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Exploring the Role of the Momentum Factor in Asset Pricing Models: An Empirical Analysis of the Oslo Stock Exchange (OSE) from July 1989 to June 2020

Master Thesis

by

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Msc in Finance

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ABSTRACT

This thesis tests if the Fama and French five-factor model including momentum can explaining stock returns on OSE. The inclusion of momentum factor enhances model performance, with an increased adjusted R^2 from 0.65 to 0.74 for momentum portfolios. These results are robust across factor constructions and show a general increase in adjusted R^2 from 0.67 to 0.70 for all portfolios, primarily driven by *size-MOM* portfolios. Comparing competing models, the five-factor model with momentum consistently outperforms the three-factor model in terms of adjusted R^2. While evidence supports the *RMW* factor in sub-samples, no statistically significant support is found for the *CMA* factor. Further testing without *CMA* is required for conclusive results. The findings hold for both the five-factor model and the five-factor model with momentum on *size-B/M* portfolios. Given the modest improvement, a parsimonious approach is recommended, favouring the three-factor model with momentum.

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List of Abbreviations

B/M	Book-to-market ratio
BE	Book Equity
bps	Bps
CAPM	Capital Asset Pricing Model
CMA	Conservative Minus Aggressive / Investment factor
COGS	Cost Of Goods Sold
CRSP	The Center for Research in Security Prices
d.f.	Degrees of Freedom
FF3	Fama French 3-factor Model
FF5	Fama French 5-factor Model
GP	Gross Profitability
GRS	Gibbons, Ross and Shanken
HAC	Heteroskedasticity and Autocorrelation Consistent
HML	High Minus Low / Value factor
Inv	Investments
ISIN	International Security Identification Number
LHS	Left Hand Side
ME	Market Equity
MKT	Market factor / Excess Market return
MOM	Momentum factor – General use
OSE	Oslo Stock Exchange
PR1YR	Prior 1-year return / Momentum factor
RHS	Right Hand Side
RMW	Robust Minus Weak / Profitability factor
SMB	Small Minus Big / Size factor
SR	Sharpe Ratio
UMD	Up Minus Down / Momentum factor
WML	Winners Minus Losers / Momentum factor
WRDS	Wharton Research Data Service

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List of Symbols

α	Intercept – used as notation in hypothesis tests
a_i	Intercept in model specification
α_{ip}	Intercept of portfolio i from 2x3 sort p (used in GRS)
b_i	Market slope
$\hat{b}$	Market slope estimate
s_i	*SMB* slope
h_i	*HML* slope
r_i	*RMW* slope
c_i	*CMA* slope
u_i	Momentum slope – generalization
R_{it}^*	Excess return of portfolio i
$\bar{R}_i$	Mean excess return of portfolio i
λ_j	Factor risk premia for factor *j*
N	Number of: assets, observations, portfolios, stocks
p	Portfolio
L	Number of portfolios
T	Sample length
Ω	Sample variance-covariance matrix
$\widetilde{W}$	GRS test statistic proposed by Kamstra and Shi (2021)
$\bar{r}_{pt}$	Mean excess return of portfolio p at time t

1 Introduction and Motivation

In 1993, Fama and French introduced the three-factor model to improve the Capital Asset Pricing Model (CAPM) by adding extra risk factors. Carhart expanded on this model in 1997 by incorporating a momentum factor, which Fama and French later examined in international markets in 2012. Momentum was consistently observed in these markets, except for Japan. Fama and French (2015) expanded the model further by including profitability and investment factors to explain stock returns, although the evidence they found was somewhat mixed. They emphasized the importance of tailoring the factors in the asset pricing model to suit the specific market being analysed, using global factors for global markets and local factors for local markets. This principle forms the basis of our research question.

Can the stock returns on Oslo Stock Exchange be explained by including a momentum factor in the Fama and French five-factor model?

While significant research has been conducted on asset pricing and momentum in the U.S. market, there is a scarcity of comprehensive studies focusing on the Norwegian market. Notably, the work by Randi Næs, Johannes Skjeltorp, and Bernt Arne Ødegaard (2008) evaluates return characteristics using three- and four-factor models with momentum but does not include the profitability and investment factor found in the five-factor model by Fama and French (2015).

The addition of the profitability and investment factor in the Fama and French three-factor model is motivated by the dividend discount model, and that much of the variation in average returns related to profitability and investment is left unexplained (Fama and French, 1993, 2011). Fama and French (2015) rearrange the dividend discount model and demonstrate that a stock's expected return depends on its price-to-book ratio and expectations of future profitability and investment. They acknowledge that the book-to-market ratio is an imperfect proxy for expected return due to the influence of market capitalization on earnings and investment forecasts. In international tests of the five-factor model, Fama and French (2017) find that the investment factor may be redundant. Our analysis yields similar results, suggesting the need for further research and testing of models with fewer factors.

The consistency of momentum across different time periods and asset classes has established it as a distinct factor. Models that exclude momentum fail to account for its existence, while models that include momentum only capture its effects without providing additional explanatory power (Fama and French, 2016; Ehsani and Linnainmaa, 2022). Variables like *size* and momentum, not explicitly linked to the dividend discount model, contribute to return forecasts by implicitly improving predictions of profitability and investment or capturing effects in the expected returns term structure (Fama and French, 2017). When assessing portfolio performance, evidence from U.S. equity mutual funds suggests that conclusions align between the three- and four-factor model, which incorporates a momentum factor. Thus, Fama and French (2017) propose extending the tests to the five-factor model and the six-factor model, which includes a momentum factor.

Highlighting the necessity of incorporating a momentum factor to detect momentum effects in stock returns, it becomes important for asset managers to implement the most appropriate model. This holds equally true for risk management scenarios, where a risk manager, intending to eliminate momentum exposure, must utilize a momentum factor to spot possible momentum-related risks. Given that global factors typically have low predictive power (R^2) on local markets, it becomes imperative for asset managers to rely on factors estimated locally. Additionally, the lack of integration between markets, particularly the higher pricing errors associated with global factors applied to local markets (Griffin, 2002), further motivates our investigation. Our contribution will be to test momentum in a five-factor model for the Norwegian market.

Chapter 2 present literature supporting a five-factor model for explaining stock returns for the U.S. market. We find evidence for a momentum factor, but a six-factor model including a momentum factor is yet to be tested. Chapter 3 translates our research question into two testable hypothesis that first test if the either of the five- and six-factor models capture all variation in excess returns, and then test if the six-factor model explain more of the cross-section of mean returns than the five-factor model. We test for factor redundancies using factor-spanning regressions and use the Fama-MacBeth two step procedure and GRS-test to answer the second part of the hypothesis. In chapter 4 we present data and exclusion criteria that we used for the Norwegian Market. Results in chapter 5 indicate that the six-factor model including momentum can explain stock returns on OSE, but that the *CMA* factor is redundant in all sub-samples we examine. We do however believe improvements between the three- and five-factor model including momentum is due to the *RMW* factor, thereby suggesting further research of models excluding CMA.

2 Literature Review

In this section we give an overview of current literature on asset pricing models relevant for our research question. We aim to test if the Fama and French five-factor model including momentum, can explain stock returns on OSE.

2.1 Asset pricing and factor models

The field of asset pricing has seen significant advancements since the pioneering work of Markowitz (1952) and Sharpe (1964). Their introduction of the Capital Asset Pricing Model (CAPM) provided a groundbreaking framework for understanding the risk-return relationship. However, recent research has revealed limitations in the CAPM.

Fama and French made influential contributions by introducing the Three-Factor Model (FF3) in their seminal paper of 1992. This model expanded upon the CAPM by incorporating additional factors to explain the cross-section of expected stock returns. Specifically, Fama and French introduced the *size* and *value* factors, which played a significant role in determining asset prices. The *size*-effect, previously identified by Banz (1981), showed that small firms on average had higher risk-adjusted returns. Similarly, the *value*-factor, proposed by Rosenberg, Reid, and Lanstein a few years later, demonstrated a positive relation between mean returns of U.S. stocks and the book-to-market ratio (B/M) (Rosenberg et al., 1985b).

In their paper "The Cross-Section of Expected Returns" (1992), Fama and French aimed to evaluate the joint roles of market beta, *size*, and book-to-market equity in explaining mean returns. They examined non-financial firms listed on the NYSE, AMEX, and NASDAQ between 1962 and 1989. Accounting and return data from CRSP and COMPUSTAT were used for the sample period. The study used monthly stock return data from July of year *t*, combined with year-end accounting data from year $t - 1$ to ensure data availability prior to return estimation.

One important finding of their research was the robust negative relation between *size* and mean returns, even after considering other variables in multivariate tests. Additionally, they found that the book-to-market equity factor consistently played a stronger role in explaining mean returns than *size*. When forming portfolios based on *size* alone, Fama and French discovered that the mean return decreased from 1.64% for the smallest ME portfolio to 0.90% for the largest ME portfolio. However, due to the high correlation between the *size* portfolios' slope estimates and *size*, it was challenging to distinguish the beta from the *size*-effect in mean returns. By allowing for unrelated variation in beta, they demonstrated that there is no relation between mean return and beta but a strong relation between mean return and *size*.

Fama and French then build upon their 1992-findings by creating factor-mimicking portfolios for *size* and B/M for the U.S. market from 1963 to 1991. Again, CRSP and COMPUSTAT is used for the sample data. To test the three-factor model, they apply the cross-sectional regressions of Fama-MacBeth (1973) – which is different from the time-series regressions applied in their 1992 paper. They find that these portfolios capture strong common variation in returns not explained by other factors. They propose a model to capture the effects of *size* and B/M not captured by the CAPM:

$$R_{it}^{*} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + \epsilon_{it}$$

Where R_{it}^{*} is the excess return of the market factor, *SMB* and *HML* are the factor-mimicking portfolio returns of *size* and B/M respectively.

From time-series regression that include the market factor, and the mimicking returns for *size* and B/M the intercepts are close to zero – meaning the model captures most of the variation related to excess returns (Fama and French, 1993). The addition of the *size* and B/M factor significantly increases R^2 to above 0.90 in 21 out of 25 instances – compared to a model with just the market factor (0.69).

Since both *size* and B/M are related to profitability, and therefore to each other, Fama and French had to find a way to isolate the return of the *size* effect from the return associated with B/M. They use a clever sorting technique that will be applied throughout this thesis. We will go into more detail about the exact construction of these factors in chapter 4, but wanted to illustrate that by this technique, Fama and French reduced the correlation of the *SMB* and *HML* to only -0.08. Effectively eliminating the *size* factor in returns from *HML*. Overall, they find that the *HML* factor earns a mean monthly return of 0.40% with a t-statistic of 2.91. The *SMB* factor earns a mean monthly return of 0.27% with a t-statistic of 1.73 (Fama and French, 1993).

In more recent times, the Fama and French three factor model has been criticized for not explaining returns related to profitability and investments. Based on this, Fama and French (2015) propose a revised model to capture the effects of these suggestions by Novy-Marx (2013) and Aharoni, Grundy, and Zeng (2013):

$$R_{it}^{*} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

Where *RMW* and *CMA* are the factor-mimicking portfolio returns of profitability and investments, respectively. By introducing these two factors, they were able to capture the variation in mean stock returns that was previously explained by the *HML* factor. The profitability and investment factors were found to provide a more comprehensive and effective explanation of the cross-section of mean stock returns, rendering the *HML* factor redundant in the five-factor model (Fama and French, 2015).

In his paper "The Other Side of Value", Novy-Marx (2013) compares the predictive power of gross profits-to-assets with the book-to-market ratio in forecasting mean returns in stocks. The paper uses COMPUSTAT stock return and accounting data for AMEX from July 1963 to December 2010. Novy-Marx investigates several proxies for profitability, including earnings-to-book equity, free cash-flow-to-book equity, and gross profits-to-assets. He finds that gross profitability exhibits the strongest predictive power. Specifically, the t-statistic associated with gross profits-to-assets is one and a half times larger than that of the variable linked to value (Novy-Marx, 2013).

Gross profitability, being a cleaner measure of profitability, is not influenced by factors such as accruals (Chan et al., 2006), R&D, and advertising expenditures (Chan et al., 2001) that have been found to impact cross-sectional returns. Novy-Marx (2013) even considers these effects in his analysis and still finds that the predictive power of gross profitability persists.

To address the potential influence of firm size, Novy-Marx (2013) explores whether returns related to high gross profitability can be attributed solely to small firms. If this were the case, one would expect the spread in profitability between large and small firms to be insignificant. However, Novy-Marx demonstrates that even after double-sorting on size, the predictive power of profitability remains significantly different from zero for the largest firms. In fact, for large firms, the monthly return spread associated with profitability is 12 bps higher than that of value, with a t-statistic of 1.88 (Novy-Marx, 2013).

Aharoni, Grundy, and Zeng (2013) finds a negative relationship between mean returns and investments. The data is from CRSP and COMPUSTAT from 1963 to 2009. Their paper revealed that estimating variables at the firm level, rather than at the per share level as done by Fama and French in 2006, significantly alters the coefficient on the expected change in investment. At the firm level, the coefficient is both negative and significant. Additionally, firm-level analysis supports Fama and French's per share results, showing significantly positive coefficients on both *B/M* and expected profitability, as well as a significantly negative coefficient on *size*.

These findings align with the notion that low-*B/M* firms are considered growth stocks. The strong relationship between *B/M* and expected investment suggests that these variables likely capture similar economic forces (Aharoni, Grundy, and Zeng, 2013). Furthermore, in their stock return regressions, when one of these variables demonstrates improved predictive ability, the predictive ability of the second variable deteriorates.

2.2 Momentum factors

Jegadeesh and Titman (1993) find that stocks with high past returns outperformed those with low past returns over a 3 to 12-month holding period. The sample period is from 1965 to 1989, using CRSP stock return data for the U.S. market. Their findings have been replicated in subsequent studies, including Moskowitz, Ooi, and Pedersen (2013), who highlighted its stronger effect in smaller and less liquid stocks.

The strategy involves ranking securities based on past *J* month performance and constructing ten equally-weighted portfolios. Buying the top-decile portfolio and selling the bottom-decile portfolio over a holding period *K* months led to significant cumulative positive returns. However, extending the holding period beyond 12 months reduced the profit by over 50%, indicating a diminishing momentum effect.

Jegadeesh and Titman (1993) rejected the hypothesis that the diminishing returns were due to the time-varying riskiness of the initial portfolios, as the direction of the estimated betas were opposite to expectation. Overall, the findings suggest that while momentum is present in the short term, it weakens over longer holding periods, indicating a potential dissipation of short-term market inefficiencies. -

The FF3 model was later extended by Carhart (1997) by adding the momentum-factor from the research by Jegadeesh and Titman. The research was done on mutual fund performance and found that the four-factor model could capture considerable variation in returns. The sample period was from 1962 to 1993 and included 1,892 diversified equity funds. The proposed model includes the FF3 factors, but add the Titman momentum-strategy, $PR1YR_t$:

$$R_{it}^{*} = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t + p_i PR1YR_t + \epsilon_{it}$$

The Carhart four-factor model, compared to the CAPM and FF3, substantially improves mean pricing errors with mean monthly absolute pricing errors of 0.35, 0.31, and 0.14, respectively (Carhart, 1997). Similar to Jegadeesh and Titman, Carhart finds that longer holding periods diminish returns but still yield a compounded 8% p.a. Notably, returns are driven by the disproportionate underperformance of last year's losers relative to the continued performance of last year's winners.

The momentum effect is evident in international markets, as demonstrated by Fama and French (2012) who applied the Carhart four-factor model to 23 countries outside the U.S. from 1989 to 2011. They test the model using cross-sectional tests and the GRS-test. They find that the model effectively captures the variation in mean returns in international markets. However, global factors perform poorly in local markets, suggesting potential challenges to the existence of parsimonious asset pricing models due to less market integration than initially assumed (Fama and French, 2012).

Not all research consistently confirms a strong momentum effect. Hong and Stein (1999) find the effect to be weaker for value stocks. Additionally, some studies suggest that the momentum effect may be influenced by behavioural biases or market frictions rather than fundamental factors (Daniel et al., 1998; Barberis, Shleifer, and Vishny, 1998). Recent work by Ehsani and Linnainmaa (2022) even suggests that momentum may not be an individual factor. They find that momentum relates to momentum in factor returns and may involve timing of other factors rather than being a distinct risk factor itself.

2.3 Factor models in international markets

Estimating market-specific factor models is crucial, as shown by Griffin (2002), who revealed an 8.41% p.a. mean difference when using a global three-factor model instead of a local one for the U.S. market. This could lead to potential errors in capital budgeting, portfolio evaluation, and risk analysis. Fama and French (2012) found that integrated pricing across regions lacked strong support, highlighting the significance of region-specific factors and limited support for integrated pricing. In a subsequent paper (2017), they tested their five-factor model in an international market context and found that it performed poorly for local portfolios. Instead, they focused on local models using factors and returns from the same region. The results showed positive relationships between mean stock returns in North America, Europe, and Asia Pacific with the book-to-market ratio and profitability, while negative relationships were observed with investment.

Our literature review supports our research question that including a momentum factor in the five-factor model could explain stock returns on OSE. However, we find weaker evidence for the profitability and investment factor. Especially the investment factor in previous literature. This motivates our robustness tests in Chapter 5.7 with competing models. While there is still some evidence supporting their ability to explain variations in stock returns, the existing research is comparatively limited. Given the potential impact of these factors on asset pricing, further investigation and empirical testing of the five-factor model are warranted.

3 Testable Hypothesis and Methodology

This chapter introduces econometric models, testing procedures, and two testable hypotheses to examine whether the incorporation of a momentum factor in the Fama and French five-factor model can explain stock returns on OSE. We use the same testing procedure as Fama and French (1993, 2012, 2015, 2017) for our models.

3.1 Econometric models

The following two models will be estimated and tested:

$$R_{it}^{*} = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW + c_i CMA_t + \epsilon_{it} \quad (1)$$

$$R_{it}^{*} = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW + c_i CMA_t + u_i MOM_t + \epsilon_{it} \quad (2)$$

Where *MOM* is a general representation of three versions of the momentum factor, *PR1YR, WML,* and *UMD.* In our formal tests, we use the *UMD* factor, while reserving the *PR1YR* and *WML* factors for conducting robustness tests of the model in Chapter 5.7. Although the selection of the momentum factor appears arbitrary due to their high correlation, we opt to use the *UMD* factor for formal tests since the factor is *size*-sorted and accounts for the strong momentum in small stocks.

Although theoretical perspectives support the existence of a momentum factor across securities and asset classes globally, determining the superior performance between the five- and five-factor model with momentum still remains uncertain. Previous studies have shown that adding more factors to complex models can lead to redundancies. For example, Fama and French (2015) find that including profitability and investment factors renders the value-factor redundant in a five-factor model. Therefore, our objective is to compare the relative performance of both models, with and without the momentum factor. This way, we can use the five-factor model as a benchmark to test if including a momentum factor explain stock returns on OSE. While achieving perfection may be elusive, imperfect models can still provide valuable insights into expected returns (Fama and French, 2017).

3.2 Testable Hypothesis

To test the model performance of the Fama and French five-factor model with and without momentum, we formulate two hypothesis:

Hypothesis 1: If the true values of the factor exposures, b_i, s_i, h_i, r_i, c_i, and u_i capture all variation in expected returns in either of the five- or six-factor models, then the intercept, a_i , in (1-2) is equal to zero for all sample stocks i (Fama and French, 2017):

$$H_0: \alpha_i = 0 \quad vs. \quad H_1: \alpha_i \neq 0$$

Hypothesis 2: The six-factor model (2) explains more of the cross-section of mean returns than (1) in the GRS-test. We reject the model if and only if some portfolio of the N assets has a non-zero intercept when its excess returns are regressed on those of portfolio p (Gibbons, Ross, Shanken, 1989):

$$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_L = 0 \quad vs \quad H_1: a_i \neq 0 \quad \forall \quad i \in [1, L]$$

Our conclusion will be based on the GRS test statistics, factor redundancies, incremental model improvements, and coinciding results.

3.3 Testing procedure

To formally test models (1) and (2) and if including a momentum factor in the Fama and French five-factor model can explain stock returns on OSE, we use the two-step Fama-MacBeth procedure, and the GRS-test. To determine factor redundancies and the presence of multicollinearity between factors, we use factor-spanning regressions combined with factor cross-correlations.

3.3.1 Factor-spanning regressions and multicollinearity

A factor-spanning regression is a method to determine the presence of collinearity between the RHS factors. The test works by regressing each factor on all other factors, except itself. If the intercepts are significant, it means the other factors fail to fully explain that factors mean returns. This does not mean, however, that the factor itself is important for tests of all portfolios but allows us to assess the potential of that factor for inclusion in model construction.

We form the following hypothesis:

$$H_0\colon a_i = 0 \quad vs \quad H_1\colon a_i \neq 0$$

For each factor, we want to find evidence for a significant intercept, hence we want to reject the null hypothesis that $a_i = 0$. Secondly, we want to obtain a low R^2 which could indicate the absence of multicollinearity between the RHS factors.

3.3.2 Estimating risk premia

The Fama-MacBeth regression is a two-step approach, with the first step involving a time-series regression to estimate $\hat{b}$ for each factor. The dependent variable in this regression is the return series of 2x3 sorted portfolios used to construct the factor mimicking portfolios.

In the second step, we utilize the previously estimated $\hat{b}$ to run a cross-sectional regression on the mean returns of the same portfolios as the dependent variable. This regression helps us obtain six values of α and λ_j, where j represents each factor. To obtain a robust estimate, we take the mean of the values and their corresponding test statistics. We show an example below for the five-factor model. The same applies for all other models as well. The regression equations for these steps are as follows:

Time-series regression:

$$R_{it}^{*} = \alpha + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \epsilon_{it}$$

Cross-sectional regression:

$$\bar{R}_i^{*} = \alpha + \lambda_{MKT} b_i + \lambda_{SMB} s_i + \lambda_{HML} h_i + \lambda_{RMW} r_i + \lambda_{CMA} c_i + \epsilon_i$$

Where R_{it}^{*} represents the excess return of portfolio i at time t and $\bar{R}_i^{*}$ represents the mean excess return of portfolio i. $MKT_t, SMB_t, HML_t, RMW_t$, and CMA_t are the factors with corresponding estimated coefficients b_i, s_i, h_i, r_i, and c_i. Finally, α represents the intercept term, and ε_{it} and ε_i are the error terms.

Applying this method, we can determine which risk factors effectively price the returns of each portfolio and assess their magnitudes. Additionally, since we are working with excess returns, we expect the intercept term to be statistically indistinguishable from zero if our pricing model is accurate (Fama and MacBeth, 1973). Therefore, we formulate two testable hypotheses:

$$H_0: \alpha = 0 \quad vs. \quad H_1: \alpha \neq 0$$

$$H_0: \lambda_j = 0 \quad vs. \quad H_1: \lambda_j \neq 0$$

In the first hypothesis, we examine the intercept term. If we fail to reject H_0 this suggests that we have captured the risk factors that price the given portfolio effectively. The second test focuses on the risk premiums (λ_j). Rejecting H_0 indicates that the corresponding risk factor is indeed priced and provides insights into the extent of its impact. To make sure that our standard errors are correct, and in turn our conclusion, we use heteroskedasticity and autocorrelation consistent (HAC) standard errors.

3.3.3 GRS-test of portfolio efficiency

In 1989, Gibbons, Ross, and Shanken developed a test to assess the ex-ante efficiency of a portfolio of assets. They explored the impact of portfolio choice and the number of assets on the ex-post mean-variance efficient frontier. (Gibbons, Ross, Shanken, 1989). For a portfolio to be mean-variance efficient, it must test the following hypothesis: that $H_0: \alpha_{ip} = 0$. The hypothesis is violated if and only if some linear combination of the α's is zero, i.e., if and only if some portfolio of the *N* assets has a non-zero intercept when its excess returns are regressed on those of portfolio *p* (Gibbons, Ross, Shanken, 1989).

We can therefore use the GRS test statistic to test the following hypotheses:

$$H_0: \alpha_1 = \alpha_2 = \cdots = \alpha_L = 0 \quad vs \quad H_1: a_i \neq 0 \quad \forall \quad i \in [1, L]$$

The application of the GRS test statistic in recent research is to rank competing models based on the size of the statistic. The idea is that models with lower GRS statistic has a better fit (Fama and French, 2015).

We use alternative statistics in conjunction with the GRS test statistic to quantitively and qualitatively assess our model's performance. We report the mean absolute value of the intercept $|a|$, mean standard errors of the intercept *s(a)*, and the mean R^2. Additionally, we report *SR(a)*, which is the maximum Sharpe ratio for excess return on portfolios of the LHS with zero intercepts on the RHS mean returns. We calculate *SR(a)* for each model as follows:

$$SR(a) = (a'S^{-1}a)^{\frac{1}{2}}$$

Where *a* is a column vector of the intercepts of the 6 regressions for each model, and *S* is the covariance matrix of residuals. We interpret the statistic as the unexplained mean returns of the model (Fama and French, 2012). One of the benefits of utilizing *SR(a)* as a summary statistic is its ability to incorporate both the regression intercepts and the covariance matrix of the regression residuals. This is advantageous as the covariance matrix plays a crucial role in determining the accuracy and precision of the alphas (Fama and French, 2012).

3.4 Three-Factor replication

To ensure that factors are constructed correctly, we first aim to reproduce the results published on the Kenneth French library[1] website for the three-factor model. To achieve this, we write a script in Python, inspired by Freda Song Dreschler[2] from Wharton Research Data Services, that replicate the *SMB* and *HML* factors of Fama and French. The replication period is from July 1970 to June 2020 and consists of monthly return observations, and annual accounting information from CRSP via WRDS. The results of the replication can be found in the appendix (appendix 17) but achieves a correlation of 0.9958 and 0.9824 for the *SMB* and *HML* of Fama and

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[2] https://www.fredasongdrechsler.com/home

French, respectively. Appendix 17 also show the plots of both the factors from the Kenneth French library, and the replicated factors.

The script is then extended to the OSE using our OBI and Refinitiv dataset. The original script uses PERMNO and PERMCO as unique identifiers, while we use ISIN. Further, the original script merges active and inactive firms, while our dataset already contain both of these. We use the same architecture to construct *RMW* and *CMA*, as the only difference in the construction of the factors is the choice of variables.

4 Data

In this section we will present an overview of the data-collection process, our sources and filtration criteria, limitations of the data, and a description of the variables constructed. We explain how we create and sort portfolios for the five-factor model, and the momentum factors. Finally, we will present summary statistics of the factors created for OSE (table 1-3).

The full data sample is from January 1980 to June 2020. As of January 1^{st,} 2023, this was the available sample length in the OBI dataset that we used, and hence why we have not looked at data after June 2020. Due to scarce data prior to 1989, we were unable to produce diversified portfolios for factor components for the period 1980 to 1989. From 1989 we have a minimum of five stocks in each portfolios, and no portfolios with missing data.

Our filtered sample contains 546 companies with corresponding accounting and return data. The final sample period is from July 1989 to June 2020, with 372 monthly return observations for each factor.

4.1 Stock return, risk-free rate, and accounting data

To avoid survivorship bias, we collected data for both active and inactive companies from OBI and Refinitiv for OSE. Stock exchange data, obtained from OBI Financial Data, included monthly information such as ticker, dividends, closing price, trading volume, adjusted monthly return, and shares outstanding from January 1980 to June 2020 (*N*=486). The monthly returns are adjusted for dividends, stock splits, and other corporate events. The dataset from OBI contained 1,043 stocks. We included only stocks with unique International Securities Identification Numbers (ISIN) information, reducing the sample to 913 stocks.

End of year accounting information was sourced from Refinitiv, including net sales, common equity, cost of goods sold, and total assets for the period 1980 to 2020 (N=40). We selected companies with ISIN information, resulting in a sample of 706 companies. The OBI stock information and Refinitiv accounting information were matched based on ISIN, resulting in a final sample of 546 companies. See appendix 1 for the distribution of accounting information in the matched sample.

4.1.1 Exclusion criteria and filtering process

To determine representative returns for OSE, it is essential to carefully select the stocks included in the sample. This is due to the potential influence of illiquid and infrequently traded stocks on the return characteristics of factor portfolios, and consequently, the obtained results.

While the specific threshold values may differ between researchers, the overarching principle is to filter the sample based on liquidity or market value of equity. Eshani and Linnainmaa (2022), and Kozak, Nagel, and Santosh (2020), excluded stocks with market values less than 0.01% of the total market value of the NYSE. Moreover, banks and financial firms were excluded from the sample in the research conducted by Fama and French (1993).

Consistent with the construction of factors for the Norwegian stock market, we opted to employ three filters recommended by Ødegaard (2021). Specifically, we excluded stocks with a price below NOK 10, market value of equity below NOK 1 million, and stocks with fewer than 20 trading days in the year $t-1$. Additionally, we exclude banks and financial firms from our sample.

By applying these three filters to our sample, we observed an increase in the correlation of our value-weighted monthly market returns from 0.93 to 0.95 when compared to Ødegaard's[3] monthly returns. For a comprehensive overview of the filtering process and a comparison with Ødegaard's filtered sample, please refer to appendix 2, which provides descriptive statistics.

[3] We run a correlation of our value-weighted monthly market returns against Ødegaard market returns. The sample can be accessed here: https://ba-odegaard.no/financial_data/ose_asset_pricing_data/index.html

It is worth noting that discrepancies between the two samples are primarily attributed to our decision to exclude stocks without ISIN from our sample. This exclusion was necessary to match Oslo Børs Information (OBI) data with our Refinitiv accounting data, thereby ensuring data consistency and accuracy.

4.1.2 The risk-free rate

As a proxy for the risk-free rate, we use monthly observations of the one-month NIBOR from July 1989 to June 2020 (*N*=372), collected from Ødegaard - estimated from government securities and NIBOR. This is in line with how Fama and French define the risk-free rate in their construction of the market-factor in the FF5, using one-month U.S. treasury bills (Fama and French, 2015).

4.2 Factor construction – independent variables

In this section we explain how we construct the *SMB*, *HML*, *RMW*, *CMA*, and momentum factors. The method applied for factor-mimicking portfolio construction and sorting is the same method used by Fama and French, both in "The Cross-Section of Expected Stock Returns (1992)" and "A Five Factor Asset Pricing Model (2015)".

The excess market return (*MKT*) is a value-weighted portfolio of monthly returns for our entire sample of OSE stocks, less the corresponding months' one-month NIBOR.

4.2.1 Fama and French (and Novy-Marx) five factors

For the five-factor model, we modify the *RMW* factor by using Novy-Marx's gross profitability measure instead of operating profitability. This adjustment is made due to limited data availability. Calculating operating profitability as done by Fama and French (2015) would require additional accounting measures, reducing our already small sample size. This limitation is mainly due to inadequate accounting information for the Norwegian stock market before 1995.

The factor-mimicking portfolios of *SMB*, *HML*, *RMW* and *CMA* are formed using a double sort (2x3) on *size* and *B/M, GP*, or *Inv*. Fama and French state in their concluding remarks in "A Five Factor Asset Pricing Model" (2015), that any of the sorts they used (2x2, 2x3, or 2x2x2x2 sort that jointly control for *size*, *B/M, OP* and *Inv*) produce similar descriptions of the LHS portfolios used to examine mean returns. We decided on the 2x3 sort, rather than the 2x2, to have a more granular overview of different portfolio characteristics.

In June of each year *t*, stocks on OSE are ranked based on *size* using the median market equity (ME) of OSE stocks. They are then divided into two *size* groups: small (*S*) and big (*B*). The book-to-market ratio (*B/M*) is calculated by dividing the book value of equity by the market value of equity reported in December of the previous year. Stocks are independently sorted into three *B/M* groups: high *(H)*, neutral *(N)*, and low *(L)*. Combining the *size* and *B/M* sorts creates six intersection portfolios: *SL*, *SN*, *SH*, *BL*, *BN*, and *BH*. The portfolios' monthly value-weighted returns are calculated from July of year *t* to June of *t + 1*, and the portfolios are reformed accordingly. This formation period in June ensures that financial reports are known in the market before forming the portfolios, following Fama and French (1992, 1993, 2015).

The $SMB_{B/M}$ factor is formed by averaging the returns of the three small portfolios (*SH*, *SN*, and *SL*) and subtracting the mean returns of the three big portfolios (*BH*, *BN*, and *BL*). The *HML* factor is the mean returns of the two high portfolios (*SH* and *BH*) minus the mean returns of the two low portfolios (*SL* and *BL*). This aims to remove most of the *size*-related returns from the *HML* factor. The correlation between $SMB_{B/M}$ and *HML* for the sample period from July 1989 to June 2020 is -0.079.

The *CMA* factor and SMB_{Inv} are constructed in a similar manner to *HML*. Investments are measured as the percentage change in book value of total assets between $t - 2$ and $t - 1$. Stocks are sorted into three groups: conservative *(C)*, neutral *(N)*, and aggressive *(A)* based on the same OSE breakpoints as before, for investments. Combining the *size* and *Inv* sorts creates six portfolios: *SC*, *SN*, *SA*, *BC, BN*, and *BA*. The SMB_{Inv} factor is formed by averaging the returns of the three small portfolios (*SC*, *SN*, and *SA*) and subtracting the mean returns of the three big portfolios (*BC*, *BN*, and *BA*). *CMA* is the mean returns of the two conservative portfolios (*SC* and *BC*) minus the mean returns of the two aggressive portfolios (*SA* and *BA*). The correlation between SMB_{Inv} and *CMA* is 0.050, indicating that *CMA* is independent of *size*-related returns.

The *RMW* factor is based on the gross-profitability-to-assets ratio (Novy-Marx, 2013). It follows the same 2x3 sort on *size* and gross-profitability-to-assets as *HML* and *CMA*. The ratio is calculated as net sales minus cost of goods sold (COGS) divided by total assets. Stocks are ranked and sorted into three groups: weak *(W)*, neutral *(N)*, and robust *(R)* profitability. Combining the *size* and *GP* sorts creates six portfolios: *SR*, *SN*, *SW*, *BR*, *BN*, and *BW*. The SMB_{GP} factor is the mean returns of the three small portfolios (*SR*, *SN*, and *SW*) minus the mean returns of the three big portfolios (*BR*, *BN*, and *BW*). The *RMW* factor is the mean returns of the two robust portfolios (*SR* and *BR*) minus the mean returns of the two weak portfolios (*SW* and *BW*). The correlation between the *RMW* factor and SMB_{GP} is 0.038.

4.2.2 The *UMD* factor

The naming of the *UMD* factor is arbitrary, and we may sometimes refer to it as the Fama-French momentum factor. We chose *UMD* to distinctly separate the momentum factor that is sorted on *size* from the original Jegadeesh and Titman (1993) and Carhart (1997) factors – which we have labelled winners-minus-losers (*WML*) and prior-one-year-return (*PR1YR*).

The *UMD* factor is double sorted on *size* in a similar way as *HML*, *CMA*, and *RMW*, using OSE breakpoints for *size* and momentum. The main difference in the sorts on momentum is that the *size*-momentum portfolios are formed monthly. Portfolios formed on momentum are calculated as the cumulative return of a stock from $t-11$ to $t-1$ months – skipping the sort month – rebalancing monthly. The winners (*W*) are the top 30%, neutral (*N*) are the middle 40%, and the losers (*L*) are the bottom 30% stocks. The intersection of the independent sort on *size* and momentum creates six value-weight portfolios: *SW, SN, SL, BW, BN*, and *BL*. SMB_{MOM} is the mean of the three small (*SW*, *SN*, *SL*) minus the mean of the three big (*BW*, *BN*, *BL*) portfolios. The *UMD* factor is then the mean of the two winner (*BW*, and *SW*) minus the mean of the two loser (*BL*, *SL*) portfolios. The correlation between SMB_{MOM} and *UMD* is 0.039.

Finally, the *SMB* factor is then the mean of $SMB_{B/M}$, SMB_{Inv}, SMB_{GP}, and SMB_{MOM}.

4.3 LHS portfolios – dependent variable

In "A Five Factor Asset Pricing Model (2015)", Fama and French form finer-sort versions of the RHS portfolios as the LHS test portfolios. Given our sample of stocks being significantly smaller than the sample used by Fama and French, we are unable to produce diversified portfolios of 5x5 sorts. In most cases where we have less than 100 stocks in a given month, we get less than 4 stocks (and in some cases 0) in each portfolio.

The alternative would be to create single-sorted portfolios of *size*, *GP*, *Inv,* and momentum. In our view, this would leave out much of the variation that we aim to explain with the RHS portfolios.

We therefore decide to use the 2x3 double-sorted portfolios used to produce the RHS factors as our LHS test portfolios.

4.4 Summary statistics

In this section we report summary statistics for all variables that are used in equation (2).

In table 1 we report factor cross-correlations. Most of the correlations are low, or negative for *SMB*, *HML*, *RMW*, and *CMA*. An intriguing finding involves the relatively strong negative correlation (-0.29) observed between *HML* and *RMW*. This suggests that investment approaches based on gross profitability tend to lean towards growth strategies, while value strategies tend to favor holding unprofitable firms. Moreover, Novy-Marx (2013) also find that while these firms appear to be typical growth firms, they have an exceptionl tendency to outperform the market despite low *B/M.*

Table 1 - Factor Cross Correlations
This table reports the factor cross correlations, of mean monthly returns of the market factor (*MKT*), *SMB*, *HML*, *CMA*, *RMW*, *PR1YR*, *UMD*, and $WML_{9,3}$ factors. The sample period is from July 1989 to June 2020 (*N*=372).

	Factor Cross Correlations							
Factor	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	*PR1YR*	*UMD*	$WML_{9,3}$
MKT	1.00							
SMB	-0.40	1.00						
HML	0.00	-0.00	1.00					
RMW	-0.16	-0.00	-0.29	1.00				
CMA	-0.03	-0.26	0.14	-0.09	1.00			
PR1YR	-0.22	0.01	-0.03	0.15	-0.04	1.00		
UMD	-0.26	0.07	-0.02	0.15	-0.03	0.97	1.00	
$WML_{9,3}$	-0.20	0.03	0.03	0.13	-0.03	0.78	0.76	1.00

We report the results of the Fama and French five factor model for OSE in table 2. The 2x3 sorts on *size* clearly show that for the full sample from July 1989 to June 2020, small firms earn significantly higher mean returns than big firms. The negative relationship between mean monthly returns and *size* is in line with results from Fama and French (1992). The mean returns of the small portfolios are significant with $p < 0.05$, except for two portfolios at $p < 0.1$. Less than half of the nine big portfolios of the same sorts are significant. This is mainly due to the high standard deviation of stock returns for these portfolios.

The 2x3 sorts on *size-B/M,* and *GP* confirm early findings by Fama and French (1992, 2015) that premiums are greater for small firms than for large firms. The small high-*B/M* portfolio *(SH)* earns a mean return of 0.75%, which is 39 bps more than the big high-*B/M (BH)* portfolio. The 2x3 sort of *size-GP* shows the *size* effect for the profitability factor, where small firms with high profitability earn on average 81 bps higher returns than big firms of the same profitability.

When looking at the full-sample mean returns in table 2 for all five factors, we find *SMB* has the highest mean monthly return of 0.56% with a t-stat of 2.62, followed by 0.51% for the market factor *MKT*. Both *RMW* and *CMA* have positive mean returns of 0.19% and 0.05% respectively, but neither are significantly different from zero at any level of interest (p>0.10). When we look at sub-periods of our sample, we see *CMA* is never significant, which is an expected result given that Fama and French (2017) also find the investment factor is perhaps a redundant factor in international tests of the five-factor model.

Table 2 - Summary Statistics for Portfolios formed on Size, B/M, GP, and INV
Mean returns, standard deviations (Std dev.), and t-statistics for the portfolios used in constructing SMB, HML, RMW, and CMA. Independent sorts were used to create two Size groups and two or three groups based on B/M, gross profitability (GP), and investment (Inv). The VW portfolios, defined at the intersections of these groups, served as the foundational components for the factors. Portfolio labels consisted of two or four letters, where the first letter represented small (S) or big (B). In the 2 X 3 sorts, the second letter indicated the B/M group (high (H), neutral (N), or low (L)), the GP group (robust (R), neutral (N), or weak (W)), or the Inv group (conservative (C), neutral (N), or aggressive (A)). The sample is from July 1989 to June 2020. (Fama, French, 2015).

	Fama-French Five Factor Model 2 X 3 Sorts					
Size-B/M	*SL*	*SN*	*SH*	*BL*	*BN*	*BH*
Mean	0.0114	0.0114	0.0075	0.0048	0.0075	0.0036
Std.	0.0715	0.0662	0.0623	0.0642	0.0642	0.0675
t-stat	3.08	3.32	2.32	1.44	2.25	1.01
Size-GP	*SW*	*SN*	*SR*	*BW*	*BN*	*BR*
Mean	0.0110	0.0081	0.0133	0.0036	0.0036	0.0052
Std.	0.0749	0.0887	0.0649	0.0671	0.0710	0.0605
t-stat	2.84	1.75	3.94	1.03	0.97	1.67
Size-Inv	*SC*	*SN*	*SA*	*BC*	*BN*	*BA*
Mean	0.0111	0.0074	0.0149	0.0076	0.0059	0.0030
Std.	0.0656	0.0772	0.0727	0.0666	0.0683	0.0661
t-stat	3.26	1.81	3.26	2.20	1.66	0.89

	Five Factor Mean Returns				
Full Period	*MKT*	*SMB*	*HML*	*RMW*	*CMA*
Mean	0.0051	0.0056	-0.0026	0.0019	0.0005
Std.	0.0553	0.0411	0.0437	0.0469	0.0412
t-stat	1.77	2.62	-1.15	0.79	0.22

The most interesting observation is that of the mean returns of the *HML* factor. Despite not being significantly different from zero, the mean return is negative at -0.26%. The economical interpretation of this is that the *HML* factor for OSE in the sample period is not able to capture the *value* premium that Fama and French find for the U.S. stock market. Rather, there appears to be an outperformance of growth firms (those with low *B/M*) relative to value firms. The pattern can be observed when looking at the returns in the 2x3 sort on *size-B/M.* Where we would expect to find a strong positive relationship between mean returns and *B/M*, we find the opposite. Higher *B/M* portfolios appear to earn lower mean returns than lower *B/M* portfolios.

Table 3 displays the results and descriptive statistics for our momentum portfolios, formed based on the sample period from July 1989 to June 2020. The table includes the mean monthly returns, standard deviation, and t-statistics for the full sample period, as well as subsamples for each factor. We present various strategies for OSE, replicating the approaches of Jegadeesh and Titman (1993), Carhart (1997), and Fama and French (2012). However, we only present the three relative strength strategies that achieved the highest mean returns, as discussed in the previous section. All combinations can be found in Appendix 7, along with full description of momentum factors in Appendix 8.

The spread in mean returns is large between the strategies in table 3. Comparing $WML_{9,3}$ and *UMD* we see that the monthly mean return differs by a factor of two. While *UMD* has a monthly mean return of 0.56% the $WML_{9,3}$ strategy has monthly mean return of 1.18%, both being significant. As we could expect, the higher return strategy is accompanied by higher standard deviation, but surprisingly outperforms on a risk-adjusted basis with a Sharpe ratio of 0.49 compared to 0.42 for *UMD*. A comparison of the Sharpe ratio of each factor is reported in appendix 18.

The momentum strategy, despite its consistent performance across different portfolio formations, does not exhibit a consistent momentum premium over time. While all six momentum strategies show means that are significantly different from zero ($p < 0.05$) for the entire sample period, the strategy performs particularly well during the sub-sample period of 2010-2020. In this sub-sample, the best-performing factor, $WML_{9,3}$, achieves a mean return of 1.58% (with a t-stat of 2.75), which is still significantly higher than the mean return of 0.96% for the *UMD* factor. For the other sub-samples, the mean returns are not significantly different from zero at any level of precision of interest ($p < 0.10$), as they fall within 1.67 standard deviations from zero.

Finally, the table reports correlations between each of the six momentum factors. As expected, the cross-correlations are high, ranging from 0.71 for *UMD* and $WML_{6,3}$ to 0.97 for *PR1YR* and *UMD*. Hence, the choice of which factor to use in an investment strategy in our view comes down to expected returns, risk, and simplicity of implementation.

Table 3 - Summary Statistics for Portfolios formed on Momentum

Summary statistics for portfolios formed on momentum (from July 1989 to June 2020). Variations of Jegadeesh & Titman (1993) that in Appendix 17 perform the highest are reported, both for the entire period, and for each sub period. Carhart *PR1YR* and the *UMD* factor are reported as well. For Jegadeesh & Titman, portfolios are formed based on *J*-month lagged returns and are held for *K*-months. Based on the *J*-month ranked returns, stocks are divided into ten deciles. The lowest past return decile comprises the sell portfolio, and the highest return decile comprises the buy portfolio, both of which are equally weighted. The reported values are mean returns for the highest minus the lowest decile portfolios. *PR1YR* is constructed as the equal-weight mean of firms with the highest 30 percent eleven-month returns lagged one month minus the equal-weight mean of firms with the lowest 30 percent eleven-month returns lagged one month. *UMD* is produced from double-sorts on size to form 6 portfolios (2x3). At the end of month t, the lagged momentum return is a stock's cumulative return for t-11 to t-1. *UMD* is then the equal weight mean of the three winners minus three loser portfolios.

	Titman & Jegadeesh (1993) - WML				Carhart (1997)	Fama-French
Full period	$J = 6, K = 3$	$J = 9, K = 3$	$J = 12, K = 3$	$J = 6, K = 6$	*PR1YR*	*UMD*
Mean	0.0112	0.0118	0.0084	0.0010	0.0057	0.0056
Std.	0.0712	0.0731	0.0759	0.0649	0.0463	0.0456
t-Stat	3.31***	3.47***	2.16**	3.28***	2.40**	2.42**
Sub period	Mean / std. (t-Stat)	Mean / std. (t-Stat)	Mean / std. (t-Stat)	Mean / std. (t-Stat)	Mean / std. (t-Stat)	Mean / std. (t-Stat)
1989-1999	0.0049/0.0709 (0.79)	0.0056/0.0729 (0.86)	0.0051/0.0767 (0.74)	0.0059/0.0654 (1.01)	0.0012/0.0406 (0.29)	0.0002/0.0472 (0.05)
2000-2009	0.0107/0.0821 (1.42)	0.0099/0.0817 (1.32)	0.0065/0.0821 (0.87)	0.0092/0.0722 (1.40)	0.0069/0.0531 (1.43)	0.0071/0.0476 (1.63)
2010-2020	0.0152/0.0619 (2.74)***	0.0158/0.0645 (2.75)***	0.0135/0.0655 (2.31)**	0.0118/0.0567 (2.34)**	0.0090/0.0357 (2.83)***	0.0096/0.0386 (2.79)***

Cross-Correlations						
Factor	*PR1YR*	*UMD*	$WML_{6,3}$	$WML_{6,6}$	$WML_{9,3}$	$WML_{12,3}$
PR1YR	1.00					
UMD	0.97	1.00				
$WML_{6,3}$	0.72	0.71	1.00			
$WML_{6,6}$	0.78	0.77	0.92	1.00		
$WML_{9,3}$	0.77	0.76	0.89	0.93	1.00	
$WML_{12,3}$	0.81	0.76	0.78	0.86	0.90	1.00

5 Results and analysis

In this chapter we present the results of our asset pricing tests of the five- and six-factor model. To answer our research question if the Fama and French five-factor model with momentum can explain stock returns on OSE, we use the Fama-MacBeth and GRS asset pricing tests. We compare the results to the five-factor model and perform robustness checks using multiple versions of the momentum factor. As a further robustness check we compare the six-factor models improvement over competing three- and four-factor models.

5.3 Results of Factor Spanning Regressions

Our objective is to determine if the returns of the dependent variable factor is explained by any of the other factors. We specifically pay attention to the intercepts of the regressions, as a non-zero intercept would indicate that the dependent variable factor is not fully explained by the other factors.

Table 4 - Factor-spanning regressions

Regression of each factor on the other four. Sample from July 1989 to June 2020. An intercept significantly different from zero rejects the null hypothesis that the dependent factor returns are captured well by the other factors in the model. T-statistics, slope estimates, and R^2 are reported.

	Int.	*MKT*	*SMB*	*HML*	*RMW*	*CMA*	Adj. R^2
MKT							
Coef.	0.010		-0.54	-0.06	-0.22	-0.07	0.19
t-stat	3.22		-8.63	-0.92	-3.76	-1.16	
SMB							
Coef.	0.010	-0.31		-0.02	-0.07	-0.05	0.16
t-stat	3.70	-8.63		-0.38	-1.61	-0.93	
HML							
Coef.	-0.00	-0.04	-0.02		-0.27	0.12	0.09
t-stat	-0.82	-0.92	-0.38		-5.64	2.24	
RMW							
Coef.	0.00	-0.17	-0.10	-0.30		-0.07	0.11
t-stat	1.11	-3.76	-1.61	-5.64		-1.27	
CMA							
Coef.	0.00	-0.05	-0.05	-0.11	-0.06		0.02
t-stat	0.66	-1.16	-0.933	2.24	-1.27		

The factor spanning regressions in table 4 show that *HML*, *RMW* and *CMA* could be redundant in a five-factor model for the entire sample period. We fail to reject the null hypothesis that $\alpha_i = 0$ in each case at any level of significance of interest

($p < 0.10$). Had it not been for the adj. R^2 being very low, this could indicate that the other factors capture all, or most, of the variation in expected returns of each of these factors. Further, the low adj. R^2 and low factor cross-correlations indicate absence of multicollinearity.

In table 5 we present results of factor spanning regressions where we regress each factor against the other factors of the five-factor model and the three momentum factors. We find a non-zero intercept for all momentum factors, and a low adj. R^2. This leads us to believe that the momentum factors can't be explained by the other factors, and that it is persistent regardless of factor construction. Overall, results from the factor-spanning regressions indicate that including momentum in the five-factor model can help explain stock returns on OSE.

Similar to table 4 earlier, we find that *MKT* and *SMB* have intercepts significantly different from zero ($p < 0.01$) for models 1 and 2, rejecting the null hypothesis that $\alpha_i = 0$. For *HML*, *RMW*, and *CMA*, we observe similar results as before. Neither produce significant intercepts in the regression.

For regressions 6-11 we test each of the momentum factors against the five-factor model. We find that for all of the momentum factors, intercepts are significantly different from zero with $p < 0.05$. We also observe that *RMW* loads positively and significantly at least to $p < 0.1$ for all the momentum factors. For the other four factors, only the market factor is significant ($p < 0.05$) but with a negative loading for each of the regressions.

It is crucial to acknowledge that conclusions regarding factor spanning can be specific to the sample being analysed. In sub-samples (Appendix 9) we do find all factors significant except *CMA*. Discrepancies observed between the results for *HML*, and *CMA* in our study and that of Fama and French (2015) suggest that factors redundant during one period might hold importance in another. It is important to note that evidence of redundancy derived from factor spanning tests is conclusive only within a specific sample (Fama and French, 2017). If a factor's average return for a given period can be explained by its exposures to other factors within a model, it serves no role in describing average returns for that specific period within that model. This conclusion remains unaltered, and no set of LHS portfolios can refute this finding (Fama, 1998; Barillas and Shanken, 2015).

Table 5
Factor-spanning Regressions

The factors of the five factor model are regressed on eachother to test if the returns of one factor are explained by the other factors. Then, momentum factors are regressed on the five factor model to test if momentum factor returns are explained by the five factor model. An intercept significantly different from zero rejects the null hypothesis that the dependent variable factor return is fully explained by the other factors. *MKT* is the value-weight return on the market portfolio of all sample stocks minus the one-month NIBOR; *SMB* (small minus big) is the size factor; *HML* (high minus low B/M) is the value factor; *RMW* (robust minus weak OP) is the profitability factor; and *CMA* (conservative minus aggressive Inv) is the investment factor. *PR1YR* is the Carhart (1997) momentum factor, $WML_{J,K}$ is the Titman & Jegadeesh (1993) factor, with portfolios formed on *J* lagged returns, and held for *K* months, and *UMD* is the Fama French (2012) momentum factor (size-sorted). Factor portfolio returns from July 1989 to June 2020 ($N = 372$).

	Dependent Variables										
	Five Factor Model					Momentum Factors					
Independent Variables	*MKT* (1)	*SMB* (2)	*HML* (3)	*RMW* (4)	*CMA* (5)	*PR1YR* (6)	*UMD* (7)	$WML_{6,6}$ (8)	$WML_{6,3}$ (9)	$WML_{9,3}$ (10)	$WML_{12,3}$ (11)
MKT		-0.2885	-0.0348	-0.147	0.0510	-0.1951	-0.2114	-0.1645	-0.2004	-0.2747	-0.2492
		(-7.84)	(-0.77)	(-3.13)	(1.16)	(-4.19)	(-4.62)	(-2.46)	(-2.71)	(-3.67)	(-3.28)
SMB	-0.5002		-0.0282	-0.090	0.0705	-0.0998	-0.0398	0.0146	-0.0030	-0.0971	-0.1640
	(-7.83)		(-0.48)	(-1.44)	(1.22)	(-1.62)	(-0.66)	(0.17)	(-0.03)	(-0.33)	(-1.63)
HML	-0.0472	-0.0220		-0.300	-0.1122	-0.0003	0.0043	0.1220	0.0750	0.1063	0.1311
	(-0.77)	(-0.48)		(5.46)	(-2.20)	(-0.00)	(0.08)	(1.53)	(0.85)	(1.19)	(1.44)
RMW	-0.1782	-0.0629	-0.2682		0.0567	0.1001	0.0976	0.1845	0.0750	0.1670	0.2783
	(-3.13)	(-1.44)	(-5.46)		(1.17)	(1.91)	(1.89)	(2.45)	(2.31)	(1.98)	(3.24)
CMA	0.0719	0.0574	-0.1169	0.0661		0.0476	0.0306	0.0858	0.0388	0.0628	0.1069
	(1.16)	(1.22)	(-2.20)	(1.17)		(0.84)	(0.55)	(1.05)	(0.43)	(0.69)	(1.15)
PR1YR	0.3738	-0.8243	-0.1734	0.0211	0.2792						
	(1.44)	(-4.28)	(-0.78)	(0.09)	(1.28)						
UMD	-0.5854	0.7739	0.0727	0.0299	-0.2557						
	(-2.29)	(4.05)	(0.33)	(0.13)	(-1.18)						
$WML_{9,3}$	-0.0365	0.0120	0.0847	0.0397	0.0047						
	(-0.67)	(0.29)	(1.82)	(0.81)	(0.10)						
Intercept	*0.0096*	*0.0074*	*-0.002*	*0.0017*	*-0.0018*	*0.0071*	*0.0066*	*0.0097*	*0.0111*	*0.0124*	*0.0104*
	*(3.67)******	*(3.81)******	*(-0.93)*	*(0.73)*	*(-0.80)*	*(2.99)****	*(2.86)****	*(2.88)****	*(2.96)****	*(3.25)******	*(2.70)******
Obs.	372	372	372	372	372	372	372	372	372	372	372
Adj R^2	0.15	0.20	0.089	0.092	0.001	0.053	0.095	0.024	0.032	0.044	0.058

5.4 Results of first step Fama-MacBeth regressions

This section presents the results of the first step of the Fama-MacBeth risk premia estimation, which involves time series regression. We use double-sorted portfolios formed on *size* and *B/M*, *GP*, *Inv*, and momentum as our LHS portfolios. These portfolios are selected because they are formed based on the characteristics that we aim to explain using the RHS factor-mimicking portfolios.

We conduct time series regressions on the five-factor model and the five-factor model with momentum. Specifically, we test if the inclusion of the *UMD* momentum factor improves the explanation of stock returns on OSE compared to the five-factor model. The UMD factor is used as a proxy due to its strong correlation with other momentum factors. However, in the two-step Fama-MacBeth procedure, all momentum factors are included as a robustness check (Appendix 26).

In table 6 and Appendix 21, we present the results of the Fama and French five-factor model, which includes the profitability and investment factors. The *RMW* factor loads positively and significantly ($p < 0.001$) for portfolios with robust profitability and negatively for weak portfolios, which is expected and desirable as the *RMW* factor aims to explain returns related to profitability. For other portfolios, the factor generally loads negatively. Similar results are found for the *CMA* factor, but it is less significant for portfolios other than *size-Inv*.

We now want to compare the performance of the five-factor model and the five-factor model plus momentum, to examine if including momentum can explain stock returns on OSE.

Table 7 and Appendix 22 report the results of the five-factor model with the inclusion of the momentum factor *UMD*. Contrary to our expectations, adding a momentum factor to the five-factor model does not improve the model and appears to make it less efficient. The mean adj. R^2 for the five-factor model with momentum is 0.66, which is lower than the 0.71 achieved by the five-factor model alone. This trend is also observed when examining the mean absolute value of the intercept for all 24 portfolios, which is 0.0019 compared to 0.0014 for the five-factor model. The *UMD* factor is only significantly different from zero in two instances outside of the *size*-MOM portfolios. These findings align with Fama and French (2014, 2015), who noted that when forming portfolios based on momentum, it is crucial for the model to include a momentum factor. This observation is consistent with our results for the portfolios in this study.

If we compare the results of the five-factor model with the five-factor model plus momentum, we see significant improvements of adj. R^2 for portfolios sorted on momentum. The mean adj. R^2 for all six portfolios increases to 0.73 from 0.66 when we include the momentum factor.

Table 6 – Estimation of Factor Loadings for the Five-Factor model

Estimation of the Fama French Five factor model on portfolios double-sorted on size B/M, OP, INV, and MOM from July 1989 to June 2020 (*N*=372). Portfolios are sorted into two size groups (S and B) using OSE median market cap. Portfolios are independently sorted into B/M, OP, INV, and mom portfolios using the 30th and 70th percentiles of OSE for each factor. This results in a 2x3 sort with 6 intersection portfolios. H/R/A/W is the 70th percentile, *L*/W/C/*L* is the 30th percentile, and *N* is the neutral middle portfolio. OLS estimates, t-stats, and Adj. R^2 is reported. Intercepts that are significantly different from zero indicate a wrongly specified model.

Size-MOM		α_i	$b_{i,1}$	$s_{i,2}$	$h_{i,3}$	$r_{i,4}$	$c_{i,5}$	Adj. R^2
Small	W	0.0011 (0.58)	0.8053 (21.60)	0.6441 (12.18)	0.0140 (0.31)	-0.0673 (-1.78)	0.0799 (1.86)	0.58
	N	0.0003 (0.21)	0.7234 (22.79)	0.6181 (13.73)	0.1283 (3.38)	-0.0305 (-0.94)	0.0082 (0.22)	0.61
	L	-0.0047 (-2.04)	1.0171 (21.72)	0.6733 (10.14)	0.0169 (0.31)	-0.1211 (-2.55)	0.0717 (1.33)	0.58
Big	W	0.0102 (5.95)	0.9198 (26.40)	0.1561 (3.16)	-0.0491 (-1.18)	-0.0663 (-1.88)	-0.0042 (-0.105)	0.70
	N	0.0034 (2.44)	0.8840 (30.85)	0.0809 (1.99)	0.0315 (0.92)	-0.0522 (-1.80)	0.0072 (0.22)	0.77
	L	0.0024 (1.05)	1.1886 (25.26)	0.1674 (2.51)	0.0107 (0.19)	-0.2004 (-4.20)	0.0231 (0.43)	0.69

Table 7 – Estimation of Factor Loadings for Five-Factor plus momentum

Estimation of the Fama French Five factor model plus *UMD* on portfolios double-sorted on size B/M, OP, INV, and MOM from July 1989 to June 2020 (*N*=372). Portfolios are sorted into two size groups (S and B) using OSE median market cap. Portfolios are independently sorted into B/M, OP, INV, and mom portfolios using the 30th and 70th percentiles of OSE for each factor. This results in a 2x3 sort with 6 intersection portfolios. H/R/A/W is the 70th percentile, *L*/W/C/*L* is the 30th percentile, and *N* is the neutral middle portfolio. OLS estimates, t-stats, and Adj. R^2 is reported. Intercepts that are significantly different from zero indicate a wrongly specified model.

Size-MOM		α_i	$b_{i,1}$	$s_{i,2}$	$h_{i,3}$	$r_{i,4}$	$c_{i,5}$	$u_{i,5}$	Adj. R^2
Small	W	-0.0012 (-0.72)	0.8862 (25.18)	0.6509 (13.52)	0.0245 (0.61)	-0.0990 (-2.89)	0.0831 (2.13)	0.3369 (8.73)	0.65
	N	0.0002 (0.16)	0.7260 (22.04)	0.6183 (13.72)	0.1286 (3.38)	-0.0315 (-0.97)	0.0083 (0.22)	0.008 (0.30)	0.60
	L	-0.0007 (-0.38)	0.8757 (22.07)	0.6614 (12.17)	-0.0016 (-0.03)	-0.0659 (-1.69)	0.0661 (1.49)	-0.588 (-13.5)	0.72
Big	W	0.0079 (5.08)	1.0003 (30.82)	0.1629 (3.69)	-0.0386 (-1.03)	-0.0978 (-3.06)	-0.0010 (-0.03)	0.3349 (9.05)	0.76
	N	0.0036 (2.50)	0.8791 (29.57)	0.0805 (1.98)	0.0309 (0.90)	-0.0503 (-1.72)	0.0070 (0.21)	-0.020 (-0.62)	0.77
	L	0.0074 (4.59)	1.0108 (29.95)	0.1524 (3.30)	-0.0125 (-0.32)	-0.1309 (-3.94)	0.0160 (0.43)	-0.740 (-19.9)	0.85

5.5 Results from two-step Fama-MacBeth regressions

In this section we report the results of the two-step Fama-MacBeth regressions. We test each model jointly on the set of LHS portfolio returns we wish to explain. The model is true if the intercepts are zero, and the factor is priced if λ_i is significantly different from zero. Overall, we find that the five-factor model can't explain returns of the *size-MOM* portfolios fully. We find that including a momentum factor is crucial for improving model performance when the LHS portfolios are formed with momentum as a characteristic.

Table 8 presents the results of the five-factor model and the five-factor model with momentum. Notably, when including the momentum factor, we observe non-zero intercepts for all LHS portfolios, which is not strictly the case for the five-factor model. Additionally, the inclusion of momentum leads to marginal model improvements for the *size-MOM* portfolios, with a mean R^2 of 0.74 compared to 0.65 for the five-factor model without momentum.

Table 8 - Estimating Risk Premia – Fama-MacBeth for FF5 and momentum

Two step Fama MacBeth regression on 2x3 double-sorted portfolios formed on size and B/M, GP, INV, and MOM from July 1989 to June 2020. The panel displays the estimated risk premiums for both the intercept and each factor. These risk premiums are calculated using the Fama-MacBeth (1973) regression method. The regressions analyse the monthly excess return of the portfolio based on the estimated factor(s). In accordance with the model's validity, the intercept (α) should be zero. A factor is considered priced if its value (λ_i) significantly deviates from zero.

Five Factor with *UMD*

Portfolio	α	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{UMD}	R^2
Size-B/M	0.000	0.0068	0.0142	-0.0026	-0.1487	0.5405	-0.1553	0.73
p-value	0.00	0.65	0.84	0.26	0.91	0.90	0.91	
Size-GP	-0.000	0.0043	0.0076	-0.0160	0.0019	0.0042	-0.0047	0.63
p-value	0.00	0.30	0.04	0.61	0.43	0.79	0.87	
Size-INV	0.000	0.0055	0.0059	-0.0238	0.0149	0.0004	-0.0621	0.68
p-value	0.00	0.38	0.06	0.56	0.76	0.87	0.28	
Size-MOM	-0.000	0.0072	-0.0482	0.1058	-0.0927	0.5110	0.0055	0.74
p-value	0.00	0.88	0.91	0.91	0.89	0.92	0.02	

Five Factor model

Portfolio	α	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	R^2
Size-B/M	0.000	0.0063	0.0056	-0.0026	0.0065	0.0313	0.72
p-value	0.06	0.05	0.26	0.29	0.93	0.88	
Size-GP	-0.000	0.0046	0.0073	-0.0137	0.0020	0.0056	0.63
p-value	0.88	0.20	0.01	0.51	0.43	0.70	
Size-INV	-0.000	0.0037	0.0071	-0.0436	0.0475	-0.0011	0.68
p-value	0.04	0.48	0.06	0.39	0.77	0.74	
Size-MOM	0.000	0.0122	0.0144	-0.0416	0.0117	-0.2426	0.65
p-value	0.02	0.75	0.86	0.75	0.97	0.81	

Although the adj. R^2 values are relatively high for both models, we struggle to estimate significant risk premia. In the five-factor model, we find monthly risk premia of 0.63% for the *MKT* factor and 0.73% and 0.71% for *SMB*, but only for

portfolios sorted on *size-B/M*, *GP*, and Inv. Risk premia for the other portfolios are not significantly different from zero ($p > 0.1$). In the five-factor model with momentum, we can estimate risk premia for *SMB* and *UMD*, with premiums of 0.76% and 0.55% respectively.
To summarize our findings from the two-step Fama-MacBeth regressions, we find that the five-factor model explains cross-sectional returns of portfolios with momentum characteristics poorly. Including momentum factors in the five-factor model improves the model in explaining these returns. Our results are in line with what Fama and French (1996) discovered that the three-factor in itself is unable to explain cross-sectional variation in momentum-sorted portfolios, which we see to hold as well for the five-factor model. This is what lead Carhart (1997) to extend the model with the *PR1YR* factor for his evaluation of persistence in mutual fund performance. Overall, we believe our findings are expected, and well founded in financial research literature.

In the next section, we use the GRS test to test all combinations of LHS portfolios. We specifically focus on the absolute values of the intercepts $|a|$, the GRS test statistics, R^2 and the Sharpe ratio of the alphas *SR(a)*. Together, these will be used to qualitatively and quantitively assess model performance.

5.6 Results from the GRS test

Table 9 reports the results of the GRS test for all models. Panel A shows the test statistics for all LHS portfolios of the five-factor models both with and without momentum. Panel B shows the critical values for each GRS test. We use the CAPM as a benchmark when comparing the two models. We reject the hypothesis that all intercepts in a set of 6 regressions are zero if the GRS statistic is larger than the critical values computed in Panel B.

Our results suggest that we reject the CAPM on all LHS portfolios. This result is in line with what we have found earlier both for the time-series and two-step Fama-MacBeth regressions (appendix 19, 23). The GRS test confirms that other models have the potential to explain cross-sectional returns better.

We fail to reject the null hypothesis for all LHS portfolios when considering both the five-factor model with and without momentum, except for portfolios sorted on momentum. This suggests that the portfolios tested do not exhibit any significant unexplained risk premiums, indicating that the model specification effectively explains returns on OSE. However, when testing the five-factor model with momentum, we observe enhancements in the R^2, $|a|$, and *SR(a)* for the LHS portfolios sorted on *size-MOM*. These findings align with the results obtained from the Fama-MacBeth regressions, emphasizing the importance of incorporating a momentum factor when estimating portfolios with momentum characteristics. As for the remaining portfolios, there is insufficient compelling evidence that the inclusion of a momentum factor in the model leads to a better explanation of returns on OSE. When evaluating the models based on the GRS statistic, the five-factor model with momentum outperforms the other model in two out of three portfolios, while it performs less strongly for portfolios formed on *size-INV*.

Table 9 - GRS Asset Pricing Test and Summary Statistics
Summary statistics for regressions to explain monthly excess returns on LHS portfolios from 2x3 sorts on size and B/M, size-Mom, size-GP, and size-INV. July 1989 to June 2020. The regressions use the CAPM, three-factor, three-factor with momentum, five-factor, and five-factor with momentum models with factors to explain the returns on LHS portfolios. Mom_1 is the *UMD* factor. Mom_2 is the *PR1YR*. Mom_3 is the best-performing WML factor ($WML_{9,3}$). The GRS statistic tests whether all intercepts in a set of 6 regressions are zero; |a| is the mean absolute intercept for a set of regressions; R^2 is the mean adjusted R^2; s(a) is the mean standard error of the intercepts; and SR(a) is the Sharpe ratio for the intercepts (Fama and French, 2015). Critical Value for each GRS test is reported in *Panel B*.

Panel A:	*Size*-B/M					*Size*-MOM				
	GRS	|a|	R^2	*s(a)*	*SR(a)*	GRS	|a|	R^2	*s(a)*	*SR(a)*
CAPM	2.31	0.0045	0.49	0.0024	0.20	11.2	0.0047	0.56	0.0020	0.35
FF5	1.58	0.0015	0.72	0.0019	0.14	10.3	0.0035	0.65	0.0019	0.39
FF5+mom_1	1.51	0.0017	0.72	0.0019	0.13	9.91	0.0026	0.71	0.0016	0.36
	Size-GP					*Size*-INV				
	GRS	|a|	R^2	*s(a)*	*SR(a)*	GRS	|a|	R^2	*s(a)*	*SR(a)*
CAPM	3.55	0.0043	0.48	0.0026	0.23	3.97	0.0049	0.61	0.0022	0.21
FF5	0.71	0.0012	0.64	0.0023	0.10	1.59	0.0025	0.75	0.0019	0.14
FF5+mom_1	0.64	0.0012	0.64	0.0024	0.10	1.81	0.0027	0.75	0.0018	0.15

Panel B:	Significance level			
	1%	5%	10%	15%
Critical Values	2.85	2.12	1.79	1.56

Overall, when we evaluate all parameters in conjunction, the five-factor model with momentum *on average* has the lowest GRS-statistic, highest R^2, and lowest *SR(a)*. However, based on results of the factor-spanning regressions we do suspect factor redundancies in the five-factor model with momentum. We therefore test competing models that excludes the *RMW* and *CMA* factor to compare the results of these models with the five- and five-factor model with momentum. The results of this analysis is presented in the next chapter.

5.7 Robustness checks

In this chapter, we examine if the six-factor model's performance is dependent on a specific momentum factor or consistent across various factor constructions. Additionally, we estimate two competing models: Fama and French's three-factor model with and without momentum. This analysis is driven by the potential redundancy of the *CMA* factor on OSE.

We test the model using the *UMD*, *PR1YR* and $WML_{9,3}$ momentum factors. The construction of *PR1YR* and $WML_{9,3}$ can be found in appendix 6 and 8.

5.7.1 Competing models

As a further robustness test, we estimate:

$$R_{it}^{*} = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t + \epsilon_{it} \quad (3)$$

$$R_{it}^{*} = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t + u_i MOM_t + \epsilon_{it} \quad (4)$$

Evidence suggest that adding a momentum factor to a three-factor model enhances its ability to capture cross-sectional returns. Carhart (1997) demonstrates this in the U.S. market, while Fama and French (2012) extend the investigation to international markets, providing supporting evidence. Fama and French (2015) expand their original three-factor model by incorporating two additional factors for the U.S. market and later test the model in international markets (2017), suggesting further exploration with a momentum factor. However, substantial research on a five-factor model with momentum, especially on a global scale, is lacking.

5.7.2 GRS test of competing models

Table 10 reports the results of the GRS test of all models, with and without combinations of the momentum factors. We find that the results are consistent across factor construction. This gives evidence to our research question that the momentum factor should be included in the five-factor model when explaining stock returns on OSE.

If we take a more granular view, the CAPM has the highest absolute value of intercept, the lowest R^2 and highest *SR(a)* out of all models. The CAPM has a 0.24% monthly return that we cannot explain. Any improvements in *SR(a)* are minor and not significant beyond the three-factor model.

We find that the majority of performance increase comes from moving from CAPM to a three-factor model. Absolute value of the intercept decreases by approximately

27 bps on average, when adding *SMB* and *HML* to the model. The reduction is less prominent for additional factors, at 1-2 bps for a five-factor model. When we look specifically at *size-MOM* portfolios, the absolute values of the intercepts are almost identical for a three- and five factor model.

Table 10 - GRS Asset Pricing Test and Summary Statistics
Summary statistics for regressions to explain monthly excess returns on LHS portfolios from 2x3 sorts on size and B/M, size-Mom, size-GP, and size-INV. July 1989 to June 2020. The regressions use the CAPM, three-factor, three-factor with momentum, five-factor, and five-factor with momentum models with factors to explain the returns on LHS portfolios. Mom_1 is the *UMD* factor. Mom_2 is the *PR1YR*. Mom_3 is the best-performing WML factor ($WML_{9,3}$). The GRS statistic tests whether all intercepts in a set of 6 regressions are zero; |a| is the mean absolute intercept for a set of regressions; R^2 is the mean adjusted R^2; s(a) is the mean standard error of the intercepts; and SR(a) is the Sharpe ratio for the intercepts (Fama and French, 2015). Critical Value for each GRS test is reported in *Panel B*.

Panel A:	*Size*-B/M					*Size*-MOM				
	GRS	|a|	R^2	*s(a)*	*SR(a)*	GRS	|a|	R^2	*s(a)*	*SR(a)*
CAPM	2.84	0.0045	0.49	0.0024	0.20	7.56	0.0047	0.56	0.0020	0.35
FF3	1.42	0.0017	0.71	0.0019	0.15	8.55	0.0034	0.63	0.0019	0.38
FF3+mom_1	1.32	0.0018	0.71	0.0019	0.14	8.35	0.0023	0.71	0.0018	0.35
FF3+mom_2	1.38	0.0019	0.71	0.0019	0.14	5.45	0.0025	0.69	0.0017	0.29
FF3+mom_3	1.29	0.0017	0.71	0.0019	0.14	3.99	0.0022	0.67	0.0019	0.24
FF5	1.27	0.0015	0.72	0.0019	0.14	8.81	0.0035	0.65	0.0019	0.39
FF5+mom_1	1.21	0.0017	0.72	0.0019	0.13	8.76	0.0026	0.71	0.0016	0.36
FF5+mom_2	1.27	0.0017	0.71	0.0019	0.14	5.81	0.0026	0.70	0.0017	0.29
FF5+mom_3	1.19	0.0016	0.71	0.0019	0.13	4.15	0.0025	0.67	0.0018	0.25
	Size-GP					*Size*-INV				
	GRS	|a|	R^2	*s(a)*	*SR(a)*	GRS	|a|	R^2	*s(a)*	*SR(a)*
CAPM	3.12	0.0043	0.48	0.0026	0.23	4.05	0.0049	0.61	0.0022	0.21
FF3	0.83	0.0013	0.58	0.0025	0.12	1.65	0.0026	0.68	0.0021	0.14
FF3+mom_1	0.69	0.0012	0.58	0.0024	0.11	1.88	0.0027	0.68	0.0021	0.15
FF3+mom_2	0.67	0.0013	0.58	0.0025	0.11	1.86	0.0027	0.68	0.0021	0.15
FF3+mom_3	0.69	0.0010	0.58	0.0025	0.12	1.79	0.0027	0.68	0.0021	0.15
FF5	0.70	0.0012	0.64	0.0023	0.10	1.59	0.0025	0.75	0.0019	0.14
FF5+mom_1	0.62	0.0012	0.64	0.0024	0.10	1.81	0.0027	0.75	0.0018	0.15
FF5+mom_2	0.61	0.0012	0.64	0.0024	0.10	1.79	0.0027	0.75	0.0018	0.15
FF5+mom_3	0.64	0.0009	0.64	0.0024	0.10	1.75	0.0026	0.75	0.0018	0.15

Panel B:	Significance level			
	1%	5%	10%	15%
Critical values	2.85	2.12	1.79	1.56

The most important result to note from the GRS test is that regardless of which model we estimate, including a momentum factor significantly improves model performance. However, the improvement in unexplained mean return, *SR(a),* is marginal between the three- and the five-factor model with momentum.

5.7.3 Sub sample performance of factors

We analyse the characteristics of the five-factor model in more detail for different sub-sample periods in table 11. The market and *SMB* factors continue to exhibit positive mean returns, although their statistical significance varies across the sub-periods. In the 2010-2020 sub-period, the *HML* factor shows significance, but interestingly, it does not function as a value premium. Instead, it displays characteristics more aligned with growth stocks. In the 2000-2009 sub-period, the *RMW* factor is significant ($p<0.1$) with a negative mean return of -0.73%. This finding suggests that stocks with robust *GP* underperform those with weak *GP* during that particular period. This contradicts the findings of Novy-Marx (2013) and Fama and French (2015), who observed a positive association between high operating profitability and higher mean returns. Furthermore, both the *RMW* and *CMA* factors appear insignificant across all tested sub-samples, indicating that they may have limited explanatory power for cross-sectional stock returns on the OSE.

Table 11 - Summary Statistics for Portfolios formed on Size, B/M, GP, and INV
Mean returns, standard deviations (Std dev.), and t-statistics for the portfolios used in constructing SMB, HML, RMW, and CMA. Independent sorts were used to create two Size groups and two or three groups based on B/M, gross profitability (GP), and investment (Inv). The VW portfolios, defined at the intersections of these groups, served as the foundational components for the factors. Portfolio labels consisted of two or four letters, where the first letter represented small (S) or big (B). In the 2 X 3 sorts, the second letter indicated the B/M group (high (H), neutral (N), or low (L)), the GP group (robust (R), neutral (N), or weak (W)), or the Inv group (conservative (C), neutral (N), or aggressive (A)). The sample is from July 1989 to June 2020. (Fama, French, 2015).

1989-1999	*MKT*	*SMB*	*HML*	*RMW*	*CMA*
Mean	0.0032	0.0100	-0.0040	0.0079	-0.0003
Std.	0.0571	0.0466	0.0466	0.0535	0.0452
t.sat	0.63	2.41	-1.00	1.63	-0.30
2000-2009	*MKT*	*SMB*	*HML*	*RMW*	*CMA*
Mean	0.0073	0.0035	0.0040	-0.0074	0.0031
Std.	0.0658	0.0428	0.0464	0.0437	0.0447
t.sat	1.21	0.91	0.94	-1.87	0.75
2010-2020	*MKT*	*SMB*	*HML*	*RMW*	*CMA*
Mean	0.0048	0.0031	-0.0073	0.0050	-0.0012
Std.	0.0410	0.0328	0.0372	0.0412	0.0329
t.stat	1.32	1.08	-2.21	1.37	-0.40

The limited enhancements observed when transitioning from a three-factor model with momentum to a five-factor model with momentum can possibly be explained by examining the results of the sub-sample statistics for the factors. This is due to the insignificance of the *CMA* factor across all sub-samples, and the significant presence of the *RMW* factor in only one sub-sample period. Considering these factors as the sole distinction between the two models, the relatively weak improvements are not surprising. These findings align with the conclusions drawn by Fama and French (2017) regarding the insignificance of the *CMA* factor in the European market as well.

6 Conclusions

In this thesis we test if the Fama and French five-factor model including momentum can explain stock returns on OSE. We find that including a momentum factor improves model performance and is necessary to price momentum risk in portfolios as it cannot be explained by other factors. This is evident from the Fama-MacBeth regression resulting in an increase in the adj. R^2 from 0.65 to 0.74 for portfolios with momentum characteristics. These results are robust to factor construction. Moreover, when including momentum in tests of all portfolios, we observe an average increase in the adj. R^2 from 0.67 to 0.70, primarily driven by the *size-MOM* portfolios. Our robustness tests on competing models consistently show that the five-factor model with momentum outperforms the three-factor model with momentum, as reflected by higher adj. R^2 values.

Our motivation for conducting robustness tests on competing models stems from the presence of redundant factors within the five-factor model, particularly those associated with investments and profitability. While we observe evidence supporting the presence of the *RMW* factor in certain sub-samples, we do not find any statistically significant evidence for the *CMA* factor. Given the findings of Fama and French (2015), who suggest that the majority of the variation linked to *B/M* can be explained by the profitability and investment factor, we rank the GRS statistics for the three-factor model and the five-factor model on portfolios categorized by *size-B/M*. This enables us to specifically identify the contributions of the *RMW* and *CMA* factors in enhancing the overall performance of the model.

The GRS statistics favour the five-factor over the three-factor model, and we cautiously attribute improvements to the *RMW* factor rather than *CMA*. However, further testing is required to establish conclusive results without the inclusion of *CMA*. These findings remain consistent when examining both the five-factor model and the five-factor model with momentum on the *size-B/M* portfolio.

Given the observed improvement of the five-factor model over the three-factor model, it is anticipated that the GRS statistics for both models with momentum would also exhibit improvement, as confirmed by our findings. However, considering the modest magnitude of this improvement, we recommend adopting a parsimonious approach by favouring the three-factor model with momentum.

6.1 Limitations and Further Research

The validity of our results is limited to the specific set of LHS portfolios tested in this thesis. These portfolios are finer sorts of our RHS factor returns. However, it would be valuable for future research to investigate the robustness of the model in explaining stock returns of other diversified portfolios. Additionally, conducting out-of-sample testing would assess the efficiency of the model in estimating expected returns, which has not been explored in this thesis. Such research could provide further validation for the use of a five-factor model with momentum in estimating expected returns for portfolios on OSE.

Further research is warranted regarding the composition of risk factors used in the five-factor model and the six-factor model including momentum. Our findings suggest that the *CMA* factor may not contribute significantly to explaining stock returns on OSE. However, we have not tested models that exclude the *CMA* factor, and it would be worthwhile to investigate if excluding this factor leads to robust results for explaining stock returns on OSE.

It is worth noting that the adj. R^2 values obtained in our thesis are lower compared to those reported by Fama and French for the U.S. market. This difference implies that there might be other factors that better explain stock returns on OSE than those utilized in the five- and the six-factor model with momentum. Further research is needed to identify and incorporate these potential factors to enhance the explanatory power of the models for OSE stock returns.

In conclusion, it is important to exercise caution when comparing our results with previous literature due to the lack of overlapping sample periods and extensive research on the Norwegian market. Our analysis is based on a specific sample period that may differ from those used in previous studies. Therefore, future research focusing on the OSE should aim to replicate our findings using the same sample period to ensure better comparability and enable more meaningful comparisons with the existing body of literature.

References

Aharoni, G., Grundy, B. D., & Zeng, Q. (2013). Stock returns and the Miller Modigliani valuation formula: Revisiting the Fama French analysis. *Journal of Financial Economics*, *110*(2), 347–357. https://doi.org/10.1016/j.jfineco.2013.08.003

Asness, C. S., Moskowitz, T. *J*., & Pedersen, *L*. H. (2013). Value and Momentum Everywhere. *Journal of Finance*, *68*(3), 929–985. https://doi.org/10.1111/jofi.12021

Banz, R. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, *9*(1), 3–18. https://doi.org/10.1016/0304-405x(81)90018-0

Barberis, *N*., Shleifer, A., & Vishny, R. (1998). A Model of Investor Sentiment. *Journal of Financial Economics*, *49*(3), 307–343.

Barillas, F., & Shanken, J. (2016). Which Alpha? *Review of Financial Studies*, *30*(4), 1316–1338. https://doi.org/10.1093/rfs/hhw101

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

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *Journal of Finance*, *52*(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chan, *K*., Chan, *L*. *K*., Jegadeesh, *N*., & Lakonishok, *J*. (2006). Earnings Quality and Stock Returns*. *The Journal of Business*, *79*(3), 1041–1082. https://doi.org/10.1086/500669

Chan, *L*. *K*., Lakonishok, *J*., & Sougiannis, T. (2001). The Stock Market Valuation of Research and Development Expenditures. *Journal of Finance*, *56*(6), 2431–2456. https://doi.org/10.1111/0022-1082.00411

Daniel, *K*., Hirshleifer, D., & Subrahmanyam, A. (1998). Investor Psychology and Security Market Under- and Overreactions. *Journal of Finance*, *53*(6), 1839–1885. https://doi.org/10.1111/0022-1082.00077

Ehsani, S., & Linnainmaa, *J*. T. (2022). Factor Momentum and the Momentum Factor. *Journal of Finance*, *77*(3), 1877–1919. https://doi.org/10.1111/jofi.13131

Fama, E. F. (1998). Determining the Number of Priced State Variables in the ICAPM. *Journal of Financial and Quantitative Analysis*, *33*(2), 217. https://doi.org/10.2307/2331308

Fama, E. F., & French, *K*. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, *47*(2), 427–465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, *K*. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 3–56. https://doi.org/10.1016/0304-405x(93)90023-5

Fama, E. F., & French, *K*. R. (2006). Profitability, investment, and mean returns. *Journal of Financial Economics*, *82*(3), 491–518. https://doi.org/10.1016/j.jfineco.2005.09.009

Fama, E. F., & French, *K*. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics*, *105*(3), 457–472. https://doi.org/10.1016/j.jfineco.2012.05.011

Fama, E. F., & French, *K*. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Fama, E. F., & French, *K*. R. (2017). International tests of a five-factor asset pricing model. *Journal of Financial Economics*, *123*(3), 441–463. https://doi.org/10.1016/j.jfineco.2016.11.004

Fama, E. F., & MacBeth, *J*. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, *81*(3), 607–636. https://doi.org/10.1086/260061

Gibbons, M., Ross, S. *L*., & Shanken, *J*. (1989). A Test of the Efficiency of a Given Portfolio. *Econometrica*, *57*(5), 1121. https://doi.org/10.2307/1913625

Griffin, *J*. H. (2002). Are the Fama and French Factors Global or Country Specific? *Review of Financial Studies*, *15*(3), 783–803. https://doi.org/10.1093/rfs/15.3.783

Hong, H., & Stein, *J*. C. (1999). A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. *Journal of Finance*, *54*(6), 2143–2184. https://doi.org/10.1111/0022-1082.00184

Hou, *K*., Xue, C., & Zhang, *L*. (2015). Digesting Anomalies: An Investment Approach. *Review of Financial Studies*, *28*(3), 650–705. https://doi.org/10.1093/rfs/hhu068

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

Kamstra, M. *J*., & Shi, R. (2020). A Note on the GRS Test. *Social Science Research Network*. https://doi.org/10.2139/ssrn.3775089

Lintner, *J*. (1965a). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, *47*(1), 13–37. https://doi.org/10.2307/1924119

Markowitz, H. M. (1952). Portfolio Selection. *Journal of Finance*, *7*(1), 77. https://doi.org/10.2307/2975974

Novy-Marx, R. (2012). Is momentum really momentum? *Journal of Financial Economics*, *103*(3), 429–453. https://doi.org/10.1016/j.jfineco.2011.05.003

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, *108*(1), 1–28. https://doi.org/10.1016/j.jfineco.2013.01.003

Rosenberg, B., Reid, *K*. B., & Lanstein, R. (1985b). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management*, *11*(3), 9–16. https://doi.org/10.3905/jpm.1985.409007

Sharpe, W. F. (1964). CAPITAL ASSET PRICES: A THEORY OF MARKET EQUILIBRIUM UNDER CONDITIONS OF RISK*. *Journal of Finance*, *19*(3), 425–442. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Titman, S., Wei, *K. J*., & Xie, F. (2004). Capital Investments and Stock Returns. *Journal of Financial and Quantitative Analysis*, *39*(4), 677–700. https://doi.org/10.1017/s0022109000003173

Ødegaard, B. (2021). Empirics of the Oslo Stock Exchange. Basic, descriptive, results 1980-2020. [Unpublished manuscript]

Ødegaard, B., Næs, R., & Skjeltorp, J. (2008). Hvilke faktorer driver kursutviklingen på Oslo Børs. *Norsk Økonomisk Tidskrift*, *2*.

Appendix

Appendix 1 - Number of companies with corresponding accounting data

The table reports the number of firms in sample with corresponding accounting data, that are also included (matched by ISIN) in OBI dataset. Refinitiv end-of-year accounting data from 1980 to 2020. The possible sample space contains 1,043 firms, while Refinitiv database contain 706 firms. After matching OBI and Refinitiv on common ISIN matching criteria, the sample is reduced to 546 firms that are included in our sample.

Year	Net Sales	COGS	D&A	NET INCOME	EQUITY	ASSETS	Int. ASSETS	CAPEX
1980	26	23	20	26	26	26	1	18
1981	27	24	21	27	27	27	1	21
1982	27	24	22	27	27	27	1	23
1983	28	25	23	28	28	28	1	24
1984	35	28	31	35	34	34	2	29
1985	38	30	34	38	38	38	2	33
1986	41	31	35	41	41	40	4	33
1987	81	64	69	81	81	81	41	69
1988	93	76	81	94	94	94	59	86
1989	104	87	89	105	106	106	92	96
1990	108	93	94	108	109	109	98	99
1991	106	93	94	107	108	108	100	107
1992	106	92	91	107	105	105	104	104
1993	113	99	98	114	111	111	108	111
1994	117	103	103	117	117	116	114	116
1995	117	102	101	116	116	116	114	113
1996	194	109	173	192	194	194	188	182
1997	213	110	188	212	213	213	209	202
1998	224	111	193	223	222	222	219	213
1999	215	103	187	215	215	215	209	202
2000	198	110	179	198	198	198	191	188
2001	200	123	180	200	199	199	192	186
2002	205	163	184	206	200	200	196	186
2003	199	164	181	199	198	197	191	183
2004	218	186	204	219	220	220	214	210
2005	242	205	236	241	239	239	225	233
2006	251	218	245	250	250	250	235	241
2007	257	224	253	257	257	256	249	248
2008	241	209	240	242	242	241	234	231
2009	237	204	232	237	238	237	230	231
2010	242	209	235	242	243	242	238	238
2011	240	207	236	241	241	240	236	230
2012	245	210	239	245	245	244	238	232
2013	232	202	228	232	232	231	228	213
2014	226	197	224	228	227	226	222	214
2015	227	196	223	227	227	227	222	215
2016	226	194	222	226	225	225	217	217
2017	225	190	220	225	225	225	220	218
2018	220	186	217	220	220	220	218	215
2019	212	177	210	212	212	212	209	206
2020	205	170	203	205	205	205	202	197

Appendix 2 – Number of stocks per year after filtering

The table reports the number of stocks in our sample for each year. The **table** includes the sample before and after applying each filter. We compare the sample to the sample reported in Ødegaard (2021). Filter 1 is stocks with share price <10 NOK, Filter 2 is stocks with less than 1m NOK MCAP, and filter 3 is less than 20 trading days in year t-1. Sample from 1980 to 2020.

	Own Filtered Sample				Ødegaard Filtered Sample			
Year	No filter	Filter 1	Filter 2	Filter 3	No filter	Filter 1	Filter 2	Filter 3
1980	66	36	36	36	96	33	33	33
1981	84	52	52	51	99	48	47	47
1982	94	72	72	71	116	60	58	58
1983	108	89	89	87	129	93	90	90
1984	123	109	109	109	149	122	121	121
1985	140	126	126	125	170	152	149	149
1986	160	139	137	137	184	157	146	146
1987	154	132	128	127	183	149	133	133
1988	140	117	112	111	165	128	113	113
1989	132	113	108	107	181	151	138	138
1990	147	126	125	124	191	163	149	149
1991	147	131	127	125	172	151	123	123
1992	134	119	107	106	172	131	101	101
1993	136	121	115	114	185	147	114	114
1994	153	142	135	135	195	164	143	143
1995	154	144	136	136	194	166	148	148
1996	170	163	150	150	206	189	170	169
1997	176	171	162	162	250	229	200	199
1998	220	211	197	197	269	248	190	190
1999	232	219	191	191	263	241	185	185
2000	213	199	184	184	259	239	183	183
2001	217	198	164	164	247	224	143	143
2002	207	194	141	141	226	210	119	119
2003	205	188	135	135	218	196	109	109
2004	180	177	137	137	207	200	132	132
2005	188	183	150	150	238	226	164	164
2006	215	213	181	181	258	249	193	193
2007	223	220	194	194	292	280	223	223
2008	266	259	213	213	286	275	144	144
2009	249	241	153	153	267	253	113	113
2010	233	226	154	154	259	251	138	138
2011	235	230	157	157	253	245	125	125
2012	232	227	151	151	243	239	119	119
2013	225	220	140	140	240	234	131	131
2014	210	205	143	143	236	231	138	138
2015	210	208	148	148	229	226	131	131
2016	205	204	144	144	221	220	130	130
2017	207	201	144	144	227	225	140	140
2018	204	203	154	154	221	219	143	143
2019	202	197	148	148	226	225	147	147
2020	207	190	140	140	222	222	127	127
Mean	181	169	139	138	211	191	135	135

Appendix 3

Factor-spanning regressions:

$$MKT_t = \alpha_i + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t$$
$$SMB_t = \alpha_i + b_i MKT_t + h_i HML_t + r_i RMW_t + c_i CMA_t$$
$$HML_t = \alpha_i + b_i MKT_t + s_i SMB_t + r_i RMW_t + c_i CMA_t$$
$$RMW_t = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t + c_i CMA_t$$
$$CMA_t = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t$$

Appendix 4

Factor-spanning regression including momentum:

$$MKT_t = \alpha_i + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + u_i UMD_t$$
$$SMB_t = \alpha_i + b_i MKT_t + h_i HML_t + r_i RMW_t + c_i CMA_t + u_i UMD_t$$
$$HML_t = \alpha_i + b_i MKT_t + s_i SMB_t + r_i RMW_t + c_i CMA_t + u_i UMD_t$$
$$RMW_t = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t + c_i CMA_t + u_i UMD_t$$
$$CMA_t = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + u_i UMD_t$$
$$UMD_t = \alpha_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t$$

Appendix 5

Construction of *Size, B/M,* profitability, investments, and momentum factors:

Sort	Breakpoints	Factors and components
2 x 3 sorts on	*Size:* OSE median	
Size and *B/M,* or		$SMB_{B/M} = (SH + SN + SL)/3 - (BH + BN + BL)/3$
Size and *GP*, or		$SMB_{OP} = (SR + SN + SW)/3 - (BR + BN + BW)/3$
Size and *Inv,* or		$SMB_{Inv} = (SC + SN + SA)/3 - (BC + BN + BA)/3$
Size and *mom*		$SMB_{Mom} = (SW + SN + SL)/3 - (BW + BN + BL)/3$
		$SMB = (SMB_{B/m} + SMB_{GP} + SMB_{Inv} + SMB_{mom})/4$
B/M: 30th and 70th OSE percentiles		$HML = (SH + BH)/2 - (SL + BL)/2$
GP: 30th and 70th OSE percentiles		$RMW = (SR + BR)/2 - (SW + BW)/2$
Inv: 30th and 70th OSE percentiles		$CMA = (SC + BC)/2 - (SA + BA)/2$
Mom: 30th and 70th OSE percentiles		$UMD = (SW + BW)/2 - (SL + BL)/2$

Appendix 6 – WML and PR1YR

As a robustness check, we create the two momentum factors WML and PR1YR. These are used to check if factor creation can influence the results of the six-factor model.

Winners minus Losers (WML)

Using the original Jegadeesh and Titman paper on momentum (1993), we construct the winners-minus-losers (*WML*) factor. Each month *t*, stocks are ranked by their past *J* month returns, creating ten decile portfolios. The top performers are categorized as winners (bottom decile) and the worst performers as losers (top decile). We buy the winner portfolio and sell the loser portfolio in month *t*, holding the position for *K* months. Simultaneously, positions from *t-K* are closed out. Our strategy includes overlapping periods, so we also hold portfolios from the previous *K-1* months at any given time *t*. We explore different combinations of *J* and *K*, in quarterly increments, denoted as $WML_{J,K}$.

Unlike the *UMD* factor, *WML* is not sorted on *size*, hence for the strategies examined later, we make no adjustments to the *SMB* factor for the *WML* factor. The correlation between *UMD* and *WML* is 0.78.

PR1YR

The Carhart *PR1YR* factor is constructed to capture the momentum effect found by Jegadeesh and Titman, but the portfolio formation is different. Each month *t*, stocks are sorted and ranked based on their past eleven month returns, lagged one month. The stocks with the top 30% and bottom 30% returns are sorted into two portfolios. The factor is constructed as the equal weight mean of the top performing portfolio minus the equal weight mean of the bottom performing portfolio. The strategy is rebalanced monthly.

The *PR1YR* factor is not sorted on *size* but has a correlation of 0.97 with the *UMD* factor. The only difference between the *PR1YR* and the *UMD* is the *size* sort.

Appendix 7- Returns of Relative Strength Portfolios

Portfolios are formed based on *J*-month lagged returns and are held for *K*-months. The values of *J* and *K* for various strategies are displayed in the first column and row of the table. Based on the *J*-month ranked returns, stocks are divided into ten deciles. The lowest past return decile comprises the sell portfolio, and the highest return decile comprises the buy portfolio, both of which are equally weighted. The table presents the mean monthly returns for these portfolios. The relative strength portfolios are established right after calculating the lagged returns to create the portfolio (Jegadeesh, Titman, 1993). July 1989 to June 2020.

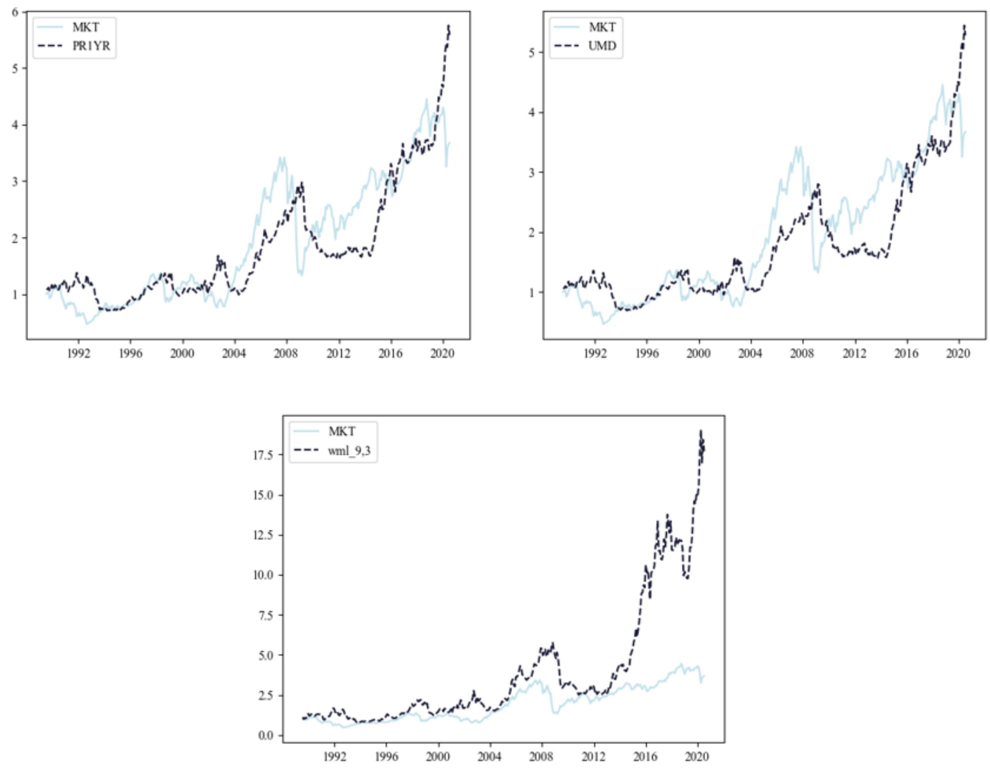
			Panel A			
	J	*K* =	3	6	9	12
3	Sell		0.0054	0.0053	0.0064	0.0078
			(1.43)	(1.49)	(1,85)	(2.27)
3	Buy		0.0145	0.0152	0.0150	0.0138
			(4.71)	(5.04)	(5.10)	(4.72)
3	Buy-sell		0.0096	0.0099	0.0085	0.0059
			(3.02)	(3.92)	(3.84)	(2.97)
6	Sell		0.0064	0.0066	0.0076	0.0097
			(1.62)	(1.74)	(2.05)	(2.66)
6	Buy		0.0177	0.0166	0.0156	0.0136
			(5.45)	(5.37)	(5.16)	(4.64)
6	Buy-sell		0.0112	0.010	0.0079	0.0039
			(3.31)	(3.28)	(2.93)	(1.57)
9	Sell		0.0064	0.0075	0.0095	0.0113
			(1.62)	(1.89)	(2.43)	(2.94)
9	Buy		0.0177	0.0164	0.0141	0.0122
			(5.45)	(5.31)	(4.71)	(4.19)
9	Buy-sell		0.0118	0.0089	0.0046	0.0009
			(3.47)	(2.81)	(1.59)	(0.33)
12	Sell		0.0087	0.0113	0.0134	0.0147
			(2.06)	(2.71)	(3.26)	(3.62)
12	Buy		0.0175	0.0145	0.0126	0.0114
			(5.28)	(4.66)	(4.18)	(3.90)
12	Buy-sell		0.0087	0.0031	-0.0008	-0.0033
			(2.44)	(0.93)	(-0.26)	(-1.07)

Appendix 8 – Momentum and the momentum factors

In this section, we present the overall results for the six momentum factors and analyse the characteristics of momentum on OSE. Momentum is a prominent feature of stock returns on OSE, captured in mean returns for all strategies examined. For the full sample period relative strength portfolios consistently exhibit positive and statistically significant means. Unlike for the U.S. market, momentum-crashes on OSE are less dramatic. February shows strong abnormal returns for relative strength portfolios, while January tends to be weaker.

We begin by reporting the cumulative return of the best performing relative strength strategies we include in our analysis (figure 1). The plots illustrate one of our key findings about the momentum factor on OSE; that momentum has its moments.

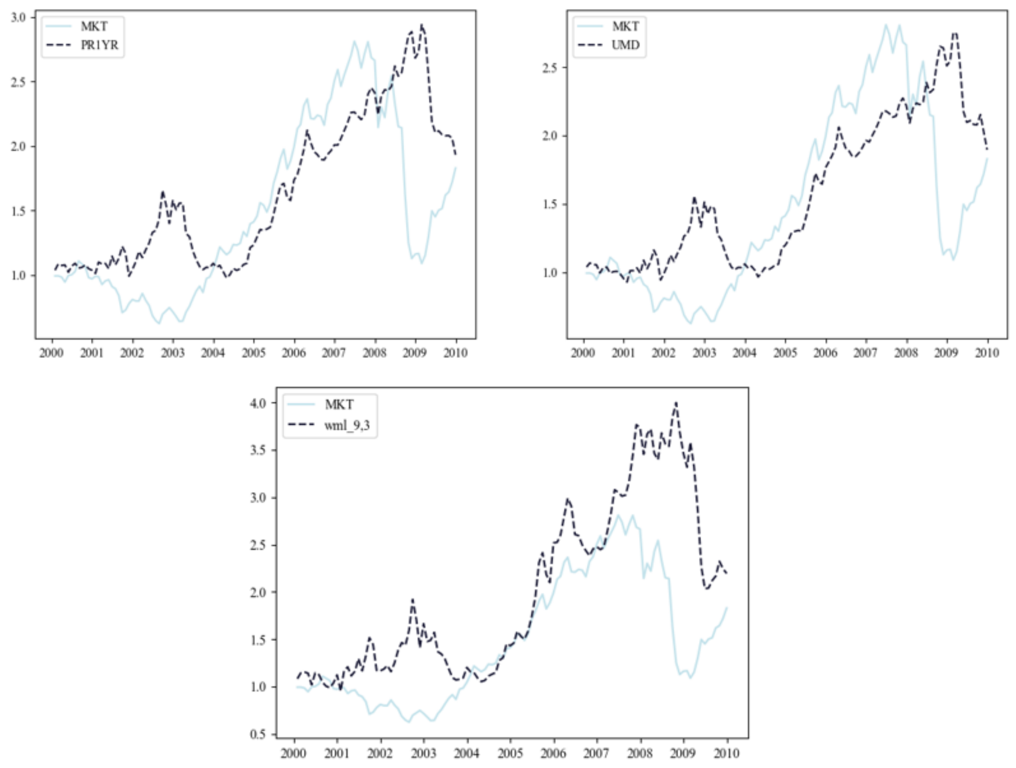
Figure 1 – Cumulative return of relative strength momentum strategies
The plot shows the cumulative returns from July 1989 to June 2020 of the three most profitable momentum strategies examined: *PR1YR*, *UMD*, and $WML_{9,3}$. The returns are compared to the cumulative returns of the value-weighted market index MKT, that contain all stocks in our sample for OSE.



The momentum factors on OSE show significant and positive mean returns for the entire sample period, but their performance varies in different sub-samples. Relative strength portfolios tend to underperform during times of distress, such as the GFC, although to a lesser extent than observed in the U.S. market. Unlike Barroso and

Santa-Clara's (2015) findings of serious crashes in momentum strategies, we do not observe such extreme negative returns on OSE. Although the drawdowns are substantial, the strategy performs well on a relative basis. Figure 2 demonstrates that momentum on OSE does not exhibit a strong negative return pattern. However, it is important for investors to be aware of the volatility and potential negative skewness and kurtosis associated with the momentum strategy.

Figure 2 – Performance of Relative strength portfolios during market distress
This figure shows the performance of relative strength portfolios *PR1YR*, *UMD*, and $WML_{9,3}$ during market distress. Cumulative returns from Jan 2000 to Dec 2009. The returns are compared to the cumulative returns of the value-weighted market index MKT, that contain all stocks in our sample for OSE.



Similar to Jegadeesh and Titman (1993) we find that formation and holding period for the relative strength momentum strategies substantially impact the mean returns of the strategy. We replicate all combinations of *J* and *K* that are presented in the original paper from 1993 (Appendix 7).

We find that the best performing strategies that gives the highest mean returns have holding periods of no more than $K = 3$. For longer holding periods, the mean returns fall, until they turn negative for $J = 12$, $K = 12$. We will keep $WML_{6,3}$, $WML_{6,6}$, $WML_{9,3}$ and $WML_{12,3}$ with the highest mean returns for further investigation. To illustrate how mean returns are affected by formation and holding periods, we report Appendix 7 as a 3D surface plot, which clearly shows how mean returns taper off as you extend holding period beyond $K = 3$.

Figure 3 – 3D Surface Plot of Appendix III
The figure shows the buy-sell mean returns for each of the *J* formation and *K* holding periods in Appendix 7. The X axis is the formation period *J*, the Y axis the holding period *K*, and the Z axis is the mean return of the buy-sell strategy for each *J* and *K*. Sample from July 1989 to June 2020.

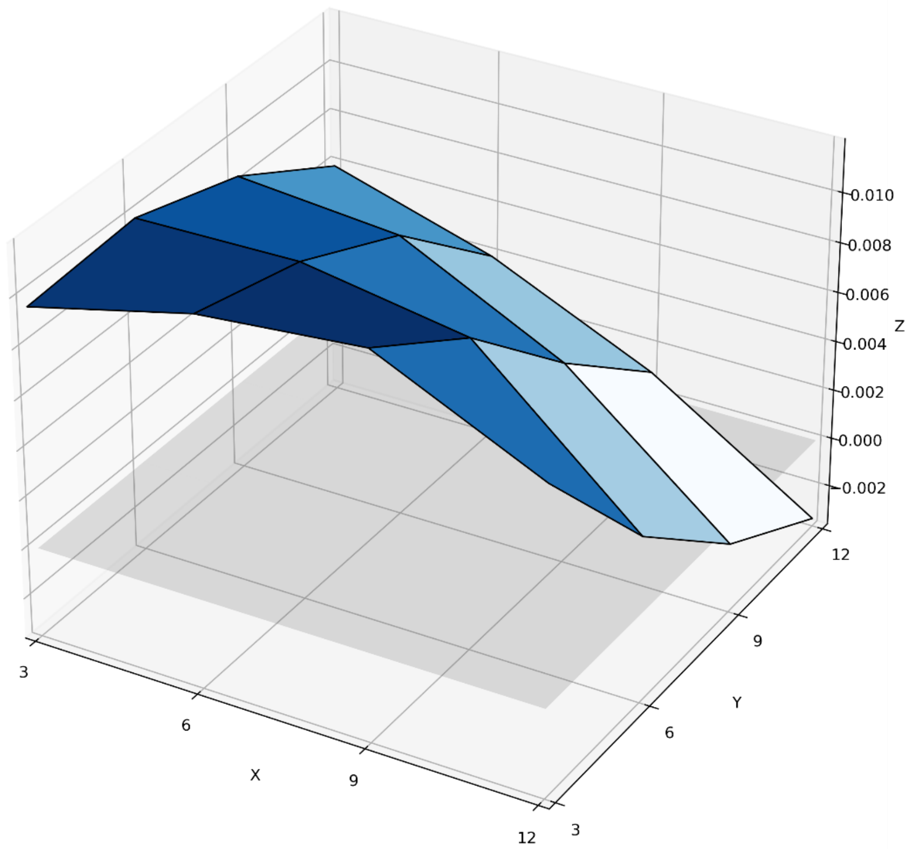


Figure 3 also shows that the effect of holding period is much stronger than extending formation period. The gradient along the Y axis (holding period) is substantially steeper than the gradient along the X axis (formation period).

Jegadeesh and Titman (1993) report positive mean returns for all sell and buy strategies in Appendix 7, with most means significantly different from zero, except for the $J = 3$, $K = 3$ strategy. Their most successful strategy is based on portfolios formed using the previous 12 months and held for 3 months, with a mean return of 1.31% and a t-statistic of 3.74. In contrast, our findings differ as we identify the $J = 9$, $K = 3$ strategy as yielding the highest mean returns.

As with the five factors in figure 7 in appendix 9 we want to look closer at the time-varying characteristics of the momentum factor. Figure 4 reports rolling t-statistics for each of the six momentum factors reported in table 3.

Figure 4 – Time-varying t-statistics, momentum factors
This figure reports the t-statistics for a 60-month (5 year) rolling window for the $WML_{6,3}$, $WML_{9,3}$, $WML_{12,3}$, $WML_{6,6}$, *PR1YR*, and *UMD*. The sample period is from July 1989 to June 2020. The blue, shaded areas indicate each instance where the p-value is below p<0.1 (t-value of 1.67). The red dashed line shows the t-statistic that corresponds to a p-value of less than 0.1.

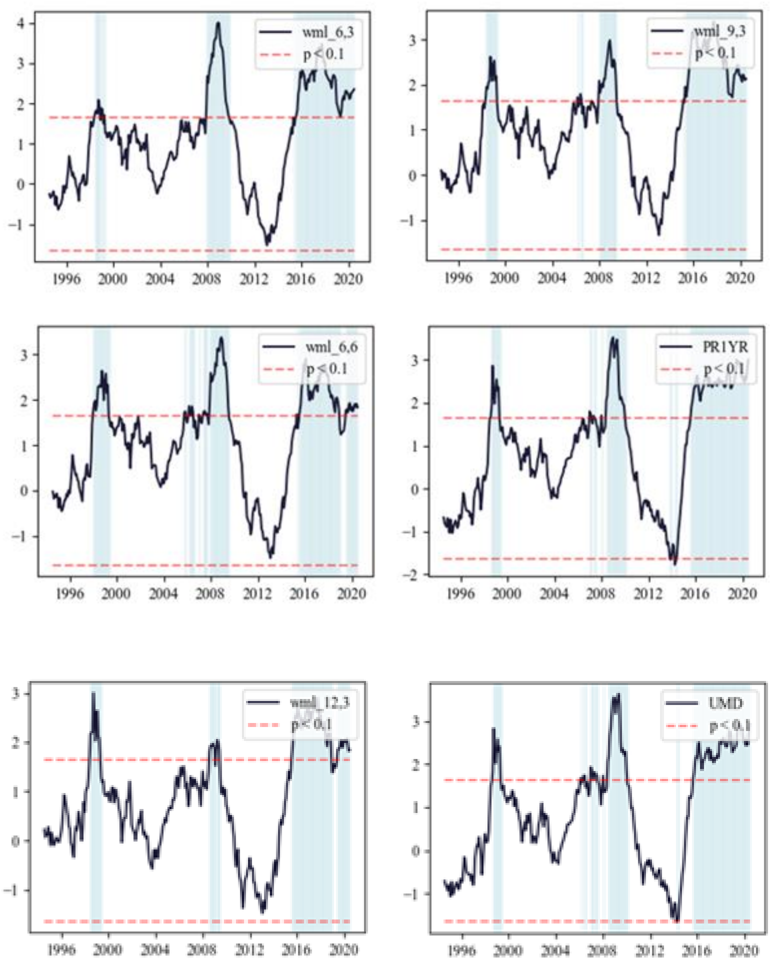


Figure 4 presented displays the time-varying t-statistics for the six momentum factors that were constructed and reported in table 3. As expected, the figure shows that the factors exhibit almost identical patterns, indicating a high level of correlation among them. This aligns with our earlier observation that the factors capture similar variations in the data.

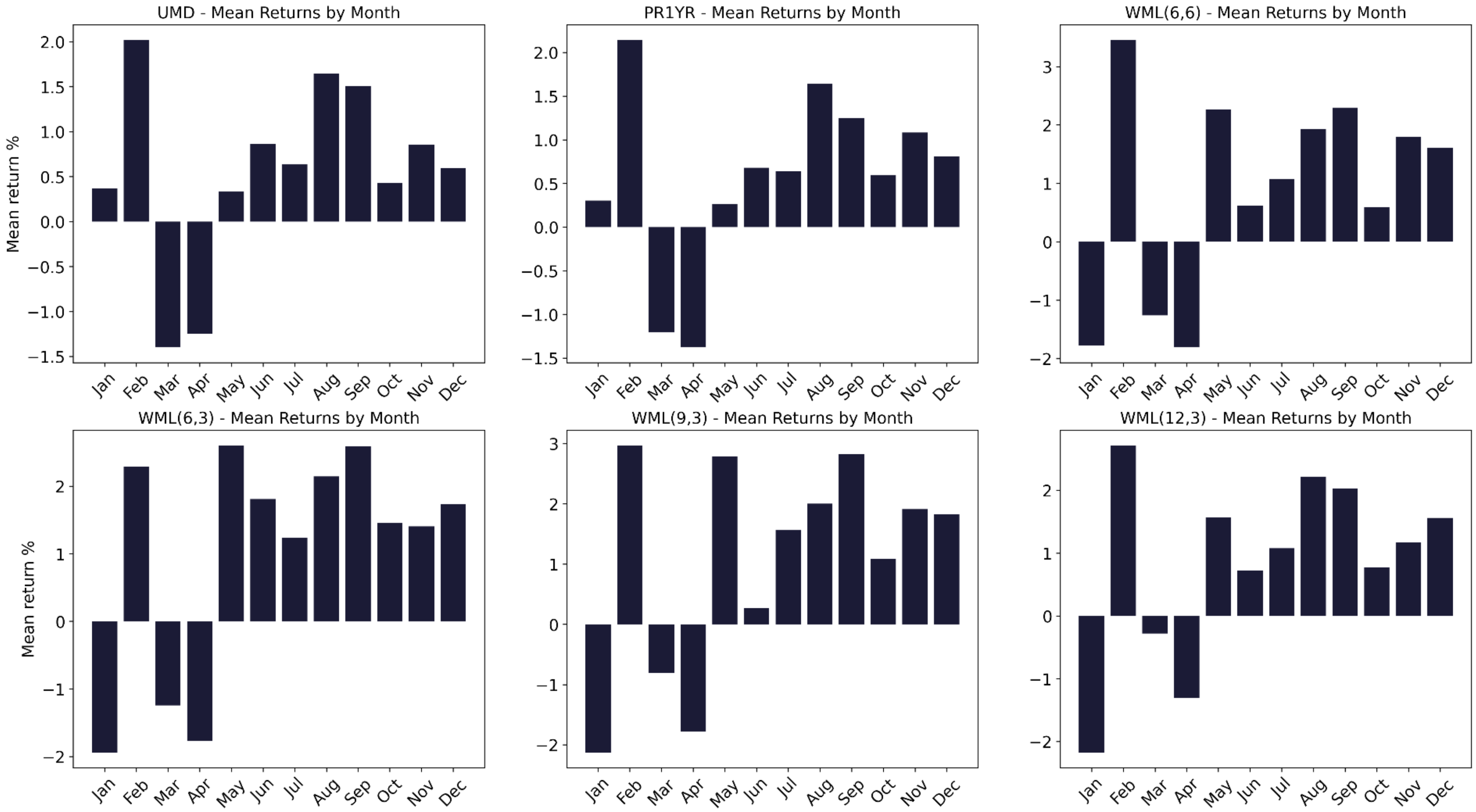
Figure 5 also provides evidence supporting our suspicion that momentum strategies are time-varying. This is evident when examining instances where the t-statistic deviates from 1.67 standard deviations from zero ($p < 0.1$). Notably, during times of crisis, such as the GFC, the t-statistic becomes insignificant when included in the data sample used for estimation. This highlights the risk of a momentum crash during such periods.

Furthermore, figure 4 offers insight into why the mean returns reported in table 3 are all positive. In all instances where the mean return is significantly different from zero, the mean is positive. There are only two cases (for *PR1YR* and *UMD*) where the mean return is both negative and significant, indicating a reversal pattern where past losers outperform past winners in the subsequent month.

We find strong seasonal patterns of momentum return for OSE that are similar across all six momentum factors. The month of February tends to perform well, along with May, August, and September. January, however, tends to perform badly in four of the strategies examined. If other months perform poorly, it tends to be March and April. This pattern is consistent across all of the six momentum factors. The monthly return for February is strongest for $WML_{6,6}$ with a mean of 3.45% and a t-stat of 2.74. The proportion of positive returns for February for the entire sample is 0.77. To further illustrate the strong momentum returns in February, we calculate the total proportion of total factor returns for the entire sample period attributable to February to be 31.4% for the *PR1YR* factor. August, another strong month for this factor, accounts for 24.1% of total returns. For *UMD*, this proportion is 30.5% (February) and 24.9% (August). Although February is consistently strong for most of the momentum factors, the under-performance of January, March, and April are never significant at $p<0.05$, and barely at $p<0.1$. For simplicity, we report the returns in figure 6 below. The tables with monthly return statistics for each momentum factor is found in appendix 10-15.

Figure 5 – Momentum strategy returns by month

This figure reports mean returns by month for $WML_{6,3}$, $WML_{9,3}$, $WML_{12,3}$, $WML_{6,6}$, *PR1YR*, and *UMD*. The sample period is from July 1989 to June 2020. The figure is based on appendix 10-15.



These results are in similar to those found by Jegadeesh and Titman (1993) who find substantial underperformance in the month of January. They find that the relative strength strategy tested loses about 7% on mean in January with a t-statistic of 3.52. One thing we did not find for OSE – in fact quite the opposite – is a strong positive return for April. Jegadeesh and Titman attribute the 3.33% mean April return to pension fund flows. These must be transferred prior to April 15, and may lead to higher investments in that month if the fund-managers follow relative strength strategies (Jegadeesh and Titman, 1993). Further, they find strong returns in the month of November and December and attribute these returns to price pressure arising from portfolio managers selling their losers for tax purposes (Jegadeesh and Titman, 1993). However, we do not find this effect for OSE – with most of the November and December means not significantly different from zero.

In an attempt to explain the weak returns in January, we compare statistics for the month of January and February for the $WML_{9,3}$. As all of the *WML* strategies exhibit similar return characteristics, we chose to only look at this specific combination of J and K as it exhibits the strongest mean returns in our sample. We plot the histogram of returns for the two decile portfolios that form $WML_{9,3}$ in figure 6, and provide descriptive statistics of mean, median, skewness, and excess kurtosis for each of these in table 12.

The underperformance of the *WML* strategy in January can be attributed to the strong performance of the past year's losers. This is a fairly common anomaly in the stock markets, first described by Wachtal (1942). Because of this anomaly, a momentum strategy that buys past winners and sells past losers will in this case perform poorly. Jegadeesh and Titman (1993) also find this effect for the U.S. stock market. We find that for the month of January the lowest past return decile portfolio (losers) outperforms significantly with a mean return of 6.03%, and a t-statistic of 3.69. The portfolio returns are positively skewed as shown in figure 6, and confirmed in table 12, with more extreme values on the positive side of the distribution. However, for the month of February, this effect completely reverses. The mean return falls to 0.38% with a t-statistic of 0.25, and the distribution is negatively skewed.

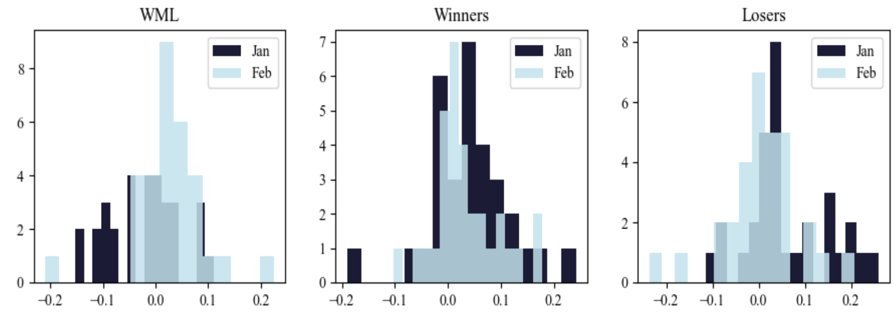
Table 12 – Descriptive statistics for $WML_{9,3}$ in January and February

This table reports mean, median, skewness, and excess kurtosis (Fisher-kurtosis) for $WML_{9,3}$ in January and February. Sample from July 1989 to June 2020.

	January			February		
Statistics	Winners	Losers	WML	Winners	Losers	WML
Mean	0.0391	0.0603	-0.0213	0.0335	0.0038	0.0300
Median	0.0382	0.0367	-0.0132	0.0179	0.0003	0.0300
Skewness	-0.1365	0.3852	-0.0758	0.5730	-0.4262	-0.5401
Kurtosis	2.3662	-0.2924	-0.6325	0.6000	2.1500	5.06

Figure 6 – Histogram of January and February returns for $WML_{9,3}$

Histogram of returns for the month of January and February for $WML_{9,3}$. The histogram Winners shows the distribution of returns for January and February for the top decile portfolio in the Winners-minus-losers strategy. The histogram Losers shows the same distribution, but for the bottom decile portfolio. Sample from July 1989 to June 2020.



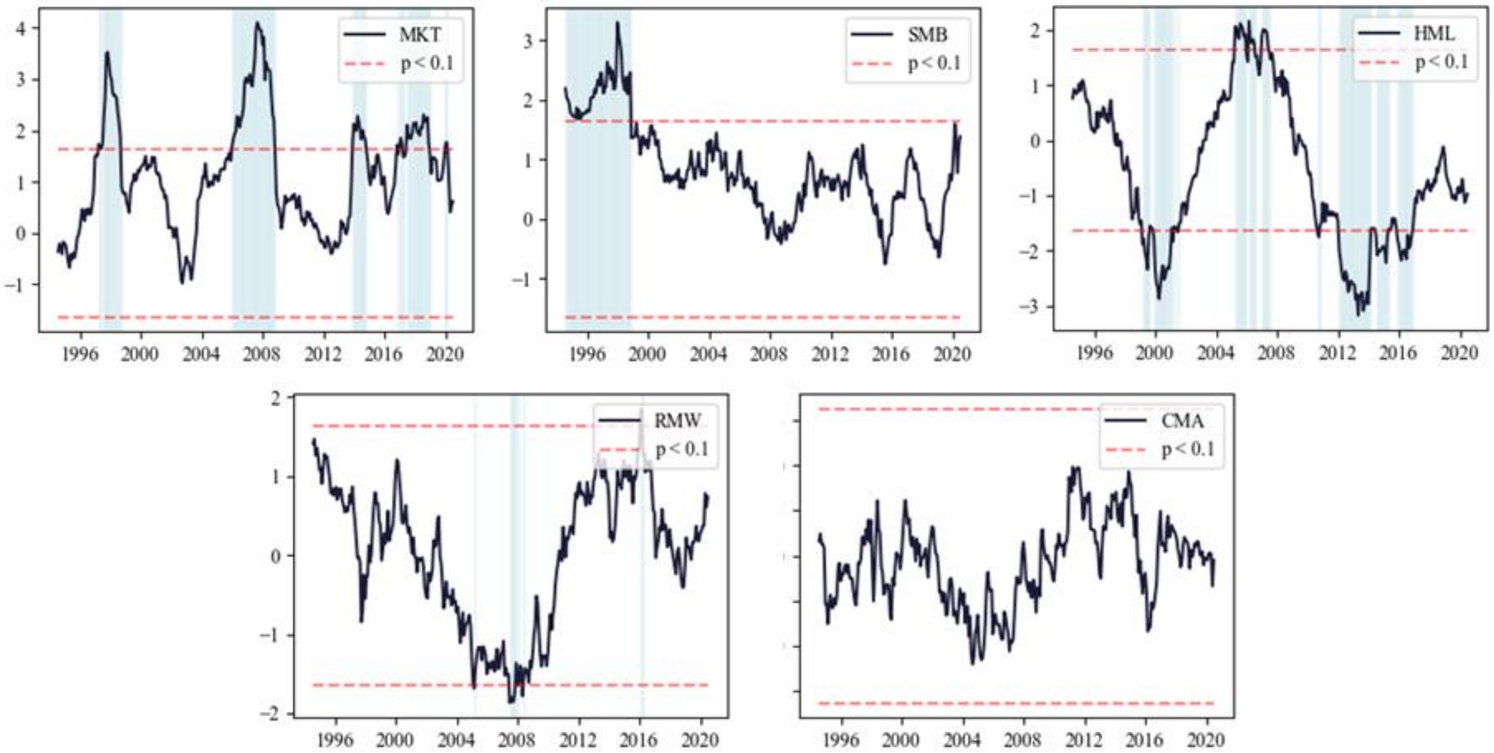
Appendix 9 – Time-varying factor characteristics

To investigate the highly time-varying characteristics of the *SMB*, *HML*, *RMW*, and *CMA* factors, we examine a rolling 60-month window throughout the entire sample period. Figure 7 displays the time-varying t-statistics for each factor. We observe that, for the most part, the mean returns of *CMA* fall within a range that is less than 1.67 standard deviations from zero ($p > 0.1$). This aligns with the findings of Fama and French (2017) for Europe and Japan, who also deemed *CMA* redundant and suggested its exclusion would have minimal impact on describing mean returns. The *RMW* factor shows brief periods of significance in 2008 and 2016. These findings further support our suspicion that *CMA* may be redundant in a five-factor model for OSE, and that *RMW*, at best, is also subject to scrutiny.

The *HML* factor, while not consistently significant throughout the entire sample period, demonstrates favorable performance during certain sub-samples. Thus, we cannot dismiss the influence of a value premium on OSE altogether. It is intriguing to note the alternating pattern between growth and value. We interpret the negative mean returns of *HML* as an indication of investor preference for growth stocks over value stocks.

In conclusion, there appears to be a rotation between value and growth premiums in the market. While we acknowledge this observation, we refrain from further analysis of its implications in this thesis, other than highlighting that *HML* is a time-varying factor on OSE.

Figure 7 – Time-varying t-statistics
This figure reports the t-statistics for a 60-month rolling window for the market factor, *SMB*, *HML*, *RMW*, and *CMA*. The sample period is from July 1989 to June 2020. The blue, shaded areas indicate each instance where the p-value is below p<0.1.



Appendix 10
Returns of Relative Strength Portfolios by Calendar Month
Relative strength portfolios formed using 6-month lagged returns and held for a duration of 6 months. Stocks are ranked in ascending order based on their 6-month lagged returns. The sell portfolio consists of equally weighted stocks from the lowest past return decile, while the buy portfolio comprises equally weighted stocks from the highest past return decile. This table presents the average monthly returns, standard deviations, and t-statistics the buy minus sell portfolio for each month. Additionally, the table includes the percentage of positive momentum portfolio returns that are positive for each month (Jegadeesh, Titman, 1993). Sample from July 1989 to June 2020.

Month	Portfolio Statistics				Proportion
	Mean	Std.	t-stat	Sharpe Ratio	r_i>0
Jan.	-0.0178	0.0661	-1.50	-0.27	0.45
Feb.	0.0345	0.0701	2.74	0.49	0.77
Mar.	-0.0123	0.0590	-1.19	-0.21	0.45
Apr.	-0.0181	0.0567	-1.77	-0.32	0.39
May	0.0226	0.0612	2.06	0.37	0.68
June	0.0062	0.0585	0.59	0.11	0.45
July	0.0107	0.0460	1.29	0.23	0.58
Aug.	0.0192	0.0637	1.68	0.30	0.58
Sept.	0.0229	0.0613	2.09	0.37	0.68
Oct.	0.0059	0.0686	0.48	0.09	0.62
Nov.	0.0179	0.0752	1.33	0.24	0.68
Dec.	0.0161	0.0722	1.25	0.22	0.55
F-Stat[a]	*25.46*				
p-Value	*0.0078*				

[a]*The F-statistics are computed under the hypothesis that the returns on the zero-cost portfolio are jointly equal in all calendar months.*

Appendix 11
Returns of Relative Strength Portfolios by Calendar Month
Relative strength portfolios formed using 6-month lagged returns and held for a duration of 3 months. Stocks are ranked in ascending order based on their 6-month lagged returns. The sell portfolio consists of equally weighted stocks from the lowest past return decile, while the buy portfolio comprises equally weighted stocks from the highest past return decile. This table presents the average monthly returns, standard deviations, and t-statistics the buy minus sell portfolio for each month. Additionally, the table includes the percentage of positive momentum portfolio returns that are positive for each month (Jegadeesh, Titman, 1993). Sample from July 1989 to June 2020.

Month	Portfolio Statistics				Proportion
	Mean	Std.	t-stat	Sharpe Ratio	r_i>0
Jan.	-0.0194	0.0702	-1.54	-0.28	0.42
Feb.	0.0229	0.0729	1.75	0.31	0.65
Mar.	-0.0124	0.0704	-0.98	-0.18	0.45
Apr.	-0.0177	0.0601	-1.63	0.29	0.42
May	0.0260	0.0702	2.06	0.37	0.71
June	0.0181	0.0632	1.59	0.29	0.55
July	0.0124	0.0503	1.36	0.24	0.65
Aug.	0.0215	0.0775	1.54	0.28	0.65
Sept.	0.0259	0.0806	1.79	0.32	0.65
Oct.	0.0146	0.0716	1.13	0.20	0.68
Nov.	0.0140	0.0781	1.00	0.18	0.71
Dec.	0.0173	0.0819	1.18	0.22	0.61
F-Stat[a]	*21.29*				
p-Value	*0.0304*				

[a]*The F-statistics are computed under the hypothesis that the returns on the zero-cost portfolio are jointly equal in all calendar months.*

Appendix 12

Returns of Relative Strength Portfolios by Calendar Month

Relative strength portfolios formed using 9-month lagged returns and held for a duration of 3 months. Stocks are ranked in ascending order based on their 9-month lagged returns. The sell portfolio consists of equally weighted stocks from the lowest past return decile, while the buy portfolio comprises equally weighted stocks from the highest past return decile. This table presents the average monthly returns, standard deviations, and t-statistics the buy minus sell portfolio for each month. Additionally, the table includes the percentage of positive momentum portfolio returns that are positive for each month (Jegadeesh, Titman, 1993). Sample from July 1989 to June 2020.

Month	Portfolio Statistics				Proportion
	Mean	Std.	t-stat	Sharpe Ratio	$r_i>0$
Jan.	-0.0212	0.0682	-1.74	-0.31	0.39
Feb.	0.0297	0.0702	2.35	0.42	0.74
Mar.	-0.0081	0.0669	-0.67	-0.12	0.49
Apr.	-0.0178	0.0740	-1.34	-0.24	0.35
May	0.0278	0.0767	2.02	0.36	0.65
June	0.0027	0.0639	0.23	0.04	0.42
July	0.0156	0.0608	1.43	0.26	0.58
Aug.	0.0200	0.0734	1.52	0.27	0.61
Sept.	0.0282	0.0718	2.19	0.39	0.65
Oct.	0.0108	0.0689	0.87	0.16	0.55
Nov.	0.0191	0.0814	1.30	0.23	0.71
Dec.	0.0183	0.0867	1.18	0.21	0.55
F-Stat[a]	*21.28*				
p-Value	*0.0306*				

[a]*The F-statistics are computed under the hypothesis that the returns on the zero-cost portfolio are jointly equal in all calendar months.*

Appendix 13

Returns of Relative Strength Portfolios by Calendar Month

Relative strength portfolios formed using 12-month lagged returns and held for a duration of 3 months. Stocks are ranked in ascending order based on their 12-month lagged returns. The sell portfolio consists of equally weighted stocks from the lowest past return decile, while the buy portfolio comprises equally weighted stocks from the highest past return decile. This table presents the average monthly returns, standard deviations, and t-statistics the buy minus sell portfolio for each month. Additionally, the table includes the percentage of positive momentum portfolio returns that are positive for each month (Jegadeesh, Titman, 1993). Sample from July 1989 to June 2020.

Month	Portfolio Statistics				Proportion
	Mean	Std.	t-stat	Sharpe Ratio	$r_i>0$
Jan.	-0.0217	0.0803	-1.51	-0.27	0.42
Feb.	0.0271	0.0656	2.30	0.41	0.71
Mar.	-0.0028	0.0693	-0.22	-0.04	0.52
Apr.	-0.0130	0.0706	-1.03	-0.18	0.35
May	0.0156	0.0795	1.09	0.20	0.65
June	0.0072	0.0698	0.57	0.10	0.49
July	0.0108	0.0576	1.04	0.19	0.61
Aug.	0.0222	0.0741	1.66	0.30	0.58
Sept.	0.0203	0.0692	1.63	0.29	0.61
Oct.	0.0077	0.0763	0.56	0.10	0.58
Nov.	0.0117	0.0929	0.70	0.13	0.65
Dec.	0.0156	0.0847	1.02	0.18	0.58
F-Stat[a]	*13.27*				
p-Value	*0.2762*				

[a]*The F-statistics are computed under the hypothesis that the returns on the zero-cost portfolio are jointly equal in all calendar months.*

Appendix 14
Returns of *PR1YR* Portfolios by Calendar Month

This table reports the monthly returns, standard deviations, t-stat, and proportion of positive return months for the Carhart *PR1YR* momentum factor. The *PR1YR* is constructed as equal-weight mean of firms with the highest 30 percent eleven-month returns lagged one month minus the equal-weight mean of firms with the lowest 30 percent eleven-month returns lagged one month (Carhart, 1997). Sample from July 1989 to June 2020, *N* = 372.

	Portfolio Statistics				Proportion
Month	Mean	Std.	t-stat	Sharpe	$r_i>0$
Jan.	0.0030	0.0446	0.38	0.07	0.52
Feb.	0.0214	0.0406	2.94	0.53	0.74
Mar.	-0.0120	0.0402	-1.67	-0.30	0.32
Apr.	-0.0138	0.0531	-1.44	-0.26	0.52
May	0.0026	0.0497	0.29	0.05	0.65
June	0.0068	0.0401	0.94	0.17	0.55
July	0.0064	0.0400	0.89	0.16	0.55
Aug.	0.0164	0.0458	2.00	0.36	0.65
Sept.	0.0125	0.0420	1.65	0.30	0.61
Oct.	0.0060	0.0440	0.75	0.14	0.68
Nov.	0.0108	0.0509	1.18	0.21	0.65
Dec.	0.0081	0.0500	0.91	0.16	0.55
F-Stat[a]	*18.22*				
p-Value	*0.0766*				

[a]*The F-statistics are computed under the hypothesis that the returns on the zero-cost portfolio are jointly equal in all calendar months.*

Appendix 15
Returns of *UMD* Portfolios by Calendar Month

This table reports the monthly returns, standard deviations, t-stat, and proportion of positive return months for the Fama French *UMD* momentum factor. Portfolios are formed at the end of month t, the lagged momentum return is a stock's cumulative return for t-11 to t-1. The intersection of the independent 2 x 3 sorts on size and momentum produces six value-weight portfolios, SL, SN, SW, BL, BN, and BW, where S and B indicate small and big, and *L*, *N*, and W indicate losers, neutral, and winners (bottom 30%, middle 40%, and top 30% of lagged momentum). *UMD* is the equal weight return of the three winner minus the three loser portfolios (Fama, French, 2012). Sample from July 1989 to June 2020, *N* = 372.

	Portfolio Statistics				Proportion
Month	Mean	Std.	t-stat	Sharpe	$r_i>0$
Jan.	0.0037	0.0448	0.46	0.08	0.52
Feb.	0.0202	0.0384	2.92	0.52	0.74
Mar.	-0.0140	0.0388	-2.00	-0.36	0.35
Apr.	-0.0125	0.0500	-1.40	-0.25	0.45
May	0.0034	0.0500	0.37	0.07	0.61
June	0.0087	0.0387	1.24	0.22	0.55
July	0.0063	0.0401	0.88	0.16	0.58
Aug.	0.0164	0.0479	1.91	0.34	0.65
Sept.	0.0151	0.0452	1.86	0.33	0.65
Oct.	0.0043	0.0417	0.57	0.10	0.61
Nov.	0.0086	0.0511	0.93	0.17	0.58
Dec.	0.0059	0.0487	0.68	0.12	0.55
F-Stat[a]	*18.03*				
p-Value	*0.0808*				

[a]*The F-statistics are computed under the hypothesis that the returns on the zero-cost portfolio are jointly equal in all calendar months.*

Appendix 16 - Returns of the Ten Decile Portfolios Formed on Past returns

The relative strength portfolios are constructed based on J-month lagged returns and held for K months. The stocks are sorted in ascending order using the J-month lagged returns, and portfolios are formed accordingly. Portfolio P1 represents an equally weighted selection of stocks from the lowest past return decile, while portfolio P2 consists of stocks from the next decile, etc (Jegadeesh, Titman, 1993). Mean monthly returns for each portfolio, standard deviations, t-statistics, and portfolio betas are reported. The betas are calculated with respect to the value-weighted index created from the sample of stocks from OSE. Sample from July 1989 to June 2020.

	$J = 6, K = 3$			$J = 9, K = 3$			$J = 12, K = 3$		
	Mean	Std.	β_i	Mean	Std.	β_i	Mean	Std.	β_i
P1	0.0064	0.0856	1.02	0.0061	0.0865	1.01	0.0087	0.0896	1.04
	(1.62)		(19.77)	(1.52)		(19.23)	(2.07)		(18.8)
P2	0.0028	0.0641	0.86	0.0027	0.0669	0.89	0.0063	0.0679	0.89
	(0.94)		(25.83)	(0.87)		(25.14)	(1.96)		(23.9)
P3	0.0047	0.0559	0.78	0.0051	0.0577	0.80	0.0045	0.0573	0.79
	(1.81)		(27.86)	(1.91)		(27.49)	(1.57)		(27.8)
P4	0.0070	0.0507	0.72	0.0053	0.0522	0.74	0.0052	0.0531	0.75
	(2.98)		(30.26)	(2.17)		(29.53)	(2.06)		(29.8)
P5	0.0062	0.0501	0.73	0.0064	0.0501	0.72	0.0063	0.0511	0.72
	(2.65)		(31.83)	(2.71)		(30.19)	(2.63)		(28.3)
P6	0.0076	0.0485	0.71	0.0074	0.0491	0.70	0.0093	0.0489	0.70
	(3.37)		(32.76)	(3.23)		(30.00)	(4.02)		(29.9)
P7	0.0083	0.0490	0.69	0.0075	0.0510	0.71	0.0084	0.0489	0.69
	(3.63)		(29.34)	(3.16)		(27.64)	(3.63)		(29.3)
P8	0.0066	0.0519	0.74	0.0094	0.0519	0.71	0.0099	0.0532	0.74
	(2.73)		(29.81)	(3.89)		(26.99)	(3.96)		(28.1)
P9	0.0105	0.0547	0.77	0.0105	0.0569	0.78	0.0096	0.0555	0.75
	(4.12)		(28.46)	(3.94)		(27.24)	(3.66)		(25.9)
P10	0.0177	0.0696	0.88	0.0179	0.0670	0.83	0.0175	0.0702	0.87
	(5.45)		(22.05)	(5.74)		(21.22)	(5.27)		(21.5)
P10-	0.0112	0.0729	-0.14	0.0118	0.0731	-0.19	0.0087	0.0759	-0.17
P1	(3.31)		(-2.36)	(3.47)		(-3.14)	(2.43)		(-2.7)

[a]*The F-statistics are computed under the hypothesis that the returns on the zero-cost portfolio are jointly equal in all calendar months.*

Appendix 17 – Replication of Fama and French three-factor model

This table reports the summary statistics for the replication of the Fama and French Three Factor model. The replication period is from July 1970 to June 2020, and uses accounting and stock information from CRSP and WRDS. The Python script is inspired by Freda Song Drechsler from Wharton Research Data Services. The replication of *SMB* and *HML* results in a correlation of 0.99 and 0.98 with Fama and French factors reported on the Kenneth French library website. The script is then used for the Norwegian market, with accounting data from Refinitiv and OBI data.

Summary Statistics for Monthly U.S. Factor Returns

Summary statistics for *SMB* and *HML* from July 1970 to June 2020 (N = 576) on the U.S. market. Results are compared to Fama French (FF) factors for the same time period. The table reports mean returns (in pct), standard deviations (in pct), and t-statistics for each factor. Correlations between *SMB* and *HML* replication, and the FF factors are reported below. At the end of each June, stocks are sorted into two *size* groups (Big and Small) using the NYSE median market cap as breakpoint. Stocks are sorted independently into three B/M portfolios using the 30th (L), and 70th (H) percentiles on NYSE B/M as breakpoints. The middle 40th (N) are assigned to a neutral B/M portfolio. HML_B is the mean return on the portfolio(s) of big high B/M stocks minus the mean return on the portfolio(s) of big low B/M stocks, HML_S is the same but for portfolios of small stocks, *HML* is the mean of HML_S and HML_B, and HML_{S-B} is the difference between them. *SMB* is the mean of the three small B/M portfolios minus the mean of the three big B/M portfolios.

	2 X 3 Replication		2 X 3 FF factor[a]	
	SMB_{rep}	HML_{rep}	*SMB*	*HML*
Mean	0.1553	0.3383	0.1372	0.3635
Std.	3.099	2.9758	3.0962	2.9040
t-Stat	1.2091	2.7280	1.0638	3.0043

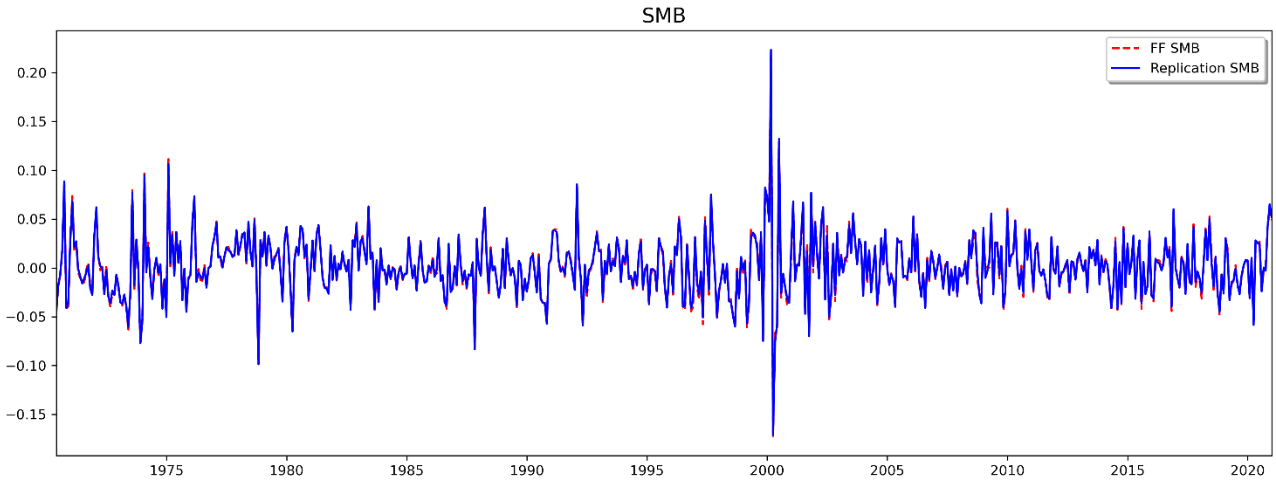
	$HML_{S,rep}$	$HML_{B,rep}$	$HML_{S-B,rep}$
Mean	0.5100	0.1665	0.3435
Std.	3.3433	3.1976	2.7037
t-Stat	3.6612	1.2516	3.0498

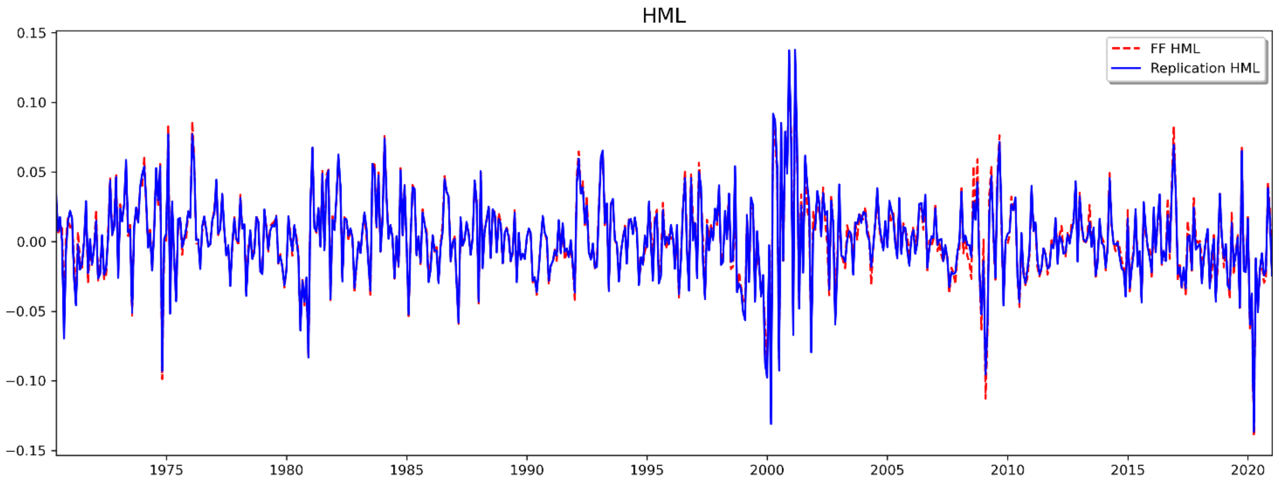
Correlations between Replication and FF factors

	SMB_{rep}	HML_{rep}
SMB	0.9959	-0.2485
HML	-0.1939	0.9818

[a]*The Fama French factors are from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Accessed via WRDS in Python through API.*

On the next page, we have plotted the two factor return series on top of each-other. The blue line is the replication of *SMB* and *HML*, while the red dashed line is the factor returns from the Kenneth French website.


SMB
FF SMB
Replication SMB
0.20
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020


HML
FF HML
Replication HML
0.15
0.10
0.05
0.00
−0.05
−0.10
−0.15
1975
1980
1985
1990
1995
2000
2005
2010
2015
2020

Appendix 18
Sharpe Ratio of Different Strategies

All calculations are based on monthly returns. The reported statistics include the highest and lowest one-month returns observed in the sample, the average excess return (annualized), the standard deviation (annualized) for each factor, excess kurtosis, skewness, and the Sharpe ratio (annualized). The sample returns are from July 1989 to June 2020.

Portfolio	Max	Min	Mean	Std.	Sharpe
R_M-R_F	15.49	-23.99	6.27	19.16	0.32
SMB	14.39	-17.46	6.91	14.24	0.47
HML	11.69	-18.53	-3.07	15.15	-0.21
RMW	21.40	-15.27	2.34	16.23	0.14
CMA	16.98	-20.20	-0.57	14.26	-0.04
$WML_{6,3}$	23.87	-24.27	13.04	24.91	0.49
$WML_{9,3}$	22.47	-21.16	13.27	25.35	0.49
$WML_{12,3}$	21.18	-24.71	10.54	25.94	0.39
$WML_{6,6}$	22.86	-20.60	11.34	22.47	0.48
UMD	14.83	-15.49	6.82	15.67	0.42
PR1YR	15.11	-15.75	7.04	15.83	0.43

Appendix 19 - Estimation of Factor Loadings for the CAPM

Estimation of the CAPM on portfolios double-sorted on size B/M, OP, INV, and MOM from July 1989 to June 2020 (*N*=372). Portfolios are sorted into two size groups (S and B) using OSE median market cap. Portfolios are independently sorted into B/M, OP, INV, and mom portfolios using the 30th and 70th percentiles of OSE for each factor. This results in a 2x3 sort with 6 intersection portfolios. H/R/A/W is the 70th percentile, *L*/W/C/*L* is the 30th percentile, and *N* is the neutral middle portfolio. OLS estimates, t-stats, and Adj. R^2 is reported. Intercepts that are significantly different from zero indicate a wrongly specified model.

Panel A: Exposure Estimates

Size-B/M		α_i	$b_{i,1}$	Adj. R^2	*Size-GP*		α_i	$b_{i,1}$	Adj. R^2
Small	H	0.0040 (1.89)	0.6395 (16.83)	0.43	Small	R	0.0090 (3.14)	0.6597 (12.84)	0.30
	N	0.0074 (2.74)	0.6498 (13.39)	0.32		*N*	0.0077 (2.46)	0.7001 (12.49)	0.29
	L	0.0076 (2.79)	0.7242 (14.77)	0.37		W	0.0062 (2.02)	0.7758 (13.97)	0.35
Big	H	-0.0017 (-0.88)	1.0732 (29.52)	0.70	Big	R	0.0020 (0.97)	0.8765 (23.85)	0.61
	N	0.0035 (1.98)	1.0240 (32.51)	0.74		*N*	-0.0021 (-1.49)	1.0843 (42.90)	0.83
	L	-0.0005 (0.76)	0.9827 (35.75)	0.78		W	0.0011 (0.45)	1.0498 (23.14)	0.59

Size-INV		α_i	$b_{i,1}$	Adj. R^2	*Size*-MOM		α_i	$b_{i,1}$	Adj. R^2
Small	A	0.0071 (2.48)	0.7434 (14.45)	0.36	Small	W	0.0053 (2.48)	0.6033 (15.51)	0.39
	N	0.0066 (3.022)	0.5685 (14.35)	0.36		*N*	0.0041 (2.15)	0.5269 (15.43)	0.39
	C	0.0063 (2.11)	0.75559 (14.09)	0.35		*L*	-0.0004 (-0.14)	0.8136 (17.45)	0.45
Big	A	-0.0030 (-1.45)	1.0537 (28.29)	0.68	Big	W	0.0112 (6.58)	0.8786 (28.59)	0.69
	N	0.0013 (0.959)	1.0147 (42.68)	0.83		*N*	0.0038 (2.74)	0.8651 (34.49)	0.76
	C	0.0013 (0.68)	0.9861 (27.06)	0.66		*L*	0.0032 (1.37)	1.1626 (27.57)	0.67

Appendix 20 – Estimation of Factor Loadings for the Three-Factor Model

Estimation of the Fama French Three factor model on portfolios double-sorted on size B/M, OP, INV, and MOM from July 1989 to June 2020 (*N*=372). Portfolios are sorted into two size groups (S and B) using OSE median market cap. Portfolios are independently sorted into B/M, OP, INV, and mom portfolios using the 30th and 70th percentiles of OSE for each factor. This results in a 2x3 sort with 6 intersection portfolios. H/R/A/W is the 70th percentile, *L*/W/C/*L* is the 30th percentile, and *N* is the neutral middle portfolio. OLS estimates, t-stats, and Adj. R^2 is reported. Intercepts that are significantly different from zero indicate a wrongly specified model.

Panel A: Exposure Estimates

Size-B/M		α_i	$b_{i,1}$	$s_{i,2}$	$hi_{,3}$	Adj. R^2	*N*
Small	H	0.0003 (0.18)	0.8772 (31.27)	0.7346 (18.26)	0.4748 (14.42)	0.76	372
	N	0.0027 (1.12)	0.8891 (18.51)	0.7363 (10.69)	0.0875 (1.55)	0.48	372
	L	0.0002 (0.12)	1.0138 (30.35)	0.8845 (18.46)	-0.6258 (-15.9)	0.77	372
Big	H	-0.0005 (-0.30)	1.0747 (31.68)	0.0093 (0.19)	0.5253 (13.19)	0.80	372
	N	0.0047 (2.67)	0.9708 (27.66)	-0.1630 (-3.23)	0.0505 (1.23)	0.75	372
	L	-0.0004 (-0.33)	0.9381 (35.95)	-0.1405 (-3.78)	-0.3741 (-12.2)	0.84	372

Size-GP		α_i	$b_{i,1}$	$s_{i,2}$	$hi_{,3}$	Adj. R^2	*N*
Small	R	0.0026 (1.15)	0.9495 (20.04)	0.8892 (13.08)	-0.1633 (-2.9)	0.54	372
	N	0.0013 (0.49)	1.0078 (18.91)	0.9455 (12.36)	-0.0254 (-0.4)	0.50	372
	W	-0.0004 (-0.16)	1.1145 (22.17)	1.0420 (14.45)	0.1240 (2.10)	0.58	372
Big	R	0.0024 (1.22)	0.8231 (20.83)	-0.1667 (-2.94)	-0.2747 (-5.9)	0.64	372
	N	-0.0012 (-0.88)	1.0325 (37.05)	-0.1599 (-4.00)	-0.0836 (-2.56)	0.84	372
	W	0.0016 (0.63)	1.0343 (20.17)	-0.0471 (-0.64)	0.0692 (1.15)	0.59	372

Size-INV		α_i	$b_{i,1}$	$s_{i,2}$	$hi_{,3}$	Adj. R^2	*N*
Small	A	0.0009 (0.043)	1.0627 (23.83)	0.9796 (15.31)	-0.1893 (-3.62)	0.62	372
	N	0.0019 (1.06)	0.8091 (22.48)	0.7403 (14.34)	0.0780 (1.85)	0.58	372
	C	-0.0010 (-0.43)	1.0996 (23.62)	1.0555 (15.81)	-0.1007 (-1.84)	0.62	372
Big	A	-0.0024 (-1.14)	1.0040 (24.23)	-0.1542 (-2.60)	-0.1591 (-3.28)	0.70	372
	N	0.0022 (1.66)	0.9739 (36.78)	-0.1253 (-3.29)	0.0397 (1.28)	0.84	372
	C	0.0013 (0.65)	0.9719 (23.78)	-0.0450 (-0.78)	-0.1332 (-2.78)	0.67	372

Appendix 21 – Estimation of Factor Loadings for the Five-Factor model

Estimation of the Fama French Five factor model on portfolios double-sorted on size B/M, OP, INV, and MOM from July 1989 to June 2020 (*N*=372). Portfolios are sorted into two size groups (S and B) using OSE median market cap. Portfolios are independently sorted into B/M, OP, INV, and mom portfolios using the 30th and 70th percentiles of OSE for each factor. This results in a 2x3 sort with 6 intersection portfolios. H/R/A/W is the 70th percentile, *L*/W/C/*L* is the 30th percentile, and *N* is the neutral middle portfolio. OLS estimates, t-stats, and Adj. R^2 is reported. Intercepts that are significantly different from zero indicate a wrongly specified model.

Panel A: Exposure Estimates

Size-B/M		α_i	$b_{i,1}$	$s_{i,2}$	$hi_{,3}$	$r_{i,4}$	$ci_{,5}$	Adj. R^2	*N*
Small	H	0.0002 (0.15)	0.8782 (30.68)	0.7329 (18.05)	0.4750 (13.87)	0.0057 (0.20)	0.0277 (0.40)	0.76	372
	N	0.0025 (1.05)	0.9035 (18.48)	0.7435 (10.72)	0.1098 (1.88)	0.0769 (1.55)	0.0356 (0.63)	0.48	372
	L	0.0003 (0.23)	1.0008 (29.50)	0.8766 (18.22)	-0.6467 (-15.9)	-0.0694 (-2.0)	-0.0172 (-0.44)	0.77	372
Big	H	-0.0004 (-0.23)	1.0659 (30.85)	0.0058 (0.12)	0.5122 (12.39)	-0.0471 (-1.3)	-0.0315 (-0.79)	0.80	372
	N	0.0046 (2.62)	0.9726 (27.15)	-0.1643 (-3.22)	0.0521 (1.21)	0.0102 (0.79)	0.0283 (0.69)	0.75	372
	L	-0.0005 (-0.39)	0.9433 (35.45)	-0.1379 (-3.66)	-0.3660 (-11.5)	0.0281 (1.04)	0.0134 (0.44)	0.84	372

Size-GP		α_i	$b_{i,1}$	$s_{i,2}$	$hi_{,3}$	$r_{i,4}$	$ci_{,5}$	Adj. R^2	*N*
Small	R	0.0017 (0.83)	1.0417 (25.24)	0.9550 (16.32)	-0.0091 (-0.18)	0.4905 (11.72)	0.0101 (0.21)	0.66	372
	N	0.0016 (0.54)	0.9932 (18.38)	0.9464 (12.35)	-0.0430 (-0.66)	-0.0787 (-1.44)	-0.1259 (-2.02)	0.51	372
	W	0.0006 (0.31)	0.9954 (25.79)	0.9399 (17.18)	-0.0851 (-1.84)	-0.6310 (-16.1)	0.1744 (3.93)	0.76	372
Big	R	0.0017 (0.94)	0.8867 (24.41)	-0.1264 (-2.45)	-0.1713 (-3.93)	0.3391 (9.20)	0.0631 (1.51)	0.71	372
	N	-0.0011 (-0.77)	1.0197 (36.12)	-0.1668 (-4.17)	-0.1036 (-3.07)	-0.0682 (-2.38)	-0.0268 (-0.82)	0.84	372
	W	0.0028 (1.28)	0.9331 (21.07)	-0.1112 (-1.77)	-0.0953 (-1.78)	-0.5394 (-12.0)	-0.1013 (-1.99)	0.71	372

Size-INV		α_i	$b_{i,1}$	$s_{i,2}$	$hi_{,3}$	$r_{i,4}$	$ci_{,5}$	Adj. R^2	*N*
Small	A	0.0010 (0.54)	1.0569 (29.25)	1.0309 (20.12)	-0.1665 (-3.85)	-0.0386 (-1.05)	-0.6111 (-14.68)	0.76	372
	N	0.0018 (1.01)	0.8210 (22.43)	0.7504 (14.45)	0.0989 (2.26)	0.0632 (1.70)	-0.0161 (0.71)	0.59	372
	C	-0.0013 (-0.71)	1.0564 (28.04)	0.9720 (18.12)	-0.2038 (-4.52)	-0.2226 (-5.82)	0.5745 (13.24)	0.77	372
Big	A	-0.0015 (0.42)	0.9690 (25.63)	-0.1466 (-2.73)	-0.1985 (-4.39)	-0.1905 (-4.97)	-0.3622 (-8.32)	0.75	372
	N	0.0020 (1.55)	0.9871 (36.84)	-0.1173 (-3.01)	0.0609 (1.90)	0.0703 (2.59)	0.0170 (0.55)	0.84	372
	C	0.0007 (0.42)	0.9695 (26.68)	-0.0877 (-1.71)	-0.1611 (-3.71)	-0.0066 (-0.18)	0.4522 (10.81)	0.75	372

Appendix 22 – Estimation of Factor Loadings for Five-Factor plus momentum

Estimation of the Fama French Five factor model plus *UMD* on portfolios double-sorted on size B/M, OP, INV, and MOM from July 1989 to June 2020 (*N*=372). Portfolios are sorted into two size groups (S and B) using OSE median market cap. Portfolios are independently sorted into B/M, OP, INV, and mom portfolios using the 30[th] and 70[th] percentiles of OSE for each factor. This results in a 2x3 sort with 6 intersection portfolios. H/R/A/W is the 70[th] percentile, *L*/W/C/*L* is the 30th percentile, and *N* is the neutral middle portfolio. OLS estimates, t-stats, and Adj. R^2 is reported. Intercepts that are significantly different from zero indicate a wrongly specified model.

Panel A: Exposure Estimates

Size-B/M		α_i	$b_{i,1}$	$s_{i,2}$	$hi_{,3}$	$r_{i,4}$	$c_{i,5}$	$u_{i,5}$	Adj. R^2
Small	H	0.0002	0.8780	0.7328	0.4750	0.0058	0.0277	-0.001	0.76
		(0.15)	(29.55)	(18.02)	(13.84)	(0.20)	(0.84)	(-0.02)	
	N	00022	0.9144	0.74444	0.1112	0.0726	0.0360	0.0456	0.48
		(0.90)	(18.03)	(10.73)	(1.90)	(1.46)	(0.64)	(0.819)	
	L	0.0009	0.9800	0.8749	-0.6494	-0.0613	-0.0180	-0.086	0.78
		(0.55)	(28.03)	(18.28)	(-16.1)	(-1.78)	(-0.47)	(-2.3)	
Big	H	0.0001	1.0485	0.0043	0.5099	-0.0402	-0.0322	-0.072	0.80
		(0.07)	(29.37)	(0.09)	(12.4)	(-1.15)	(-0.81)	(-1.85)	
	N	0.0045	0.9786	-0.1638	0.0529	0.0079	0.0286	0.0250	0.75
		(2.49)	(26.37)	(-3.22)	(1.23)	(0.22)	(0.69)	(0.54)	
	L	-0.006	0.9465	-0.1377	-0.3656	0.0268	0.0135	0.0132	0.84
		(-0.45)	(34.27)	(-3.64)	(-11.5)	(0.98)	(0.44)	(0.43)	

Size-GP		α_i	$b_{i,1}$	$s_{i,2}$	$hi_{,3}$	$r_{i,4}$	$ci_{,5}$	$u_{i,5}$	Adj. R^2
Small	R	0.0021	1.0263	0.9537	-0.0111	0.4965	0.0095	-0.064	0.66
		(1.03)	(24.01)	(16.31)	(-0.22)	(11.80)	(0.199)	(-1.39)	
	N	0.0017	0.9922	0.9463	-0.0432	-0.0784	-0.1259	-00042	0.50
		(0.61)	(17.69)	(12.33)	(-0.66)	(-1.42)	(-2.01)	(-0.01)	
	W	0.000	1.0133	0.9414	-0.0828	-0.6380	0.1751	0.0745	0.76
		(0.04)	(25.39)	(17.24)	(-1.79)	(-16.3)	(3.95)	(1.70)	
Big	R	0.0009	0.9143	-0.1240	-0.1677	0.3283	0.0642	0.1148	0.72
		(0.50)	(24.50)	(-2.43)	(-3.89)	(8.94)	(1.55)	(2.81)	
	N	-0.0008	1.0090	-0.1677	-0.1050	-0.0640	-0.0272	-0.044	0.85
		(-0.54)	(32.52)	(-4.20)	(-3.10)	(-2.23)	(-0.84)	(-1.4)	
	W	0.0029	0.9273	-0.1117	-0.0960	-0.5371	-0.1015	-0.024	0.71
		(1.34)	(20.18)	(-1.78)	(-1.81)	(-11.8)	(-1.99)	(-0.47)	

Size-INV		α_i	$b_{i,1}$	$s_{i,2}$	$hi_{,3}$	$r_{i,4}$	$ci_{,5}$	$u_{i,5}$	Adj. R^2
Small	A	0.0008	1.0636	1.0315	-0.1646	-0.0412	-0.6108	0.0277	0.76
		(0.43)	(28.37)	(20.10)	(-3.82)	(-1.18)	(-14.67)	(0.67)	
	N	0.0019	0.8164	0.7500	0.0983	0.0650	-0.0162	-0.019	0.59
		(1.06)	(21.48)	(14.47)	(2.24)	(1.74)	(-0.38)	(-0.46)	
	C	-0.0011	1.0496	0.9715	-0.2047	-0.2199	0.5743	-0.028	0.76
		(-0.59)	(26.85)	(18.16)	(-4.53)	(-5.72)	(13.22)	(-0.66)	
Big	A	-0.0011	0.9550	-0.1478	-0.2004	-0.1850	-0.3628	-0.058	0.75
		(-0.63)	(24.39)	(-2.76)	(-4.43)	(-4.80)	(-8.34)	(-1.36)	
	N	0.0021	0.9855	-0.1174	0.0607	0.0709	0.0169	-0.006	0.84
		(1.56)	(35.43)	(-3.09)	(1.89)	(2.59)	(0.55)	(-0.21)	
	C	0.0008	0.9690	-0.1612	-0.0878	-0.0063	0.4522	-0.002	0.75
		(0.42)	(25.69)	(-3.70)	(-1.70)	(-0.17)	(10.79)	(-0.06)	

Appendix 23 - Estimating Risk Premia – Fama-MacBeth

Two step Fama MacBeth regression on 2x3 double-sorted portfolios formed on size and B/M, GP, INV, and MOM from July 1989 to June 2020. The panel displays the estimated risk premiums for both the intercept and each factor. These risk premiums are calculated using the Fama-MacBeth (1973) regression method. The regressions analyse the monthly excess return of the portfolio based on the estimated factor(s). In accordance with the model's validity, the intercept (α) should be zero. A factor is considered priced if its value (λ_i) significantly deviates from zero.

CAPM							
Portfolio	α	λ_{MKT}					R^2
Size-B/M	0.0007	0.0082					0.57
p-value	0.00	0.00					
Size-GP	0.0008	0.0087					0.49
p-value	0.00	0.00					
Size-INV	0.0008	0.0080					0.54
p-value	0.00	0.01					
Size-MOM	0.0003	0.0103					0.58
p-value	0.00	0.00					
Fama & French Three Factor							
Portfolio	α	λ_{MKT}	λ_{SMB}	λ_{HML}			R^2
Size-B/M	0.000	0.0061	0.0047	-0.0022			0.72
p-value	0.14	0.04	0.04	0.34			
Size-GP	-0.000	0.0046	0.0076	-0.0116			0.55
p-value	0.94	0.14	0.00	0.17			
Size-INV	-0.000	0.0064	0.0051	-0.0109			0.61
p-value	0.05	0.04	0.03	0.29			
Size-MOM	0.000	0.0104	-0.0041	-0.0139			0.64
p-value	0.00	0.00	0.24	0.73			
Fama & French Five Factor							
Portfolio	α	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	R^2
Size-B/M	0.000	0.0063	0.0056	-0.0026	0.0065	0.0313	0.72
p-value	0.06	0.05	0.26	0.29	0.93	0.88	
Size-GP	-0.000	0.0046	0.0073	-0.0137	0.0020	0.0056	0.63
p-value	0.88	0.20	0.01	0.51	0.43	0.70	
Size-INV	-0.000	0.0037	0.0071	-0.0436	0.0475	-0.0011	0.68
p-value	0.04	0.48	0.06	0.39	0.77	0.74	
Size-MOM	0.000	0.0122	0.0144	-0.0416	0.0117	-0.2426	0.65
p-value	0.02	0.75	0.86	0.75	0.97	0.81	

Appendix 24 - Estimating Risk Premia – Fama-MacBeth for FF3 and momentum

Two step Fama MacBeth regression on 2x3 double-sorted portfolios formed on size and B/M, GP, INV, and MOM from July 1989 to June 2020. The panel displays the estimated risk premiums for both the intercept and each factor. These risk premiums are calculated using the Fama-MacBeth (1973) regression method. The regressions analyse the monthly excess return of the portfolio based on the estimated factor(s). In accordance with the model's validity, the intercept (α) should be zero. A factor is considered priced if its value (λ_i) significantly deviates from zero.

Three Factor with *UMD*

Portfolio	α	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{UMD}	R^2
Size-B/M	0.0000	0.0062	0.0048	-0.0025	0.0059	0.72
p-value	0.06	0.04	0.04	0.28	0.30	
Size-GP	-0.000	0.0045	0.0078	-0.0132	-0.0059	0.55
p-value	0.83	0.16	0.00	0.30	0.79	
Size-INV	0.000	0.0065	0.0051	-0.0117	-0.0723	0.61
p-value	0.72	0.29	0.06	0.56	0.18	
Size-MOM	0.000	0.0127	-0.0056	0.0023	0.0055	0.73
p-value	0.15	0.00	0.08	0.89	0.02	

Three Factor with *PR1YR*

Portfolio	α	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{PR1YR}	R^2
Size-B/M	0.000	0.0062	0.0047	-0.0023	0.0011	0.72
p-value	0.06	0.05	0.04	0.31	0.96	
Size-GP	-0.000	0.0044	0.0079	-0.0137	-0.0082	0.55
p-value	0.84	0.17	0.00	0.29	0.74	
Size-INV	-0.000	0.0062	0.0047	-0.0183	-0.0802	0.61
p-value	0.62	0.93	0.10	0.45	0.22	
Size-MOM	0.000	0.0125	-0.0048	0.0010	0.0065	0.73
p-value	0.29	0.00	0.14	0.95	0.00	

Three Factor with $WML_{9,3}$

Portfolio	α	λ_{MKT}	λ_{SMB}	λ_{HML}	$\lambda_{WML9,3}$	R^2
Size-B/M	0.000	0.0062	0.0047	-0.0026	0.0208	0.72
p-value	0.06	0.05	0.05	0.25	0.63	
Size-GP	-0.000	0.0050	0.0073	-0.0050	0.0267	0.55
p-value	0.85	0.15	0.00	0.84	0.79	
Size-INV	-0.000	0.0076	0.0059	-0.0023	-0.0925	0.62
p-value	0.38	0.10	0.03	0.89	0.18	
Size-MOM	-0.000	0.0123	-0.0049	0.0013	0.0150	0.69
p-value	0.50	0.00	0.12	0.94	0.00	

Appendix 25 – Estimation of Factor Loadings for the three-factor model

Estimation of the Fama French Three factor model on portfolios double-sorted on size B/M, OP, INV, and MOM from July 1989 to June 2020 (*N*=372). Portfolios are sorted into two size groups (S and B) using OSE median market cap. Portfolios are independently sorted into B/M, OP, INV, and mom portfolios using the 30th and 70th percentiles of OSE for each factor. This results in a 2x3 sort with 6 intersection portfolios. H/R/A/W is the 70th percentile, *L*/W/C/*L* is the 30th percentile, and *N* is the neutral middle portfolio. OLS estimates, t-stats, and Adj. R^2 is reported. Intercepts that are significantly different from zero indicate a wrongly specified model.

Size-MOM		α_i	$b_{i,1}$	$s_{i,2}$	$hi_{,3}$	Adj. R^2	*N*
Small	W	0.0010 (0.56)	0.8181 (22.20)	0.6606 (12.50)	0.0398 (0.92)	0.57	372
	N	0.0003 (0.17)	0.7292 (23.44)	0.6230 (13.96)	0.1384 (3.79)	0.60	372
	L	-0.0048 (-2.08)	1.0400 (22.42)	0.6964 (10.46)	0.0592 (1.08)	0.57	372
Big	W	0.0101 (5.89)	0.9323 (27.19)	0.1647 (3.35)	-0.0284 (-0.71)	0.69	372
	N	0.0033 (2.37)	0.8983 (31.72)	0.0887 (2.19)	0.0484 (1.46)	0.77	372
	L	0.0021 (0.88)	1.2264 (25.99)	0.1968 (2.91)	0.0753 (1.36)	0.68	372

Appendix 26 - Estimating Risk Premia – Fama-MacBeth for FF5 and momentum

Two step Fama MacBeth regression on 2x3 double-sorted portfolios formed on size and B/M, GP, INV, and MOM from July 1989 to June 2020. The panel displays the estimated risk premiums for both the intercept and each factor. These risk premiums are calculated using the Fama-MacBeth (1973) regression method. The regressions analyse the monthly excess return of the portfolio based on the estimated factor(s). In accordance with the model's validity, the intercept (α) should be zero. A factor is considered priced if its value (λ_i) significantly deviates from zero.

Five Factor with *UMD*

Portfolio	α	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{UMD}	R^2
Size-B/M	0.000	0.0068	0.0142	-0.0026	-0.1487	0.5405	-0.1553	0.73
p-value	0.00	0.65	0.84	0.26	0.91	0.90	0.91	
Size-GP	-0.000	0.0043	0.0076	-0.0160	0.0019	0.0042	-0.0047	0.63
p-value	0.00	0.30	0.04	0.61	0.43	0.79	0.87	
Size-INV	0.000	0.0055	0.0059	-0.0238	0.0149	0.0004	-0.0621	0.68
p-value	0.00	0.38	0.06	0.56	0.76	0.87	0.28	
Size-MOM	-0.000	0.0072	-0.0482	0.1058	-0.0927	0.5110	0.0055	0.74
p-value	0.00	0.88	0.91	0.91	0.89	0.92	0.02	

Five Factor with *PR1YR*

Portfolio	α	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{PR1YR}	R^2
Size-B/M	-0.000	0.0064	0.0115	-0.0026	-0.1065	0.3797	-0.1179	0.73
p-value	0.00	0.53	0.75	0.26	0.88	0.86	0.86	
Size-GP	0.000	0.0044	0.0076	-0.0156	0.0019	0.0042	-0.0050	0.63
p-value	0.00	0.28	0.03	0.59	0.43	0.79	0.86	
Size-INV	-0.000	0.0057	0.0052	-0.0251	0.0112	0.0004	-0.0775	0.69
p-value	0.00	0.44	0.16	0.60	0.85	0.86	0.35	
Size-MOM	0.000	0.0089	-0.0252	0.0519	-0.0508	0.2571	0.0033	0.74
p-value	0.00	0.72	0.86	0.88	0.84	0.89	0.89	

Five Factor with $WML_{9,3}$

Portfolio	α	λ_{MKT}	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	$\lambda_{WML9,3}$	R^2
Size-B/M	0.000	0.0085	0.0181	-0.0026	-0.1534	0.6161	-0.3566	0.73
p-value	0.00	0.76	0.88	0.26	0.92	0.91	0.92	
Size-GP	0.000	0.0039	0.0078	-0.0243	0.0019	0.0059	-0.0307	0.63
p-value	0.00	0.63	0.13	0.83	0.43	0.75	0.91	
Size-INV	0.000	0.0071	0.0066	-0.0092	0.0102	0.0004	-0.1003	0.68
p-value	0.00	0.22	0.02	0.85	0.82	0.87	0.26	
Size-MOM	0.0086	0.0086	-0.0108	0.0198	-0.0387	0.0708	0.0180	0.70
p-value	0.00	0.36	0.73	0.79	0.62	0.86	0.14	

Appendix 27 – Rolling window Fama and MacBeth Risk premia estimation

Figure shows a rolling 60-month (5 year) risk premia estimation for the two-step Fama and MacBeth regressions. The figure is only for the size-B/M LHS portfolios. Sample from July 1989 to June 2020. Dashed red line shows critical value equivalent to a significance level of p<0.05. Plot legend at the bottom of the figure.