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Factor Momentum in the U.S. and Norwegian Markets

An emprical study investigating momentum in factor returns using stock data of the U.S. and Norwegian markets

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Abstract

Factors exhibit momentum as strong as that in individual stocks. Importantly, momentum in factor returns has strong and robust predictive power for future performance of factors. This thesis finds that the impact of factor momentum is economically and statistically significant in both the U.S. and Norwegian markets. For example, the good (vs. bad) performance of the factor in the previous year leads to an increase of about 87 basis points (bps) in returns for an average factor in the Norwegian stock market. It is also found that factor momentum can transmit into the cross-section of stock returns, leading to an important question: *Does momentum in factor returns relate to momentum in individual stock returns?* This thesis aims to shed light on this puzzling issue by addressing the following sub-research questions: (1) How strong are factor momentum profits in different markets (i.e., U.S. and Norway)? (2) When and where can factor momentum be observed? (3) To what extent can factor momentum explain the cross-sectional momentum in individual stock returns? And (4) does factor momentum stem from individual stock momentum? Using individual stock and various factor data in the U.S. and Norwegian markets, this thesis provides strong evidence for substantial presence of factor momentum and its nontrivial contribution to the cross-section of individual stock returns in both markets. Furthermore, in the U.S. market, factor momentum is found to primarily concentrate in a few of principal component (PC) factors with highest eigenvalues. The momentum found in these factors appears to subsume individual stock momentum (e.g., in the form of the up-minus-down factor), while the reverse is not true. Indeed, incidental momentum in factor returns caused by individual stock momentum has poor performance in explaining the factor momentum profits. Although factor momentum found in a smaller set of factors in the Norwegian market is not sufficient to exhibit the same results, existing evidence from both markets supports that momentum is not independent of other risk factors, and that momentum in returns of other factors is sufficient to explain most of stock momentum profits. Future research should further compare momentum in factor returns and momentum as an independent factor in other assets and regions to validate the robustness of these findings.

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1. Introduction

Since momentum was introduced in the financial research literature over 30 years ago (e.g., Jegadeesh & Titman, 1993), it has emerged into a highly robust, diverse, and profitable investment strategy for investors across various assets classes and regions (Wiest, 2023). For example, Carhart (1997) demonstrates that mutual funds categorized in the top decile based on one-year past returns outperform funds in the bottom decile by a difference of 67 basis points (bps) in monthly returns. In the domain of commodity futures markets, Miffre and Rallis (2007) identify an average annual return of 9.38 bps across 13 profitable momentum strategies that buy (vs. sell) the commodity futures with good (vs. bad) performance in the preceding 12 months. In a similar vein, Jostova, Nikolova, Philipov, and Stahel (2013) discover a monthly momentum profit of 59 bps when trading corporate bonds (and 192 bps when trading noninvestment grade bonds), while a recent study on a digital asset market by Liu, Tsyvinski, and Wu (2022) reveals that the momentum strategy in the above-median size group of cryptocurrencies yields a statistically significant weekly return of 3.2 bps. Furthermore, it is also found that momentum profits, at least in the stock market, extend beyond the U.S. to include other major developed regions such as Europe and the Asia Pacific (e.g., Fama & French, 2012; Rouwenhorst, 1998).

Momentum, due to its significant implications for various investment applications, has garnered substantial attention in previous research (Wiest, 2023). However, our current understanding of its puzzling impact on future asset returns and complex relationship with other risk factors remains limited, leading to the strong need for further research and exploration in this research area. Importantly, recent momentum research has revealed that factors exhibit similar momentum to that observed in stock returns (e.g., Avramov, Cheng, Schreiber, & Shemer, 2017). Furthermore, momentum in factor returns, often referred to as *factor momentum*, possesses strong predictive power not only for future factor returns but also for the future performance of individual stocks (e.g., Ehsani & Linnainmaa, 2022).

Given that individual stock momentum is also an important component driving stock returns, a natural question arises: *what is the exact relationship between factor momentum and individual stock momentum*? Ehsani and Linnainmaa (2022) find that factor momentum subsumes various forms of individual stock momentum. However, they also state that momentum profits in stock returns, net of factor momentum, cannot be completely ruled out. The main purpose of this thesis is to revisit this pivotal research question and extend it slightly by examining a smaller set of factors and utilizing data from a smaller market, such as Norway. To accomplish this, this thesis empirically addresses four sub-research questions as follows:

1) Does factor momentum exist, and to what extent can it predict future factor returns?
2) When and where is factor momentum observed?
3) To what extent does factor momentum contribute to the cross sections of stock returns and can this contribution account for all momentum profits in stock returns?
4) Is momentum a distinct factor, and does factor momentum stem from the "momentum factor"?

By addressing these research questions, this thesis aims to shed further light on the complex relationship between factor momentum and individual stock momentum and examine the persistence of the findings using a narrower set of factors and/or data from the Norwegian stock market.

Firstly, the initial analysis in this thesis examines the relationship between factors' past returns and their future returns using a dataset consisting of 20 "nonmomentum" US and global factors. The pooled regression results reveal that factors experiencing a prior year of losses yield a monthly factor return of 2 bps (p-value = 0.78), while factors with a prior year of gains generate a monthly factor return of 49 bps (p-value < 0.01), indicating the strong predictive power of past returns and the predominance of positive autocorrelations in factors. A robustness check using more recent data for a smaller set of factors in the US market further validates these findings, demonstrating their robustness across different factor structures.

Momentum strategies trading the abovementioned 20 factors demonstrate significant profitability compared to the equal-weighted strategy. Specifically, the winner portfolios in both time-series and cross-sectional factor momentum strategies exhibit significantly higher annualized returns (5.93% with t-value = 10.03 and 6.45% with t-value = 8.98, respectively) relative to the equal-weighted portfolio (4.10% with t-value = 7.77). Furthermore, a decomposition analysis reveals that the superior profitability of the time-series (vs. cross-sectional) factor momentum strategy stems from exploiting positive autocorrelations between factor returns, and not relying on negative cross-serial covariances.

Secondly, building upon previous studies (e.g., Haddad, Kozak, & Santosh, 2020), a set of 54 factors are reconstructed using the characteristic signals data published by Kozak (2020). After excluding 7 factors related to momentum, five groups of principal components (PCs) sorted by their eigenvalues are derived from these factors. The subsequent analysis indicates that the factor momentum strategy trading the first group of top 10 PCs with highest eigenvalues yields significantly higher returns compared to strategies trading other groups of PC factors. This result suggests that factor momentum primarily concentrates in the first few highest-eigenvalue PC factors as predicted by the Kozak, Nagel, and Santosh (2018)'s sentiment-based mispricing model. In a similar vein, although factor momentum initially spreads to both high- and low-eigenvalue PC factors in the first half of the testing sample, likely due to the participation of arbitrageurs (Ehsani & Linnainmaa, 2022), the momentum exhibited by the first group of PC factors fully explains momentum in the remaining four PC groups in the second half, rendering their corresponding alpha statistically insignificant.

Thirdly, using individual stock data from the US market and assuming that stock returns adhere to the Fama and French (2015)'s five-factor model, a cross-sectional momentum strategy is found to gain an average return of 64 bps per month (t-value = 2.03). This total profit is attributed to two main components: 28 bps contributed by factor autocovariances, and 31 bps contributed by the residuals. While the sensitivity of factor autocovariances' contribution to the choice of asset pricing model is confirmed (e.g., due to omitted factor bias), factor momentum retains its important role even when various formation and holding periods are considered. Hence, the results suggest further investigation into the difference between the profits derived from factor momentum and individual stock momentum inherent in stock returns.

By utilizing 10 momentum-sorted portfolios obtained from the data library of Kenneth French, subsequent analyses investigate the performance of the Fama and French (2015)'s five-factor model augmented with factor momentum derived from the first 10 PC factors mentioned above in explaining the portfolio returns. Results show that this model outperforms the six-factor model that incorporates Carhart (1997)'s UMD momentum factor, leading to a significant reduction in alphas across all 10 portfolios. Moreover, the GRS test proposed by Gibbons, Ross, and Shanken (1989) fails to reject the null hypothesis that these alphas are jointly equal to zero only for the model including factor momentum. In addition, factor momentum found in the first 10 PC factors subsumes the momentum profits of the UMD factor, while the reverse is not true. In contrast, factor momentum found in PC factors with lower eigenvalues or in standard risk factors could not fully capture individual stock momentum as represented by the UMD factor.

Fourthly, a set of 47 momentum-neutral factors is constructed using a factor weight adjusting technique proposed by Ehsani and Linnainmaa (2022). The findings indicate that factor momentum in momentum-neutral factors can account for all the observed momentum profits in standard factors, but the reverse is not true, suggesting that factor momentum is not solely driven by individual stock momentum. Furthermore, the unconditional correlations between the UMD factor and other risk factors, while statistically insignificant, can be misleading. It is found that, momentum exhibits substantial positive (negative) correlations with other factors when being conditional upon the positive (negative) past-year performance of factor returns. These results suggest that momentum may not be an independent risk factor and can be entirely explained by the autocorrelations of other factors (Ehsani & Linnainmaa, 2022).

Finally, the analyses are extended to incorporate Norwegian stock data. The results demonstrate the presence of factor momentum in the Norwegian market, with significant and economically meaningful profits. Specifically, following a year of losses, the average factor earns a monthly return of 9 bps, whereas a year of gains leads to a monthly return of 96 bps. Moreover, factor momentum contributes to the cross-section of stock returns, although the transmission is more limited due to the use of a smaller set of factors in the chosen asset pricing model. Consistent with the previous findings, the factor momentum observed in this restricted set of factors fails to fully capture the momentum profits derived from the Carhart (1997)'s UMD factor. Similarly, comparable outcomes concerning the conditional correlations between the UMD factor and other risk factors are identified, suggesting that momentum may also not represent an independent factor in the Norwegian market.

This thesis naturally relates to the existing body of literature on momentum, including both individual stock momentum studies (e.g., Lewellen, 2002; Moskowitz, Ooi, & Pedersen, 2012), and a smaller set of research on factor momentum, such as Avramov et al. (2017), Haddad et al. (2020), and Arnott, Clements, Kalesnik, and Linnainmaa (2021). In fact, a significant proportion of this thesis entails a close replication of Ehsani and Linnainmaa (2022)'s paper to revisit the puzzling but pivotal relationship between factor and individual stock momentums. Further, this thesis offers a marginal contribution to the existing literature by examining the transmission of factor momentum to the cross section of stock returns using various formation and holding periods, as well as extending the analysis to Norwegian stock data with a more restricted set of factors.

The remaining of this thesis is structured as follows. Section 2 outlines the different data sets utilized to investigate the abovementioned research questions. Section 3 explains the methodological approaches employed for the subsequent analyses. Section 4 presents the primary outcomes derived from all analyses. Particularly, the initial four subsections of Section 4 closely replicate Ehsani and Linnainmaa (2022)'s study to address the four sub-research questions proposed earlier, in addition to a series of additional robustness tests using a smaller set of factors. In the last part of Section 4, all sub-research questions, excluding the second one, are reexamined using Norwegian stock data. Finally, the last two sections provide a summary of the findings, describe the limitations of the thesis, and suggest avenues for future research.

2. Data

The section explains the sources and the use of data throughout the thesis.

2.1 Off-the-shelf factors (22 anomalies)

These monthly data include 15 U.S. and 7 global factors collected and made available by Ehsani and Linnainmaa (2022) through their replication package. According to these authors, the data were collected from three different data libraries of Kenneth French, AQR, and Robert Stambaugh. Table 1 presents the names, start dates, and major descriptive statistics of all factors. These data are used in the analyses shown in Sections 4.1, 4.3, and 4.4.

Table 1. Descriptive Statistics of 22 factors

Factors	Original Study	Start Date	Annual Return			
			Mean	SD	SE	t-Value
		U.S. Factors				
Accruals	Sloan (1996)	Jul 1963	2.813 %	6.633 %	0.882	3.187
Betting against beta	Frazzini and Pedersen (2014)	Jul 1963	9.799 %	11.243 %	1.496	6.552
Cash flow to price	Rosenberg, Reid, and Lanstein (1998)	Jul 1963	3.379 %	8.643 %	1.150	2.939
Investment	Titman, Wei, and Xie (2004)	Jul 1963	3.291 %	6.900 %	0.918	3.585
Earnings to price	Basu (1983)	Jul 1963	3.482 %	8.888 %	1.182	2.945
Value	Rosenberg et al. (1998)	Jul 1963	3.649 %	9.727 %	1.294	2.820
Liquidity	Pástor and Stambaugh (2003)	Jan 1968	4.444 %	11.563 %	1.604	2.771
Long-term reversals	De Bondt and Thaler (1985)	Jul 1963	2.490 %	8.669 %	1.153	2.159
Net share issues	Loughran and Ritter (1995)	Jul 1963	2.757 %	8.209 %	1.092	2.524
Quality minus junk	Asness, Frazzini, and Pedersen (2019)	Jul 1963	4.597 %	7.738 %	1.029	4.465
Profitability	Novy-Marx (2013)	Jul 1963	3.106 %	7.470 %	0.994	3.126
Residual variance	Ang, Hodrick, Xing, and Zhang (2006)	Jul 1963	1.552 %	17.259 %	2.296	0.676
Size	Banz (1981)	Jul 1963	2.733 %	10.415 %	1.386	1.973
Short-term reversals	Jegadeesh (1990)	Jul 1963	5.951 %	10.627 %	1.414	4.209
Momentum	Jegadeesh and Titman (1993)	Jul 1963	7.752 %	14.492 %	1.928	4.021
		Global Factors				
Betting against beta	Frazzini and Pedersen (2014)	Feb 1987	9.599 %	9.667 %	1.685	5.697
Investment	Titman et al. (2004)	Jul 1990	1.938 %	6.046 %	1.113	1.741
Value	Rosenberg et al. (1998)	Jul 1990	3.955 %	7.360 %	1.355	2.918
Quality minus junk	Asness et al. (2019)	Jul 1989	6.247 %	6.821 %	1.235	5.058
Profitability	Novy-Marx (2013)	Jul 1990	4.273 %	4.731 %	0.871	4.905
Size	Banz (1981)	Jul 1990	1.084 %	7.071 %	1.302	0.833
Momentum	Jegadeesh and Titman (1993)	Nov 1990	7.912 %	12.087 %	2.238	3.535

Notes: The global factors were calculated for developed markets excluding the U.S. The end date of all factors is December 2019. This table is an exact replication of Ehsani and Linnainmaa (2022, p. 1882)'s Table I.

2.2 Fama/French 5 research factors – US market (US FF5)

US FF5 data refer to the Fama and French (2015)'s five factors for the U.S. market that are publicly accessible through the data library of Kenneth French. These data include monthly and daily factor returns of the following factors: size (SMB), value (HML), market (MKTRF), profitability (RMW), and investment (CMA). See Table 2 for their descriptive statistics. These data are used in the analyses shown in Sections 4.1, 4.2, 4.3, and 4.4.

Table 2. Descriptive Statistics of US FF5 + UMD + BAB + QMJ

Factors	Original Study	Start Date	Annual Return			
			Mean	SD	SE	t-Value
Investment	Titman et al. (2004)	Jul 1963	3.496 %	7.143 %	0.925	3.781
Value	Rosenberg et al. (1998)	Jul 1963	3.646 %	10.298 %	1.333	2.735
Market factors	CAPM	Jul 1963	6.644 %	15.586 %	2.018	3.292
Profitability	Novy-Marx (2013)	Jul 1963	3.343 %	7.700 %	0.997	3.353
Size	Banz (1981)	Jul 1963	2.752 %	10.458 %	1.354	2.033
Momentum (UMD)	Jegadeesh and Titman (1993)	Jul 1963	7.388 %	14.637 %	1.895	3.8986
BAB	Frazzini and Pedersen (2014)	Jul 1963	9.460 %	11.335 %	1.467	6.447
QMJ	Asness et al. (2019)	Jul 1963	4.588 %	7.967 %	1.031	4.449

Notes: FF5 refers to size, value, market, profitability, and investment; BAB = betting against beta; QMJ = quality minus junk. The end date of all factors is March 2023

2.3 KNS characteristic signals

The KNS characteristics signals data refer to the panel daily data involving values of characteristic signals for each individual stock that can be collected from the data library of Serhiy Kozak (Kozak, 2020). The data include a total of 54 different characteristics for 6552 individual stocks from the 1st of June 1963 until the 1st of November 2019. These data are used in the analyses shown in Sections 4.2 and 4.4.

2.4 KNS characteristic-managed portfolios (54 factors)

The KNS 54 factors or the characteristics-managed portfolios data refer to portfolios constructed by Kozak, Nagel, and Santosh (2020) in which the values of characteristic signals were used to weigh individual stocks. These data are available both at the monthly and daily levels and can be collected from the data library of Serhiy Kozak. The data include monthly and daily returns of 54 factors during between July 1963 and December 2019. The descriptive statistics of these factors can be found in Table A.1 of the Appendix. These data are used in the analyses shown in Sections 4.2, 4.3, and 4.4.

2.5 Betting against beta (BAB)

BAB (betting against beta) factor, which goes long leveraged low-beta and shorts high-beta assets, was proposed by Frazzini and Pedersen (2014) and its monthly and daily data can be collected from the data library of Andrea Frazzini. Its descriptive statistics can be found in Table 2. These data are used in the analysis shown in Section 4.3.

2.6 Quality minus junk (QMJ)

QMJ (quality minus junk) factor, that is long high-quality and short low-quality stocks, was proposed by Asness et al. (2019) and its monthly and daily data can be collected from the data library of Andrea Frazzini. Its descriptive statistics can be found in Table 2. These data are used in the analysis shown in Section 4.3.

2.7 Individual stock returns – US market

The original sample of US stock returns used in this thesis covers about 25,945 stocks listed on NYSE, AMEX, and Nasdaq (i.e., exchange codes of 1, 2, and 3) that are identified on Center for Research in Security Prices (CRSP) as ordinary common shares (i.e., share codes of 10 and 11) from 1963 to March 2023. Both monthly and daily stock returns were obtained from the Wharton research data services. These data are used in the analyses shown in Sections 4.2, 4.3, and 4.4.

2.8 Ten momentum-sorted portfolios

Table 3. Descriptive Statistics of 10 momentum-sorted portfolios

Portfolios	Start Date	Annual Return			
		Mean	SD	SE	t-Value
P1	Jan 1927	4.093 %	34.161 %	3.482	1.175
P2	Jan 1927	8.878 %	28.150 %	2.869	3.094
P3	Jan 1927	9.354 %	24.178 %	2.464	3.795
P4	Jan 1927	10.791 %	21.929 %	2.235	4.828
P5	Jan 1927	10.726 %	20.490 %	2.089	5.136
P6	Jan 1927	11.476 %	20.016 %	2.040	5.625
P7	Jan 1927	12.188 %	18.937 %	1.930	6.314
P8	Jan 1927	13.258 %	18.359 %	1.871	7.085
P9	Jan 1927	14.170 %	19.336 %	1.971	7.190
P10	Jan 1927	17.718 %	22.322 %	2.275	7.787

Notes: P1-10 are portfolios sorted by past 12-month returns skipping one month

These data involve 10 portfolios sorted by NYSE prior one-year returns skipping a month (i.e., from month t-12 to month t-2). These 10 portfolios, constructed both on a monthly and daily basis, include NYSE, AMEX, and NASDAQ stocks and are made available at the data library of Kenneth French. The data span from January 1927 to March 2023. Table 3 presents the major descriptive statistics of these portfolios. These data are used in the analysis shown in Section 4.3.

2.9 Fama/French 3 research factors – Norwegian market (Norway FF3)

Norway FF3 data refer to the Fama and French (1993)'s three factors for the Norwegian market that have been calculated and made publicly accessible by Bernt Arne Ødegaard at his own website. These data include monthly and daily factor returns of the following factors: size (SMB) and value (HML). The market (MKTRF) factor was calculated based on the OBX total return index and risk-free rates that are also available at the above website. Table 4 presents the major descriptive statistics of these factors. These data are used in the analysis shown in Section 4.5.

Table 4. Descriptive Statistics of Norway FF3 + UMD

Factors	Original Study	Start Date	Annual Return			
			Mean	SD	SE	t-Value
Value	Rosenberg et al. (1998)	Jul 1981	4.746 %	20.128 %	3.115	1.524
Market factors	CAPM	Jul 1981	8.724 %	20.134 %	3.116	2.800
Size	Banz (1981)	Jul 1981	13.924 %	16.921 %	2.619	5.317
Momentum (UMD)	Jegadeesh and Titman (1993)	Jul 1981	14.983 %	21.662 %	3.353	4.469

Notes: FF3 refers to size, value, and market factors; The end date of all factors is March 2023

2.10 Individual stock returns – Norwegian market

The original sample of Norwegian stock returns used in this thesis covers about 1,059 stocks listed on Oslo Stock Exchange until November 2020 and on Euronext (after OSE merged with Euronext) from December 2020 till now (i.e., March 2023). Both monthly and daily stock returns were obtained from Titlon, the financial database for Norwegian academic institutions. These data are used in the analysis shown in Section 4.5. Table 5 summarizes the sources of all data sets mentioned above and how they are used throughout this thesis.

Table 5. Data sources and use in the thesis

Panel A: **Data sources**

No.	Data	Freq.*	Source
1	22 factors	M	Replication data provided by Ehsani and Linnainmaa (2022) at: https://onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1111%2Fjofi.13131&file=jofi13131-sup-0002-ReplicationCode.zip
2	US FF5	M & D	Data library of Kenneth French which is publicly available at: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
3	KNS characteristic signals	D	Data library of Serhiy Kozak publicly available at: https://sites.google.com/site/serhiykozak/data References: Kozak (2020)
4	KNS 54 factors	M & D	Data library of Serhiy Kozak which is publicly available at: https://sites.google.com/site/serhiykozak/data References: Kozak et al. (2020)
5	BAB	M & D	Data library of Andrea Frazzini which is publicity available at: https://pages.stern.nyu.edu/~afrazzin/data_library.htm References: Frazzini and Pedersen (2014)
6	QMJ	M & D	Data library of Andrea Frazzini which is publicity available at: https://pages.stern.nyu.edu/~afrazzin/data_library.htm References: Asness et al. (2019)
7	Individual stock returns in the US	M & D	Downloaded from Wharton research data services: https://wrds-www.wharton.upenn.edu/
8	10 momentum-sorted portfolios	M & D	Data library of Kenneth French which is publicly available at: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
9	Norway FF3	M & D	Data library of Bernt Arne Ødegaard which is publicly available at: https://ba-odegaard.no/financial_data/ose_asset_pricing_data/index.html
10	Individual stock returns in Norway	M & D	Downloaded from Titlon – Financial data for Norwegian academic institutions: https://titlon.uit.no/

Notes: Freq. = frequency of data (M = Monthly, D = Daily); All links were accessible on the 30th of May 2023

Panel B: The use of data in the thesis

		Analysis				
No.	**Data**	4.1 The impact of factor momentum on factor returns	4.2 The concentration of factor momentum in high-eigenvalue PCs	4.3 Relationship between factor momentum and individual stock momentum	4.4 Relationship between momentum and other factors	4.5 Factor momentum in the Norwegian stock market
1	22 factors	X		X	X	
2	US FF5	X	X	X	X	
3	KNS characteristic signals		X		X	
4	KNS 54 factors		X	X	X	
5	BAB			X		
6	QMJ			X		
7	Individual stock returns in the US		X	X	X	
8	10 momentum-sorted portfolios			X		
9	Norway FF3					X
10	Individual stock returns in Norway					X

3. Methodology

3.1 Time-Series and Cross-Sectional Factor Momentum Strategies

The initial phase of this thesis's analysis is devoted to comparing the profitability of time-series and cross-sectional strategies when trading 20 nonmomentum factors (22 US and global factors listed in Table 1 excluding two momentum factors). The methodology adopted in this analysis draws upon previous research (e.g., Asness, Moskowitz, & Pedersen, 2013; Moskowitz et al., 2012). Specifically, to implement a *cross-sectional momentum* (XSMOM) strategy, all factors were initially ranked based on their historical one-year returns (i.e., from month t-12 to month t-1). This strategy is to long the factors whose returns are above the median (i.e., termed "winners") and to short the factors whose returns are below the median (i.e., termed "losers"). The total profits of this cross-sectional factor momentum strategy are furthered decomposed into three distinct components based on the methodologies proposed by Lo and MacKinlay (1990) and Lewellen (2002). The calculation for the return of a factor f in month t, given its portfolio position, can be expressed as follows:

$$\pi_t^f = \omega_t^f r_t^f \tag{1}$$

where r_t^f is the return of a factor f in month t and ω_t^f is the weight of a factor f in month t. Note that this weight is positive for factors with above-average returns and negative for factors with below-average returns:

$$\omega_t^f = r_{t-12,t-1}^f - \bar{r}_{t-12,t-1} \tag{2}$$

In the equation (2) above, $r_{t-12,t-1}^f$ is the average past return of a factor f from month t-12 to t-1 (i.e., a formation period of 12 months skipping one month) and $\bar{r}_{t-12,t-1}$ is the cross-sectional average of all factors' past returns over the same period from month t-12 to t-1.

As such, the expected profit to a cross-sectional factor momentum strategy in month t can be decomposed into different components as follows:

$$\begin{aligned} E[\pi_t^{XSMOM}] &= E\left[\sum_{f=1}^{F} \frac{1}{F}(r_{t-12,t-1}^f - \bar{r}_{t-12,t-1})r_t^f\right] \\ &= \frac{1}{F}\sum_{f=1}^{F} cov(r_{t-12,t-1}^f, r_t^f) - cov(\bar{r}_{t-12,t-1}, \bar{r}_t) + \frac{1}{F}\sum_{f=1}^{F}(\mu^f - \bar{\mu})^2 \end{aligned} \tag{3}$$

where $\bar{r}_t$ is the cross-sectional average of all factors' returns in month t, μ^f is factor f's unconditional expected return, and $\bar{\mu}$ is the unconditional mean across all factors. The above equation can be rewritten in matrix notation as below:

$$E[\pi_t^{XSMOM}] = \frac{1}{F}tr(\Omega) - \frac{1}{F^2}\iota'\Omega\iota + \sigma_\mu^2 = \frac{F-1}{F^2}tr(\Omega) - \frac{1}{F^2}[\iota'\Omega\iota - tr(\Omega)] + \sigma_\mu^2 \quad (4)$$

where $\Omega \equiv E\left[(r_{t-12,t-1}^f - \mu)(r_t^f - \mu)'\right]$ is the autocovariance matrix of corresponding factor returns, $tr(\Omega)$ is the trace of matrix Ω, ι is an (N x 1) vector of ones, and σ_μ^2 is the cross-sectional variance of unconditional expected returns.

Secondly, to implement a *time-series factor momentum* (TSMOM) strategy, one needs to take long positions on factors exhibiting positive returns over the preceding one-year period, specifically from month t-12 to month t-1 (i.e., referred to as "winners") and short positions on those displaying negative returns in the same historical period. The monthly total profits generated by this strategy are further decomposed into different components using the same method proposed in previous research (e.g., Ehsani & Linnainmaa, 2022; Moskowitz et al., 2012). The decomposition can be expressed as follows:

$$\begin{aligned} E[\pi_t^{TSMOM}] &= \frac{1}{F}E\left[\sum_{f=1}^{F} r_{t-12,t-1}^f\, r_t^f\right] = \frac{1}{F}\sum_{f=1}^{F}\left[cov\left(r_{t-12,t-1}^f, r_t^f\right) + (\mu^f)^2\right] \\ &= \frac{1}{F}Tr(\Omega) + \frac{1}{F}\sum_{f=1}^{F}(\mu^f)^2 \end{aligned} \quad (5)$$

The benchmark strategy in this analysis is the equal-weighted strategy, wherein all factors are assigned an equal weight irrespective of their historical returns. The monthly profit of the equal-weighted strategy, across F factors, can be presented as below:

$$E[\pi_t^{EW}] = \frac{1}{F}\sum_{f=1}^{F} r_t^f \quad (6)$$

Following Ehsani and Linnainmaa (2022), the standard error of each component in the above decomposition is computed using the block bootstrapping method. This method involves randomly resampling the months, with replacement, for each factor with a total of 1,000 bootstrap samples.

3.2 Constructing KNS Factors, Momentum-Neutral Factors, and Principal Components (PCs)

a) KNS and momentum-neutral factors

In the second major analysis, the focus is on investigating the concentration of factor momentum in high-eigenvalue factors. To achieve this, 54 factors are reconstructed (i.e., referred to as KNS factors) by utilizing the characteristic signals data provided by Kozak (2020). These data contain the daily values of 54 characteristic signals for each stock. A total of seven factors is excluded from the analysis due to their strong connection with momentum (see Ehsani & Linnainmaa, 2022, p. 1888), resulting in a reduced sample of 47 factors for further examination.

Additionally, following the methodology outlined by Ehsani and Linnainmaa (2022), a set of 47 momentum-neutral factors is derived from the abovementioned 47 KNS factors. This is accomplished by adjusting the factor weights to ensure their statistical independence from past returns. The process involves three major steps, as presented below.

Step 1: Impose restrictions on the sample.

Following Kozak et al. (2020), the initial step is to gather daily data from all stocks listed on NYSE, Amex, and Nasdaq. Next, to mitigate the impact of highly illiquid and small-cap stocks, all stocks with market values of equity smaller than 0.01% of the total stock market value at any point in time are excluded from the dataset (Ehsani & Linnainmaa, 2022).

Step 2: Compute factor weights of stocks using daily data.

For characteristic j, the weight of a stock s in month t can be computed as follows (e.g., Frazzini & Pedersen, 2014; Kozak, 2020):

$$w_{s,j,t} = \frac{rc_{s,j,t} - \overline{rc}_{s,j,t}}{\sum_{s=1}^{S_t} \left| rc_{s,j,t} - \overline{rc}_{s,j,t} \right|} \tag{7}$$

where $rc_{s,j,t}$ is a cross-sectional rank of stock s on characteristic j in month t and $\overline{rc}_{s,j,t}$ is the mean of $rc_{s,j,t}$ over S stocks at time t. Specifically, one can compute this rank as: $rc_{s,j,t} = \frac{rank(c_{s,j,t})}{S_t+1}$ where $c_{s,j,t}$ is value of characteristic j for stock s in month t and S_t is the number of stocks in the current period.

As demonstrated by Ehsani and Linnainmaa (2022), the weights of momentum-neutral factors are equivalent to the residuals derived from regressing the original factor weights on past stock returns. In other words, the momentum-neutral weight of a stock s in month t can be computed as follows:

$$w_{s,j,t}^{neutral} = w_{s,j,t} - (\beta_{0,s,j,t} + \beta_{1,s,j,t} r_{s,t-12,t-2}) \quad (8)$$

where $\beta_{0,s,j,t}$ and $\beta_{1,s,j,t}$ are regression coefficients when regressing the original factor weight $w_{s,j,t}$ on individual stock returns over the past 11 months from month t-12 to t-2 (i.e., $r_{s,t-12,t-2}$).

Step 3: Compute daily and monthly factor returns.

Based on the weights derived in step 2, the monthly (or daily) return of a factor associated with characteristic j at time t can be calculated as follows: $f_{j,t} = \sum_{s=1}^{S_{t-1}} (w_{s,j,t-1} * r_{s,t})$ where $r_{s,t}$ represents the monthly (or daily) return including dividends of a stock s at time t. The same approach is applied to compute the returns of momentum-neutral factors. Note that any characteristic with missing values during a specific period would receive a weight of zero, resulting in a corresponding factor return of zero (Kozak, 2020).

b) Extracting principal components (PCs) from factors

In the next analysis, a five-step procedure proposed by Ehsani and Linnainmaa (2022, p. 1889) is adopted to examine if factor momentum is mainly observed in high- or low-eigenvalue factors. The procedure starts with the implementation of a principal component analysis (PCA) based on the correlation matrix of daily factor returns until month t.

Subsequently, the resulting eigenvectors are utilized to predict the monthly returns of the principal component (PC) factors until month t+1. To ensure comparability, the returns of the PC factors until month t are adjusted by subtracting the mean and scaling by the average of all original KNS factors' variances.

Finally, a time-series factor momentum strategy is implemented to compute the profit in month t+1. This strategy involves taking long positions on factors exhibiting positive average returns from month t-11 to t and going short factors with negative average returns during the same historical period. This "out-of-sample" approach to calculate the return of the strategy in month t+1 helps alleviate any potential look-ahead bias since the estimation of the eigenvectors for the PC factors is not dependent on any data in month t+1 (Ehsani & Linnainmaa, 2022).

3.3 Decomposing Equity Momentum Profits

The objective of the next analysis is to explore the connection between individual stock momentum and factor momentum. This is achieved by decomposing the cross-section of stock returns into four distinct components: (1) *factor autocovariances*, (2) *factor cross-serial covariances*, (3) *variation in mean returns*, and (4) *autocovariances in residuals*. The expected payoff of stock s using a cross-sectional momentum strategy, according to Ehsani and Linnainmaa (2022, p. 1894), can be calculated as follows:

$$E\left[\pi_{s,t}^{mom}\right] = E\left[\left(R_{t-12,t-2}^{s} - \bar{R}_{t-12,t-2}\right)\left(R_{t}^{s} - \bar{R}_{t}\right)\right] \tag{9}$$

where $R_{t-12,t-2}^{s}$ is the return of a stock s in the prior year skipping one month from t-12 to t-2, while R_t^s is the return of a stock s in month t, and $\bar{R}_t$ is the equal-weighted average return across all stocks in the same period.

Assuming that asset returns are governed by a certain factor model (e.g., the Fama and French (2015)'s five-factor model), the excess return of stock s in month t can be computed as:

$$R_{s,t} = \sum_{f=1}^{F} \beta_s^f \, r_t^f + \varepsilon_{s,t} \tag{10}$$

where r_t^f is the return o factor f, β_i^f is stock i's beta coefficient on factor f, and $\varepsilon_{i,t}$ is the stock-specific return component.

By combining the two equations (9) and (10), and as suggested by Ehsani and Linnainmaa (2022), the expected return of the cross-sectional momentum strategy using S stocks can be expressed as follows:

$$\begin{aligned} E[\pi_t^{mom}] = & \underbrace{\sum_{f=1}^{F}\left[cov(r_{\mathrm{t-12,t-2}}^{f}, r_t^f)\sigma_{\beta^f}^2\right]}_{(1)\ factor\ autocovariances} + \underbrace{\sum_{f=1}^{F}\sum_{g\neq f}^{F}\left[cov\left(r_{\mathrm{t-12,t-2}}^{f}, r_t^{g}\right)cov(\beta^f,\beta^g)\right]}_{(2)\ factor\ cross-serial\ covariances} \\ & + \underbrace{\sigma_\eta^2}_{(3)\ variation\ in\ mean\ returns} + \underbrace{\frac{1}{S}\sum_{s=1}^{S} cov\left(\varepsilon_{s,\mathrm{t-12,t-2}}, \varepsilon_{s,t}\right)}_{(4)\ autocovariances\ in\ residuals} \end{aligned} \tag{11}$$

where $cov(.)$ and σ^2 are covariance and variance functions respectively, F is the number of factors, and S is the number of individual stocks.

Based on equation (9), the contribution of portfolio p to the total profits of the cross-sectional momentum strategy can be computed as follows:

$$\pi_{p,t}^{mom} = \left(R_{t-12,t-2}^{p} - \bar{R}_{t-12,t-2}\right)\left(R_t^p - \bar{R}_t\right) \tag{12}$$

where the return of portfolio p in month t R_t^p is the weighted average of stock returns in the same portfolio: $R_t^p = \frac{\sum_{s=1}^{S_{p,t}}(r_{s,t} * me_{s,t-1})}{\sum_{s=1}^{S_{p,t}} me_{s,t-1}}$. Note that $me_{s,t-1}$ is the market value of equity of stock s in month t-1.

Consequently, the four distinct sources of the cross-section of stock returns can be calculated as below:

(1) Factor autocovariances

As shown in equation (11), the calculation of the first term depends on the covariance matrix between the average past returns of factors from month t-12 to t-2 and the corresponding returns of those factors in month t. This autocovariance factor matrix can be defined as:

$\boldsymbol{F_{autocov}} =$

Factor average past returns from month t-12 to t-2	**Factor return month t** 1	2	…	F
1	$cov(r^1_{t-12,t-2}, r^1_t)$	$cov(r^1_{t-12,t-2}, r^2_t)$	$\cdots$	$cov(r^1_{t-12,t-2}, r^F_t)$
2	$cov(r^2_{t-12,t-2}, r^1_t)$	$cov(r^f_{t-12,t-2}, r^f_t)$	$\cdots$	$cov(r^2_{t-12,t-2}, r^F_t)$
$\vdots$	$\vdots$	$\vdots$	$\cdots$	$\vdots$
F	$cov(r^F_{t-12,t-2}, r^1_t)$	$cov(r^F_{t-12,t-2}, r^2_t)$	$\cdots$	$cov(r^F_{t-12,t-2}, r^F_t)$

In addition, given a certain factor structure that governs stock returns, it is necessary to conduct rolling regressions to compute beta coefficients of the factors. As suggested by Ehsani and Linnainmaa (2022), the month-specific beta coefficients for each portfolio are calculated using three months of daily data from month t-2 to t. The covariance matrix of factor betas $\mathbf{B}_{cov}$ is calculated using these monthly estimates of beta coefficients. A typical element of this $\mathbf{B}_{cov}$ matrix is $cov(\beta^f, \beta^g)$, which is the covariance between betas of factors f and g.

Hence, the first component, factor autocovariances, is equivalent to the sum of all *diagonal* elements of the *F x F* matrix, which is the result of the multiplication of the two matrices $\boldsymbol{F_{autocov}}$ and $\mathbf{B}_{cov}$.

(2) Factor cross-serial covariances

Similarly, the factor cross-serial covariances are equivalent to the sum of all *off-diagonal* elements of the *F x F* matrix resulting from the multiplication of the two matrices $\boldsymbol{F_{autocov}}$ and $\mathbf{B}_{cov}$.

(3) Variation in mean returns

While the first two components are influenced by the specific factor structure chosen, the third component, variation in mean returns, is independent of the selected asset pricing model. In fact, this component can be computed as the variance of portfolio-specific returns. The return of each portfolio can be derived by simply taking the mean return across all stocks within the same portfolio.

(4) Autocovariances in residuals

The final component, autocovariances in firm-specific returns, is calculated by subtracting the sum of the remaining three components from the total profits of the strategy (Ehsani & Linnainmaa, 2022).

To determine the standard errors of these components, a block bootstrapping method (i.e., resampling within each portfolio's months) is employed with 1,000 bootstrap samples. Following Ehsani and Linnainmaa (2022), four different factor models are tested. These models include (1) Capital Asset Pricing Model (CAPM), (2) the three-factor model proposed by Fama and French (1993), (3) the Fama and French (2015)'s five-factor model, and (4) a seven-factor model proposed by Ehsani and Linnainmaa (2022) (which is the five-factor model augmented with two more factors, namely BAB (Betting against beta) and QMJ (Quality minus junk) proposed by Frazzini, Kabiller, and Pedersen (2018)).

3.4 Calculating Momentum Profits Using Different Formation and Holding Periods

Furthermore, as part of an additional robustness check, the decomposition of cross-section of stock returns is re-estimated under varying formation and holding periods. On the one hand, the "formation" period can be defined as the number of periods (e.g., months) during which historical data is inspected to construct the signal used for portfolio formation. On the other hand, the holding period refers to the duration (e.g., usually expressed in months) over which the portfolios are held after formation to calculate portfolio returns (e.g., Moskowitz et al., 2012; Wiest, 2023).

Importantly, existing evidence from previous literature has shown that momentum profits largely depend on the choice of these formation and holding periods (e.g., Pan, 2010; Wiest, 2023). For example, Moskowitz and Grinblatt (1999) stated that short formation periods (e.g., less than one month) or excessively long formation horizons (e.g., 24 months and beyond) would lead to suboptimal performance for individual stock momentum strategies. In fact, the most profitable formation periods typically fall within the range of 6 to 12 months. In a similar vein, Chou, Ko, and Yang (2019) showed that the profitability of a momentum strategy based on 25 value-weighted portfolios, sorted by growth and size, diminishes when extending the holding period from 3 months to 12 months.

To address the above concerns, the decomposition of total profits from the cross-sectional momentum strategy utilizing 100 momentum-sorted portfolios, is re-calculated under various formation and holding periods. Particularly, four different formation periods (k = 1, 3, 6, and 12 months) and four different holding period (h = 1, 3, 6, and 12 months) are tested.

Following Jegadeesh and Titman (1993), one month between the formation and holding periods is skipped to avoid the short-term reversal effect (Wiest, 2023). In addition, to avoid the issue of overlapping observations when the holding period (h) exceeds one month, a procedure proposed by Jegadeesh and Titman (1993) is employed. Specifically, for each (k, h), a single time series of monthly returns is derived by averaging the returns of h "actively held" portfolios in the current period (see more details in Moskowitz et al. (2012, p. 234)). This approach ensures that the observations are non-overlapping, resulting in more precise computation of standard errors of the components (Ehsani & Linnainmaa, 2022).

All analyses in this thesis are done using R version 4.2.2 (R Core Team, 2022).

4. Results

4.1 The Impact of Factor Momentum on Factor Returns

a) Factors' future returns conditional on their own past performance

This session aims to address the first sub-research question concerning the profitability of different trading strategies relying on momentum. The initial testing sample includes the data on the 22 factors (i.e., 15 US and 7 global factors) provided by Ehsani and Linnainmaa (2022) as presented in Table 1. Following these authors, a series of regressions is implemented in which each factor's return in the current month is used as the dependent variable, and the independent variable is a dummy indicating the performance of the factor during the last 12 months (i.e., from month t-12 to t-1). Specifically, this dummy indicates whether the factor's average return in the prior year is positive (i.e., 1 if positive, and 0 if negative). Table 6 shows the results of these regressions.

Table 6. Impact of Factor's Past Returns on Own Future Returns

	Intercept			Slope		
Anomaly	$\hat{\alpha}$	t-value ($\hat{\alpha}$)	p-value ($\hat{\alpha}$)	$\hat{\beta}$	t-value ($\hat{\beta}$)	p-value ($\hat{\beta}$)
Pooled	0.023	0.279	0.781	0.473	4.535	0.000
			15 U.S. Factors			
Accruals	0.150	1.184	0.237	0.101	0.650	0.516
Betting against beta	-0.221	-0.632	0.527	1.319	3.534	0.000
Cash flow to price	0.128	0.781	0.435	0.235	1.158	0.247
Investment	0.120	0.974	0.330	0.245	1.546	0.123
Earnings to price	0.101	0.616	0.538	0.302	1.458	0.145
Value	0.038	0.205	0.838	0.410	1.781	0.075
Liquidity	0.157	0.742	0.458	0.356	1.292	0.197
Long-term reversals	-0.253	-1.663	0.097	0.758	3.850	0.000
Net share issues	0.173	1.324	0.186	0.089	0.487	0.627
Quality minus junk	0.087	0.650	0.516	0.435	2.508	0.012
Profitability	0.040	0.222	0.824	0.337	1.674	0.095
Residual variance	-0.464	-1.638	0.102	1.062	2.737	0.006
Size	-0.104	-0.616	0.538	0.583	2.509	0.012
Short-term reversals	0.485	1.427	0.154	0.014	0.039	0.969
Momentum	0.716	2.697	0.007	-0.095	-0.288	0.773
			7 Global Factors			
Betting against beta	0.191	0.578	0.564	0.838	2.304	0.022
Investment	-0.064	-0.408	0.683	0.382	1.944	0.053
Value	0.036	0.151	0.880	0.472	1.770	0.078
Quality minus junk	0.395	1.761	0.079	0.125	0.492	0.623
Profitability	0.138	1.033	0.302	0.257	1.616	0.107
Size	-0.063	-0.389	0.698	0.285	1.326	0.186
Momentum	0.669	1.774	0.077	0.017	0.039	0.969

Notes: Testing data involved 22 factors downloaded from the replication package of Ehsani and Linnainmaa (2022). The observation period starts in July 1964 and ends in December 2019.

Since the model only contains the "positive-return-in-the-past" dummy with an intercept, on the one hand, the intercept can be interpreted as the current average monthly return of a factor following a year with negative performance. On the other hand, the slope can be interpreted as the difference in average returns between up and down prior years. As shown in Table 6, the slopes in all regressions are positive (except for the US momentum factor). Furthermore, the slope estimates of five US factors and one global factor are significant at the 5% level, while four other factors (i.e., two US and two global factors) are marginally significant at the 10% level. Based on the estimates of the intercept, four US factors including betting against beta, long-term reversals, residual variance, and size have negative (but not significant) average monthly returns following a year of underperformance.

To calculate the total effects in a diversified portfolio, the same regression is run using the whole data set in which all 20 nonmomentum factors (i.e., excluding two momentums factors) are pooled by time. The corresponding standard errors are corrected for heteroskedasticity across factors (or "clusters"). The results of the pooled regression show that a prior year of losses would lead to a monthly factor return of 2 bps (p-value = 0.78), while a prior year of gains would lead to a monthly factor return of 49 bps (i.e., 0.02 + 0.47 = 0.49, p-value of the slope < 0.01), indicating that the prior returns are very informative about the future returns of factors and their autocorrelations are mostly positive.

While this analysis is a close replication of Ehsani and Linnainmaa (2022)'s Table II, it is important to note that these authors seem to have mistakenly kept the two momentum factors when running the pooled regression (although they claimed that these two factors were excluded), leading to a small difference between results shown in Table 6 and their Table II.

As a robustness check, this analysis is rerun using only the Fama and French (2015)'s five factors (FF5) with data up to March 2023 for the U.S. market. As shown in Table A.2 in the Appendix, the majority of these factors exhibits strong positive autocorrelations such that a prior year of positive performance (compared to a year of underperformance) would lead to an increase of about 48 bps (from 2 bps) for an average factor, which is in line with the findings of Ehsani and Linnainmaa (2022).

b) The profitability of time-series and cross-sectional factor momentum strategies

While previous research has extensively investigated the differences between time-series and cross-sectional momentum strategies when trading individual assets like stocks (e.g., Moskowitz et al., 2012), it is not clear if one would observe the same relationship between these two momentum strategies when trading factors. In this part, using the same data of 20 factors, the profitability of two trading strategies based on time-series and cross-sectional momentum is analyzed and compared against the equal-weighted portfolio.

A cross-sectional factor momentum strategy can be defined as a trading strategy in which an investor would short factors earning below-median returns relative to the other factors over the previous 12-month period (i.e., losers) and long those with above-median returns (i.e., winners) (e.g., Asness et al., 2013). A time-series momentum strategy, however, is used when an investor longs factors with positive average returns over the past 12 months, and shorts those with negative average returns (e.g., Moskowitz et al., 2012). The equal-weighted portfolio, our benchmark, is used when an investor invests equally across all factors (Ehsani & Linnainmaa, 2022).

Table 7. Profitability of Time-Series and Cross-Sectional Factor Momentum Strategies

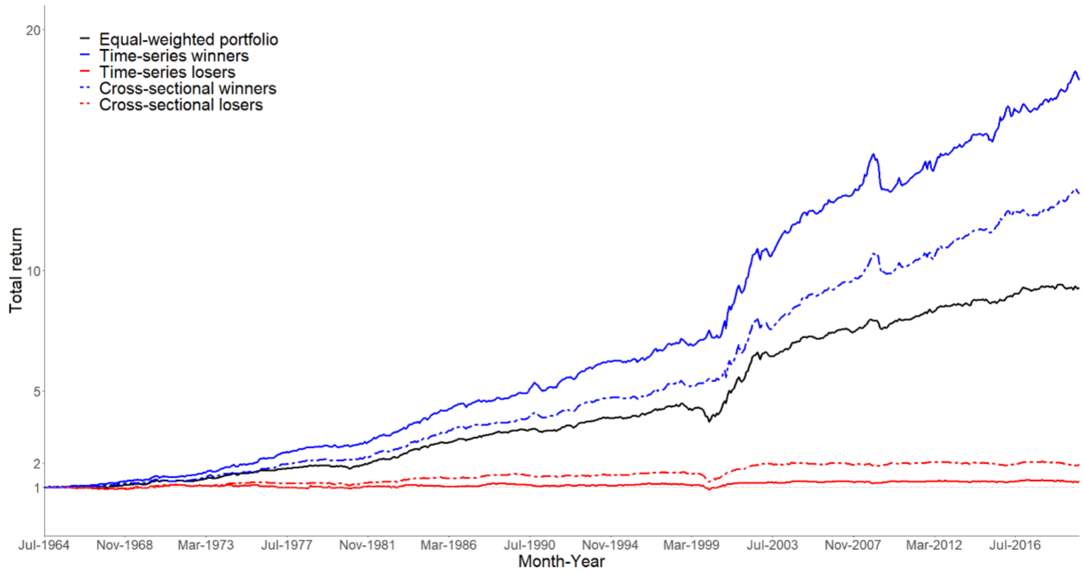
Strategy	Annualized return				
	Mean	**SD**	**SE**	**t-val**	**Sharpe ratio**
Equal-weighted portfolio	4.095 %	3.927 %	0.044	7.768	1.043
Time-series factor momentum	3.921 %	4.165 %	0.047	7.014	0.941
Winners	5.932 %	4.408 %	0.049	10.027	1.346
Losers	0.760 %	6.456 %	0.073	0.864	0.118
Cross-sectional factor momentum	2.399 %	3.555 %	0.040	5.029	0.675
Winners	6.450 %	5.350 %	0.060	8.981	1.206
Losers	1.687 %	5.259 %	0.059	2.390	0.321

Notes: Testing data involved 20 factors (22 factors presented in Table 1 excluding two momentum factors). The observation period starts in July 1964 and ends in December 2019. The two momentum strategies were rebalanced monthly.

As shown in Table 7, the results show that the annualized returns on the average factor for the winner portfolios in both time-series (5.93%, t-value = 10.03) and cross-sectional strategies (6.45%, t-value = 8.98) are considerably higher than that of the equal-weighted one (4.10%, t-value = 7.77), while the loser portfolios in both strategies (0.76% with t-value = 0.86 and 1.69% with t-value = 2.39 respectively) underperform the benchmark.

Because the winner and loser portfolios when using a cross-sectional strategy always have the same number of factors, the mean return of this strategy (2.40%, t-value = 5.03) is closer to the mean of the returns between the two legs. In contrast, the mean return of the time-series factor momentum strategy (3.92%, t-value = 7.01) is closer to that of its winner leg because there seem to be more long factors than short ones in the testing sample.

Figure 1. Cumulative Returns of Momentum Strategies Over Time



<u>Notes</u>: Same data as those used in Table 7. The volatilities of momentum strategies are scaled to be equal to those of the equal-weighted strategy.

As shown in Figure 1, after the volatilities of all strategies are scaled to be equal to that of the equal-weighted strategy, the cumulative returns computed for the time-series winner portfolio are larger than those of all other portfolios at any time, and the winner-loser gap is larger for the time-series strategy compared to that of the cross-sectional one. For example, at the end of the observation period (i.e., December 2019), the total cumulative return of the time-series winner strategy is 17.9%, while the cross-sectional winner strategy only earns 13.2%, followed by the equal-weighted strategy (9.27%) and two loser strategies (both lower than 2%).

Importantly, when the time-series factor momentum cumulative return is regressed on cross-sectional factor momentum cumulative return, the slope is estimated to be around 1.00 (t-value = 42.90) with a positive and significant intercept (0.13, t-value = 5.15). When the regression is reversed, the slope of time-series factor momentum is estimated to be around 0.73 (t-value = 42.90), but the intercept is negative and not significant (-0.04, t-value = -1.84). These results indicate that while time-series factor momentum can fully explain the cross-sectional momentum profits, the reverse is not supported, in line with the findings of Ehsani and Linnainmaa (2022).

One potential question is that would the above results still hold if these strategies are implemented using a more restricted set of factors? To address this concern, the above analysis is rerun using the more updated FF5 data. The results, as shown in Table A.3 in the Appendix, show the same core patterns. Indeed, the winner portfolios in both time-series and cross-sectional strategies (6.3% and 6.1% respectively) outperform the equal-weighted one (4.0%), while the loser portfolios in both strategies (-0.2% and 0.9% respectively) underperform the benchmark. Figure A.1, however, shows that the differences in cumulative returns between the time-series winner and cross-sectional winner portfolios are not as large as when a larger set of factors is used. This seems to suggest that the existence of positive factor autocorrelations is robust, but their magnitude is sensitive to the selected sample of factors. Indeed, a larger set of factors seems to exhibit stronger autocorrelations than a smaller one.

c) Decomposing factor momentum profits

So why does cross-sectional momentum strategy perform worse than the time-series momentum one? Following previous research (e.g., Ehsani & Linnainmaa, 2022; Lewellen, 2002; Lo & MacKinlay, 1990), this question is examined by decomposing the total returns of both time-series and cross-sectional factor momentum strategies into distinct sources of profits (see Section 3.1 for more methodological details).

As shown in Table 8, the total profits of a cross-sectional factor momentum strategy (2.05%, t-value = 3.14) mostly come from the positive autocovariances between factor returns (2.58%, t-value = 2.62). The results suggest that, in the testing sample, a factor's high return in the past typically leads to high returns in the future. Another positive source of cross-sectional factor momentum profits is the cross-sectional variance of mean returns, which is often larger when some factors consistently yield a much higher (or lower) returns than the others.

Table 8. Sources of Factor Momentum Profits

Strategy	Decomposition	Sign	Annualized premium	Standard error
Cross-sectional factor momentum	Autocovariances	+	2.576 %	0.985
	Cross-serial covariances	-	1.005 %	0.517
	Variance of mean returns	+	0.478 %	0.143
	Cross-sectional factor momentum	=	**2.050 %**	**0.652**
Time-series factor momentum	Autocovariances	+	2.670 %	1.050
	Mean squared returns	+	1.757 %	0.394
	Time-series factor momentum	=	**4.428 %**	**1.165**

Notes: Standard errors were computed using the block bootstrapping method with 1,000 bootstrap samples.

The cross-serial covariances between factor returns represent the last source of profits to the total returns of a cross-sectional factor momentum strategy. This last source would contribute positively if one factor's high return in the past would predict other factors' high returns in the future. However, the factor returns in this testing sample typically exhibit positive cross-serial covariances, meaning that a past high factor return would typically signal high returns on other factors. This leads to a negative contribution of cross-serial covariances to the total profits of a cross-sectional factor momentum strategy (i.e., -1.01%, t-value = 1.94).

On the other hand, an investor using a time-series factor momentum strategy only bets on the autocorrelations of factors, which are in this case typically significant and highly positive. Indeed, the autocorrelations between factor returns contribute a total of 2.67% (t-value = 2.54), while the mean-squared returns contribute 1.76% (t-value = 4.46), resulting in a total profit of 4.43% (t-value = 3.80) for the time-series factor momentum strategy. To sum up, the main reason why the cross-sectional strategy is less profitable than the time-series counterpart seems to reside in the positive cross-serial covariances which produce a negative contribution to cross-sectional factor momentum profits.

Similarly, the above analysis is rerun using the FF5 data as a robustness check. Results shown in Table A.4 of the Appendix indicate that both strategies are equally benefited from factor autocovariances (2.17%, t-value = 1.66). However, since the five-factor data also exhibit positive cross-serial covariances, a negative contribution of 0.25% (t-value = 0.69) is added to the cross-section momentum profits, leading to the outperformance of the time-series strategy (3.61%, t-value = 2.81) compared to the cross-sectional one (2.09%, t-value = 1.50). Importantly, the difference between the two strategies seems to be more modest, suggesting that time-series factor momentum is more profitable in a more comprehensive set of factors.

4.2 The Concentration of Factor Momentum in High-Eigenvalue Principal Components

In line with previous research (e.g., Avramov et al., 2017), the previous analysis of this thesis has provided strong evidence that factor momentum exists and is very informative about the future profits of factors. But why and when are factors (positively) autocorrelated? Building upon a model of sentiment investors proposed by Kozak et al. (2018), Ehsani and Linnainmaa (2022) claim that factor momentum emerges when sentiment is highly persistent, and therefore, momentum profits should be more significant among the high-eigenvalue factors. To explore this concentration of factor momentum, the next analysis aims to test whether more factor momentum can be found in the high-eigenvalue factors than in low-eigenvalues.

Following the footsteps of previous studies (e.g., Ehsani & Linnainmaa, 2022; Haddad et al., 2020), a total of 54 factors is reconstructed using the characteristic signals data provided by Kozak (2020) and the universe of CRSP and Compustat ordinary common shares listed on NYSE, AMEX, and Nasdaq from January 1963 to March 2023.

Table 9. Profitability of Factor Momentum Strategy When Trading PC Factors

Sample	Set of PCs				
	1-10	11-20	21-30	31-40	41-47
Full Sample					
$\bar{r}$	0.164	0.104	0.105	0.061	0.110
$SD(\bar{r})$	0.669	0.506	0.495	0.495	0.699
Sharpe ratio	0.245	0.205	0.212	0.122	0.157
$SE(\bar{r})$	0.028	0.021	0.021	0.021	0.030
$t(\bar{r})$	5.781	4.828	5.009	2.890	3.699
First Half					
$\bar{r}$	0.205	0.139	0.178	0.100	0.165
$SD(\bar{r})$	0.530	0.446	0.367	0.437	0.588
Sharpe ratio	0.387	0.311	0.485	0.229	0.281
$SE(\bar{r})$	0.032	0.027	0.022	0.026	0.035
$t(\bar{r})$	6.459	5.200	8.094	3.827	4.695
Second Half					
$\bar{r}$	0.122	0.068	0.032	0.021	0.054
$SD(\bar{r})$	0.782	0.559	0.588	0.544	0.793
Sharpe ratio	0.156	0.122	0.054	0.038	0.068
$SE(\bar{r})$	0.047	0.034	0.035	0.033	0.048
$t(\bar{r})$	2.608	2.036	0.907	0.639	1.130

Notes: PC factors are sorted by their eigenvalues (e.g., 1 = highest, 47 = lowest); The first half of the sample starts from July 1973 up to and including September 1996. The second half spans from October 1996 to the beginning of December 2019; $\bar{r}$ is the average monthly return (see Section 3.2 for more computational details); SD = standard deviation and SE = standard error; SE = SD/sqrt(N) where N is the sample size; Sharpe ratio = $\bar{r}/SD(\bar{r})$; $t(\bar{r}) = \bar{r}/SE(\bar{r})$.

Results from Table 9 show that, when using the full sample, the average month return of the time-series factor momentum strategy yielded by trading the first 10 PC factors with highest eigenvalues ($\bar{r}$ = 0.16, t-value = 5.78) is much higher than when trading other sets of PC factors with lower eigenvalues ($\bar{r}$s < 0.11, t-values > 2.80). The same pattern, that trading the first set of PC factors generates higher average returns (as well as Sharpe ratio), can also be observed when only the first or second half of data is used. These results support the previous claim that factor momentum profits concentrate more in high-eigenvalue factors.

Furthermore, it is less profitable to implement the factor momentum strategy in the second half than in the first half of the data. Indeed, the average monthly returns when trading the same set of PC factors (e.g., PC11-20) are always higher in the first half (e.g., 0.14, t-value = 5.20) than in the second half of the sample (e.g., 0.07, t-value = 2.04). In addition, all the returns are not statistically significant at the 10% level in the second half, except for the first 20 PC factors (whose returns are significant at the 5% level). These results are slightly different from those of Ehsani and Linnainmaa (2022, p. 1890, see their Panel A-Table III), probably due to the used stock data and the way equal values (ties) are ranked in different software (i.e., Stata vs. R). However, the core results remain, suggesting that factor momentum profits indeed concentrate highly in the first few PC factors with top eigenvalues (Arnott et al., 2021).

Table 10. Regressions of High-Eigenvalue on Low-Eigenvalue PC Factors

	Dependent Variable: FMOM $_{PC1-10}$				
Independent Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
$\alpha_{\text{first half}}$	0.078 (2.143)	0.151 (3.990)	0.122 (3.126)	0.180 (4.633)	0.160 (4.164)
$\alpha_{\text{second half}}$	0.086 (2.447)	0.098 (2.626)	0.108 (2.897)	0.124 (3.233)	0.107 (2.836)
FMOM $_{PC11-20}$	0.318 (6.221)	0.473 (9.306)			
FMOM $_{PC21-30}$	0.290 (5.308)		0.474 (8.804)		
FMOM $_{PC31-40}$	0.152 (2.824)			0.375 (6.919)	
FMOM $_{PC41-47}$	0.133 (3.320)				0.309 (7.996)
Fama/French 5 Factors					
mktrf	-0.005 (-0.791)	-0.007 (-1.148)	-0.004 (-0.690)	-0.004 (-0.570)	-0.004 (-0.573)
smb	0.005 (0.600)	0.014 (1.462)	0.011 (1.163)	0.007 (0.702)	0.004 (0.397)
hml	-0.040 (-3.453)	-0.054 (-4.407)	-0.044 (-3.546)	-0.053 (-4.196)	-0.052 (-4.149)
rmw	-0.026 (-2.144)	-0.030 (-2.433)	-0.027 (-2.172)	-0.045 (-3.441)	-0.020 (-1.573)
cma	0.049 (2.686)	0.051 (2.628)	0.063 (3.257)	0.058 (2.905)	0.059 (2.986)
N	557	557	557	557	557
Adj. R^2	28.3 %	18.4 %	17.2 %	13.1 %	15.4 %

Notes: t-values are inside the brackets. Same data as in Table 9. The dependent variable is FMOM$_{PC1-10}$ which is factor momentum profits when trading the first 10 PC factors.

Table 10 and Table 11 present results of regressions when the dependent variable was the returns of the factor momentum strategies when trading the first 10 PC factors (Table 10) or the other sets of PC factors (Table 11). In addition, these regressions include two intercepts (i.e., $\alpha_{\text{first half}}$ and $\alpha_{\text{second half}}$) to capture the incremental returns in the first and second halves of the sample (Ehsani & Linnainmaa, 2022, p. 1892). As shown in both Table 10 and Table 11, the correlations between the momentum strategies when trading different sets of PC factors are all positive and strongly significant (e.g., effect of FMOM$_{PC11-20}$ on FMOM$_{PC1-10}$ in Model 2 of Table 10 is 0.47, t-value = 9.31). Since the PC factors resulted from the PCA analysis are uncorrelated by definition (e.g., Shukla & Trzcinka, 1990), the highly significant correlations between their factor momentum profits seem to indicate that momentum profits co-exist in these factors or, in other words, the profitability of factor momentum occurs at the same time across all PC factors.

Table 11. Regressions of Low-Eigenvalue on High-Eigenvalue PC Factors

	Dependent Variable (Set of PCs)			
Independent Variable	**FMOM $_{PC11-20}$**	**FMOM $_{PC21-30}$**	**FMOM $_{PC31-40}$**	**FMOM $_{PC41-47}$**
$\alpha_{\text{first half}}$	0.071	0.138	0.046	0.101
	(2.384)	(4.849)	(1.532)	(2.477)
$\alpha_{\text{second half}}$	0.026	0.007	-0.017	0.022
	(0.900)	(0.255)	(-0.588)	(0.560)
FMOM $_{PC1-10}$	0.288	0.261	0.214	0.338
	(9.306)	(8.804)	(6.919)	(7.996)
Fama/French 5 Factors				
mktrf	0.006	-0.001	-0.003	-0.004
	(1.138)	(-0.122)	(-0.639)	(-0.521)
smb	-0.005	0.002	0.015	0.027
	(-0.615)	(0.226)	(2.004)	(2.649)
hml	0.005	-0.018	-0.005	-0.006
	(0.489)	(-1.888)	(-0.539)	(-0.439)
rmw	0.002	-0.005	0.035	-0.034
	(0.200)	(-0.569)	(3.614)	(-2.510)
cma	0.011	-0.013	0.005	-0.001
	(0.746)	(-0.907)	(0.344)	(-0.065)
N	557	557	557	557
Adj. R^2	13.5 %	16.9 %	9.4 %	15.4 %

Notes: t-values are inside the brackets. Same data as in Table 9.

As for the estimates of the intercept, the alphas of the first half are typically larger than those of the second half of the sample (i.e., Models 2-5 in Table 10 and Models 1-3 in Table 11). In addition, the majority of the alphas associated with the first half is significant, both in Table 10 and Table 11, indicating that, during the first half of the sample, it is necessary to use more than just 10 first PC factors to subsume all the profits of factor momentum strategies. In contrast, during the second half of the sample, since the estimates of $\alpha_{\text{second half}}$ are all positive and significant in Table 10 but not significant in Table 11, it suggests that factor momentum in the first 10 PC factors fully captures the momentum profits in other PC factors with lower eigenvalues. In conclusion, these results support that factor momentum concentrates mostly in a few factors with highest eigenvalues, as predicted by the Kozak et al. (2018)'s model (e.g., Arnott et al., 2021; Ehsani & Linnainmaa, 2022).

4.3 Relationship Between Factor Momentum and Individual Stock Momentum

If factor momentum is very informative about the factors' future returns, then does factor momentum relate to individual stock returns? If yes, then how large is the contribution of factor momentum to individual stock returns compared to that of individual stock momentum? This section aims to address these two questions through two main analyses. First, the impacts of different sources, including factor momentum, of the cross-section of stock returns are quantified. Second, the relationship between factor and individual stock momentum is explored through pricing momentum-sorted portfolios.

a) Explaining the cross-section of stock returns by factor momentum

In line with prior studies (e.g., Ehsani & Linnainmaa, 2022; Haddad et al., 2020), the decomposition analysis employs a dataset comprising all CRSP and Compustat stocks listed on NYSE, AMEX, and Nasdaq spanning from July 1963 to March 2023, and identified by CRSP as ordinary common shares. As noted by Ehsani and Linnainmaa (2022), implementing a cross-sectional momentum strategy on individual stock returns does not yield profitable results due to the counteracting effect of numerous small and illiquid stocks with negative past returns. To mitigate this issue, as suggested by Ehsani and Linnainmaa (2022), all stocks are sorted based on their average past returns from month t-11 to t-2 and subsequently divided into 100 equal quantiles. Further restrictions on the sample include: 1) excluding all stocks with less than 42 months of historical data, and 2) excluding all observations with missing past returns (i.e., from month t-12 to t-2), missing returns in the current month, and missing market value of equity in the previous month (which is utilized in computing the strategy's weights). Consequently, the final test sample consists of 100 value-weighted portfolios, created from approximately 4,486 individual stocks, spanning from 31st January 1963 to 30th December 2022.

Table 12. Decomposition of Equity Momentum Profits under the FF5* Model

Panel A: Autocovariance matrix of factor returns

Average factor return from month t - 12 to t - 2	Month t return				
	MKTRF	SMB	HML	RML	CMA
MKTRF	0.039	-0.388	0.063	0.012	-0.091
SMB	-0.316	0.191	0.370	0.193	0.155
HML	-0.302	0.023	0.220	0.156	0.181
RMW	-0.103	-0.024	0.019	0.073	0.022
CMA	-0.083	0.098	0.062	0.141	0.101

Panel B: Covariance matrix of factor betas

	MKTRF	SMB	HML	RMW	CMA
MKTRF	0.127				
SMB	0.063	0.274			
HML	0.066	0.068	0.515		
RMW	0.013	0.059	0.145	0.581	
CMA	0.010	0.009	-0.208	0.033	0.674

Panel C: Decomposition estimates

Sign	Component		
+	Factor autocovariances	$\sum_{f=1}^{F}\left[cov(r_{-t}^{f}, r_{t}^{f})\sigma_{\beta f}^{2}\right]$	0.281%
+	Factor cross-serial covariances	$\sum_{f=1}^{F}\sum_{g\neq f}^{F}\left[cov\left(r_{-t}^{f}, r_{t}^{g}\right)cov(\beta^{f}, \beta^{g})\right]$	-0.044%
+	Variance of mean returns	σ_{η}^{2}	0.093%
+	Residual autocovariances	$\frac{1}{N}\sum_{t=1}^{N}\left[cov(\varepsilon_{i,-t}, \varepsilon_{i,t})\right]$	0.312%
=	Total		0.642%

Note: * FF5 model refers to the Fama and French (2015)'s five factors, namely market (MKTRF), size (SMB), value (HML), profitability (RMW), and investment (CMA). The last term (residual autocovariances) is computed as the difference between the total strategy return and the sum of the other three components.

Results from Table 12 show that a cross-sectional momentum strategy gains an average monthly return of 0.64% (t-value = 2.03) under the FF5 model. As shown in equation (11), the momentum profits in the cross-section of stock returns can be decomposed into four distinct parts: (1) *factor autocovariances*, (2) *factor cross-serial covariances*, (3) *variation in mean returns*, and (4) *autocovariances in residuals*. The positive autocorrelations in factor returns, or time-series factor momentum, contribute to the total profits through the first component, and this contribution is scaled by the positive cross-sectional variation in factor betas. In short, factor autocovariances contribute about 44% to the total profits though not significant (0.28%, t-value = 1.38). In fact, previous results in this thesis have shown that factor momentum appears to be weaker in a smaller set of factors. Indeed, as shown in Table 13, when more factors are used (i.e., FF5 + BAB + QMJ), the contribution of time-series factor momentum considerably increases to 0.68% (t-value = 1.99).

Table 13. Decomposition of Equity Momentum Profits Across Four Asset Pricing Models

	Asset pricing model			
Component	**CAPM**	**FF3**	**FF5**	**FF5 + BAB + QMJ**
Factor autocovariances	0.005	0.142	0.281	0.676
	[0.043]	[0.097]	[0.203]	[0.34]
Factor cross-serial covariances		-0.039	-0.044	-0.143
		[0.031]	[0.057]	[0.116]
Variance of mean returns	0.093	0.093	0.093	0.093
	[0.042]	[0.042]	[0.042]	[0.042]
Residual autocovariances	0.544	0.446	0.312	0.016
	[0.267]	[0.237]	[0.241]	[0.269]
Total	0.642	0.642	0.642	0.642
	[0.316]	[0.316]	[0.316]	[0.316]

Notes: Standard errors are inside the square brackets. They are calculated using a block bootstrapping method with 1,000 bootstrap samples.

As for the second component, factor cross-serial covariances, its contribution becomes positive when the cross-serial covariances in factor returns and the covariances between factor betas share the same signs (Ehsani & Linnainmaa, 2022). However, this is not always the case in this context. Specifically, Panel A of Table 12 shows that while the off-diagonal elements of the factor autocovariance matrix are mostly positive for the four factors: size (SMB), value (HML), profitability (RMW), and investment (CMA), the market factor (MKTRF) exhibits negative cross-serial covariances with most of other factors. In contrast, panel B in the same table shows that the pairwise covariances between the factor loadings (betas) are mostly positive, except for one covariance between betas of CMA and HML factors (-0.21). This component subsequently makes a negative contribution to the total profit (-0.04, t-value = -0.77) under the FF5 model, and this negative impact is reinforced when more factors (e.g., FF5 + BAB + QMJ) are included (e.g., -0.14, t-value = -1.23).

The third component of this decomposition, variation in mean returns, contributes a fixed proportion of 14% of the total profit (t-value = 2.21) irrespective of the selected factor structure, which is in line with previous literature (Conrad & Kaul, 1998).

Finally, the autocovariances in residuals contribute 0.31% (t-value = 1.29) to the total profits when using FF5 model and this contribution decreases to 0.02% (t-value = 0.06) when more factors are used (i.e., FF5 + BAB + QMJ). These results suggest that omitting relevant factors from the underlying asset pricing model would lead to unprecise estimation of factor loadings and their covariances, which in turn leads to underestimation of factor momentum (and of course overestimation of "residual" momentum). In other words, as the transmission of factor momentum to the cross section of stock returns depends on the covariances of stocks' factor betas, it is important to correctly specify the underlying asset pricing model (Ehsani & Linnainmaa, 2022).

b) Factor autocovariances and cross-serial covariances with different formation and holding periods

The previous analysis (part a) has adopted the established convention in the previous literature (e.g., Moskowitz et al., 2012) to form a cross-sectional stock momentum strategy trading using a formation period of 12 months (i.e., k = 12) with a one-month holding period (i.e., h = 1) skipping a month (i.e., month t-12 to month t-2). This section aims to extend the previous part by employing various time horizons to explore the sensitivity of the performance of this strategy as well as its components under the seven-factor asset pricing model (i.e., FF5 + BAB + QMJ). Specifically, four different formation periods ranging from 1 to 12 months and four holding periods ranging from 1 to 12 months are considered. The outcomes of this analysis are presented in Table 14.

Panel C of Table 14 shows that a cross-sectional stock momentum strategy employing a three-month formation and holding periods yields an average monthly return of 88 bps (t-value = 1.81). This is the most profitable strategy among all. In addition, this strategy typically achieves its highest level of profitability when being held for a duration of 3 months. In contrast, when employing a one-month holding period, this strategy tends to earn relatively smaller and statistically insignificant total profits, except in the case where the 12-month formation period is used.

Table 14. Decomposition of Equity Momentum Profits: Alternative Formation and Holding Periods

Panel A: Factor autocovariances

Holding period	Formation period				Formation period			
	1	3	6	12	1	3	6	12
	Average returns				**SD**			
1	0.529	0.415	0.614	0.676	0.916	0.757	0.476	0.340
3	0.601	0.589	0.652	0.572	0.616	0.542	0.407	0.301
6	0.681	0.636	0.591	0.457	0.431	0.399	0.344	0.283
12	0.561	0.516	0.431	0.184	0.318	0.299	0.279	0.251

Panel B: Factor cross-serial covariances

Holding period	Formation period 1	3	6	12	Formation period 1	3	6	12
	Average returns				**SD**			
1	0.043	0.041	-0.084	-0.143	0.341	0.259	0.169	0.116
3	-0.023	-0.039	-0.131	-0.122	0.217	0.189	0.141	0.108
6	-0.127	-0.131	-0.134	-0.098	0.149	0.136	0.119	0.101
12	-0.113	-0.104	-0.090	-0.027	0.117	0.107	0.098	0.091

Panel C: Total profits

Holding period	Formation period 1	3	6	12	Formation period 1	3	6	12
	Average returns				**SD**			
1	0.249	0.303	0.604	0.642	0.788	0.534	0.469	0.316
3	0.747	0.867	0.699	0.613	0.503	0.478	0.405	0.275
6	0.592	0.499	0.624	0.535	0.429	0.382	0.332	0.258
12	0.612	0.624	0.494	0.275	0.285	0.271	0.259	0.210

Notes: This table reports annualized average returns and standard deviations for factor autocovariances and factor cross-serial covariances when using the seven-factor model (i.e., FF5 + BAB + QMJ). The standard errors were corrected using the Jegadeesh and Titman (1993)'s approach for overlapping returns when the holding period is longer than one month. Standard deviations were computed using the block bootstrapping method with 1,000 bootstrap samples

Panels A and B of Table 14 provide an estimation of factor autocovariances and factor cross-serial covariances with varying time horizons. Specifically, factor autocovariances are highest when a one-month holding period and a twelve-month formation period are used (68 bps, t-value = 1.99). When the formation period is less than 12 months combined with a one-month holding period, factor autocovariances consistently contribute minimal and statistically insignificant values. For relatively longer formation periods (e.g., 6-12 months), factor autocovariances tend to diminish when the holding period increases.

In contrast, factor cross-serial covariances are typically negative across all studied time horizons, except for two positive and insignificant contributions observed when a one-month holding period is used. Interestingly, the negative contribution of factor cross-serial covariances is most pronounced when the formation period is 12 months combined with a one-month holding period (-14 bps, t-value = -1.23). Nevertheless, none of the factor cross-serial covariances in Panel B show statistically significant values at both 5% and 10% levels.

c) Pricing portfolios using individual stock and factor momentum

The up-minus-down (UMD) factor (i.e., return on high momentum stocks minus the return on low momentum stocks) presented in the Carhart (1997)'s four-factor model is often considered as the most popular way to capture individual stock momentum (Eberhart, Maxwell, &

Siddique, 2004; Moskowitz et al., 2012). Hence, to investigate the contribution of individual stock momentum, this section follows previous studies (e.g., Arnott et al., 2021) to conduct a series of regressions in which a six-factor model (i.e., Fama and French (2015)'s five factors augmented with the Carhart (1997)'s UMD factor) is used to explain monthly excess returns of 10 momentum-sorted portfolios. Similar models are built but the UMD factor is replaced by factor momentum, which can be constructed from either the off-the-shelf 20 nonmomentum factors downloaded from Ehsani and Linnainmaa (2022) (see Table 6), or the first 10 PC factors derived in section 4.2). Note that the benchmark is the regressions in which the independent variables only include the intercept and the Fama and French (2015)'s five factors.

As show in Table 15, in the models without any momentum factor (i.e., FF5 only), the alphas for the loser (-0.78, t-value = -4.16) and the winner portfolios (0.58, t-value = 4.92) are significantly different (1.356, t-value = 5.03). In addition, the average absolute monthly alpha across all ten portfolios is rather large (0.26) and the GRS test proposed by Gibbons et al. (1989) shows that the alphas across all deciles are significantly different from zero (F-value = 4.42, p-value < 0.01).

When FF5 is augmented with the UMD factor, the model explains momentum profits in stock returns better. Indeed, the alphas for the loser (-0.11, t-value = -1.01) and the winner portfolios (0.17, t-value = 2.36) are closer but still significantly different (0.28, t-value = 2.53). The average absolute alpha is reduced to 0.12 but the GRS test is still significant (F-value = 3.25, p-value < 0.01).

The two models in which FF5 is augmented with factor momentum (i.e., $FMOM_{ind.}$, and $FMOM_{PC1-10}$) outperform the previous two models. Specifically, for the model using factor momentum constructed from the 20 off-the-shelf factors (i.e., FF5 + $FMOM_{ind}$), the alphas for the loser (-0.07, t-value = -0.43) and the winner portfolios (0.18, t-value = 1.74) are no longer significantly different (0.24, t-value = 1.17). The average absolute alpha is reduced to 0.11 though the GRS test is still significant (F-value = 2.50, p-value < 0.01). Similarly, for the model with factor momentum created from the first 10 PC factors (i.e., FF5 + $FMOM_{PC1-10}$), the alphas for the loser (-0.20, t-value = -0.98) and the winner portfolios (0.11, t-value = 0.89) are also not significantly different (0.30, t-value = -0.20). Furthermore, the average absolute monthly alpha is reduced further to 0.10 and, importantly, the GRS test is no longer significant (F-value = 1.71, t-value > 0.05), meaning that the null hypothesis that the alphas across all ten deciles are zero cannot be rejected. The results seem to suggest that individual stock momentum seems to be subsumed by factor momentum, especially when using the highest-eigenvalue factors.

Table 15. Pricing Momentum-Sorted Portfolios with UMD and Factor Momentum

	Asset Pricing Model						
	FF5	FF5 + UMD		FF5 + $FMOM_{ind.}$		FF5 + $FMOM_{PC1-10}$	
Decile	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{b}_{umd}$	$\hat{\alpha}$	$\hat{b}_{fmom}$	$\hat{\alpha}$	$\hat{b}_{fmom}$
Losers	-0.776	-0.110	-0.934	-0.065	-2.468	-0.197	-0.031
	(-4.155)	(-1.009)	(-36.460)	(-0.430)	(-20.052)	(-0.978)	(-10.889)
2	-0.345	0.152	-0.696	0.170	-1.786	0.091	-0.023
	(-2.653)	(2.381)	(-46.586)	(1.648)	(-21.376)	(0.675)	(-12.035)
3	-0.221	0.163	-0.539	0.152	-1.296	0.136	-0.020
	(-2.083)	(2.720)	(-38.266)	(1.694)	(-17.754)	(1.270)	(-13.259)
4	-0.149	0.085	-0.328	0.123	-0.944	0.130	-0.013
	(-1.842)	(1.388)	(-22.797)	(1.771)	(-16.690)	(1.519)	(-10.453)
5	-0.155	-0.033	-0.172	-0.021	-0.466	0.022	-0.008
	(-2.364)	(-0.544)	(-12.154)	(-0.327)	(-9.004)	(0.304)	(-8.322)
6	-0.117	-0.080	-0.051	-0.051	-0.226	-0.038	-0.004
	(-1.876)	(-1.280)	(-3.498)	(-0.816)	(-4.414)	(-0.537)	(-4.083)
7	-0.116	-0.167	0.071	-0.146	0.104	-0.127	0.001
	(-1.908)	(-2.753)	(5.010)	(-2.337)	(2.042)	(-1.800)	(1.097)
8	0.042	-0.119	0.226	-0.087	0.450	-0.097	0.007
	(0.642)	(-2.142)	(17.365)	(-1.358)	(8.618)	(-1.348)	(6.992)
9	0.090	-0.142	0.326	-0.101	0.664	-0.098	0.008
	(1.156)	(-2.452)	(23.964)	(-1.366)	(11.065)	(-1.138)	(6.613)
Winners	0.580	0.174	0.569	0.176	1.401	0.106	0.020
	(4.915)	(2.364)	(32.994)	(1.741)	(17.064)	(0.891)	(11.864)
Winners	1.356	0.284	1.503	0.241	3.869	0.303	0.051
- Losers	(5.029)	(2.526)	(56.970)	(1.169)	(23.083)	-0.197	-0.031
N	666	666		666		557	
Avg.	0.259	0.123		0.109		0.104	
GRS F-value	4.421	3.251		2.502		1.705	
GRS p-value	0.000 %	0.041 %		0.595 %		7.630 %	

Notes: Dependent variables were monthly excess returns of each of 10 portfolios sorted by average returns of the past 11 months from t-12 to t-2. The first decile was the losers' portfolio, while the tenth decile was the winners' portfolio. The last regression used the difference between the winners and losers' returns as the dependent variable. Table only reports alphas (i.e., intercept) and coefficient estimates of momentum factors (i.e., UMD, $FMOM_{ind.}$, and $FMOM_{PC1-10}$). $FMOM_{ind}$ is factor momentum constructed from 20 factors presented in Table 6, while $FMOM_{PC1}$-10 is factor momentum constructed from the first 10 PC factors derived in Section 4.2. Note that factor momentum strategy is to go long (short) factors with positive (negative) returns in the prior year.

A further analysis in which the Carhart (1997)'s UMD factor is regressed on the Fama and French (2015)'s five factors and/or factor momentum created by different sets of PC factors shows that the five-factor model cannot fully explain the UMD's profits since the intercept of this model is still positive and strongly significant (alpha = 0.65, t-value = 3.50) (see Table 16). However, when factor momentum constructed from the 10 highest-eigenvalue PC factors is included, the intercept is reduced to nonsignificant (alpha = 0.06, t-value = 0.37). In other words, factor momentum found in a few highest-eigenvalue PC factors seems to be able to fully capture the UMD form of stock momentum. Factor momentum found in lower-eigenvalue PC factors, however, cannot explain the UMD's profits to the same extent since alphas are all positive and significant, except for the alpha of the model with factor momentum from PC factors 21 to 30 that is also reduced to insignificant: alpha = 0.27 (t-value = 1.52) (see Table 16).

Table 16. Explaining UMD by Factor Momentum from PC Factors

Subset of PCs	Alpha $\hat{\alpha}$	$t(\hat{\alpha})$	Factor Momentum $\hat{b}_{fmom}$	$t(\hat{b}_{fmom})$	FF5	R^2
None	0.649	3.498			Y	10.8 %
1-10	0.059	0.366	0.035	15.081	Y	36.9 %
11-20	0.416	2.302	0.024	7.138	Y	18.4 %
21-30	0.268	1.520	0.033	9.692	Y	23.8 %
31-40	0.515	2.907	0.026	7.711	Y	19.5 %
41-47	0.365	2.108	0.024	9.932	Y	24.4 %

Notes: Table only reports estimates of intercept and coefficient associated with factor momentum. Same data as in Table 15.

4.4 Relationship between momentum and other factors

a) Correlations between individual stock momentum and other factors

Individual stock momentum (e.g., Carhart (1997)'s UMD factor) has long seen as an additional factor in asset pricing models (e.g., Fama & French, 2018). One useful feature of the UMD factor is that, while it is informative about future stock returns (see significant coefficients of UMD in Table 15), it also exhibits very low correlations with other factors (Ehsani & Linnainmaa, 2022). For example, Table 16 shows that the Fama and French (2015)'s five-factor model alone only explains 9.5% of the UMD's total variance, leaving the remaining 90.5% of the variation to the "unknown" factor(s). However, Ehsani and Linnainmaa (2022) pointed out that the interconnection between these factors might not be as simple as it seems. The authors explained that these correlations should be conceptually stronger when being conditional upon the past performance of the factor returns. For example, when a certain factor, such as value (HML), has a positive performance during the last 12 months, UMD will go long all stocks with high book-to-market value ratios (i.e., "value" stocks), and go short all stocks with low book-to-market value ratios (i.e., "growth" stocks), leading to a positive correlation between UMD and HML in the holding month(s). In contrast, when HML has a poor performance, UMD would go short value stocks and long growth stocks, leading to a negative correlation between these factors. In short, the above examples suggest that when disregarding the past performance of the factor returns, the positive and negative correlations between UMD and other factors might cancel out each other over time, leading to trivial "unconditional" correlations.

Table 17. Unconditional and Conditional Correlation between UMD and Factor Returns

	Unconditional Correlations	Conditional Correlations			Test 1 $H_o: \hat{\rho}^+ = \hat{\rho}^-$		Test 2 $H_o: \hat{\rho} = \hat{\rho}_{mom}$	
Factor	$\hat{\boldsymbol{\rho}}$	$\hat{\boldsymbol{\rho}}^+$	$\hat{\boldsymbol{\rho}}^-$	$\hat{\boldsymbol{\rho}}_{mom}$	**z-Value**	**p-Value**	**z-Value**	**p-Value**
Pooled	0.042	0.451	-0.510	0.646	13.213	0.000	18.927	0.000
U.S. Factors								
Accruals	0.126	0.295	-0.146	0.281	2.946	0.003	5.443	0.000
Betting against beta	0.182	0.406	-0.215	0.374	3.805	0.000	6.688	0.000
Cash flow to price	-0.130	0.232	-0.586	0.403	10.165	0.000	11.339	0.000
Investment	-0.025	0.185	-0.368	0.329	6.675	0.000	7.100	0.000
Earnings to price	-0.172	0.198	-0.616	0.445	11.864	0.000	11.504	0.000
Value	-0.197	0.170	-0.581	0.445	12.347	0.000	10.438	0.000
Liquidity	-0.031	0.035	-0.146	0.065	1.678	0.093	2.161	0.031
Long-term reversals	-0.088	0.101	-0.427	0.279	6.824	0.000	6.977	0.000
Net share issues	0.108	0.355	-0.422	0.412	6.000	0.000	10.443	0.000
Quality minus junk	0.278	0.460	-0.410	0.549	6.045	0.000	11.051	0.000
Profitability	0.109	0.457	-0.411	0.442	6.639	0.000	11.256	0.000
Residual variance	0.214	0.672	-0.555	0.662	10.542	0.000	18.375	0.000
Size	-0.035	0.155	-0.389	0.308	6.432	0.000	7.160	0.000
Short-term reversals	-0.298	-0.382	-0.196	-0.092	3.923	0.000	-2.193	0.028
Global Factors								
Betting against beta	0.220	0.239	0.151	0.161	-0.848	0.396	0.729	0.466
Investment	0.058	0.402	-0.436	0.483	6.106	0.000	8.065	0.000
Value	-0.155	0.149	-0.478	0.378	7.215	0.000	5.820	0.000
Quality minus junk	0.417	0.477	-0.182	0.520	1.761	0.078	4.922	0.000
Profitability	0.274	0.325	-0.020	0.294	0.280	0.780	2.601	0.009
Size	0.069	0.089	0.048	0.085	0.201	0.841	0.370	0.712

Notes: This table reports (un)conditional correlations between the Carhart (1997)'s UMD factor and returns of the 20 individual factors presented in Table 6; $\hat{\boldsymbol{\rho}}$ is unconditional correlation between factor return and UMD, $\hat{\boldsymbol{\rho}}^+$ (or $\hat{\boldsymbol{\rho}}^-$) is the same as $\hat{\boldsymbol{\rho}}$ but conditional upon the prior-one-year return of the factor being positive (or negative), and $\hat{\boldsymbol{\rho}}_{mom}$ is the correlation between time-series factor momentum and UMD. The correlations were transformed using the Fisher (1915)'s z-transformation method before being tested for their equality with z-tests. Specifically: $z = \left(atanh(\hat{\rho}^+) - atanh(\hat{\rho}^-)\right) / \sqrt{\frac{1}{N^+-3} + \frac{1}{N^--3}}$; where N^+ (N^-) is the number of observations used to estimate $\hat{\rho}^+$ ($\hat{\rho}^-$) and $atanh(x) = \frac{1}{2} ln\left(\frac{1+x}{1-x}\right)$.

Specifically, Table 17 shows that the unconditional correlations between UMD and the 20 factors were rather small. However, when we only consider the current monthly factor returns with a prior year of good performance (or bad performance), the corresponding conditional correlations $\hat{\rho}^+$ (or $\hat{\rho}^-$) are considerably more pronounced. For example, in the testing period between July 1963 and March 2023, while the unconditional correlation between UMD and value (HML) is only -0.20, its conditional correlation upon a positive (negative) prior year is

0.17 (-0.58) which is considerably higher (lower). In addition, the difference between these two conditional correlations is also strongly significantly different from 0 (z-value$_{test1}$ = 12.35, p-value$_{test1}$ < 0.01). In a similar vein, when HML's returns are conditional upon its time-series momentum, its correlation with UMD becomes significantly more positive ($\hat{\rho}_{mom}$ = 0.45, z-value$_{test2}$ = 10.44, p-value$_{test2}$ < 0.01). In fact, the correlations conditional upon positive one-prior-year factor returns are mostly positive (except for the short-term reversals factor which has very little connection to past returns by definition (see Ehsani & Linnainmaa, 2022, p. 1908, footnote 25). In contrast, correlations between UMD and other factors conditional upon negative one-prior-year factor returns are all negative. Importantly, the differences between these conditional correlations are all significantly different at the 5% level (except for liquidity factor with a marginally significant difference at the 10% level).

Same results are obtained when only seven factors (FF5 + BAB + QMJ) are used (see Table A.5), indicating the robustness of the findings. In short, these results suggest that momentum and other risk factors are correlated, but these correlations change over time.

b) Factor momentum is *not* incidental to individual stock momentum

Given that a factor can be considered as a portfolio which is a combination of stocks in a certain way, then one might naturally expect that individual stock momentum might lead to momentum in factor returns. If this is true, then factor returns after excluding any impact of individual stock momentum will not benefit anymore from factor momentum. Then the challenge is how to exclude this incidental momentum caused by individual stock momentum from factor returns. As show in section 3.2, Ehsani and Linnainmaa (2022) proposed a procedure to adjust the factor weights as little as possible so that they are no longer dependent on stock-level momentum (or past returns of individual stocks). For example, as for the size (SMB) factor, the weights used to construct small-cap versus large-cap stock portfolios would not depend on their past returns, meaning that the performance of the small-cap stocks in the past is not different from that of the large-cap ones. The factors created using these "momentum-neutral" weights were referred to as "momentum-neutral" factors (Ehsani & Linnainmaa, 2022). In this section, PCA is run using either the original factors or momentum-neutral factors. Based on its results, the 10 highest-eigenvalue PC factors constructed from either the standard factors or momentum-neutral factors are traded using a factor momentum strategy. The momentum profits in trading the 10 highest-eigenvalue PC factors extracted from original vs. momentum-neutral factors are subsequently used as the dependent variable in a regression model in which the independent variables include the Fama and French (2015)'s five factors and the other factor momentum (that was not used as the dependent variable).

Table 18. Explaining Factor Momentum in Momentum-Neutral Factors

	Dependent Variable			
	Momentum in Original Factors		Momentum in Momentum-Neutral Factors	
Independent Variable	(1)	(2)	(3)	(4)
Alpha	0.163 (5.519)	0.032 (1.316)	0.143 (7.128)	0.074 (4.587)
Momentum in original factors				0.422 (18.690)
Momentum in momentum-neutral factors		0.920 (18.690)		
FF5 factors	Y	Y	Y	Y
N	557	557	557	557
R^2	2.60 %	40.40 %	0.10 %	38.90 %
Annualized Information ratio	0.810	0.193	1.046	0.673

Notes: The original factors in this table include 47 factors created based on KNS characteristic data (i.e., 54 factors presented in Table A.1 excluding 7 momentum-related factors). The momentum-neutral factors are created from these 47 original factors but do not include incidental momentum caused by individual stock momentum (see section 3.2 for more methodological details). Annualized information ratio is computed as the ratio between annualized mean return and its annualized standard deviation.

As shown in Table 18, when only controlling for the FF5 model, the momentum profit when trading the first 10 PCs extracted from the original factors is positive and significant (alpha = 0.16, t-value = 5.52) with an annualized information ratio of 0.81. In a similar model, the alpha obtained when trading the first 10 PCs extracted from the momentum-neutral factors is also positive and significant (alpha = 0.14, t-value = 7.13), but the momentum profit is higher since it gains an annualized information ratio of 1.05 (> 0.81). Importantly, the correlation between factor momentums in both original and momentum-neutral factors is consistently positive and significant across all models, only factor momentum in momentum-neutral factors can fully explain that in original factors. Indeed, Table 18 shows that when controlling for both the five-factor model and factor momentum in original factors, the momentum profit in momentum-neutral factors is still positive and strongly significant (alpha = 0.07, t-value = 4.59). In contrast, when controlling for both the five-factor model and factor momentum in momentum-neutral factors, the momentum profit in original factors is reduced to nonsignificant (alpha = 0.03, t-value = 1.32). These results suggest that momentum profits of a factor momentum strategy are not merely a consequence of individual stock momentum, in support of the findings by Ehsani and Linnainmaa (2022).

4.5 Factor Momentum in the Norwegian Stock Market

While existing evidence in previous studies (e.g., Fama & French, 2012) supports that strong momentum returns exist in the majority of developed markets around the world (i.e., North America, Europe, and Asia Pacific), these authors also suggest that the global models poorly performed to explain regional portfolio returns. It is therefore interesting and important to examine whether the above findings relating to factor momentum would hold in the Norwegian stock market. This part proceeds as follows. First, an initial analysis is run to analyze the profitability of time-series factor momentum strategy on factor returns using Fama and French (1993)'s three factors in the Norwegian stock market between July 1981 and March 2023. Second, a decomposition analysis is conducted using Norwegian stock-level data to quantify the transmission of factor momentum into the cross section of stock returns. Finally, a regression analysis is run to investigate whether factor momentum can price momentum-sorted portfolios in the Norwegian stock market better than the Fama and French (1993)'s three-factor model and the three-factor model augmented with the Carhart (1997)'s UMD factor. All the methodologies used in this part are the same as those used in the above part.

a) The impact of factor momentum on factor returns – Norwegian market

Results of the regressions in Table 19 show that, in the Norwegian stock market, the prior-one-year performance only has a significantly effect on future returns for the value (SMB) factor (β = 1.24, t-value = 2.29) or for the basket of factors (pooled: β = 0.96, t-value = 2.49). Past returns, however, are not significantly predictive of future performance of factors market (MKTRF), size (SMB), and momentum (UMD) (βs < 0.71, t-values < 0.75).

Table 19. Impact of Factor's Past Returns on Own Future Returns – Norwegian Data

	Intercept			Slope		
Anomaly	$\hat{\alpha}$	**t-value($\hat{\alpha}$)**	**p-value($\hat{\alpha}$)**	$\hat{\beta}$	**t-value($\hat{\beta}$)**	**p-value($\hat{\beta}$)**
			Norway Fama/French 3 Factors			
Pooled	**0.085**	**0.249**	**0.803**	**0.957**	**2.493**	**0.013**
Value	-0.360	-0.836	0.404	1.239	2.292	0.022
Market factors	0.225	0.256	0.798	0.706	0.746	0.457
Size	0.969	1.660	0.098	0.239	0.378	0.705
Momentum	0.894	1.797	0.073	0.421	0.698	0.486

<u>**Notes**</u>: Data include Fama and French (1993)'s three factors for the Norwegian stock market between July 1981 and March 2023.

These results are very similar to those of global factors shown in Table 6. On average, it is found that factor returns are also positively autocorrelated in Norway, but this autocorrelation mostly occurs for the value factor. As for an average factor, a prior year of good performance might lead to an average monthly return of 96 bps compared to the average monthly return of 8.5 bps following a prior year of underperformance.

In addition, results in Table 20 show that the time-series factor momentum strategy trading factors clearly outperforms the cross-sectional factor momentum strategy in Norway. Indeed, while the equal-weighted portfolio earns an average of 8.86% in terms of annualized profit (t-value = 4.81), the annualized returns on the average factor for the winner portfolios in both time-series (13.42%, t-value = 5.96) and cross-sectional strategies (11.16%, t-value = 4.43) are considerably higher than this benchmark. Like in the US market, the loser portfolios in both time-series (2.06%, t-value = 0.49) and cross-sectional factor momentum strategies (4.88%, t-value = 1.54) underperform the no-strategy portfolio.

Table 20. Profitability of Time-Series and Cross-Sectional Factor Momentum Strategies – Norwegian Data

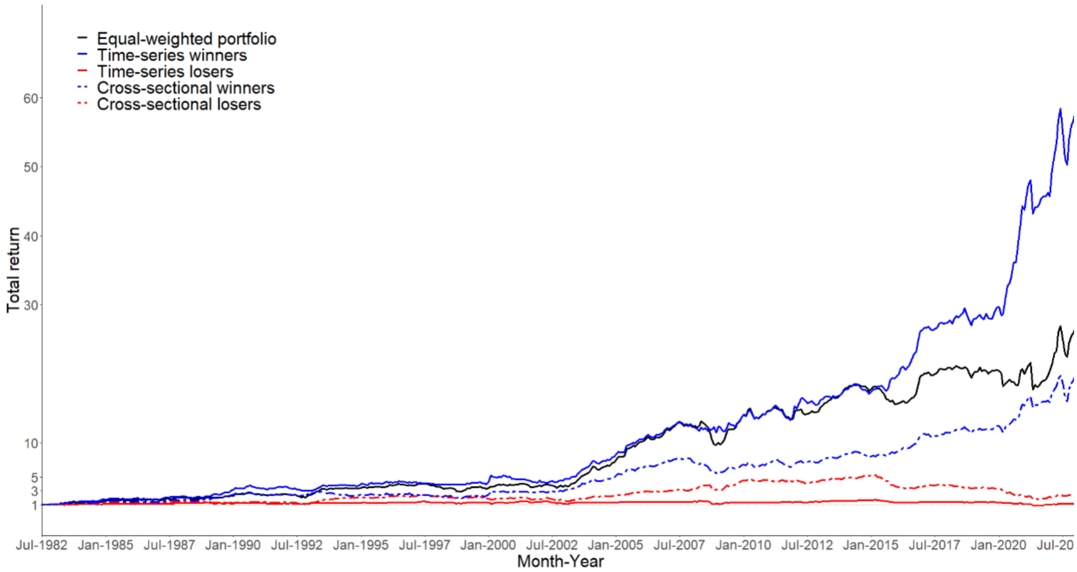
Strategy	Annualized return				
	Mean	SD	SE	t-val	Sharpe ratio
Equal-weighted portfolio	8.859 %	11.753 %	0.153	4.812	0.754
Time-series factor momentum	7.724 %	12.501 %	0.163	3.940	0.618
Winners	13.415 %	14.059 %	0.188	5.959	0.954
Losers	2.062 %	20.712 %	0.349	0.492	0.100
Cross-sectional factor momentum	4.528 %	12.584 %	0.164	2.295	0.360
Winners	11.159 %	16.085 %	0.210	4.429	0.694
Losers	4.879 %	20.170 %	0.264	1.543	0.242

Notes: Same data as in Table 19.

Finally, Figure 2 shows that the cumulative scaled returns for the time-series winner portfolio are very close to the equal-weighted portfolio from the start of our observation period (July 1981) until the beginning of 2015, but after that, these time-series winners become increasingly profitable compared to the benchmark until now. The equal-weighted portfolio consistently performs better than both loser portfolios, and surprisingly, the cross-sectional winner portfolio. These results suggest that while the cross-sectional factor momentum winner portfolio might be more profitable than the equal-weighted strategy, it is too volatile.

A similar decomposing analysis is also run to understand more about the different sources of profits of these strategies in the Norwegian market. As shown in Table 21, factor autocorrelations contribute a significant proportion to the total profits of both strategies: 98% in the cross-section factor momentum strategy (annualized premium: 8.53, t-value = 1.76) and 51% in the time-series factor momentum strategy (annualized premium: 8.68, t-value = 2.02), which is in line with the US results. Similarly, the factor returns in Norway also exhibit positive cross-serial covariances, leading to a negative contribution of 1.81% (t-value = 0.54) to the total profit of the cross-sectional momentum strategy.

Figure 2. Cumulative Returns of Momentum Strategies Over Time – Norwegian Data



The above results are in line with what is found in the US market, such that the time-series factor momentum strategy is more profitable than the cross-sectional strategy because it simply bets on the autocorrelations between factor returns and does not depend on their cross-serial covariances.

Table 21. Decomposition of Factor Momentum Profits – Norwegian Data

Strategy	Decomposition	Sign	Annualized premium	Standard error
Cross-sectional factor momentum	Autocovariances	+	8.529 %	4.854
	Cross-serial covariances	-	1.807 %	3.374
	Variance of mean returns	+	1.939 %	1.906
	Cross-sectional factor momentum	=	**8.661 %**	**5.434**
Time-series factor momentum	Autocovariances	+	8.681 %	4.293
	Mean squared returns	+	8.321 %	2.854
	Time-series factor momentum	=	**17.003 %**	**4.939**

Notes: Standard errors were computed using the bootstrapping method with 1,000 bootstrap samples.

b) Factor momentum and individual stock momentum – Norwegian market

As shown in the panel A of Table 22, the factor autocovariances (i.e., the diagonal elements) are positive for both the market (MKTRF) and value (HML) factors, but negative for the size (SMB) factor, meaning that high past returns on SMB predict lower returns of its own future performance. Many negative off-diagonal elements (i.e., factor cross-serial covariances) are also associated with SMB. On the one hand, high past returns on SMB predict lower returns on

HML. On the other hand, high past returns on MKTRF and HML predict lower returns on SMB. Other cross-serial covariances in factor returns are positive, for example, low past returns on HML predict lower returns on MKTRF and vice versa. Panel B in Table 22, however, shows that all pairwise covariances between the factor betas are positive, meaning that, for example, stocks with high size beta will also have higher market and HML betas.

Table 22. Decomposition of Equity Momentum Profits under the FF3* Model – Norwegian Data

Panel A: Autocovariance matrix of factor returns

	Month t return		
Average factor return from month t-12 to t-2	MKTRF	SMB	HML
MKTRF	0.194	-1.022	0.767
SMB	1.192	-0.009	-0.783
HML	0.297	-0.061	1.250

Panel B: Covariance matrix of factor betas

	MKTRF	SMB	HML
MKTRF	0.178	0.094	0.030
SMB	0.094	0.215	0.029
HML	0.030	0.029	0.145

Panel C: Decomposition estimates

Sign	Component		
+	Factor autocovariances	$\sum_{f=1}^{F}\left[cov(r_{-t}^{f}, r_{t}^{f})\sigma_{\beta f}^{2}\right]$	0.214 %
+	Factor cross-serial covariances	$\sum_{f=1}^{F}\sum_{g\neq f}^{F}\left[cov\left(r_{-t}^{f}, r_{t}^{g}\right)cov(\beta^{f}, \beta^{g})\right]$	0.024 %
+	Variance of mean returns	σ_{η}^{2}	0.510 %
+	Residual autocovariances	$\frac{1}{N}\sum_{t=1}^{N}\left[cov(\varepsilon_{i,-t}, \varepsilon_{i,t})\right]$	1.432 %
=	Total		2.180 %

Notes: * FF3 refers to the Fama and French (1993)'s three factors, namely market (MKTRF), size (SMB), and value (HML). The last term (residual autocovariances) was computed as the difference between the total strategy return and the sum of the other three components.

Panel C in Table 22 shows that the total profit of this cross-sectional momentum strategy is 2.18% (t-value = 3.24). Of this total monthly return, the factor autocovariances contribute 0.21% (t-value = 0.98), the factor cross-serial covariances contribute 0.02% (t-value = 0.27), and the variance of mean returns contribute 0.51% (t-value = 3.00). Almost 66% of the total profits comes from the autocovariances between past and future residuals (1.43%, t-value =

2.55). Previous results show that the accuracy of this decomposition can suffer from model misspecification, especially omitted-factor bias. As shown in Table 23, it could be that some momentum in omitted factors would have been attributed to the residuals, implying that it is important to identify the true asset pricing model for the focal market (Ehsani & Linnainmaa, 2022).

Table 23. Decomposition of Equity Momentum Profits Across Two Asset Pricing Models – Norwegian Data

	Asset pricing model	
Component	CAPM	FF3
Factor autocovariances	0.029 [0.137]	0.214 [0.219]
Factor cross-covariances		0.024 [0.090]
Variance of mean returns	0.510 [0.170]	0.510 [0.170]
Residual autocovariances	1.641 [0.544]	1.432 [0.562]
Total	2.180 [0.672]	2.180 [0.672]

Notes: Standard errors are inside the square brackets. They were calculated using a block bootstrapping method with 1,000 bootstrap samples

To study whether UMD or factor momentum can better capture the profits from stock returns, all stocks trading in the Norwegian stock market are sorted into 5 portfolios based on prior one-year returns skipping a month (i.e., from month t-12 to t-2). The monthly excess returns of these portfolios are then regressed on three different models: Fama and French (1993)'s three-factor model (FF3), FF3 + Carhart (1997)'s UMD, and FF3 + $FMOM_{ind}$ (i.e., factor momentum constructed from Fama/French 3 factors for the Norwegian market) (see Table 24).

Results show that, the alphas for the loser (-2.34, t-value = -5.35) and the winner portfolios (0.30, t-value = 1.04) are significantly different (2.64, t-value = 4.49) in the models without any momentum factor (i.e., FF3 only). This model also yields an average absolute monthly alpha of 0.65 and the GRS test (Gibbons et al., 1989) is significant, meaning that the alphas across five portfolios are significantly different from zero (F-value = 6.26, p-value < 0.01).

Under the FF3 model augmented with the UMD factor, the alpha for the losers is still negative and significant (-1.33, t-value = -3.49), but the alpha for the winner portfolio becomes negative and insignificant (-0.36, t-value = -1.42). These results are in line with previous findings in the Norwegian market that the cross-section momentum winner strategy is very volatile (see Figure 2). Nonetheless, the difference between these alphas is still positive and significant (0.97, t-value = 2.12), indicating positive momentum profits. The average absolute alpha is reduced to 0.45 but the alphas across all portfolios are still significantly different from 0 (F-value = 3.51, p-value < 0.01).

Table 24. Pricing Momentum-Sorted Portfolios with UMD and Factor Momentum – Norwegian Data

	Asset Pricing Model				
	FF3	FF3 + UMD		FF3 + $FMOM_{ind.}$	
Decile	$\hat{\alpha}$	$\hat{\alpha}$	$\hat{b}_{umd}$	$\hat{\alpha}$	$\hat{b}_{fmom}$
Losers	-2.335	-1.327	-0.603	-2.248	-0.194
	(-5.351)	(-3.485)	(-10.366)	(-5.117)	(-1.463)
2	-0.224	0.189	-0.247	-0.140	-0.190
	(-0.906)	(0.798)	(-6.853)	(-0.565)	(-2.545)
3	0.195	0.324	-0.077	0.212	-0.038
	(1.017)	(1.654)	(-2.588)	(1.094)	(-0.647)
4	0.173	-0.039	0.127	0.099	0.165
	(0.792)	(-0.179)	(3.779)	(0.456)	(2.501)
Winners	0.301	-0.362	0.397	0.102	0.447
	(1.035)	(-1.420)	(10.194)	(0.365)	(5.285)
Winners	2.636	0.965	1.001	2.350	0.642
- Losers	(4.487)	(2.119)	(14.384)	(4.056)	(3.661)
N	268	268		268	
Avg.	0.646	0.448		0.560	
GRS F-value	6.258	3.509		5.960	
GRS p-value	0.002 %	0.436 %		0.003 %	

Notes: Dependent variables were monthly excess returns of each of 5 portfolios sorted by average returns of the past 11 months from t-12 to t-2. The first decile was the losers' portfolio, while the fifth decile was the winners' portfolio. The last regression used the difference between the winners and losers' returns as the dependent variable. This table only reports alphas (i.e., intercept) and coefficient estimates of momentum factors (i.e., UMD, $FMOM_{ind.}$). $FMOM_{ind}$ is factor momentum constructed from 3 factors presented in Table 4. Note that factor momentum strategy is to go long (short) factors with positive (negative) returns in the prior year.

Finally, the FF3 + $FMOM_{ind}$ model earns negative alpha for the loser portfolio (-2.25, t-value = -5.12) and positive alpha for the winner portfolio (0.10, t-value = 0.37), which are significantly different from each other (2.35, t-value = 4.06). The average absolute monthly alpha (0.56) however is higher than that of the Carhart (1997)'s four-factor model while still being smaller than that of the FF3 model. The GRS test, similarly, is strongly significant at the 1% level (F-value = 5.96, p-value < 0.01). These results suggest that the three-factor model augmented with factor momentum performs worse than the Carhart (1997)'s four-factor model. As explained by Ehsani and Linnainmaa (2022), since the sorting factor used to sort the portfolios is the same as that used to construct the UMD factor, it is expected that the four-factor model should explain well the momentum profits. In addition, as consistently being shown in this thesis, factor momentum is stronger when using a larger set of factors. Using only three factors, the extracted factor momentum seems to be insufficient to outperform the UMD factor in explaining the momentum profits in portfolio returns of the Norwegian market.

c) Individual stock momentum (UMD) and other factors

Like the UMD factor in the U.S. market, the UMD factor in the Norwegian market also possesses very low unconditional correlations with other individual factors (i.e., FF3). Indeed, a simple linear regression with UMD as the dependent variable shows that the FF3 model can only explain 3.4% of the total variance, meaning that the "residuals" predict a total of 96.6% of the total variance in UMD. As explained above, this low unconditional correlation is however misleading, and it is important to time other factors to reveal their true correlations. Indeed, results in Table 25 show that when controlling for the past performance, the correlations between UMD and other factors are much stronger. For example, while the unconditional correlation between UMD and the value (HML) factor is only -0.07 in the testing period (i.e., July 1981 to March 2023), its correlation conditional upon a positive (negative) prior year is 0.01 (-0.18) which is considerably higher (lower) than the unconditional one. Additionally, the two conditional correlations are also significantly different from each other (z-value = 2.27, p-value = 0.02 < 0.05). In general, the correlations between UMD and the three factors conditional upon a prior year with good (bad) performance are all positive (negative) and the differences between these two conditional correlations for each factor are all significant at the 5% level (except for the size (SMB) factor with a significant test at the 10% level). These results suggest that, just like in the U.S. market, the UMD factor in the Norwegian market may not be a distinct risk factor. In contrast, UMD seems to considerably correlate with all other individual factors, although the signs of these correlations are switching over time (depending on whether UMD goes long or short other factors at the current period) (Ehsani & Linnainmaa, 2022).

Table 25. Unconditional and Conditional Correlation between UMD and Factor Returns – Norwegian Data

	Unconditional Correlations	Conditional Correlations			Test 1 $H_o: \hat{\rho}^+ = \hat{\rho}^-$		Test 2 $H_o: \hat{\rho} = \hat{\rho}_{mom}$	
Factor	$\hat{\boldsymbol{\rho}}$	$\hat{\boldsymbol{\rho}}^+$	$\hat{\boldsymbol{\rho}}^-$	$\hat{\boldsymbol{\rho}}_{mom}$	**z-Value**	**p-Value**	**z-Value**	**p-Value**
Pooled	-0.118	0.036	-0.293	0.200	5.002	0.000	4.527	0.000
Value	-0.072	0.013	-0.184	0.074	2.267	0.023	2.148	0.032
Market factors	-0.141	0.085	-0.437	0.342	5.743	0.000	4.048	0.000
Size	-0.055	0.000	-0.234	0.057	1.753	0.080	2.015	0.044

Notes: This table reports (un)conditional correlations between the Carhart (1997)'s UMD factor and returns of the 3 individual factors reported in Table 4; $\hat{\boldsymbol{\rho}}$ is unconditional correlation between factor return and UMD, $\hat{\boldsymbol{\rho}}^+$ (or $\hat{\boldsymbol{\rho}}^-$) is the same as $\hat{\boldsymbol{\rho}}$ but conditional upon the prior-one-year return of the factor being positive (or negative), and $\hat{\boldsymbol{\rho}}_{mom}$ is the correlation between time-series factor momentum and UMD. The correlations were transformed using the Fisher (1915)'s z-transformation method before being tested for their equality with z-tests (see Table 17 for more details).

5. Conclusion

Previous research has long shown that the cross-sectional variations in stock returns can be well predicted by their momentum, which are often measured as previous one-year stock returns (e.g., Jegadeesh & Titman, 1993). Momentum has also been found in other asset classes and its influence appears to be all-pervasive, leading many researchers to consider it as an independent (and uncorrelated) factor with other risk factors (Asness et al., 2013). In this thesis, I closely follow Ehsani and Linnainmaa (2022)'s paper to show that the unconditional correlations between individual stock momentum and other factors (e.g., Fama/French five factors, etc.) are indeed small but misleading. This is because the momentum factor typically exhibits strong time-varying correlations with other factors when controlling for the positive or negative performance of the previous year's returns. Consistent findings were found when investigating the relationship between the UMD (i.e., up minus down) factor and the Fama/French three factors with the context of the Norwegian stock market.

Following emerging research in the field (e.g., Avramov et al., 2017), this thesis provides empirical evidence that factors exhibit momentum, which can predict well their future returns. Specifically, in both the US and Norwegian stock markets, factors characterized by negative returns in the preceding year earn minimal premiums that lack statistical significance, while factors with positive returns over the previous year produce substantial premiums. For example, among the 3 factors in the Norwegian stock market, after a year of losses, the average factor yields a monthly return of 9 bps and 96 bps after a year of gains. Consequently, this phenomenon enables the implementation of profitable time-series factor momentum trading strategies that effectively take advantage of the positive autocorrelations inherent in factor returns (Moskowitz et al., 2012).

In addition, I replicated the construction of the 47 factors using the Kozak (2020)'s characteristic signals data and found that, in the second half of the testing sample, factor momentum primarily concentrates in a few PC factors (extracted from these 47 factors) with highest eigenvalues, but it is not the case in the first half of the sample. Ehsani and Linnainmaa (2022) argue that this might result from the entry of arbitrageurs such that arbitrageurs may have acquired a greater understanding of momentum and how to capitalize on its potential benefits over time.

Importantly, factor momentum is found to explain the profits of cross-sectional variations in stock returns. The magnitude of this influence is dependent on the accuracy of the estimation of factor loadings, which might suffer from asset pricing model misspecification (e.g., omitted factor bias). Using US data, it is found that factor momentum outperforms individual stock momentum (i.e., Carhart (1997)'s UMD factor) in explaining momentum profits in momentum-sorted portfolios' returns, indicating that factor momentum captured in the first few highest-eigenvalue PC factors accounts for a substantial proportion of the profits derived from individual stock momentum (Ehsani & Linnainmaa, 2022). In contrast, factor momentum found in a smaller set of off-the-shelf factors in the Norwegian stock market performs worse than individual stock momentum in pricing the returns of momentum-sorted portfolios. Hence, these results might be contingent upon the number of used factors, or more importantly the strength of autocorrelations between factor returns.

Finally, factor momentum captured in momentum-neutral factors subsumes the momentum observed in standard factors. This observation suggests that factor momentum does not only result from individual stock momentum but also pertain to the factor loadings or characteristics associated with factor themselves, which is not specific to any individual stock (Ehsani & Linnainmaa, 2022).

6. Limitations and Future Research

Three avenues for future research can be identified. Firstly, in the final part of this thesis, an attempt was made to replicate the findings concerning factor momentum in the US stock market using Norwegian stock data. However, the results are limited due to the scarcity of readily available data for factor returns in this market. In fact, the factor momentum observed in this restricted set of three factors proved insufficient to account for the Carhart (1997)'s UMD momentum factor, and the three-factor model augmented with factor momentum failed to fully capture momentum profits in stock returns. Therefore, future research focusing on the Norwegian market should strive to acquire data encompassing a broader range of factors to examine whether factor momentum can indeed account for various forms of individual stock momentum, as asserted by Ehsani and Linnainmaa (2022).

Secondly, empirical evidence suggests that factor momentum and its ability to subsume individual stock momentum may vary depending on the choice of factors and the characteristics of the market (e.g., the persistence of investor sentiment (see Ehsani & Linnainmaa, 2022)). Hence, further research should extend upon the abovementioned analyses, by utilizing international stock data covering major regions such as North America, Europe, Japan, and Asia Pacific (Fama & French, 2012), to explore the extent to which global and local factor momentum can explain global and regional individual stock momentum.

Finally, emerging evidence in previous research suggests the presence of momentum in relatively new asset markets such as cryptocurrencies, though time-series and cross-sectional momentum strategies do not consistently generate significant payoffs in these market (e.g., Grobys & Sapkota, 2019). Hence, future research could explore the extent to which momentum in cryptocurrencies (i.e., individual asset momentum) is influenced by exposure to systematic risk factors that might themselves exhibit momentum (i.e., factor momentum).

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Appendix

Table A.1. Descriptive Statistics of the 54 KNS Factors

Factor	Start Date	Annual Return			
		Mean	SD	SE	t-Value
Accruals	Jul 1963	-0.050 %	0.152 %	0.020	-2.478
Firm Age	Jul 1963	0.016 %	0.152 %	0.020	0.815
Asset turnover	Jul 1963	0.049 %	0.152 %	0.020	2.423
Beta Arbitrage	Jul 1963	-0.010 %	0.152 %	0.020	-0.476
Cash flow to price	Jul 1963	0.054 %	0.152 %	0.020	2.667
Composite Issuance	Jul 1963	-0.072 %	0.152 %	0.020	-3.547
Debt Issuance	Jul 1963	0.016 %	0.152 %	0.020	0.803
Dividend Growth	Jul 1963	-0.031 %	0.152 %	0.020	-1.510
Dividend Yield	Jul 1963	0.019 %	0.152 %	0.020	0.940
Cash flow duration	Jul 1963	-0.055 %	0.152 %	0.020	-2.733
Earnings to price	Jul 1963	0.056 %	0.152 %	0.020	2.761
Exchange Switch	Jul 1963	-0.036 %	0.152 %	0.020	-1.775
Piotrowski's F-score	Jul 1963	0.052 %	0.152 %	0.020	2.558
Growth in LTNOA	Jul 1963	-0.021 %	0.152 %	0.020	-1.017
Gross Margins	Jul 1963	-0.005 %	0.152 %	0.020	-0.265
Investment Growth	Jul 1963	-0.060 %	0.152 %	0.020	-2.985
Investment Growth	Jul 1963	-0.077 %	0.152 %	0.020	-3.829
Industry Momentum	Jul 1963	0.058 %	0.152 %	0.020	2.891
Industry Momentum-Reversal	Jul 1963	0.214 %	0.152 %	0.020	10.611
Industry Relative Reversals	Jul 1963	-0.171 %	0.152 %	0.020	-8.478
Industry Relative Reversals (Low Volatility)	Jul 1963	-0.314 %	0.152 %	0.020	-15.519
Investment	Jul 1963	-0.081 %	0.152 %	0.020	-3.996
Abnormal Corporate Investment	Jul 1963	-0.037 %	0.152 %	0.020	-1.808
Investment-to-Capital	Jul 1963	-0.025 %	0.152 %	0.020	-1.217
Initial Public Offering	Jul 1963	-0.003 %	0.152 %	0.020	-0.145
Idiosyncratic Volatility	Jul 1963	-0.022 %	0.152 %	0.020	-1.075
Leverage	Jul 1963	0.028 %	0.152 %	0.020	1.396
Long-term Reversals	Jul 1963	-0.044 %	0.152 %	0.020	-2.153
Momentum (6 months)	Jul 1963	0.034 %	0.152 %	0.020	1.659
Momentum (1 year)	Jul 1963	0.076 %	0.152 %	0.020	3.772
Momentum-Reversal	Jul 1963	-0.038 %	0.152 %	0.020	-1.860
Share Issuance	Jul 1963	-0.078 %	0.152 %	0.020	-3.848
Share Issuance (monthly)	Jul 1963	-0.068 %	0.152 %	0.020	-3.374
Net Operating Assets	Jul 1963	-0.101 %	0.152 %	0.020	-4.986
Price	Jul 1963	0.000 %	0.152 %	0.020	-0.017
Gross Profitability	Jul 1963	0.042 %	0.152 %	0.020	2.097
Share Repurchases	Jul 1963	0.051 %	0.152 %	0.020	2.525
Return on Assets	Jul 1963	0.068 %	0.152 %	0.020	3.341
Return on Assets	Jul 1963	0.025 %	0.152 %	0.020	1.241
Return on Book Equity	Jul 1963	0.081 %	0.152 %	0.020	4.027
Return on Equity	Jul 1963	0.029 %	0.152 %	0.020	1.436
Return on Market Equity	Jul 1963	0.084 %	0.152 %	0.020	4.134

Seasonality	Jul 1963	0.093 %	0.152 %	0.020	4.587
Sales Growth	Jul 1963	-0.033 %	0.152 %	0.020	-1.639
Short Interest	Jul 1963	-0.003 %	0.152 %	0.020	-0.128
Share Volume	Jul 1963	-0.009 %	0.152 %	0.020	-0.427
Size	Jul 1963	-0.031 %	0.152 %	0.020	-1.528
Sales-to-Price	Jul 1963	0.066 %	0.152 %	0.020	3.276
Short-term Reversal	Jul 1963	-0.078 %	0.152 %	0.020	-3.865
Standardized Unexpected Earnings	Jul 1963	0.097 %	0.152 %	0.020	4.802
Value-Momentum	Jul 1963	0.052 %	0.152 %	0.020	2.559
Value-Momentum-Profitability	Jul 1963	0.074 %	0.152 %	0.020	3.649
Value - Profitability	Jul 1963	0.107 %	0.152 %	0.020	5.315
Value	Jul 1963	0.043 %	0.152 %	0.020	2.135
Value (monthly)	Jul 1963	0.029 %	0.152 %	0.020	1.430

Table A.2. RC - Impact of Factor's Past Returns on Own Future Returns Using U.S. FF5

	Intercept			Slope		
Anomaly	$\hat{\alpha}$	**t-value($\hat{\alpha}$)**	**p-value($\hat{\alpha}$)**	$\hat{\beta}$	**t-value($\hat{\beta}$)**	**p-value($\hat{\beta}$)**
			U.S. Fama/French 5 Factors			
Pooled	**0.021**	**0.198**	**0.843**	**0.476**	**3.381**	**0.001**
Investment	0.093	0.785	0.433	0.317	2.024	0.043
Value	-0.022	-0.114	0.909	0.511	2.160	0.031
Market factors	0.101	0.241	0.810	0.600	1.319	0.187
Profitability	0.046	0.245	0.806	0.345	1.657	0.098
Size	-0.071	-0.430	0.667	0.540	2.375	0.018
Momentum	0.623	2.394	0.017	-0.015	-0.046	0.963

Table A.3. RC - Profitability of Time-Series and Cross-Sectional Factor Momentum Strategies Using U.S. FF5

Strategy	Annualized return				
	Mean	**SD**	**SE**	**t-val**	**Sharpe ratio**
Equal-weighted portfolio	3.998 %	4.535 %	0.050	6.695	0.882
Time-series factor momentum	3.837 %	5.948 %	0.065	4.899	0.645
Winners	6.340 %	6.579 %	0.072	7.308	0.964
Losers	-0.178 %	9.885 %	0.114	-0.131	-0.018
Cross-sectional factor momentum	3.274 %	5.863 %	0.064	4.241	0.558
Winners	6.060 %	6.548 %	0.072	7.029	0.926
Losers	0.905 %	8.672 %	0.095	0.792	0.104

Figure A.1. RC – Cumulative Returns of Different Momentum Strategies Using U.S. FF5

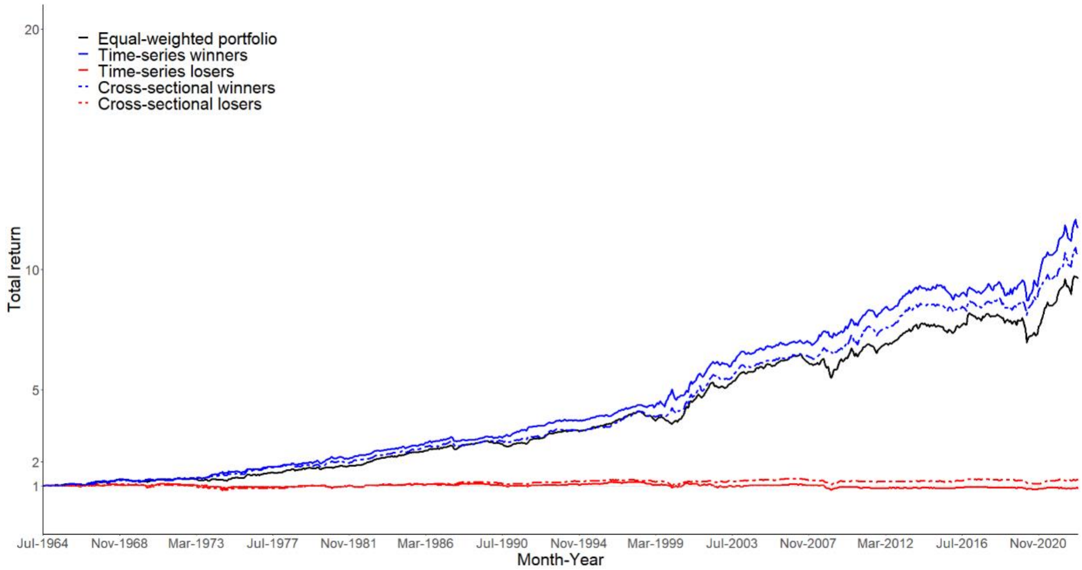

Table A.4. RC – Sources of Factor Momentum Profits Using U.S. FF5

Strategy	Decomposition	Sign	Annualized premium	Standard error
Cross-sectional factor momentum	Autocovariances	+	2.165 %	1.303
	Cross-serial covariances	-	0.246 %	0.355
	Variance of mean returns	+	0.173 %	0.277
	Cross-sectional factor momentum	=	**2.092 %**	**1.397**
Time-series factor momentum	Autocovariances	+	2.165 %	1.303
	Mean squared returns	+	1.450 %	0.491
	Time-series factor momentum	=	**3.614 %**	**1.288**

Notes: Standard errors were computed using the bootstrapping method with 1,000 bootstrap samples.

Table A.5. RC – Unconditional and Conditional Correlation with Momentum Factors for the Seven-Factor Model (FF5 + BAB + QMJ)

	Unconditional Correlations	Conditional Correlations			$Test$ 1		$Test$ 2	
					$H_o: \hat{\rho}^+ = \hat{\rho}^-$		$H_o: \hat{\rho} = \hat{\rho}_{mom}$	
Factor	$\hat{\rho}$	$\hat{\rho}^+$	$\hat{\rho}^-$	$\hat{\rho}_{mom}$	**z-Value**	**p-Value**	**z-Value**	**p-Value**
Pooled	-0.008	0.447	-0.558	0.634	14.140	0.000	20.529	0.000
Betting against beta	0.194	0.386	-0.146	0.360	3.372	0.001	5.908	0.000
Investment	-0.007	0.169	-0.296	0.316	6.241	0.000	6.090	0.000
Value	-0.194	0.176	-0.579	0.433	12.352	0.000	10.793	0.000
Maket factors	-0.171	0.183	-0.576	0.406	11.309	0.000	9.780	0.000
Quality minus junk	0.296	0.468	-0.253	0.518	5.019	0.000	9.453	0.000
Profitability	0.086	0.399	-0.453	0.412	6.603	0.000	11.094	0.000
Size	-0.068	0.146	-0.427	0.307	7.218	0.000	7.872	0.000

Table A.6. Explaining UMD by Factor Momentum from FF3 – Norwegian Data

	Alpha		**Factor Momentum**			
	$\widehat{\boldsymbol{\alpha}}$	$\boldsymbol{t}(\widehat{\boldsymbol{\alpha}})$	$\widehat{\boldsymbol{b}}_{\boldsymbol{fmom}}$	$\boldsymbol{t}(\widehat{\boldsymbol{b}}_{\boldsymbol{fmom}})$	**FF3**	**R2**
None	1.670	4.286			Y	3.40%
$FMOM_{ind.}$	1.426	3.775	0.547	4.786	Y	11.2 %