy in the country dataset, which suggests that the dataset may be prone to experiencing momentum crashes. When momentum crashes occur, the momentum strategy becomes ineffective in identifying assets that will continue to perform well, leading to a significant drop in returns (Singh et al., 2022). The triple momentum strategy, with its multi-level momentum approach, is specifically designed to mitigate these limitations and minimize the impact of momentum crashes. Therefore, it is likely that the reason no other strategy was able to outperform the triple momentum strategy in the country dataset is due to the presence of momentum crashes in the dataset, which the other strategies were unable to effectively mitigate.

Our study's empirical findings reveal notable differences in momentum strategy performance for country data compared to prior academic research. This may be due to the limited literature on the newly developed triple momentum strategy, which we found to be the best-performing strategy for our country's dataset. The scarcity of previous research on this strategy makes it challenging to compare our results with those of other academics. The results of our study indicate that the triple momentum strategy proposed by Singh et al. (2022) exhibits optimality within our country dataset. This finding suggests the potential viability of applying the triple momentum strategy to other markets as well. Nonetheless, additional research is necessary to substantiate the observed differences and investigate their underlying reasons. Our study's results indicate that the triple momentum strategy is a promising avenue for further exploration of momentum trading strategies.

One notable finding that emerged from the analysis of the country-specific data is the comparatively lower Sharpe ratios associated with the relative, long-short absolute, and long-short dual when compared to the benchmark. This finding is particularly intriguing given that these very same strategies had previously demonstrated relatively large Sharpe ratios when evaluated using the industry and multi-asset fund datasets. Upon examination of the graphical representations of cumulative returns presented in Appendix A3, it becomes evident why the aforementioned strategies may have yielded lower Sharpe ratios compared to the benchmark. Specifically, Figure A3.1 in Appendix A3, demonstrates that the relative momentum strategy ceased to be effective after the global financial crisis of 2008, failing to generate satisfactory returns in the post-crisis period. Similar patterns are observed in Figures A3.2 and A3.4, which respectively depict the cumulative returns of the long-short absolute and long-short dual momentum strategies. These results suggest that the observed lower Sharpe ratios may be attributable to the declining effectiveness of these momentum strategies in generating returns in the aftermath of the global financial crisis.

In contrast to the aforementioned momentum strategies, Figure A3.5 and Appendix A3 illustrates the cumulative returns of the long-short dual momentum strategy, exhibiting a distinct pattern. While the strategy experiences a decline in returns following the financial crisis, it subsequently rebounds and continues to generate positive returns until 2021, after which a substantial decline is observed. The observed decline in the effectiveness of the strategy after the year 2021 suggests a potential shift in the underlying market dynamics. This may indicate that the assumptions and parameters used in the strategy, which were based on historical data and market conditions, may no longer be appropriate in the current market environment.

The results of the analysis on the multi-asset fund dataset indicate that the triple momentum strategy outperforms the other strategies in terms of the Sharpe ratio. This finding is consistent with the results of the country analysis, which also demonstrated that the triple momentum strategy is the best-performing strategy. This consistency in the performance of the triple momentum strategy could be because the momentum signals that make up the strategy capture a wider range of market trends, which may be advantageous in various asset classes. Moreover, the similarity in performance between the multi-asset fund dataset and the country dataset for the triple momentum strategy may indicate that the triple momentum strategy is not highly sensitive to differences in asset classes or market environments. However, further research would be needed to confirm this hypothesis.

Upon examining the results of the multi-asset fund analysis, it becomes apparent that two of the Sharpe ratios stand out due to their deviation from the other Sharpe ratios. Specifically, the Sharpe ratios pertain to the long-only absolute momentum and long-only dual momentum strategies. By analyzing the cumulative returns of these two strategies, as depicted in Figure A2.1 in Appendix A2, it becomes evident that they exhibit comparable trends. More precisely, both strategies manage to recover from the financial crisis but subsequently suffer a marked decline in returns after 2021. This suggests that long-only momentum strategies, which rely solely on past performance and do not employ short positions, may be more susceptible to market volatility and disruptions in recent years and thus may no longer be appropriate in the current market environment.

Throughout the empirical analysis, it has been consistently observed that the performance measures, namely the Sharpe ratio and alpha from the CAPM and FFC models, lead to different optimal strategies. Several potential reasons have been identified for this discrepancy. Firstly, the Sharpe ratio measures the excess return earned per unit of total risk, while alpha from the CAPM and FFC models measures the excess return earned above the expected return given the level of systematic risk. Secondly, the two models have different underlying assumptions and are sensitive to different sources of risk. While the CAPM assumes that the only source of risk is systematic risk, which is measured by the beta coefficient, and that investors are only compensated for this risk. On the other hand, the FFC model incorporates additional factors such as size, value, and momentum, which can lead to different optimal strategies. Finally, it is worth noting that the choice of performance measure can depend on the investment objectives and preferences of the investor. For instance, an investor who seeks to maximize risk-adjusted returns may prefer the Sharpe ratio, while an investor who has a preference for certain types of risk or return factors may prefer to use alpha from the FFC model over other measures. Additionally, the Sharpe ratio is a more appropriate measure to assess the performance of individual strategies against each other.

The risk measures reported in the datasets exhibit a noteworthy observation. The comparison of the long-short and long-only approaches of the momentum strategies, namely the absolute and dual momentum strategies, reveals that the long-only approach exhibits lower risk levels than the long-short version of the same strategy in the country and fund datasets. Specifically, the lower MDD of long-only compared to long-short suggests that short selling may increase the risk of the strategy. This suggests that investors may benefit from avoiding short-selling and adopting long-only strategies to mitigate their downside risk. It is observed that both the VaR and CVaR tend to decrease when transitioning from the long-short to the long-only version of the momentum strategy. This finding implies that the long-only approach may be more suitable for risk-averse investors. No trends like this are observed in the industry dataset, indicating that the risk characteristics of the momentum strategies in the industry dataset differ from those in the country and fund datasets.

The empirical analysis also reveals that increasing the number of best/worst assets N included in the momentum strategies tends to lower the risk of the strategies for every risk measure in the industry dataset. This suggests that investors seeking to reduce risk may benefit from including a larger number of assets in their momentum strategies. However, it is worth noting that including more assets may come at the cost of lower returns, as including more assets may come at the cost of lower returns, as a more diversified portfolio may have a lower potential for outperformance. Ultimately, the optimal number of assets to include in a momentum strategy may depend on the individual investor's risk preferences and investment objectives. In the country dataset, there is evidence of decreased risk in the VaR parameter when the parameter N is increased. A similar trend is observed for the CVaR measure, with one exception noted for the long-only dual momentum strategy.

Lastly, the selection of an appropriate historical period plays an important role in evaluating and interpreting the outcomes of momentum strategies. In this study, a specific historical period of 18 months was utilized to analyze the performance of the strategies under consideration. However, it is important to acknowledge that the choice of historical period introduces a subjective element and can significantly impact the observed performance characteristics of the momentum strategies. Therefore, it is essential to exercise caution when extrapolating the findings to alternative time frames or datasets, as the results may vary based on the specific historical context employed.

This chapter presents an interpretation and discussion of the empirical findings on momentum strategies in various markets and asset classes that were presented in the previous chapter. The results indicate that the optimal parameter K for most momentum strategies is consistent with previous literature. However, the best-performing momentum strategies differ across markets and asset classes, which may be considered a limitation of the research. Specifically, the long-only dual momentum strategy appears to be the most effective in the US industry dataset, while the triple momentum strategy performs the best in the multi-asset fund and developed country datasets. Our results also suggest that the triple momentum strategy is a promising avenue for further exploration of momentum trading strategies. In summary, our findings contribute to the existing literature on momentum strategies and provide insights into the effectiveness and applicability of different markets and asset classes.

Chapter 7

Conclusion

This thesis aims to investigate the performance of momentum strategies across a wide range of markets and asset classes, comprising 40 US industries, 8 multi-asset funds, and 19 developed countries. To achieve this, various momentum strategies are examined, such as relative momentum, long-short absolute momentum, long-only absolute momentum, long-short dual momentum, long-only dual momentum, and triple momentum. To achieve this objective, we first compute summary statistics for each dataset and depict the relationship between the assets in the datasets using two risk parameters: standard deviation and beta. The methodology section provides a comprehensive account of the procedures involved in calculating momentum strategies and assessing their performance. Furthermore, this chapter outlines the benchmark strategy that was selected for comparative analysis, namely a naive strategy. The methodology encompasses a range of theoretical frameworks, including portfolio theory, asset pricing theory, performance measurement, risk measurement, and momentum investing strategies.

The momentum strategies computed for each dataset are presented in detail in the empirical findings of this study. Various combinations of lookback periods (K) and different numbers (N) of best/worst-performing assets were tested for each momentum strategy, except for the absolute momentum strategies, where N was fixed for self-evident reasons. The industry dataset had both parameters, K and N, that varied across strategies. The fund dataset utilized fixed values of N=3 and K=12. For the country dataset, K=12 months was set as the lookback period, while N was varied for N=3 and N=5. Naturally, the performance of our momentum strategies has been contrasted with that of the benchmark strategy to assess their profitability with a conventional portfolio allocation strategy.

Our analysis primarily relied on the Sharpe ratio as the performance metric to compare and evaluate various investment strategies. Based on this metric, we were able to identify the most profitable strategies - those with the highest Sharpe ratio. Our findings suggest that the long-only dual momentum strategy is the best-performing strategy for analyzing US industry data. In the context of multi-asset fund data, the triple momentum strategy achieved the highest Sharpe ratio. Concerning the country dataset, the triple momentum strategy has emerged as the most profitable investment approach, surpassing the benchmark strategy. Furthermore, our findings reveal that no single optimal parameter combination of K lookback periods and N best/worst-performing assets exists that performs equally well across all datasets. However, K=12 month is deemed the optimal lookback period for most strategies. By examining the strategy that has achieved the highest Sharpe ratio across the datasets, the triple momentum strategy emerges as the top-performing strategy for two out of the three datasets. These findings are noteworthy as they highlight the potential effectiveness of the newly developed triple momentum strategy as a viable investment approach. Risk measures were employed as a part of this thesis, and the results indicate that the long-only versions of the momentum strategies generally provide the best means to minimize the level of risk in two out of the three datasets.

We also applied regression models for the CAPM and FFC and used the alpha values from the regressions to further evaluate the performance of the strategies. The alpha values were not overall consistent with the Sharpe ratio, indicating a discrepancy between the two performance measures. The Sharpe ratio incorporates the total risk, including both systematic and unsystematic risk, while alpha considers only the systematic risk that cannot be diversified away. When evaluating the industry portfolio dataset using alpha CAPM, the long-short dual momentum strategy emerges as the optimal strategy, while the alpha FFC designates the triple momentum strategy as optimal. In the case of the multi-asset fund dataset, both alpha values indicate the long-short dual momentum strategy as the optimal choice. Lastly, in the country-level dataset, both alpha values concur that the triple momentum strategy is optimal. This finding highlights the importance of considering multiple performance metrics to gain a comprehensive understanding of the strategies' profitability.

In conclusion, this thesis provides a comprehensive analysis of momentum strategies across different markets and asset classes. The empirical findings demonstrate the performance of momentum strategies in generating profitable returns. This thesis posits that there is a tendency for the two recently developed extended strategies to outperform conventional standalone strategies. The long-only dual momentum strategy emerges as the top performer in the US industry dataset, while the triple momentum strategy shows promising results in both the multi-asset fund and country datasets. The optimal parameter combinations differ across datasets, highlighting the importance of customization and adaptation to specific market conditions. Furthermore, the inclusion of risk measures and regression analysis provides additional insights into the strategies' performance. The discrepancy between alpha values and the Sharpe ratio suggests that factors beyond risk-adjusted returns contribute to the strategies' profitability. Thus, considering multiple performance metrics is crucial for a comprehensive assessment of momentum strategies. This study contributes to the existing literature on momentum investing and offers valuable insights for investors seeking to incorporate momentum strategies into their investment decisions.

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Appendix

A1 Cumulative returns of momentum strategy and naive strategy with industry data

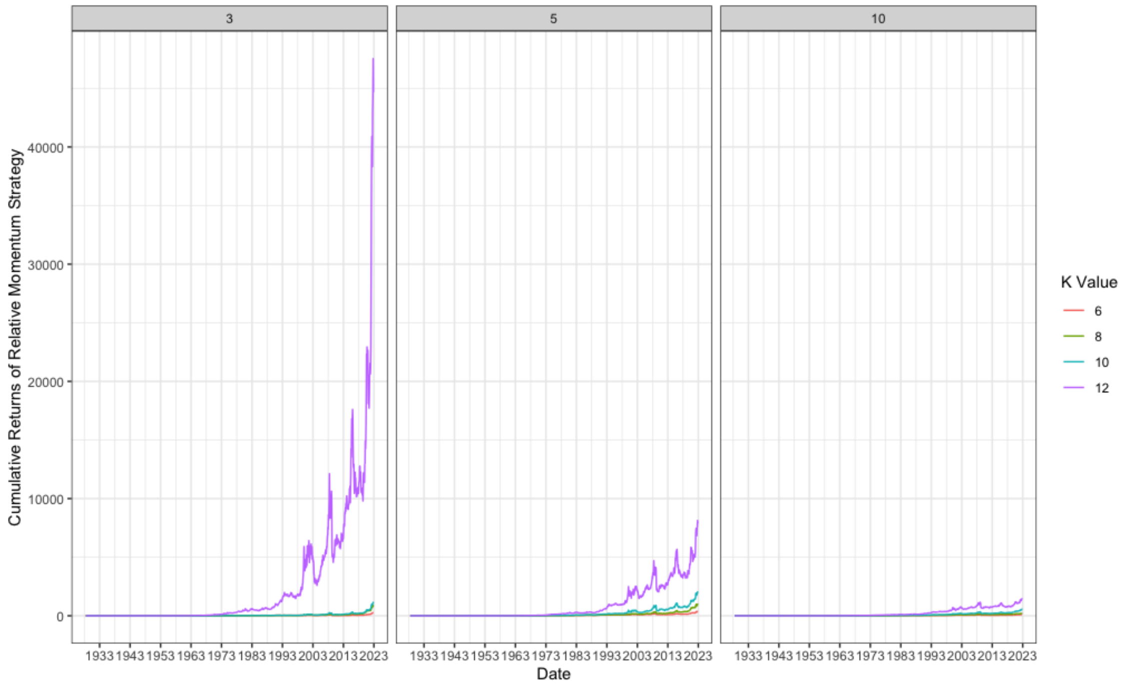

Figure A1.1: Cumulative returns of relative momentum strategy

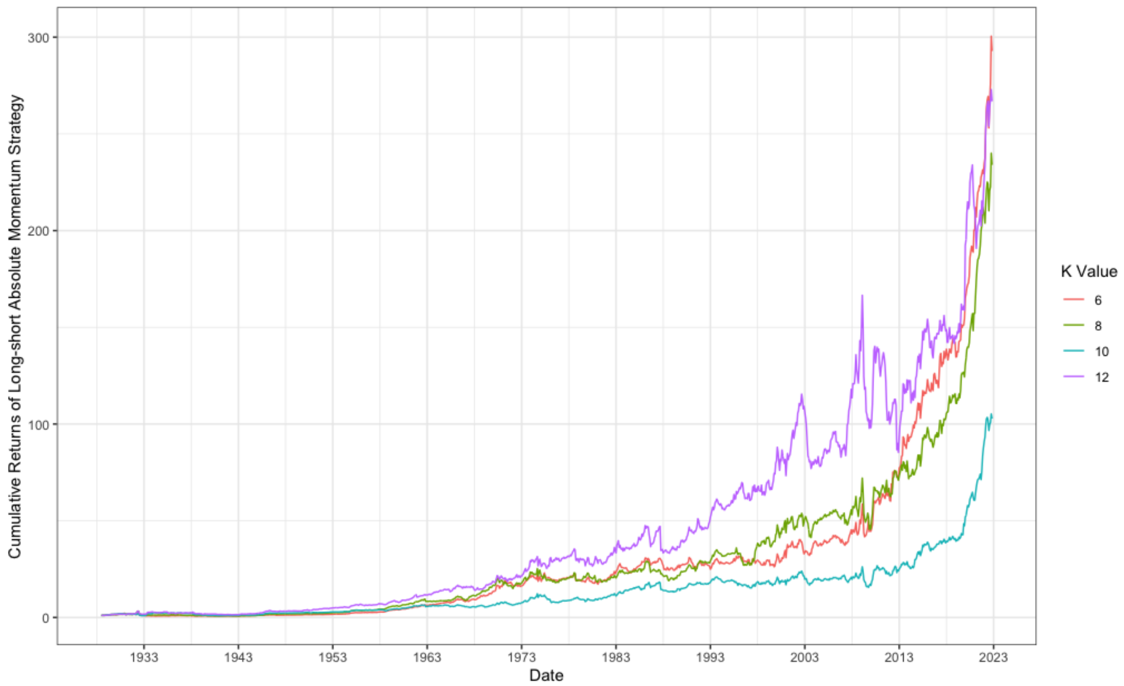

Figure A1.2: Cumulative returns of long-short absolute momentum strategy

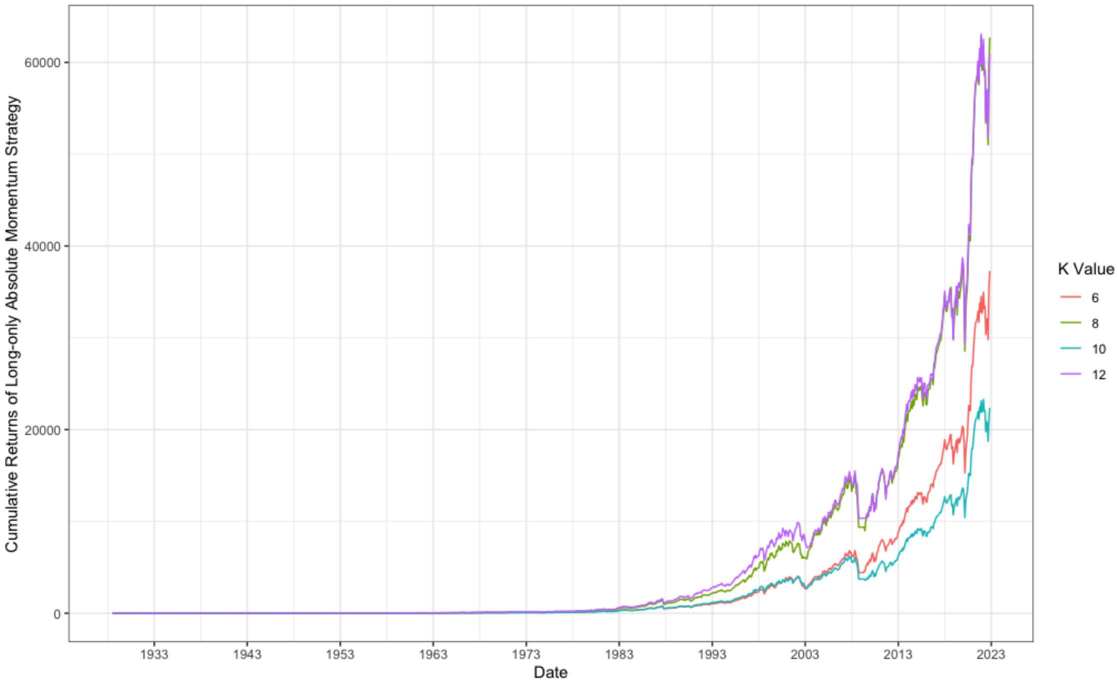

Figure A1.3: Cumulative returns of long-only absolute momentum strategy

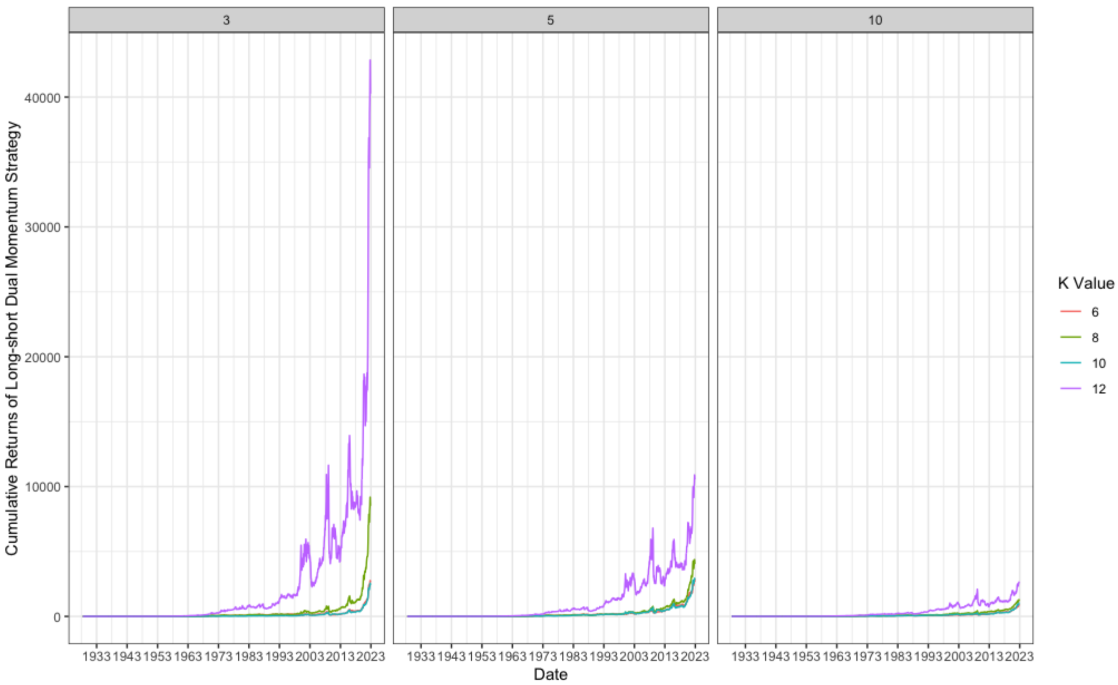

Figure A1.4: Cumulative returns of long-short dual momentum strategy

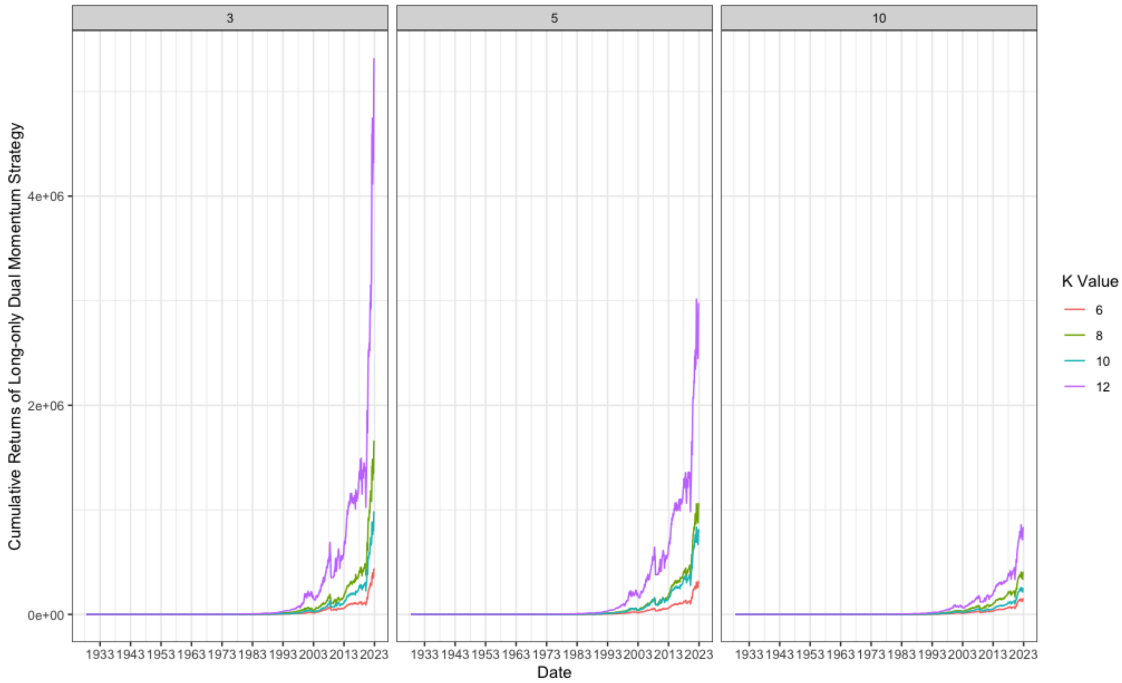

Figure A1.5: Cumulative returns of long-only dual momentum strategy

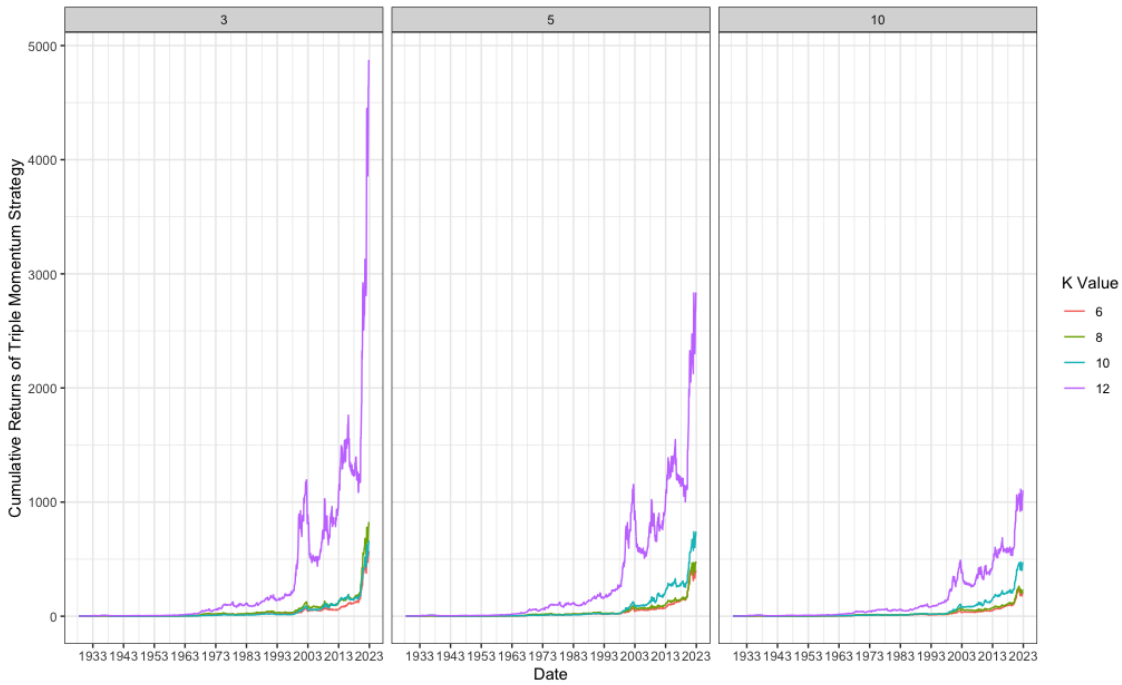

Figure A1.6: Cumulative returns of triple momentum strategy

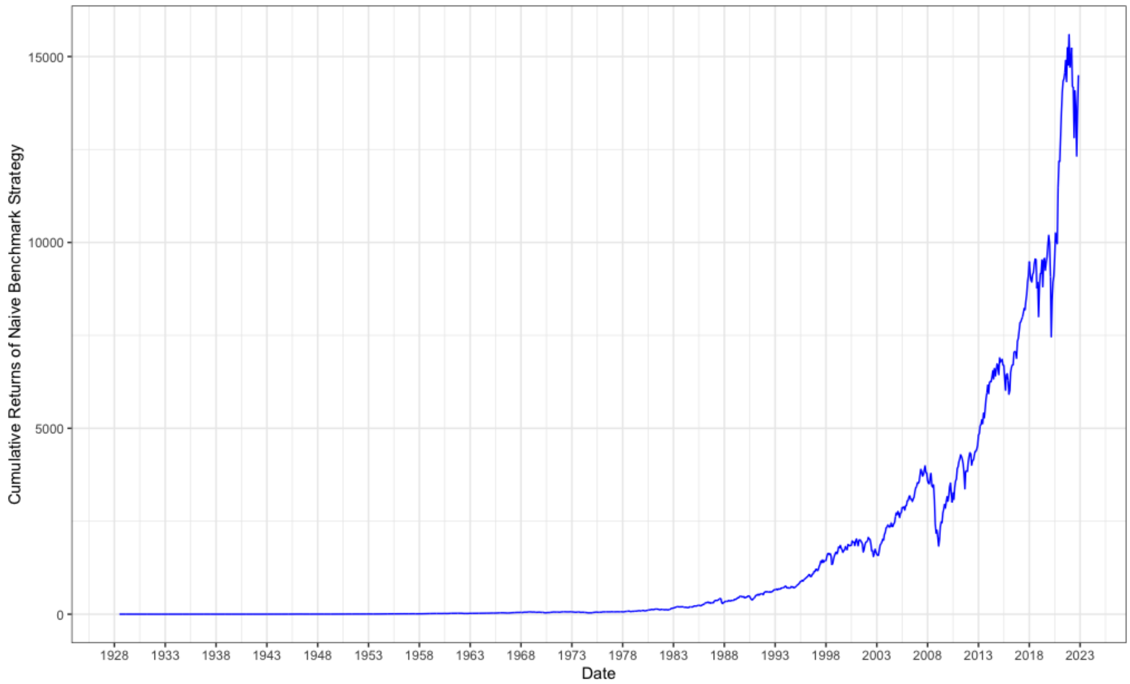

Figure A1.7: Cumulative returns of the naive benchmark strategy

A2 Cumulative returns of momentum strategy and naive strategy with fund data

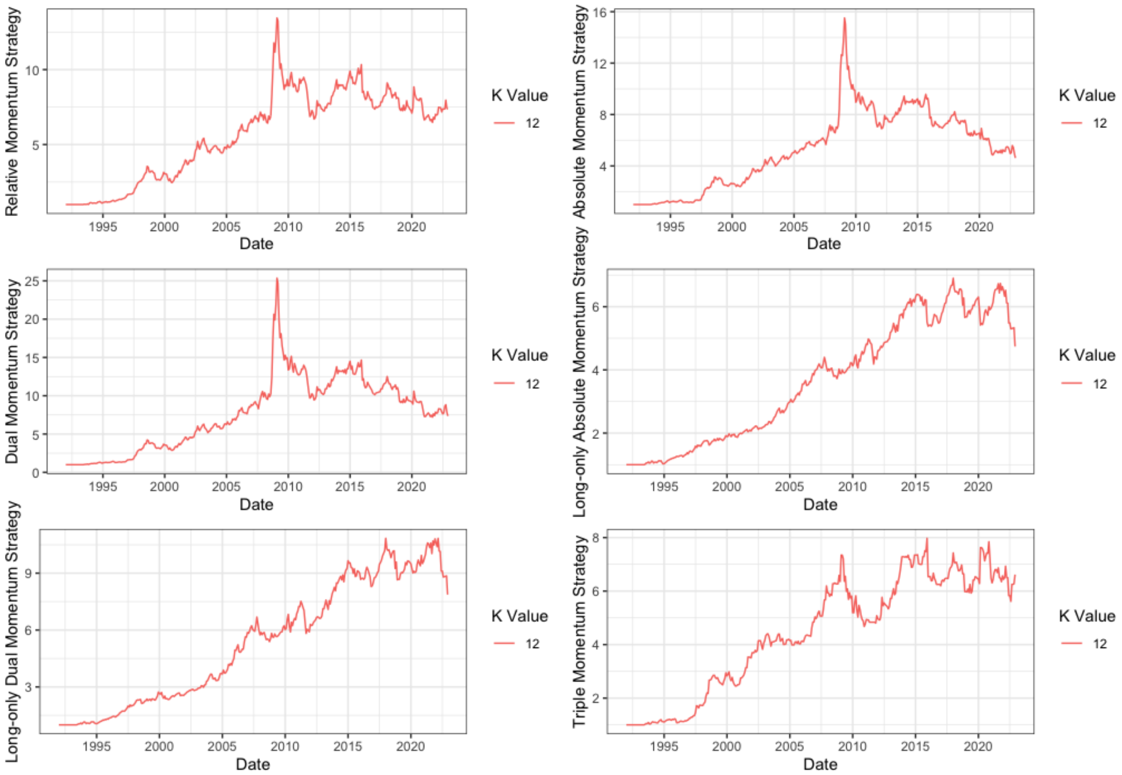

Figure A2.1: Cumulative returns of the momentum strategies

Figure A2.2: Cumulative returns of the naive benchmark strategy

A3 Cumulative returns of momentum strategy and naive strategy with country data

Figure A3.1: Cumulative returns of relative momentum strategy

Figure A3.2: Cumulative returns of long-short absolute momentum strategy

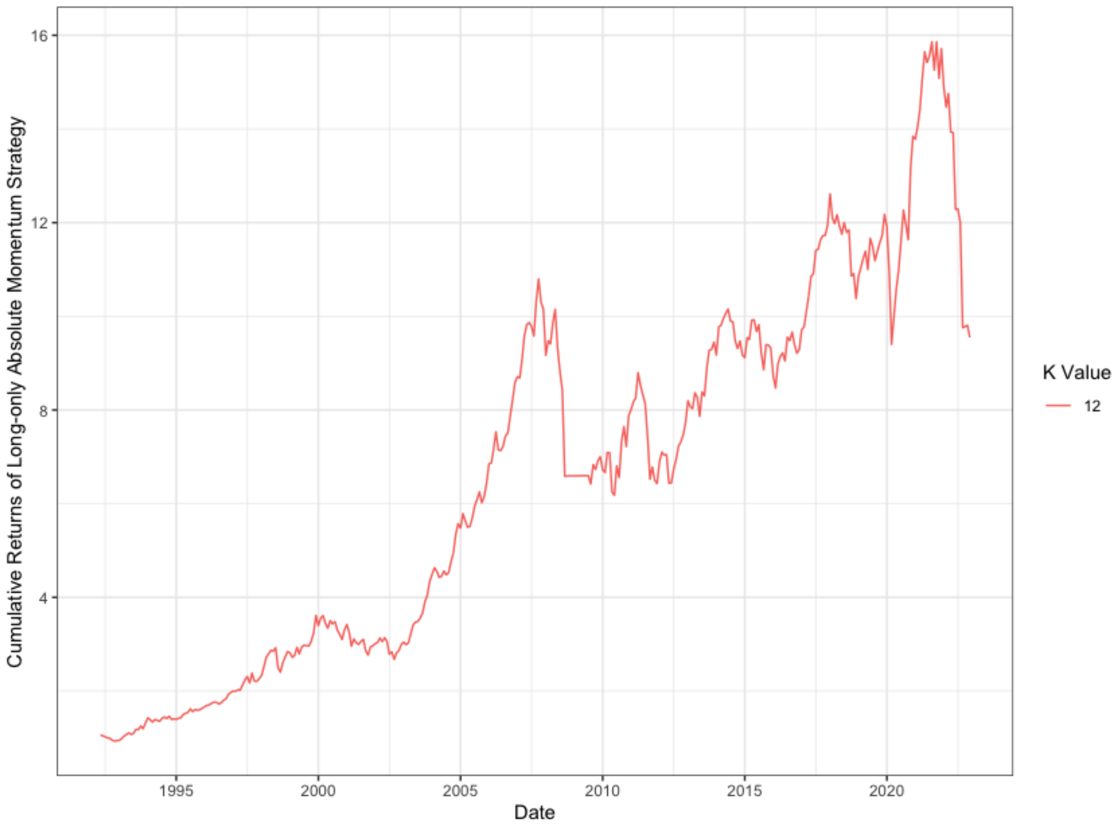

Figure A3.3: Cumulative returns of long-only absolute momentum strategy

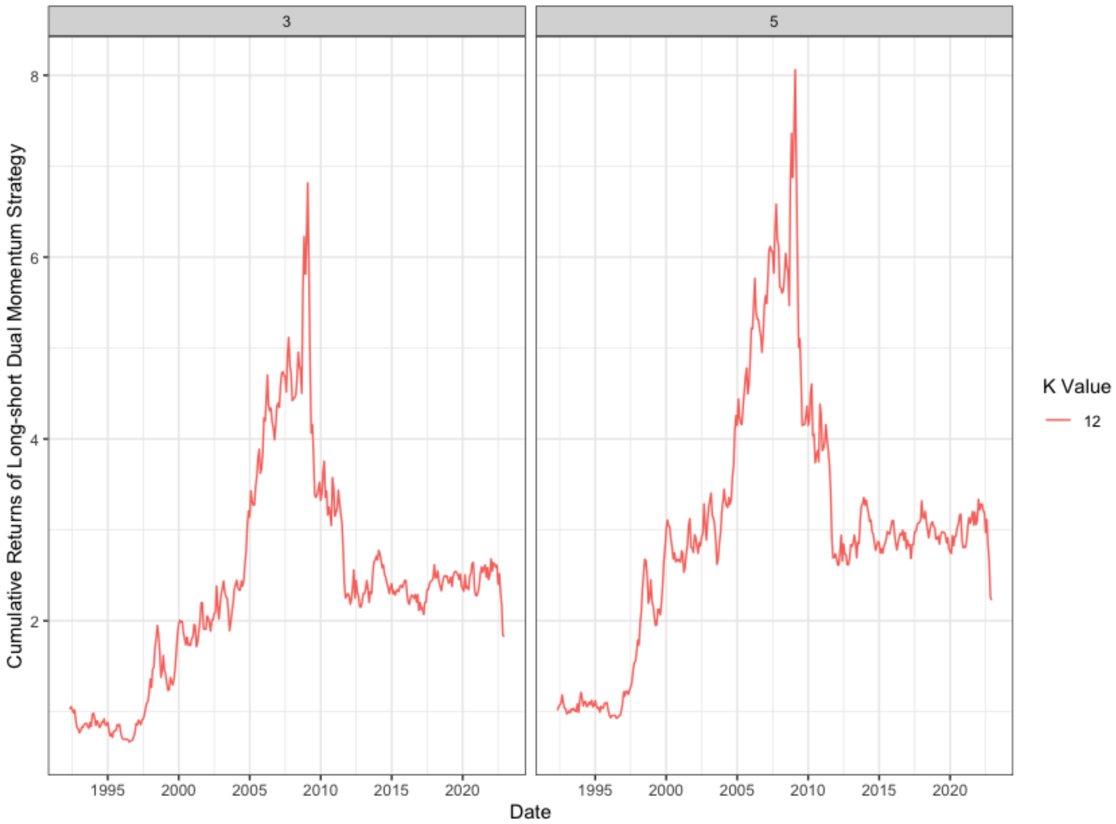

Figure A3.4: Cumulative returns of long-short dual momentum strategy

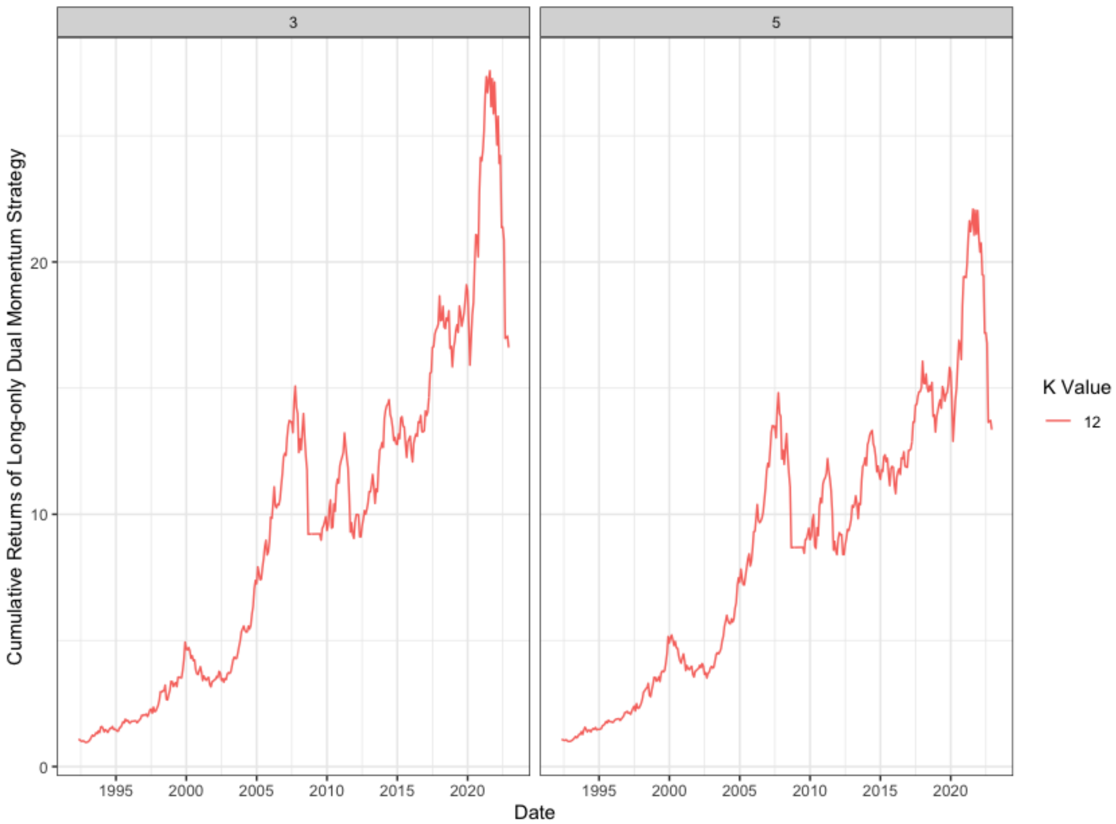

Figure A3.5: Cumulative returns of long-only dual momentum strategy

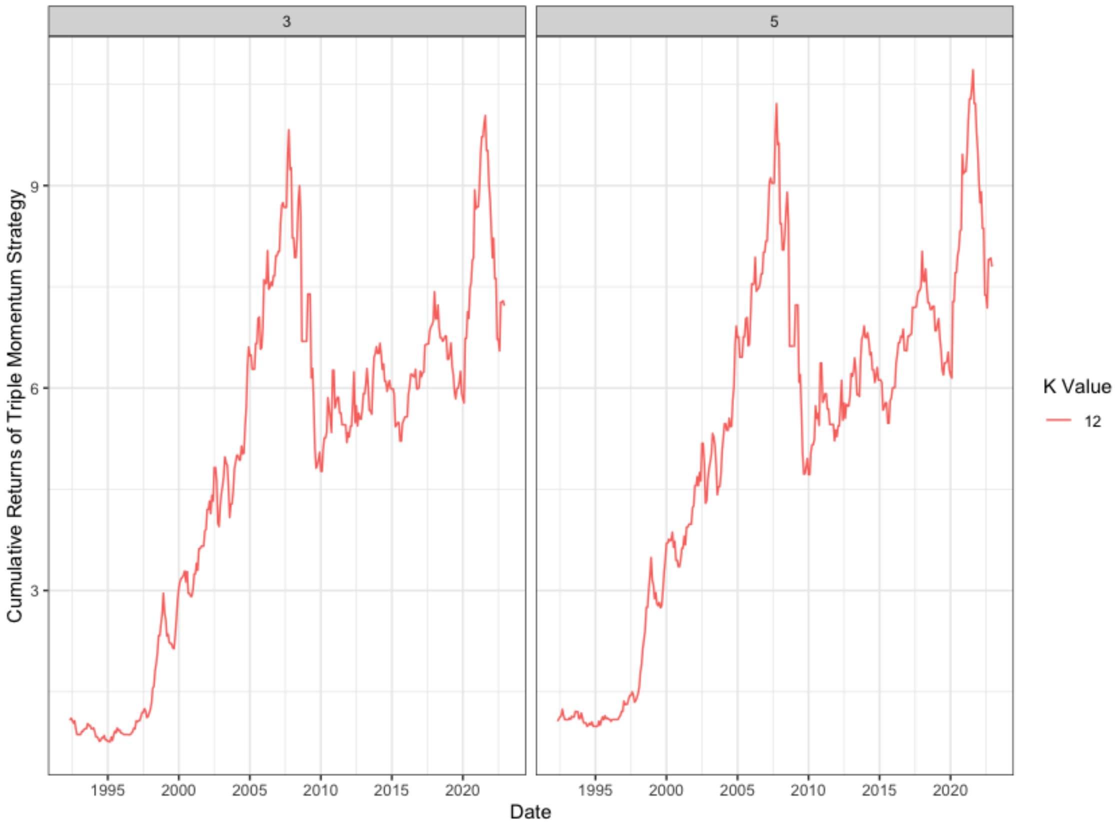

Figure A3.6: Cumulative returns of triple momentum strategy

Figure A3.7: Cumulative returns of the naive benchmark strategy

A4 Discussion Paper Mari Gaupset - Responsible

As part of our master's thesis, we are required to write a discussion paper on the competency goals of "international" or "responsible". These concepts are integral to the University of Agder School of Business and Law's key principles. Throughout our two-year master's program, these concepts have been incorporated into our courses, and they will continue to be relevant to our future careers. In this paper, we will explore how our topic, hypotheses, and findings related to the concept of "responsibility".

This master's thesis focuses on investigating the performance of various momentum strategies across a broad range of markets and asset classes, including 40 US industries, eight multi-asset funds, and 19 developed countries. The paper evaluates the efficacy of several momentum strategies like relative momentum, long-short absolute momentum, long-only absolute momentum, long-short dual momentum, long-only dual momentum, and triple momentum. The research employs a comprehensive methodology, encompassing portfolio theory, asset pricing theory, performance measurement, risk measurements, and momentum investing strategies. The study's findings suggest that momentum strategies potentially generate additional returns for investors, exceeding what could be achieved through passive investment strategies. However, the profitability of such strategies may vary depending on the specific dataset or market.

Discussing responsibility in the context of this thesis implies addressing the ethical challenges that emerge when applying momentum investment strategies. Investment strategies invariably involve decision-making processes that directly affect stakeholders, such as investors, fund managers, and the larger economic environment. Consequently, the responsible application of these strategies becomes a critical consideration. The concept of responsibility has gained increasing importance in recent years, particularly in the field of finance and investment. The application of momentum strategies, like any investment decision, has implications that extend beyond the mere pursuit of profits. These strategies shape the economic environment, influence market stability, and can potentially impact the financial well-being of individuals and institutions. Consequently, it is essential to consider the ethical dimensions and responsibilities tied to the application of momentum strategies.

The potential for generating abnormal returns, as observed in the thesis, implies a level of risk that needs to be responsibly managed. Investors, particularly those with less market knowledge, rely heavily on the expertise, integrity, and responsible conduct of fund managers. Thus, fund managers have a responsibility to ensure that they manage their client's assets with a high degree of care and diligence.

The thesis has demonstrated that different momentum strategies can lead to varying levels of risk and returns. The choice of strategy, and how these strategies are implemented, can therefore have significant implications for investors. The fiduciary duty of investment managers necessitates that they act in the best interests of their clients. This duty includes responsibly choosing and executing investment strategies that align with the risk tolerance and financial goals of their clients.

Moreover, the use of momentum strategies can contribute to price fluctuations and market volatility. If widely used, these strategies can exacerbate market movements, leading to potential asset bubbles or market crashes. This systemic risk poses an ethical challenge. Fund managers, while seeking to maximize returns for their clients, must also consider the potential for their actions to contribute to broader market instability. While regulation plays a critical role in managing these systemic risks, the responsibility cannot be entirely offloaded to regulatory bodies. Investment managers themselves need to be mindful of their role in maintaining stable, functioning markets. Excessive risk-taking or the blind pursuit of profits, without regard for potential market impacts, can be seen as irresponsible conduct.

Further, the momentum strategies investigated in the thesis are largely silent on environmental, social, and governance (ESG) factors. The global push towards responsible investing underscores the importance of considering ESG factors in investment decisions. While momentum strategies focus on financial returns, a responsible approach to investing recognizes the need to balance financial objectives with social and environmental considerations. It is becoming increasingly clear that companies with strong ESG practices often demonstrate better long-term financial performance and are better equipped to manage operational and reputational risks (Friede, Busch, & Bassen, 2015). Thus, ignoring ESG factors may not only be seen as a failure to address broader societal responsibilities, but it could also potentially undermine the long-term financial performance of an investment portfolio. In light of these considerations, it is suggested that fund managers need to adopt a more responsible approach when applying momentum strategies. This approach should involve transparent communication with clients about the risks and potential returns associated with these strategies. It should also include a commitment to considering the broader market impacts of their actions and incorporating ESG factors into their investment decisions.

One of the challenges associated with momentum investment strategies is the potential for market instability. Momentum strategies, particularly when used on a large scale, can contribute to market volatility and the creation of asset price bubbles (Chabot, Ghysels, & Jagannathan, 2019). This volatility can lead to significant financial losses for investors, particularly those who are less informed or less able to respond to rapid market changes. Therefore, the responsible application of momentum strategies necessitates a consideration of the broader market impacts, particularly potential disruptions to market stability. Another ethical challenge relates to the fair distribution of investment returns. Momentum strategies have been found to generate “abnormal” returns that cannot be explained by traditional risk factors, such as the market, size, and value factors. This implies that these strategies enable some investors to earn returns above what could be expected given their level of risk (Fama & French, 1996). This suggests that some investors may be gaining at the expense of others, raising questions about fairness and equity in the distribution of investment returns. These dynamics can have severe consequences for market participants. The 2008 Global Financial Crisis serves as a reminder of the potential fallout from such events. Consequently, the ethical responsibility of investment managers extends beyond their direct clients to the broader market participants.

While this may seem like a positive outcome for those who can access and use these strategies, it raises questions about the fairness of the investment process. Are these abnormal returns being generated at the expense of other market participants? And if so, is this an equitable outcome? In a fair and efficient market, investment returns should be commensurate with the level of risk taken. When this is not the case, it could potentially lead to wealth disparities and social inequality. The management of these ethical challenges necessitates the active engagement of multiple stakeholders, including financial regulators, fund managers, and investors themselves. Regulatory bodies play a critical role in preventing market instabilities. Given that the large-scale use of momentum strategies can potentially exacerbate price volatility and contribute to asset price bubbles, regulatory bodies should actively monitor market trends and intervene when necessary. The tools at their disposal could range from issuing guidelines on the use of momentum strategies to introducing trading restrictions during periods of extreme price volatility. Further, regulators can promote greater transparency by requiring fund managers to disclose their use of momentum strategies. Disclosure requirements would ensure that investors are well-informed about the strategies employed in managing their investments and the associated risks. This, in turn, would enable investors to make more informed decisions and could potentially lead to a more equitable distribution of investment returns (Comerton-Forde & Rydge, 2006).

Fund managers also have a significant role to play in managing these ethical challenges. As fiduciaries, they should act in the best interest of their clients. This implies a responsibility to consider the broader impacts of their actions, including potential disruptions to market stability and the fairness in the distribution of investment returns. Additionally, ensuring that investment returns are distributed equitably among investors could involve providing equal access to investment opportunities and transparently communicating the risks and potential returns associated with different investment strategies.

The integration of ESG criteria into momentum strategies presents another avenue for managing these ethical challenges. ESG investing has gained significant traction in recent years (Bassen & Kovacs, 2008). By considering ESG factors, fund managers can contribute to positive social and environmental outcomes while also achieving financial returns. This approach would align momentum strategies with the broader goals of sustainable development and responsible investing. For instance, a fund manager could apply a momentum strategy within a universe of companies that meet certain ESG criteria. This could potentially help to mitigate some of the ethical challenges associated with momentum strategies, while also contributing to positive societal impact.

The exploration of ethical challenges associated with the use of momentum investment strategies and the identification of potential mitigation measures underline the overarching theme of responsibility in the context of financial investing. Fundamentally, responsibility extends beyond the immediate scope of generating returns to include the consideration of broader societal impacts and the equitable distribution of returns among investors. At the core of these considerations is the concept of fiduciary duty. Fund managers, as fiduciaries, are entrusted with managing other people's money, and this role comes with a responsibility to act in the best interest of their clients. This responsibility should extend to include the broader impacts of their investment decisions on market stability and the fair distribution of investment returns.

However, the responsibility of financial investing does not rest solely with fund managers. Investors themselves also have a role to play in promoting responsible investment practices. By demanding greater transparency about the strategies employed in managing their investments, investors can encourage fund managers to adopt more responsible practices. Furthermore, by choosing to invest in funds that incorporate ESG criteria or adhere to responsible investment principles, investors can contribute to the shift toward a more sustainable financial system. Regulatory bodies also bear significant responsibility in this context. Through active market surveillance and the implementation of suitable regulatory measures, they can prevent the potentially destabilizing effects of momentum strategies and ensure greater transparency in the use of these strategies. Moreover, by fostering a regulatory environment that encourages responsible investing, regulators can contribute to aligning the financial system with broader societal goals. Lastly, the integration of ESG factors into momentum strategies can serve as a pathway toward responsible investing. This approach allows for the pursuit of financial returns while also contributing to positive social and environmental outcomes. Furthermore, it aligns with the broader trend towards sustainable development and reflects the increasing recognition of the role that the financial sector can play in addressing global challenges such as climate change and social inequality.

In conclusion, responsibility in the context of momentum investment strategies involves a multifaceted approach that includes regulatory oversight, responsible conduct by fund managers, and the active engagement of investors. Through such a comprehensive approach, it is possible to mitigate the ethical challenges associated with these strategies and promote a more responsible and sustainable financial system. The findings of this discussion paper underscore the need for ongoing research and dialogue on these issues to ensure that the evolution of investment strategies aligns with the principles of responsibility and ethical conduct.

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A5 Discussion Paper Kristine Sørbø - International

As part of our master's thesis requirements, we are required to write a discussion paper focusing on either the competency goal of "international" or "responsible". These two competencies are key concepts emphasized by the University of Agder School of Business and Law and have been integrated into our coursework over the past two years. We believe that these three concepts will remain relevant throughout our future careers. This paper aims to explore the relationship between our research topic and findings, and the concept of "international".

This master thesis study is focused on testing various momentum strategies across multiple markets and asset classes. To accomplish this, we apply different momentum strategies in the US equity market, utilizing industry portfolios. Additionally, we examine the profitability of these strategies in 19 developed countries and evaluate their performance on eight different funds, which include developed and emerging markets, US bonds, and Real Estate Investment Trusts (REITs). In our thesis, we aim to identify the optimal momentum strategy for various datasets and determine the most optimal strategy overall. Furthermore, we will investigate two key parameters of the strategies and identify the combination that yields the best performance. To accomplish this, we will utilize performance measures such as the Sharpe ratio, alpha from the CAPM and Fama French Carhart model and maximum drawdown. We apply hypothesis testing to evaluate the statistical significance of the performance measures.

The empirical findings demonstrate that different performance measures yield varying optimal strategies, and each dataset identifies distinct strategies as optimal. In the case of the US industry portfolio dataset, the long-only variant of the dual momentum strategy emerges as the optimal approach when the Sharpe ratio serves as the primary performance measure. Conversely, for the country and fund datasets, the newly developed triple momentum strategy exhibits the highest performance according to the Sharpe ratio. The results imply that long-only strategies tend to excel when evaluated based on the Sharpe ratio, while long-short strategies demonstrate superiority when assessed through alpha analysis.

Moreover, all strategies utilize a lookback period (K) for momentum return. Further, some strategies determine the best or worst performing assets (N) from the momentum returns and decides to buy the best and sell the worst. In our analysis, we varied K and N to ascertain if specific parameter values or combinations thereof consistently yielded superior results across strategies and datasets. However, no such overarching outcomes emerged. Nevertheless, it appears that employing a 12-month lookback period (K) tends to yield the best performance across most strategies. The optimal value of N differed among the strategies and datasets. For the industry dataset, N=3 demonstrated superior performance across most strategies, while for the country dataset, N=5 outperformed across several strategies.

Momentum investing is a widely studied investment strategy that has been extensively researched by academics and practitioners alike. According to studies by Jagadeesh and Titman (1993), Moskowitz, Ooi, and Pedersen (2012), and Antonacci (2013), momentum strategies have delivered significant positive returns across a range of asset classes, including equities, bonds, and commodities. In recent years, momentum trading has become an increasingly popular strategy among investors seeking to generate alpha in financial markets. Momentum trading involves buying assets that have exhibited positive performance over a certain time period and selling assets that have exhibited negative performance over the same period (Jegadeesh & Titman, 1993). While there are many different types of momentum trading strategies, including relative, absolute, dual, and triple momentum strategies, they all rely on the same basic principle: that recent performance is a good predictor of future performance. However, momentum trading strategies do not exist in a vacuum, and are subject to a wide range of international trends and forces that can impact their effectiveness. In this discussion paper, I will explore some of the key international trends and forces that may influence momentum trading strategies and discuss how these trends and forces may impact the research question, findings, and units of analysis in our thesis on momentum trading strategies. Specifically, I will consider trends and forces related to globalization, technological advances, macroeconomic conditions, regulatory changes, and market dynamics.

Globalization and international trade have been major drivers of economic growth and development in recent decades, and they have also created new opportunities and challenges for investors who employ momentum trading strategies. As markets become more interconnected, investors may be able to take advantage of momentum trading opportunities in multiple regions simultaneously, potentially increasing the diversification and robustness of their portfolios (Fama & French, 2012). However, globalization also means that changes in international trade relationships, such as tariffs or sanctions, can have ripple effects across multiple markets, potentially impacting the performance of momentum trading strategies. Moreover, globalization has also led to increased competition among investors, potentially making it more difficult for momentum traders to generate alpha in crowded markets (Baltas, 2019). To assess the impact of globalization and international trade on momentum trading strategies, we employ country-level data to test the effectiveness of different momentum trading strategies across a range of global markets.

Technological advances have transformed the landscape of financial markets, and they have also created new opportunities and challenges for investors who employ momentum trading strategies. Advances in trading technology and data analysis tools have enabled more sophisticated momentum trading strategies to be developed and deployed, potentially allowing investors to identify profitable trades more accurately and better manage their portfolios. Additionally, the rise of algorithmic trading and artificial intelligence has led to the development of new momentum trading models that rely on complex statistical analysis and machine learning algorithms (Li & Tam, 2018; Lim et al., 2019). However, these technological advances have also increased the speed and complexity of trading, potentially creating new risks and challenges for investors. Moreover, the growing use of technology in financial markets may also lead to increased competition among investors, potentially making it more difficult for momentum traders to generate alpha.

Macroeconomic trends can have a significant impact on momentum trading strategies, as they can influence the performance of individual assets and entire markets. For example, changes in interest rates, inflation, and economic growth can impact the prices of stocks, bonds, and other assets, potentially creating opportunities for momentum traders to identify and exploit trends. Additionally, macroeconomic factors can impact investor sentiment and behavior, potentially leading to changes in market dynamics that can either support or undermine momentum trading strategies (Hutchison & O'Brian, 2020). However, macroeconomic trends can also create significant risks and challenges for momentum traders. For example, sudden shifts in market sentiment or unexpected changes in government policies can cause significant volatility and uncertainty, potentially leading to losses for momentum traders (Ilmanen & Ross, 2014). To assess the impact of macroeconomic trends on momentum trading strategies, we use intermediate and long-term US bonds as a proxy for changes in interest rates and inflation and analyze their impact on the performance of different momentum trading strategies.

Regulatory changes can have a significant impact on momentum trading strategies, as they can influence the rules and regulations governing financial markets and the behavior of investors. For example, changes in securities laws, accounting standards, or tax policies can impact the prices of individual assets or entire markets, potentially creating opportunities for momentum traders to identify and exploit trends. However, regulatory changes can also create significant risks and challenges for momentum traders. For example, changes in margin requirements or short-selling rules can impact the ability of investors to execute momentum trading strategies, potentially leading to losses, or missed opportunities. Moreover, regulatory changes can also impact investor sentiment and behavior, potentially leading to changes in market dynamics that can either support or undermine momentum trading strategies (Ross et al. 2017).

Market structure and dynamics can have a significant impact on momentum trading strategies, as they can influence the behavior of investors and the availability of profitable trading opportunities. For example, changes in market liquidity, volatility, or fragmentation can impact the prices of individual assets or entire markets, potentially creating opportunities for momentum traders to identify and exploit trends. However, market structure and dynamics can also create significant risks and challenges for momentum traders. For example, sudden changes in investor sentiment or unexpected events can cause significant volatility and uncertainty, potentially leading to losses for momentum traders (Bastidon, 2017). Understanding the ways in which market structure and dynamics may impact momentum trading strategies is therefore critical for investors seeking to succeed in today's complex and dynamic financial landscape. To evaluate the effectiveness of momentum trading strategies across different market structures and dynamics, we analyze the performance of eight funds encompassing developed and emerging market equities, US bonds, and real estate investment trusts (REITs), and consider the impact on the performance of these strategies.

In conclusion, this discussion paper has explored the relationship between the international competency goal and momentum trading strategies. Momentum trading is a popular investment strategy that has shown significant positive returns across various asset classes, including equities, bonds, and commodities. However, momentum trading strategies are subject to a wide range of international trends and forces that can impact their effectiveness, including globalization, technological advances, macroeconomic conditions, regulatory changes, and market dynamics. To assess the impact of these trends and forces on momentum trading strategies, we have employed industry, multi-asset fund, and country-level data to test the profitability of different momentum trading strategies across a range of global markets. Our analysis shows that momentum trading strategies can be effective in capturing positive returns in different markets and asset classes, but they are also subject to risks and challenges related to global trends and forces. For example, changes in international trade relationships, technological advances, macroeconomic trends, and regulatory changes can impact the performance of momentum trading strategies. In summary, our thesis on testing various momentum strategies across multiple markets and asset classes aims to identify the optimal momentum strategy for various datasets and determine the most optimal strategy overall. Furthermore, we investigate two key parameters of the strategies and identify the combination that yields the best performance. Our analysis is based on performance measures such as the Sharpe ratio, alpha from the CAPM and Fama French Carhart model, and maximum drawdown, and we use hypothesis testing to evaluate the statistical significance of the performance measures. The results of our thesis will contribute to the growing body of research on momentum trading strategies and provide insights for investors in financial markets.

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