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A Fama-French Replication and Extension including Momentum: Evidence from the US and the UK Stock Market

Master Thesis

by
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Abstract

This paper examines the effects of size, value, profitability, investments, and momentum on the cross-sectional and time-series relation between expected returns and risk in the US and the UK markets, from July 1990 to December 2021. We replicate the international study of Fama and French (2017) and extend the research by constructing a six-factor model, adding momentum. The objective is to analyze which model performs better in the markets. The robustness of the models is tested through factor spanning regressions, GRS tests, and Fama-MacBeth regressions. For the six-factor model, evidence shows that, through factor spanning regressions, the SMB and HML factors in the US and the HML, RMW, and CMA in the UK are redundant. Further, the Fama-MacBeth regressions show that the models unconvincingly explain excess returns.

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1 Introduction and Motivation

Multifactor investing has proliferated over the past decade and contained 122.85 billion USD in assets as of June 2022 (ETF, 2022). S&P Global presented a market analysis of the cyclicality of single-factor indices showing that these strategies can cause long cyclical drawdowns (S&P Global, 2018). Additionally, the returns of each factor have varied dramatically over the long term. Thus, by implementing a diversification strategy through multiple factors, an investor can generate more stable returns because of the factors' low correlations. The theory is that the factors can soften the effect of drawdowns and increase the potential for overperformance. This is the appeal of creating functioning asset pricing models as they create frameworks fit to predict returns and quantify risk. However, asset pricing models are based on unrealistic assumptions in the real market, such as linearity, perfect information, and efficient markets.

According to asset pricing theory, assets can earn risk premia when exposed to systematic risk factors. The Fama and French three-factor model (market, size, and value risk) has been a cornerstone of asset pricing since its introduction in 1993 (Fama and French, 1993). However, identifying all these risk factors to create an optimal pricing model is yet to be done. In 1997, Carhart introduced a four-factor model, adding factor capturing the momentum anomaly. This model was tested by Fama and French in an international setting (2012), finding evidence of momentum and evidence against integrated asset pricing across regions. One of the more recent developments is Fama and French's construct a five-factor model adding a profitability and investment factor to the acknowledged three-factor model (Fama and French, 2015a). Their findings suggested collinearity in the value factor, but they argue the conclusions might be sample-specific and that the model requires further research. Applying the model to a different sample regarding the period and markets helps test these findings. An international test of the five-factor model was conducted in 2017 (Fama and French, 2017), finding a weak size-effect in North America and non-existence in Europe for the size-BM sorts and a repeating pattern of redundancy in the investment factor for Europe and Japan.

Based on this previous research, this thesis will test the Fama and French five-factor model and our six-factor model, adding momentum to the US and UK markets. The procedure is three-folded. Firstly, the research paper “International tests of a five-factor asset pricing model” (Fama and French, 2017) is conceptually replicated and tested for the US and the UK markets. This is done to assess our model construction and correlation with the results found by Fama and French. They argue for global market integration, implying that the model should be adaptable to all open markets (2015c). However, in line with Griffin, asset pricing models are best-performed country-specific (Griffin, 2001). Thus, this research limits the analysis to two global markets, the US and the UK. Secondly, the five-factor model for our sample period is constructed for the US and the UK. The model will be constructed following the same approach as in the replication; however, certain aspects of the model is amplified to improve significance. This will be the benchmark to which the six-factor model is compared. Lastly, our proposed model, the six-factor model, including momentum, will be composed for the sample period and tested in the US and the UK. De Bondt and Thaler (1985, 1987) find that stock prices overreact to information. Thus, a long strategy in stocks that previously performed well and a short strategy in stocks previously performing poorly yields positive returns. The robustness and multicollinearity of the six-factor model is tested against the five-factor model. This is an essential aspect since collinearity undermines the statistical significance of the independent variable. Hence, the research question becomes:

Can the inclusion of a momentum factor in the Fama and French five-factor model explain stock returns in the US and the UK markets?

The analysis conducted in our thesis shows that the six-factor model performs better than the five-factor model in the US and UK markets. Several factors prove redundant in the two models through factor spanning regressions, GRS tests, and Fama-MacBeth regressions. Through the factor spanning test, evidence shows that the size factor and value factor are redundant for the six-factor model in the US market. In contrast, the value, profitability, and investment factors are redundant for the six-factor model in the UK market. However, based on Fama-MacBeth regression, the models are insufficient in describing stock returns.

The thesis is structured as follows. In section 2 a thorough review of the literature is conducted and discrepancies are identified which form the purpose of the analysis. Section 3 provides a reflection upon the choice of markets subject to model implementation. In section 4, descriptions of the methods used to conduct the study is given. Section 5 presents how data retrieval and cleaning are performed, assumptions taken for the analysis, and a presentation of summary statistics. Building upon the data, section 6 lays forward the results of our investigation and presents findings of the robustness tests conducted on the models. Lastly, section 7 discusses the main findings of the research and suggests further research.

2 Literature Review

2.1 Asset Pricing Models

The first big breakthrough in asset pricing models was the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964), Lintner (1965) and Mossin (1966). Their conclusion is that, in equilibrium, systematic risk (undiversifiable) is captured by the market beta, β_i. However, Lakonishok and Shapiro (1986) discovered that returns are also influenced by various measures of idiosyncratic risk. Hence, the CAPM included anomalies (diversifiable) abnormal returns, α, characterized by firm fundamentals affecting returns (Stapleton and Subrahmanyam, 1983). Thus, other models are developed to better explain stock returns and measure excess returns.

2.1.1 Fama-French three-factor model (FF3F)

Banz (1981) finds empirical evidence of a relationship between the market value of a common stock (size) and its return. Average returns on small stocks are too high given the beta estimates and returns on large stocks are too low. Fama and French (1993) find that the market beta has limited explanatory power. Contrarily, market equity and book-to-market equity explain the cross-sectional variation in average returns that is missed by the univariate beta. Another observation is that value stocks yield higher returns, on average, than growth stocks. The introduction of these risk factors led to a multifactor asset pricing model capturing several of the CAPM anomalies; Fama French's three-factor model (1993):

$$r_{it} - r_{ft} = \alpha_i + \beta_{i1}[r_{mt} - r_{ft}] + \beta_{i2}SMB_t + \beta_{i3}HML_t + \varepsilon_{it} \qquad (\mathbf{1})$$

Through time-series regressions they verify that portfolios constructed to imitate risk factors related to *size* and *book-to-market equity* increase the variation in stock returns explained by a market portfolio (1992). However, evidence from Reinganum (1981), Lakonishok and Sharpiro (1986), and Fama and French (1993) show that the relationship vanishes in recent periods.

2.1.2 Fama-French five-factor model (FF5F)

After extensive tests, Fama and French (2015a) recognized that the FF3F lacked implementational support and was not enough to predict returns. Fama and French (2006) found considerable variations in average returns related to profitability and investment, thus, unexplained by the three-factor model. This was also established by Titman, Wei, and Xie (2004) and Novy-Marx (2013). This notion was further tested by Novy-Marx (2013) who found that profitable stocks generate higher returns than unprofitable stocks and gross profitability explains most earning-related anomalies. Additional research by Aharoni, Grundy, and Zeng (2013) shows a negative relation between investment and average returns. Thus, low investment stocks generate higher returns than high investment stocks. In 2015, Fama and French built upon their renowned FF3F and introduced two new risk factors to the model: profitability (*RMW*) and investment (*CMA*):

$$r_{it} - r_{ft} = \alpha_i + \beta_{i1}[r_{mt} - r_{ft}] + \beta_{i2}SMB_t + \beta_{i3}HML_t + \beta_{i4}RMW_t + \beta_{i5}CMA_t + \varepsilon_{it} \qquad (\mathbf{2})$$

Analysis of the US market concluded that the FF5F predicts returns better than FF3F. The research also found that the value factor (*HML*) becomes redundant as new factors are added. Research conducted by Fama and French (2015b) find that the list of anomalies shrinks when the five-factor model is implemented. However, Fama and French (2017) suggests future research to add additional factors, including momentum, to the model.

2.2 Momentum Effect

Research conducted by De Bondt and Thaler (1985, 1987) shows that stock prices overreact to information. This indicate that if a stock is doing good, it should continue to go up, and contrary, if a stock is doing bad, it should continue to go down. Thus, a long strategy in stocks, previously performed well and a short strategy in stocks previously performing poorly yields positive returns. The determinant of the profits is, however, debated. Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999) point to behavioral models as explanation of momentum returns, due to bias in investors' interpretation. Conrad and Kaul (1998) claim the profitability is due to cross-sectional variations in average returns, rather than time-series variations. This contradicts Jegadeesh and Titman's (1993) finding that the first year does well while the next two years do poorly with momentum strategies. They test overlapping strategies, selecting stocks based on J-month lagged returns (*J = 3, 6, 9, 12*) and holding the strategies correspondingly. To avoid short-term reversals, especially for small illiquid stocks, time is skipped (1 month) before execution in their modelling. Hence, portfolios are created based on 6-month lagged returns and held respectively. The result of a delayed response to news leads to an undervaluation of short-term views and an overvaluation of long-term views. Jagadeesh and Titman (1993) find evidence that momentum exists in US stock returns, hence, stocks that have been doing well continue to prosper in the future.

Taking the analysis one step further, Mark Carhart (1997) added momentum to the FF3F model. He researched mutual funds and claimed that the model would lead to a more accurate measure of returns. The momentum factor (*WML*) is non-overlapping and, thus, computed differently than the one of Jagadeesh and Titman (1993). Six value-weighted portfolios are formed on *size* and prior (2-12 months) returns monthly. After the portfolios are constructed, *WML* is the average return on the two winner portfolios minus the average return on the two low looser portfolios. The resulting model was a four-factor asset pricing model, including momentum (Carhart, 1997):

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,i}\left[r_{m,t} - r_{f,t}\right] + \beta_{2,i}\, SMB_t + \beta_{3,i}\, HML_t + \beta_{4,i}\, WML_t + \varepsilon_{i,t} \quad (\mathbf{3})$$

As a critique, Daniel et al. (2018) find evidence that winner stocks are overpriced and proves the presence of bubbles in financial markets. Asness et al. (2013) find that value and momentum correlates across stock returns but are negatively correlated with each other.

2.3 Implementing Models in Different Markets

Previously, the focus was to develop and adapt new factors to asset pricing models and test these in the US stock market. This meant that returns were measured in a common currency, USD, such that exchange risk equals zero. From the 2000s, economists started testing the models on different markets. Fama and French (1998), tested the FF3F model globally under the null hypothesis that markets are integrated and, thus, can explain expected returns in all countries using one set of risk factors. They realized that a world B/M factor (*WHML*) explains international returns better than previous asset pricing models. Global portfolios are highly diversified, thus asset pricing tests on global portfolios are less noisy than country-specific ones (Fama and French, 1998). Additionally, Capaul et al. (1993) argue that the value premium is prevalent in international stock returns. Based on their analysis, Fama and French (1998), concluded that value stocks have higher returns than growth stocks in equity markets worldwide.

Griffin (2015) tested whether a global or domestic version of the FF3F model explain time-series variation in stock returns better. Evidence showed that country-specific models had higher explanatory power in addition to having lower pricing errors. Contrastingly, Liew and Vassalou (2000) find that Fama and French predict future economic growth in numerous global markets. Supplementary, research conducted by Campbell (1995) found evidence that predictability of returns in emerging markets are more likely, than in developed countries, to be influenced by country-specific information. Thus, global asset pricing models, assuming integration of capital markets, wither when explaining the cross-sectional average returns in emerging markets.

In 2012, Fama and French carried out an international study of the four-factor model, including momentum. The goal was to test the implementation of the model in developed markets, in four different regions (North America, Europe, Japan, and Asia Pacific). Their findings suggest momentum premiums in average stock returns in all regions, except for Japan. They do not find evidence of integrated pricing across the regions. Furthermore, Fama and French (2017) tested the five-factor model on international markets. Their study found that the global FF3F and FF5F have low predictive power on regional portfolios. Thus, by creating local versions of the models the predictive performance enhances. For North America, Europe, and Asia Pacific the value, profitability and investment patterns in average returns are captured. For Japan, the value effect in average returns is the sole pattern. Further, they find that the investment factor might be redundant because it does not capture variation in small stocks sorted on operational profitability.

2.4 Gaps in the Literature

Fama and French (1993) find redundancy in the value factor when implementing the three-factor model in the US. However, in 2017, the economists observe that the HML factor is important for describing average returns in all four regions during 1990 – 2015. Additionally, they find different levels of significance of the factors depending on the region the model was implemented. Most dominantly was the pattern of collinearity in the investment factor for Europe and Japan. These differences illustrate a gap which requires further research. Fama and French (2017) suggest adding momentum to their five-factor model. Jegadeesh and Titman (1993) test momentum using overlapping strategies while Carhart (1997) uses a non-overlapping strategy. However, by using an overlapping strategy one must consider transaction costs in the model construction. Thus, by implementing Carhart's non-overlapping strategy transaction costs become trivial, which decreases errors in the modelling. Fama and French (2012) conducted an international test on a consolidated global market arguing for market integration of global markets. However, Griffin (2015) finds evidence of higher explanatory power using country-specific models. Additionally, Fama and French (2017) argues for market integration of European, Asian, and North American countries. This shows contradictions in the literature, which is tested by applying the model to two different countries, the US and the UK. Based on the gaps in the literature on asset pricing models the research question of the thesis becomes:

Can the inclusion of a momentum factor in the Fama and French five-factor model explain stock returns in the US and the UK markets?

3 Description of the Stock Markets

Restraints in the selection of regions are important for the power of the test, but in contrast to Fama and French (2017), market integration is not a concern when choosing the markets subject for analysis. The goal is to create two local models, using the same factors and construction procedure, for each market. Both the United States and the United Kingdom are developed markets, showing patterns of industrialization. However, historically, it is apparent that the UK stock market has been more resilient to global crisis than the US market (Groves, 2022). Yet, there has also been several crises in both the US and the UK, which have been country specific. Among these are the 9/11 terrorist attack in the US, resulting in a 11% fall in the S&P 500 (Pisani, 2021), and the implementation of Brexit, resulting in a 35% fall in the FTSE 100 (Groves, 2022). Thus, market integration is not present, and separate analysis of the markets are required to analyze the adaptability of the models.

The reason why the US and the UK are interesting and feasible to study is three-folded. Firstly, one can argue that the markets are efficient, meaning prices reflect all available information (Fama, 1970). Because of technological advancements both the US stock markets, and the London Stock Exchange presents liquid markets where investors can make rapid trades. Moreover, there is a high volume of trades made daily which results in extremely analyzed markets. The average daily volume in 2021 was 37.3 million over the NYSE (NYSE, 2022b) and 9.2 million over the LSE (Statista, 2022a). Secondly, the stock markets are broad with a large number of stocks and composed of numerous industries. The LSE is, as of June 2022, composed of 1455 UK based stocks (London Stock Exchange, 2022a) and the NYSE has a total of 1729 domestic stocks listed (NYSE, 2022a). Lastly, the depth of the market is decisive for the comprehensibility of the model adaption. At the end of 2021, domestic stocks listed on NYSE had a collective market cap of 2880 trillion USD which accounts for 60% of the world's market value, making US the world's largest national economy (Statista, 2022b). Respectively, domestic stocks on LSE had a collective market cap of 2.48 trillion GBP, which accounts for 6.2% of the world market value, making the UK the third largest economy in the world, after Japan (London Stock Exchange, 2022a). Additionally, the markets have a long history with effective regulations. The reason why Japan is not chosen for the analysis is based on insignificant results from testing the five-factor model in 2017 (Fama and French, 2017). Japan is disparate from the US and the UK regarding regulations, negative interest rates, recessions, and overall market dynamics.

4 Methodology

The following section focuses on the formal structure and econometric models applied to examine a six-factor model, including the momentum factor that can explain stock returns in two different regions. First, the econometric models are presented before methods used to evaluate portfolio exposure, and the performance of the models are described. Finally, the testable hypothesis is presented before alternative methodologies are discussed briefly.

4.1 Econometric Model

This study tests whether a six-factor model, including momentum, can describe US and UK stock returns. The five-factor model of Fama and French (2015, 2017) is used as the benchmark. Therefore, the approach of Fama and French (2017) is followed. They base their framework on Fama and French's five-factor model (2015) and Fama and French's four-factor model (2012), which examines international stock returns. Accordingly, the following five-factor asset pricing model is used as the benchmark model:

$$R_{it} - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it} \quad \textbf{(4)}$$

In the above model, the approach of a US investor is taken; thus, all returns are in US dollars (Fama and French, 2017) R_{it} is the US dollar return on asset i for month t, and R_{ft} is the risk-free rate retrieved from the one-month US Treasury bill rate.

MKT_t is the value-weighted market portfolio excess return, and e_{it} is a zero-mean residual. The remaining variables are differences between the returns on diversified portfolios of small and big stocks (SMB_t), high and low B/M stocks (HML_t), stocks with robust and weak profitability (RMW_t), and stocks of low and high investment firms (conservative minus aggressive, CMA_t).

In an attempt to capture momentum returns, a six-factor model is proposed by following the approach of the momentum factor of Fama and French (2012) and Carhart (1997). Moreover, it is assessed to which extent stock returns in the US and the UK can be described by a six-factor model adding the momentum factor to Fama and French's five-factor model (2015a). Therefore, model (1) is enhanced with a momentum return, WML_t, which is the difference between the month t returns on diversified portfolios of the winners and losers of the past year:

$$R_{it} - R_{ft} = a_i + b_i MKT_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + w_i WML_t + e_{it} \quad \textbf{(5)}$$

4.2 Testing Procedures

The following section focuses on the factor models' empirical tests by explaining the techniques' rationale and how to apply them. First, a factor spanning test is conducted to identify possible redundant factors. Further, Fama-MacBeth regression is used. This is a two-step procedure to estimate portfolio exposures and risk premiums (Fama and MacBeth, 1973) before model performance is evaluated based on GRS-test developed by Gibbson et al. (1989).

4.2.1 Factor spanning test

Factor spanning aims to test whether a factor is important to describe average excess returns for the US and the UK for both the benchmark and the six-factor model. An emblematic problem of regressions on time series data is the presence of autocorrelation between the independent variables. If one carries out the regression and overlooks this aspect, the results will be wrong. To avoid this problem in our model, auxiliary regression is implemented, which is a secondhand regression. The process entails regressing each explanatory variable on the remaining factors to see to what extent one factor's average return is explained by the others (Appendix 4). If the regression intercept is significant, other factors do not capture the effects of the dependent factor. This, again, indicates that the factor adds explanatory power to the model. It is, however, important to be aware that a factor's average excess return that is not fully explained by other factors does not automatically mean that it helps describe average excess returns for all portfolios.

4.2.2 Fama-MacBeth regression

Given that panel data is implemented on portfolio excess returns and risk factors in the two-factor models, inference problems may occur. Possible breaches that may take place are measurement errors and multicollinearity. Multicollinearity occurs when the factors are very highly correlated with each other. A high correlation between the factors may lead to inappropriate conclusions on the significance of the model (Brooks, 2019, p. 215). To address this problem, a two-step cross-sectional regression of portfolio excess returns on risk factors proposed by Fama and MacBeth (1973) is run. The two-step regression is designed to estimate portfolio exposure, indicating that the relationship between risk factor premium and portfolio excess returns is tested.

In the first step of Fama and MacBeth's methodology, time-series regressions are run on portfolios that have been two-way sorted. In this regression step, the monthly portfolio excess returns are used as dependent variables, whereas the RHS factors are the independent variables. To perform the regression, the coefficients and portfolio excess returns are assumed to be constant. Thus, the following first-step regression model is estimated using OLS:

$$R_{i,t} = \alpha_i + b_{i,1}MKT_{1,t} + s_{i,2}SMB_{2,t} + h_{i,3}HML_{3,t} + r_{i,4}RMW_{4,t} + c_{i,5}CMA_{5,t} + w_{i,6}WML_{6,t} + u_{i,t}$$
$$t = 1, \dots, T \qquad \textbf{(6)}$$

Where α_i is the intercept, $b_{i,1}, s_{i,2}, h_{i,3}, r_{i,4}, c_{i,5}$, and $w_{i,6}$ are the factor loadings, $u_{i,t}$ is the error term, and T is the number of time steps observations. The factor loadings are estimations of the true coefficients, identified as $\hat{b}_{i,1}, \hat{s}_{i,2}, \hat{h}_{i,3}, \hat{r}_{i,4}, \hat{c}_{i,5}$, and $\hat{w}_{i,6}$ measure the sensitivity of each individual portfolio to each of the factors (Brooks, 2019, p. 591).

In the second step of the Fama-MacBeth methodology, a cross-sectional regression is run to estimate the risk premium for each period. Besides, a linear relationship between the excess returns of the portfolios and its sensitivity to the risk factor is tested. The regression results can identify whether the exposure to a risk factor yields a factor risk premium, indicating that it is tested whether an investor can expect to be rewarded for higher risk exposure (Brooks, 2019, p. 591). To be compensated for any additional risk, the regression parameters, λ, must be positive. In this step, the factor loadings defined in the first step of the regression are defined as the independent variables, whereas the excess portfolio returns are the dependent variables. This yields the following regression models for the second step:

$$R_{i,t} = \lambda_{0,t} + \lambda_{1,t}\hat{b}_{i,1} + \lambda_{2,t}\hat{s}_{i,2} + \lambda_{3,t}\hat{h}_{i,3} + \lambda_{4,t}\hat{r}_{i,4} + \lambda_{5,t}\hat{c}_{i,5} + \lambda_{6,t}\widehat{w}_{i,6} + u_{i,t} \quad i = 1, \dots, N \qquad \textbf{(7)}$$

Where $\lambda_{0,t}$ is the intercept, $\lambda_{i,1}, \lambda_{i,2}, \lambda_{i,3}, \lambda_{i,4}, \lambda_{i,5}$, and $\lambda_{i,6}$ are the parameter estimates of the risk premiums for each period. Furthermore, $u_{i,t}$ is the error term, and N is the number of portfolios. From the OLS regressions for each cross-section regression, we obtain T estimates of risk premium for each of the factors.

4.2.3 GRS test

The Gibbson Ross Shankes (GRS) statistic test (1989) is implemented to compare the performance of the five-factor and the six-factor models. As stated in our hypothesis, the intercept must be zero for the factor models to explain expected excess returns in the US and the UK. The GRS statistic tests the null hypothesis that all intercepts in a set of 25 (5 x 5) regressions are equal to zero (Fama and French, 2012). If the null hypothesis is rejected, the model has unexplained abnormal returns, meaning that the model does not include all relevant risk factors. If the null hypothesis is not rejected, however, the model seems to include all necessary risk factors to explain excess returns as the intercept is not significantly different from zero. Hence, the significance of the models can be concluded based on the results of the GRS statistic.

4.3 Alternative Methodologies

The second step of Fama-MacBeth regression uses estimated factor loadings from the first step regression as independent variables for the cross-sectional regressions. Due to the use of the estimated factor loadings, errors in variables can occur. To reduce the problem of errors in the independent variables, a rolling window procedure can be implemented. A Rolling window is an estimation approach allowing for time-varying estimators (Brooks, 2017, p. 592). After the first model is estimated, one observation is removed until the end of the sample period. Hence, the method obtains more accurate risk premiums estimates. Another approach to address the problem of constant independent variables is the Generalized Method of Moments (GMM). Overidentified systems occur hhen it exists more moment conditions than unknown conditions. Thus, the method helps select the best estimates that minimize the variance of the moment conditions. However, since this thesis focus on explaining stock returns, and no other securities, it is sufficient to use the two-step methodology of Fama-MacBeth (1973).

4.4 Testable Hypothesis

Several gaps in the literature were identified when previous research was reviewed. After the construction of the three-factor model (Fama and French, 1993) the economists next research added a momentum factor and tested the four-factor model on global markets (Fama and French, 2012). Furthermore, in 2015, Fama and French created a five-factor model building on the three-factor model disregarding their findings in 2012 on momentum. When the five-factor model was tested in global markets (Fama and French, 2017), Fama and French suggested a test of a six-factor model including momentum. Momentum is not explained in their new model, which they explain as counterintuitive, since momentum has not disappeared in latter periods. Therefore, this led way to the model tested in this research paper. There were several open questions after Fama and French's research in 2012 and 2017, from the model implementation in global markets. These considerations can be viewed in detail in the literature review gaps (section 2.4).

An additional contradiction is apparent in the model's calculation and implementation of momentum. Both Carhart (1997) and Jegadeesh and Titman (1993) analyze momentum strategies in the market; however, they are implemented in different ways. Carhart uses a non-overlapping strategy, while Jegadeesh and Titman use an overlapping strategy. Since the model does not consider transaction costs as a factor, an overlapping momentum strategy would lead to biases and an inaccurate depiction of excess returns. Therefore, the momentum strategy implemented by Carhart (1997) and Fama and Fench (2012) is the most appropriate. By identifying these gaps in the literature and following recommendations suggested by researchers, the following research question is recognized:

Can the inclusion of a momentum factor in the Fama and French five-factor model explain stock returns in the US and the UK markets?

The theory is that momentum will have explanatory power on market expected returns. However, additional factors can create multicollinearity based on previous literature on complex models. Thus, a theory is that one or more factors will become redundant and should be eliminated from the model. The goal is to construct an asset pricing model that captures all excess returns resulting in zero anomalies. If the true values of the factor exposures, b_i, s_i, h_i, r_i, and c_i, capture all differences in expected returns, then the intercept, a_i, in (1) is equal to zero for all sample stocks i (Fama and French, 2017), resulting in the following null and alternative hypotheses:

$H0$*: The six-factor model, including momentum, can fully explain portfolio returns,* $a_i = 0$

$H1$*: The six-factor model, including momentum, cannot fully explain portfolio returns,* $a_i \neq 0$

5 Data and Variables

The following section presents the data and variables used to measure returns in the US and the UK stock markets. For a better overview of the data and, thus, a logical flow of the analysis, description of the data is presented by country. Firstly, the data collection process and assumptions made are explained. Secondly, the assumptions taken in the portfolio- and factor- constructions are discussed. Thirdly, summary statistics are presented for the replication period, the extended period, and the six-factor model, in the two markets.

5.1 Data Collection

To maintain consistency and comparability in the analysis the models are constructed from raw data and based on the same set of assumptions. All data analysis is conducted in R. For the US stock market all stock returns and accounting data is retrieved from CRSP and Compustat through WRDS. The securities subject to analysis is the US based common stocks, share code 10 and 11. The reasoning is that US preferred stocks have more similarities with bonds than with stocks, and thus different characteristics. The common stocks collected is traded on the NYSE, AMEX, and NASDAQ, exchange code 1, 2, and 3 respectively. Since the model will measure expected returns on a time-series, delisted returns are also included in the dataset for the period they exist. Firms delisted from the exchange in the period have missing returns. Therefore, the missing values are supplemented with the delisted returns. Only observations for which both accounting and stock price data are kept.

For the UK stock market all stock returns and accounting data is retrieved from Refinitiv Eikon through Worldscopes and Datastream. The securities subject to analysis is the common stocks based in the UK, traded on the London Stock Exchange. All variables retrieved from the database is quoted in GBP. The dataset includes both active and inactive stocks since the model will measure expected returns of time-series. Further, only observations for which both accounting and stock price data are kept.

5.1.1 June as starting point

Fama and French chooses the end of June as a starting point for portfolio construction to avoid look-ahead bias. The accounting data used to form the variables are known before the returns they explain. The model is constructed based on a variety of firms with different fiscal year-ends. Thus, data is matched for all fiscal year-ends in calendar year $t - 1$ with the return for July of year t to June of $t - 1$ (Fama and French, 1992). This causes the gap between the accounting data and matching returns to vary across firms (Fama and French, 1992). Firms are required to file the 10-K reports within 90 days of the fiscal yearend. However, 19.8% do not comply and another 40% announce their results in April (Alford et al., 1994). Fama and French (1993) states that most firms end the fiscal year in December, but do not present their audited annual reports to shareholders until June 30th. Market capitalization is available immediately, while accounting data is published yearly. Hence, the market capitalization reported in June of year *t* is used as a benchmark for the whole year. The assumption is a constant linear growth or decrease of the market cap from January 1st to December 31st.

5.1.2 The risk-free rate

Since the research is conducted taking the view of the US investor the risk-free rate used across the countries is the one-month US Treasury bill. The rate is retrieved monthly, for the corresponding sample period, from Kenneth R. French's website (French, n.d.).

5.1.3 Exchange rates

The research conducted takes the view of a US investor who can choose to invest in the US or the UK. For the investment strategies to be comparable, all data in the sample are quoted in US dollars. The data for the UK are, therefore, converted to US dollars based on the exchange rate for each month of the dataset. The exchange rate is retrieved from the Wall Street Journal's historical data library (WSJ, 2022). Since the firms, subject to data retrieval, have been constrained to companies with their main operations domestically, the accounting data is reported in the local currency.

5.1.4 Elimination of penny stocks

Penny stocks, in the US, are characterized as shares issued by extremely small companies at less than 5 US dollars per share, that are new to the market (SEC, 2013). Returns generated from this stock group are misleading as they do not reflect the growth of a company, but instead shows minimal fluctuations in price. These stocks are typically traded over the counter and do not qualify for exchange listing (NASDAQ, 2017). This is based on the US Security and Exchange Commission's (SEC) Penny Stock Reform Act, 3a51-1, (SEC, 2005) implemented to suppress fraud with penny stocks. In the UK, however, penny stocks are defined as stocks traded to a share price below 1 GBP. In contrast to exchanges in the US, in the UK penny stocks are traded on the LSE in the Alternative Investment Market (AIM) following separate trading rules (London Stock Exchange, 2022b). The data collected for the US automatically exclude penny stocks from the sample. However, the data retrieved for the UK includes penny stocks, and these are removed from the sample. The elimination of observations follows the US definition.

5.2 Sorting Variables

Both the portfolio- and factor- constructions are conducted using a double sorting technique. The process entails first sorting stocks based on firm fundamentals, and secondly sorted on another, independent characteristic. This sorts stocks into different groups, ranging from high to low values of the sorting variable. The next step is to group all stocks with the same combination sort into portfolios. The result is a set of portfolios consisting of stocks with similar features. This is effective as it isolates the effect of variables from one another.

5.2.1 Size

Size is defined as market capitalization at the end of each June of year t. The value is calculated for each stock every year by multiplying the closing price with the number of shares outstanding. See Appendix 1 for the formula. All stock prices in the dataset are denoted in absolute values since it is incoherent with negative stock prices. This will, thus, result in market equities above zero for all observations in the dataset.

5.2.2 Value

Value is the ratio of a stock's book equity at the end of fiscal year $t - 1$ and the market capitalization at the end of December of year $t - 1$. The book equity is calculated by summing the shareholder equity, deferred taxes, and investment tax credit together (Appendix 1). If a firm's fiscal year does not end in December this will lead to a time-gap between the calculation of the book equity and the market equity. Another option is to measure the book-to-market equity ratio at the end of the fiscal year. This would, however, result in different ratios across firms because of differences in firm characteristics and market changes throughout the year. Thus, the most feasible is to be time-consistent with the comparison. In both WRDS and Datastream there is a variable for the book equity. However, for certain stocks, in the US, the information is not provided. Thus, for missing values the book equity is calculated by taking the difference between total assets and liabilities. In contrast to the market capitalization, book equity can be negative and are, thus, kept in the dataset.

5.2.3 Operational profitability

Operational profitability is defined as the operating profit after deducting interest expenses relative to book equity, all measured at the end of fiscal $t - 1$ (Appendix 1). For the UK data, variables retrieved to calculate the operational profitability is the EBITDA, interest expenses, and book equity from Refinitiv Eikon.

5.2.4 Investment

Investment behavior is a ratio defined as the change in total assets from year $t - 2$ to year $t - 1$ divided by $t - 2$ total assets, all measured at fiscal year-ends (Appendix 1). As it is conceptionally implausible with negative book values of assets, these observations are omitted in the dataset.

5.2.5 Momentum

Momentum is defined as the cumulative return from $t - 12$ to $t - 2$. Month t – 1 is skipped because of the one-month short-term reversal phenomenon. This is consistent with the non-overlapping strategy implemented by Carhart (1997).

5.3 Dependent Variable Constructions

Fama and French have tested a variety of different portfolio constructions to find the optimal number. They stress that by creating too many portfolios, a large part of them will be poorly diversified. In 2017, Fama and French found that different portfolio constructions gave the same results in the tests of a given model. Thus, for simplification the economists stick to the 5×5 sort constructing 25 portfolios with value weighted returns for each double-sort (Fama and French, 2015a). This assumes a sufficient number of observations, which is met in the markets where our research is conducted. The portfolios are the intersections, from the sorts, of each of the identified firm characteristics. The double sorting process is performed at the end of each June based on the firms' accounting data from the previous fiscal year. The portfolios are held for one year before they are resorted. Fama and French (1992 and 1993) find evidence indicating that size is the most prevailing effect in the market the sample stocks are first sorted on size and then on value, operating profitability, investment, and momentum. This creates three sets of 25 portfolios used for the five-factor model, and four sets of 25 portfolios for the six-factor model. This process is carried out on both the US and the UK market.

5.4 Independent Variables Construction

The independent variables of the three-factor model of Fama and French (1993) are based on factor mimicking portfolios. These factor portfolios are constructed on two size groups (small and big) and three value groups (low, neutral, and high) of the stocks. The motivation for the breakpoint is the evidence of Fama and French (1992) proving that BM-ratios have higher explanatory power for average stock returns than firm size. In 2015, Fama and French tested different version of portfolio sorts of the independent variables. They find, however, that the 2 x 2 and the 2 x 2 x 2 x 2 sorts do not preform significantly better than the 2 x 3 sorts. Based on this reasoning our factors will be constructed on a 2×3 sort of factor premiums creating 6 portfolios independently distributed.

The market factor is constructed as the value-weighted return of all stocks in the market in excess of the risk-free rate. The value-weight is based on market capitalization of each firm each month of the sample period compared to the total market capitalization of the firms every month. Based on sorts on size, value, profitability, investment, and momentum the stocks are assigned to separate groups. Fama and French (2012) insinuate that the explanatory power of international models is unaffected by the choice of factor breakpoints. Size is divided into a small or big group based on the domestic median breakpoint: NYSE and LSE. The other variables are divided into three groups using the 30% and 70% breakpoints in each market.

This leads to three B/M groups (low, neutral, and high), three groups of investment (conservative, neutral, and aggressive), three profitability groups (weak, neutral, and robust), and three groups on momentum (winners, neutral, and losers). The intersection between size and each of the other sorts results in six portfolios (Appendix 1). Following the portfolio constructions, factors are calculated monthly from returns of stocks assigned to the different portfolios.

5.5 Summary Statistics

This section aims to summarize the data in an easy format, so the results are clearly interpretable. First, Fama and French's research *"International test of a five-factor asset pricing model"* from 2017 is conceptually replicated in the US and the UK. Secondly, the five-factor model is tested for the extended period in the two markets. Lastly, the six-factor model, including momentum, is tested in the extended period on the two markets.

5.5.1 Replication period

The conceptual replication part of the research paper attempts to achieve the same results as the ones realized by Fama and French (2017). Thus, our data collection and variable assumptions are similar to the economists', explained in the previous section. Our empirical tests examine whether the five-factor model explains average returns in portfolios formed on size, B/M, profitability, and investment. This is shown by model (4). Fama and French (2017) test the model in 23 countries, on four continents. This entails extensive research and complex presentations of results. Thus, our replication will focus on two countries on two different continents, the US and the UK. In 2017, Fama and French use analyze North America, including the US and Canada, as a whole. However, based on the results found by Mittoo (1992), Canada is excluded from our sample since it is reasonable to assume that the US and Canada are close to one market for securities. The sample period is from June 1990 to December 2015.

For the US, the exogenous variables, factors, constructed in our analysis are compared with the ones composed by Fama and French (2017), through a regression. The five factors of Fama and French are retrieved from French's website (French, n.d.), and covers the period of 1990 to 2015. The results in Table 1 shows that the replication of Fama and French (2017) is quite compelling for the US (compared with the results of North America). The intercepts of all four factors are zero, and the coefficients are all close to one which indicates almost perfect correlation. Additionally, all the adjusted R^2 are high, indicating that most of the dependent variables of Fama and French (retrieved from French's page) are explained by the replicated factors. Finally, interpreting the t-stats, all factors are statistical significance. *SMB* and *CMA* are most convincing, since all three criteria are close to fulfilled. *HML* and *RMW*, however, meet the criteria at a slightly lower level, but are still convincing. The factors are not perfectly replicated since we did not follow their procedure strictly. The corresponding regression equations is found in Appendix 2.

The US				
	SMB$_{rep}$	**HML**$_{rep}$	**RMW**$_{rep}$	**CMA**$_{rep}$
Intercept	0.00	0.00	0.00	0.00
Coefficient	0.99	0.94	0.94	0.98
t-stat	145.66	76.55	44.58	88.74
Adj R^2	0.99	0.95	0.94	0.97

Table 1. *Regression analysis of the four time-series size, value, profitability, and investment premiums in the US for June 1990 to December 2015, 307 months.*

In the UK, the factors created from the 2 x 3 sorts for the UK are compared to the ones composed by Fama and French (2017), through a regression. Fama and French's five factors are acquired from French's website (French, n.d.), and covers the period of 1990 to 2015. This is used as the performance benchmark for our model. Fama and French has not made the factors constructed for the UK public. Thus, our analysis of the UK market is compared to the Fama and French's factor constructions for Europe. This is a gross estimation as Fama and French test one version of the model on 16 countries. Thus, the result of the replication of Fama and French (2017) is implausible for the UK (compared with the results of Europe). The summary of the replication performance is shown in Table 2. The intercepts of all four factors are zero, meaning a non-significant intercept which rejects the notion of systematic error.

However, the coefficients are low for each factor indicating that the correlation between our factors are low compared to those of Fama and French. This is tied to the low adjusted R^2 apparent for all the factors, which indicates a low proportion of explained variance. Lastly, interpreting the t-stats, all factors are statistical significance. The *SMB* and *HML* are most convincing, however, at a much lower level than those for the US. The replication is not perfect, however, intelligibly analyzing Europe as a whole is improbable. Fama and French (2017) defends their decision by arguing for market integration within Europe. However, the 16 markets analyzed collectively in the Europe test is vastly different in structure, size, regulations, and fundamental market mechanisms. The corresponding regression equations can be found in Appendix 2.

The UK				
	SMB$_{rep}$	**HML**$_{rep}$	**RMW**$_{rep}$	**CMA**$_{rep}$
Intercept	0.00	0.00	0.00	0.00
Coefficient	0.40	0.43	0.10	0.26
t-stat	15.25	10.11	3.66	8.27
Adj R^2	0.44	0.27	0.04	0.19

Table 2. *Regression analysis of the four time-series size, value, profitability, and investment premiums in the UK for June 1990 to December 2015, 307 months.*

5.5.2 Extended period

This section attempts to lay forward descriptive statistics for factor returns in the two different markets from June 1990 to December 2021, using the five-factor model. The five-factor model is tested to have a benchmark for comparison of the six-factor model. The decision of sample period is based on the start date of Fama French (2017), extended to the most recent date point with all necessary data available. The sample period entails large volatilities in stock returns, including the low-performance period of the Covid-19 Pandemic. As a result, the momentum factor might vary substantially in periods and across different regions, when added to the model in the next section. Another reason for the period extension is the increased globalization of markets the latter years and better online brokerages leading to exceeding retail investing. This might lead to increased anomalies, based on investment sentiments. A sample period of 30 years leads to a robust forecast of excess returns as it captures several periods with high volatility.

Table 3 shows the mean, standard deviation, and t-statistics of the exogenous factors used to explain excess returns in the US. In the US market the market portfolio is statistically significant at the 1% level with t = 3.40. Whilst the *RMW* portfolio is significantly different from zero (t = 2.29) at the 5% level. Respectively, the average returns of the portfolios are 0.78% and 0.33%, which are the highest returns for the period. The investment portfolio is significant on a 10% level with a t-statistic of 1.74 and average returns of 0.19%. The size portfolio is statistically insignificant (t = 1.00), which echo the evidence of Fama and French (2012). The highest standard deviation is the market portfolio with an average of 4.33. High standard deviations might imply high dispersions in the cross-sectional variation. This is favored because it means that more information is captured to estimate the risk premia. The corresponding regression equations can be found in Appendix 3.

The US					
	MKT	**SMB**	**HML**	**RMW**	**CMA**
Mean	0.78	0.17	0.10	0.33	0.19
Std dev	4.33	3.11	3.22	2.74	2.06
t-stat	3.40	1.00	0.53	2.29	1.74

Table 3. *Means, standard deviations, and t-statistic of the five factors returns for the US for June 1990 to December 2021, 354 months.*

Further, testing the correlation between the factors is important as it can uncover multicollinearity. If multicollinearity is ignored the resulting standard errors of the coefficients are impacted. The regression would also be sensitive to minor changes, in the model construction. Additionally, significance test might give wrong conclusions because confidence intervals are wide (Brooks, 2019, p. 215). Table 4 show the correlations between the factor portfolio returns. This is a useful tool for the analysis as it shows whether multicollinearity exists in the model. Ideally, the factors are independent from one another with a correlation coefficient equal to one. For the US the market portfolio is negatively correlated with all other factors, except for the *SMB* portfolio. The least correlated factors are the *SMB* and *CMA* portfolios with a correlation of -0.03 and the correlation between *SMB* and *HML* of -0.04. The two factors that are most correlated and, thus, show the highest level of multicollinearity is the *HML* and *CMA* with a correlation of 0.65. Further analysis of this detection is conducted in the section on factor spanning (Section 6.1).

The US					
	MKT	**SMB**	**HML**	**RMW**	**CMA**
MKT	1	0.26	-0.16	-0.40	-0.32
SMB	0.26	1	-0.04	-0.42	-0.03
HML	-0.16	-0.04	1	0.42	0.65
RMW	-0.40	-0.42	0.42	1	0.30
CMA	-0.32	-0.03	0.65	0.30	1

Table 4. *Correlation matrix of five factors for the US for June 1990 to December 2021, 354 months.*

Table 5 shows the mean, standard deviation, and t-statistics of the factors constructed to explain excess returns for the UK. The descriptive statistics show that the market portfolio and the *SMB* portfolio are significant at the 2% significance level (t = 2.46 and t = 4.14). The average returns for these portfolios are 0.63% and 0.80%, respectively, which are the highest of the factor returns. The factor with the lowest average return is the *HML* portfolio of 0.10% indicating almost no explanation of excess returns. Another interesting observation is the negative average return of the investment factor (-0.14%), which indicates that investments have a negative effect on excess returns. An explanation of this can be companies' negative rates of return or negative revenues from high expenses relative to earnings. The highest standard deviation is assigned the *MKT* portfolio with an average of 4.86. It is followed by the size portfolio with an average standard deviation of 3.71. The corresponding regression equations can be found in Appendix 3.

The UK					
	MKT	**SMB**	**HML**	**RMW**	**CMA**
Mean	0.63	0.80	0.10	-0.14	0.22
Std dev	4.86	3.71	3.17	3.43	2.82
t-stat	2.46	4.14	0.62	-0.81	1.47

Table 5. *Means, standard deviations, and t-statistic of the five factors returns for the UK for June 1990 to December 2021, 354 months.*

Further, table 6 show the correlations between the factors in the UK for the sample period 1990 – 2021. The market portfolio is positively correlated with all other factors. The least correlated factors are the *HML* and *RMW* portfolios with a correlation of 0.01 and the correlation between *MKT* and *SMB* of 0.02. The two factors that are most correlated and, thus, indicate the highest level of multicollinearity is the *SMB* and *HML* with a correlation of -0.43. This observation is followed by the *SMB* and *RMW* with a correlation of -0.35. These results are different than the ones found in the US for the same period. Further analysis of this detection is conducted in the section 6.1 on factor spanning.

The UK					
	MKT	**SMB**	**HML**	**RMW**	**CMA**
MKT	1	0.02	0.04	-0.19	-0.09
SMB	0.02	1	-0.30	-0.35	-0.02
HML	0.04	-0.30	1	0.01	0.14
RMW	-0.19	-0.35	0.01	1	-0.04
CMA	-0.09	-0.02	0.14	-0.04	1

Table 6. *Correlation matrix of five factors for the UK for June 1990 to December 2021, 354 months.*

5.5.3 Momentum factor inclusion

The next part of the analysis expands the model by including momentum. The, now, six-factor model is tested on the US and the UK for the sample period 1990 to 2021. An international test of our purposed model will follow the steps taken by Fama and French’s (2017) international test. The following section will present some descriptive statistics and a correlation matrix to get an overview of the explanatory power of the model by adding momentum. These observations and comparisons to the five-factor model will further be analyzed in Section 6.

Table 7 shows the mean, standard deviation, and t-statistics of the factors composed to explain excess returns in the US. In the US market the market portfolio and the *RMW* portfolio are still the only significant factors (t = 3.40 and t = 2.29) at the 5% level. The momentum factor (*WML*) is insignificant at the 5% level; however, it is significant at the 10% level with t = 1.65. Respectively, the average return of the *WML* portfolio is 0.42%, which is the second highest for the period. The highest standard deviation for the six-factor model is the momentum portfolio (4.82), in contrast to the five-factor model where the market portfolio was the highest (4.33). This high standard deviation might imply high dispersions in the cross-sectional variation; thus, more information is captured to estimate the risk premia.

The US						
	MKT	**SMB**	**HML**	**RMW**	**CMA**	**WML**
Mean	0.78	0.16	0.10	0.33	0.19	0.42
Std dev	4.33	3.10	3.22	2.74	2.06	4.82
t-stat	3.40	1.00	0.53	2.29	1.74	1.65

Table 7. *Means, standard deviations, and t-statistic of the six factors returns for the US for June 1990 to December 2021, 354 months.*

Further, based on the rational given regarding multicollinearity a correlation matrix is presented showing the correlation between factors. Table 8 shows the correlations between the factor portfolio returns. For the US the market portfolio is still the most negatively correlated with the *RMW* portfolio (-0.40) for the six-factor model. Furthermore, the *WML* portfolio shows the same pattern with a correlation of -0.30 with the market portfolio. The most correlated factors are the *HML* and *CMA* portfolios, which are depicting as a positive correlation of 0.65. This is the same result as for the five-factor model. The least correlated factors are the *WML* and *CMA* with a correlation of 0.00. This indicates no relationship between momentum and investments. Additionally, there is a very low correlation between *SMB* and *WML* (-0.06) also indicating limited association between size and momentum. There is a negative correlation between the momentum (*WML*) and value (*HML*) of -0.19. This is consistent with the observations of Asness et al. (2013), and Cakici et al. (2013). They conclude that this makes it impossible to combine them into efficient portfolios. Further analysis of these detections is conducted in the section 6.1 on factor spanning.

The US						
	MKT	**SMB**	**HML**	**RMW**	**CMA**	**WML**
MKT	1	0.27	-0.16	-0.40	-0.32	-0.30
SMB	0.27	1	-0.04	-0.44	-0.04	-0.06
HML	-0.16	-0.04	1	0.42	0.65	-0.19
RMW	-0.40	-0.44	0.42	1	0.30	0.11
CMA	-0.32	-0.04	0.65	0.30	1	0.00
WML	-0.30	-0.06	-0.19	0.11	0.00	1

Table 8. *Correlation matrix for six factors for the US for June 1990 to December 2021, 354 months.*

Table 9 shows the mean, standard deviation, and t-statistics of the factors composed to explain excess returns in the UK for the six-factor model in the extended period. In the UK the market portfolio, size portfolio, and momentum portfolio are significant factors (t = 2.46, t = 4.14, and t = 2.35) with 98% confidence. The average return of the *WML* portfolio is 0.32%, which is the third highest for the period. The highest standard deviation for the six-factor model is the market portfolio (4.86), which deviates from the conclusion of the five-factor model where the investment portfolio was the highest (5.45). This high standard deviation might imply high dispersions in the cross-sectional variation; thus, more information is captured by the market to estimate the risk premia.

The UK						
	MKT	**SMB**	**HML**	**RMW**	**CMA**	**WML**
Mean	0.63	0.80	0.10	-0.14	0.22	0.32
Std dev	4.86	3.71	3.17	3.43	2.82	2.58
t-stat	2.46	4.14	0.62	-0.81	1.47	2.35

Table 9. *Means, standard deviations, and t-statistic of the six factors returns for the UK for June 1990 to December 2021, 354 months.*

Next, the relationship between the factors constructed as independent variables for the six-factor model is shown using a correlation matrix, Table 10. When the six-factor model is tested in the UK market the all the factors are positively correlated with the market portfolio except the profitability and investment factor. The factors that have the most apparent relationship is the *SMB* and *RMW* portfolios with a correlation of -0.35. This differs from the result from the five-factor model. An explanation of this mechanism is the *WML* factor, which has a noticeable positive correlation with the *RMW* factor (0.16). Additionally, the *WML* portfolio has the weakest relationship with the *CMA* factor, with -0.01 in correlation. This indicates close to no relationship between momentum and investments of the firms. Moreover, there is a very low correlation between *WML* and *HML* (0.03) also indicating limited association between momentum and value. Further analysis of these detections is conducted in section 6.1 on factor spanning.

The UK						
	MKT	**SMB**	**HML**	**RMW**	**CMA**	**WML**
MKT	1	0.02	0.04	-0.19	-0.09	0.24
SMB	0.02	1	-0.30	-0.35	-0.02	-0.29
HML	0.04	-0.30	1	0.01	0.14	0.03
RMW	-0.19	-0.35	0.01	1	-0.04	0.16
CMA	-0.09	-0.02	0.14	-0.04	1	-0.01
WML	0.24	-0.29	0.03	0.16	-0.01	1

Table 10. *Correlation matrix for six factors for the UK for June 1990 to December 2021, 354 months.*

5.6 Test Portfolios

In the following the tradeoffs between different sorts of test portfolio construction is disregarded. Thus, portfolios are constructed based on the composition of the replication study, the 5 x 5 portfolio sort. Regressions are run on three sets of 25 left-hand-side portfolios for the five-factor model and four sets of 25 left-hand-side portfolios for the six-factor model. The portfolios are constructed as described in section 5.3.

Table 11 shows the average monthly percentage excess returns on the portfolios formed by double sorts on size and BM, size and OP, size and Inv, along with size and MOM in the US. Panel A shows the average monthly percentage excess returns for the Size-BM portfolio, while holding profitability, investments, and momentum constant. It is evident that long strategies on small firms, on average, (0.97%) outperforms long strategies on big companies (0.77%) when controlling for firm value. This pattern, the size-effect, is apparent in each of the BM columns except for the Low BM stocks where the small stocks have a considerably lower average return (0.48%). These stocks can be categorized as growth, microcap stocks and have underperformed historically. A common trait among these stocks is low, or negative, profits at a high relative price. Further, the high BM stocks (value stocks) seem to outperform the low BM (growth stocks) on average, known as the value effect. This pattern is consistent for all size portfolios except for the big size stocks and the fourth size-portfolio where there is no relation between average return and BM as the spread is – 0.10% and -0.08. Hence, the effect seems to vanish as the firm size increases.

Panel B shows the average monthly percentage excess returns for the Size-OP portfolio, while holding book-to-market equity, investments, and momentum constant. It is perceptible that in the size-OP average returns increase as profitability increases in all size quintiles. Thus, a long strategy on robust stocks outperforms long strategies on weak stocks. This proves the profitability effect (Novy-Marx, 2013). Another observation is that the spread in average return which increases with OP is centered around 0.30% and the average return decrease with size is less severe than in the Size-BM sorts. For low profitability the returns decrease from 0.78% to 0.64%

and for high profitability stocks returns decline from 1.10% to 0.94%. This converts to a spread of 0.14% and 0.16%, respectively, which shows a stable trend regardless of the market capitalization. Hence, there is a size-effect evident in the Size-OP sorts.

Panel C shows the average monthly percentage excess returns for the Size-INV portfolio, while holding book-to-market, profitability, and momentum constant. In line with Fama and French (2015a, 2017) our results displays a decline in average returns with investments, regardless of the size. Accordingly, the average excess return is higher for firms with low investments (conservative) than for firms with high investments (aggressive), regardless of the size. Another take-away is that most firms with small market capitalization have higher average returns than the large caps, which illustrates the size-effect. However, this is not a consistent pattern in the average return throughout the clusters. The outlier is the high investment portfolio which presents a negative spread (-0.26), which illustrates that the size effect is not present. This is equivalent to the observation made on the Size-BM portfolios in the low BM column.

Panel D shows the average monthly percentage excess returns for the Size-MOM portfolio, while holding book-to-market, profitability, and investments constant. The average excess return is higher for firms with high price sensitivity (high momentum) than for firms with low price sensitivity (low momentum), regardless of size. Thus, last year's winners show positive momentum returns, however, this increase is not consistent. The size effect appears in the size-MOM portfolios also for the low momentum portfolio. Our observations are aligned with the ones discovered by Fama and French (2012) for North America.

Table 12 illustrates the average monthly percentage excess returns on the portfolios formed by double sorts on size and BM (Panel A), size and OP (Panel B), size and Inv (Panel C), as well as size and MOM (Panel D) in the UK. It is purposeful to compare patterns in average returns across size-clusters of a market. However, comparisons across regions will be misleading (Fama and French, 2017), because the size of the firms in the US and the UK are extremely different. The biggest stock (megacap) on the London stock exchange is approximately 10% of the market value of the biggest company in the US.

Panel A shows the average monthly percentage excess returns for the Size-BM portfolio, while holding profitability, investments, and momentum constant. The results show that long strategies on small firms outperforms long strategies on big companies, in most BM portfolios. This is a consistent pattern throughout the Size-BM portfolios. However, the size-effect pattern is extremely inconsistent between the columns. The lowest return difference, Low BM portfolio, has a spread of 0.15% and the largest return difference, High BM, has a spread of 1.81%. This reveals a stronger size-effect for value stocks than for growth stocks. Further, high BM firms (growth stocks) seem to outperform low BM firms (value stocks) on average. This pattern is consistent for all size portfolios, except for the big stocks which have a slightly higher returns for Low BM stocks (0.41%) compared to the high BM portfolio (0.37%). This indicates no relation between average return and BM and is the same effect as the one detected in the US market. Thus, inconsistencies in the spread of average returns are observed throughout the size-portfolios, holding the BM portfolio fixed. The spread in small size-portfolio is 1.62%, while -0.04% for the big portfolio.

Panel B shows the average monthly percentage excess returns for the Size-OP portfolio, while holding book-to-market equity, investments, and momentum constant. It is observable that in the size-OP average returns decrease as profitability increases in all size quintiles, except in the third OP-portfolio. Thus, a long strategy on firms with high profitability (robust stocks) outperforms long strategies on firms with low profitability (weak stocks). This proves the profitability effect. Another observation is that the spread in average return between the high OP-portfolios and low OP-portfolios is scattered and inconsistent throughout the size-portfolios with the highest spread in the second size-portfolio (1.05%). Similarly, the average return-decrease with size, controlling for profitability, shows a random in contrast to the Size-BM sorts. For low profitability the returns decrease from 1.27% to 0.16% and for high profitability stocks returns decline from 2.07% to 0.32%, which shows a strong size-effect. However, the effect disappears in the second OP-portfolio with a spread of – 0.28.

Panel C shows the average monthly percentage excess returns for the Size-INV portfolio, while holding book-to-market, profitability, and momentum constant. In contrast to our observations in the US market, the investment effect is not consistent, when controlling for size, in the UK market. The effect emerges in the second- and big- size portfolios, however, the other portfolios show no relation between investments and average returns. Another detection is that most firms with small market capitalization have higher average returns than the large caps, which illustrates the size-effect. However, this is not a consistent pattern in the average return throughout the clusters. The outlier is the second INV portfolio which presents a negative spread (-0.05), which illustrates that the size effect is not present. This is equivalent to the observation made on Size-OP portfolios in the second BM column.

Panel D shows the average monthly percentage excess returns for the Size-MOM portfolio, while holding book-to-market, profitability, and investments constant. The average excess return is higher for previous “winner” stocks (high momentum) than for previous “loser” stocks firms (low momentum), regardless of size. This is a consistent pattern and proves a relation between average return and momentum. Additionally, there is a stronger momentum-effect for small-size firms than for big-size firms with spreads of 2.03% and 0.48% correspondingly. The size effect appears in the second-, fourth-, and high- MOM portfolios, however, the effect is absent in the Low- and third- Mom portfolios. These observations correspond to the ones revealed by Fama and French (2012) for Europe.

6 Results and Analysis

This section aims to present the results of the methodologies introduced in section 4. First, any possible redundant factors are identified through factor spanning test. To go deeper into the factor model analysis, the results of Fama-MacBeth is presented before the study on model performance is conducted by using the GRS test.

6.1 Factor Spanning Test

Building upon the results found in the summary statistics the factor spanning test takes the analysis one step further. The correlation matrices constructed in section 5 showed somewhat high correlations between certain factors. Thus, by executing an auxiliary regression the statistical adequacy of the original regression model is tested (Brooks, 2019, p. 647). The goal of this analysis is to use auxiliary regression to identify collinearity in the factor models. In 2017, Fama and French emphasize that the investment factor is on a shaky ground. It is interesting to examine whether this result holds for the five-factor model and a six-factor model (including momentum), in other markets (US and UK), for the extended period (1990 – 2021).

6.1.1 Test of the six-factor model in the US

The results from the factor spanning test on the US market is shown in Table 13. The test shows that the market factor is not redundant, hence, has explanatory power in the model. The intercept in the market regression is strongly positive for the US with a return of 1.10% (t = 5.54) which is higher than the average return of the factor (0.78%). An explanation of this effect is the negative *RMW*, *CMA*, and *WML* factors. The size factor is positive (0.22%) and exceeds the average returns of the factor (0.16%). However, the intercept is insignificant for the period when it is regressed on the other five factors which implies redundancy. This contradicts the results found by Fama and French (2017), where the *SMB* factor appeared redundant in all regions except North America. The intercept of the value factor is negative for the US with a return of -0.23% which exceeds the average return of the factor (0.10%). The justification of the negative intercept is due to positive values for *MKT*, *SMB*, *RMW*, and especially the high value of *CMA* (0.91). The intercept is insignificant for *HML* (t = -1.83), which indicates redundancy at the 5% level. The test suggests that the profitability factor is important to explain average return in the US. This is indicated by the strongly positive intercept of the *RMW* regression (0.46% per month, t = 3.95), showing a factor significance on the 1% level. Further, the intercept of the *CMA* factor is strongly positive with 0.46% average return per month (t = 2.91). This indicates significance with 99% confidence. Thus, the investment factor has explanatory power of average returns in the US in the extended period. Lastly, there is evidence that the momentum factor helps describe average returns in the US. The intercept in the *WML* regression is 0.56% per month (t = 2.25), which exceeds the average return of the factor (0.42%). These findings confirm the observations in section 5.5.3, regarding the inclusion of momentum, where *MKT* and *RMW* were significant at the

5% level. Our previous discoveries based on simple linear regression insinuated that the *CMA* and *WML* was significant at the 10% level. However, through factor spanning one can observe significance at the 5% level for the respective factors.

Table 13. *Regressions in which five factors explain average excess returns on the sixth for June 1990 to December 2021 in the US, 354 months. The factors are constructed using separate sorts on stocks into two size groups and three B/M groups, three OP groups, three Inv groups, or three MOM groups.*

	The US: Coefficient						
	Int	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**WML**
MKT	1.10		0.18	0.16	-0.43	-0.66	-0.21
SMB	0.22	0.10		0.17	-0.54	0.04	0.04
HML	-0.23	0.06	0.11		0.41	0.91	-0.13
RMW	0.46	-0.14	-0.31	0.38		-0.11	0.10
CMA	0.24	-0.11	0.01	0.42	-0.06		0.03
WML	0.56	-0.31	0.12	-0.55	0.27	0.26	

	The US: t-statistic							
	Int	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**WML**	**Adj R^2**
MKT	5.54		2.51	1.84	-4.81	-5.27	-4.98	0.29
SMB	1.45	2.51		2.50	-8.39	0.44	1.33	0.22
HML	-1.83	1.84	2.50		8.10	14.71	-5.29	0.54
RMW	3.95	-4.81	-8.39	8.10		-1.50	2.37	0.41
CMA	2.91	-5.27	0.44	14.71	-1.50		1.61	0.48
WML	2.25	-4.98	1.33	-5.29	2.37	1.61		0.15

6.1.2 Test of the six-factor model in the UK

The results of the factor spanning test in the UK are displayed in Table 14. The analysis shows that the size and momentum factors are important for describing average returns in the UK, when the six-factor model is implemented. The intercept of the size factor has the highest explanatory power of 0.88% per month (t = 5.19) and is 3.71 standard errors from zero. The momentum factor has an explanatory power of 0.39% (t = 3.03) and has standard deviation of 2.58. Both factors are significant on the 1% level, accepted with 99% confidence. This confirms our observations presented in section 5.5.3. However, through the factor spanning analysis *MKT* becomes insignificant, and thus redundant (t = 1.56).

Table 14. *Regressions in which five factors explain average excess returns on the sixth for June 1990 to December 2021 in the US, 354 months. The factors are constructed using separate sorts on stocks into two size groups and three B/M groups, three OP groups, three Inv groups, or three MOM groups.*

	The UK: Coefficient						
	Int	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**WML**
MKT	0.40		0.05	0.09	-0.33	-0.19	0.54
SMB	0.88	0.02		-0.35	-0.33	0.01	-0.34
HML	0.30	0.04	-0.30		-0.09	0.15	-0.08
RMW	0.18	-0.15	-0.32	-0.09		-0.07	0.15
CMA	0.22	-0.07	0.01	0.13	-0.05		0.03
WML	0.39	0.15	-0.19	-0.05	0.09	0.02	

	The UK: t-statistic							
	Int	**MKT**	**SMB**	**HML**	**RMW**	**CMA**	**WML**	**Adj R^2**
MKT	1.59		0.63	1.10	-4.43	-2.17	5.51	0.12
SMB	5.19	0.63		-6.47	-6.53	0.17	-5.09	0.26
HML	1.85	1.10	-6.48		-1.70	2.74	-1.29	0.11
RMW	1.06	-4.43	-6.53	-1.70		-1.15	2.17	0.17
CMA	1.45	-2.17	0.17	2.74	-1.15		0.50	0.02
WML	3.03	5.51	-5.03	-1.29	2.17	0.50		0.15

The result of the factor spanning tests lead to mixed evidence in the US and the UK markets. In the US both the regression on the size and value factors generates intercepts that are statistically insignificant from zero. For the UK, however, the market, value, profitability, and investment are redundant in describing monthly excess returns. Thus, the explanatory power of the factors is fully absorbed by the other factors in their regressions. To investigate these observations further the regression approach of Fama and MacBeth (1973) is performed in the section 6.2 on factor spanning.

6.2 Factor Exposure

In the next sections, the results of the six-factor model are presented. The same tests and procedure are conducted on the five-factor model for the same period. However, the factor exposure estimates, and the corresponding significance level turn out to be very similar for the five-factor model and six-factor model in both markets. Therefore, the following analysis focus on the factor exposures related to the six-factor model.

6.2.1 Six-factor model in the US

Table 15 contains Panel A, B, C, and D to present the results of first step of Fama-MacBeth regression model (6) for the six-factor model in the US. The panels show the factors exposure and the significance of the estimated parameters using time-series regression on portfolios sorted on size-BM, size-OP, size-INV, and size-MOM.

The first part of the analysis elaborates on the results of the US portfolios. The study finds that the portfolios have significant, positive, exposure to the market factor for all four portfolio sorts, close to 1%. In the size-BM sort all portfolios that belong to the small and medium size group are positively exposed to the size factor. The exposure is largest for the small-size, low-value stocks where the highest exposure is 1.27%. However, the exposure decreases significantly for big-size and high-value stock groups before they turn negative for big stock groups. This pattern of the size factor is recurring for portfolios sorted on size-OP, size-INV, and size-MOM.

Portfolios sorted on size-BM shows that the loadings of the value factor are strongly positive for high-value firms, with exposure of 0.73% to 0.83% for the big stocks. Following the observations made by Fama and French (2015a), exposures are negative for growth stocks and increase with firm value. For portfolios sorted on size-OP the value factor exposure is negative for small and medium firms with weak profitability. However, the sign of the value factor exposure differs for each portfolio sorted on size-OP without any clear pattern. For the value factor exposures in portfolios sorted on size-INV, however, the exposures are significantly negative for firms having a conservate investment strategy. Further, the exposure increases with firm size and aggressive investment strategy. For portfolios sorted on size-MOM, low momentum firms have positive factor exposures, and the exposure increases with firm size.

The profitability factor only shows a few moderate, positive exposures for the portfolios sorted on size-BM. However, several portfolios for growth stocks sorted on size-BM have negative exposure to the same factor. The exposure of the profitability factor for portfolios sorted on size-OP are, as expected, negative for weak profitability stocks and positive for robust stocks. Additionally, we find that portfolios sorted on size-INV have negative exposure between -0.09% and -0.53% for aggressive stocks, whereas the portfolios sorted on size-MOM shows slightly positive exposure for the portfolios of medium size and momentum implemented strategy.

Portfolios for growth stock groups sorted on size-BM have negative exposure to the investment factor. Furthermore, there are few portfolios exposed to the investment factor for the size-OP sorted portfolios. However, medium-high firms with weak profitability show negative investment exposure. Portfolios sorted on size-INV have high positive investment exposure to firms that are large and aggressive (0.83%), whereas the exposure become negative for large firms having a conservative investment strategy (-0.65%). For the last sort, size-MOM, the investment shows positive exposure to small-size and low momentum firms.

Only two portfolios in the smallest firm groups of the size-BM sorts have slightly positive exposures to the momentum factor. Additionally, only two portfolios in the value firm group generate slightly negative exposure to the momentum factor. The exposure sign varies for each portfolio without any logical pattern. As expected, for portfolios sorted on size-OP, some momentum exposures are positive for firms with robust profitability. However, the exposures are small and there are several portfolios without any clear pattern. For portfolios sorted on size-INV, there are some negative exposures to the momentum factors containing big firms with aggressive investment strategies. The exposure to the momentum factor sorted on size-MOM is negative for low momentum stocks (losers) and positive for high momentum stocks (winners). This is aligned with the findings of Carhart (1997) that the inclusion of momentum leads to a more accurate measure of returns.

6.2.2 Six-factor model in the UK

Table 15 contains Panel A, B, C, and D to present the results of first step of Fama-MacBeth regression model (6) for the six-factor model in the UK market. As for the US stocks, the study finds that the portfolios have significant, positive, exposure to the market factor for all four portfolio sorts. The size factor also generates same results for the UK as for the US, indicating that small and medium size groups show significant, positive exposures for all portfolio sorts. Portfolios sorted on size-BM have positive exposure to value factor for value firms, whereas the exposure are negative for weak firms for portfolios sorted on size-OP. The sign of the value factor exposure differs for each portfolio sorted on size-INV and size-MOM without any clear pattern.

As of the US market, the profitability factor for the UK market shows a few moderate, positive exposures for the portfolios sorted on size-BM. However, there is an unclear pattern of exposure to the profitability factor on size-OP, size-INV, and size-MOM sorts. Moving over to the investment factor, portfolios for big firms sorted on size-BM and size-INV show negative exposure to the investment factor. However, there are few portfolios exposed to the investment factor for the size-OP and size-MOM sorted portfolios. Finally, the momentum factor shows several portfolios without any clear pattern for portfolios on all sorts. To summarize the results of the first step Fama-MacBeth regression, the market and size factor is overall significant for both the US and the UK stocks market.

6.3 GRS test

After evaluating each factor exposure on all four portfolio sorts, the overall model performance is assessed through GRS statistics. To evaluate the intercepts of the models, it is first interesting to look at the estimated intercepts from Fama-MacBeth first-step regression. The results of the US and the UK are shown in Table 15. For the US, only three portfolios sorted on size-BM have intercepts that are significantly different from zero at a 10% significance level. Two slightly positive intercepts are found in the regressions containing small size stocks and high company value. Furthermore, there are also two portfolios sorted on size-OP that shows intercepts significantly different from zero, also at a 10% significance level. For this portfolios sort, the bad model fit is for the portfolio containing both big stocks and small stocks with weak profitability. We find five portfolios sorted on size-INV that have intercepts significantly different from zero. The portfolios mainly contain small stocks with low to medium investment strategies, but the findings do not follow any clear pattern. For the portfolios sorted on size-MOM, however, only three portfolios holding small firms are significantly different from zero at a 10% significance level. The intercepts follow the same pattern for the five-factor model, indicating the six-factor model does not explain US stock returns better than the five-factor model. The inferences of the UK intercepts are different from the US results. For all portfolio sorts, most portfolios have intercepts that are significantly different to zero at a 5% significance level for both the five-factor and the six-factor model.

Secondly, the results of the GRS test are assessed. In table 16 we show the results of the GRS test. Panel A present the results for sorts on size-BM, Panel B describe results for sorts on size-OP, Panel C present results for sorts on size-INV, and Panel D present sorts on size-MOM results. The models are compared by evaluating their GRS statistics and the corresponding p-values. Intercepts that are significantly different from zero contradict the null hypothesis of insignificantly intercepts and increase the value of the GRS statistic. A low GRS value indicate that the model is a better fit to describe average excess return, whereas a high value implies bad model performance. For US, all four sorted portfolios have lower GRS statistic for the six-factor model than the five-factor model and is therefore a better fit to describe average excess returns in the US. However, all p-values are lower than 0.10 which indicate that at a 10% significance level, the null hypothesis that all intercepts are equal to zero is rejected for all tested models. Based on the results of the GRS statistic on the UK data, the same conclusion remains for the UK. Hence, the five-factor model nor the six-factor model are sufficient in describing total monthly average excess returns of US and UK stocks.

Tabel 16. *GRS statistics for the US and the UK for June 1990 to December 2021, 354 months. The GRS statistics tests if the intercepts of all N time-series regressions are equal to zero.*

*Panel A. 5 x 5 Size-BM portfolios for US and UK for June 1991 to December 2021, 354 months***.**

	The US		**The UK**	
Model factors	**GRS**	**p(GRS)**	**GRS**	**p(GRS)**
MKT SMB HML RMW CMA	2.59	0.00	1.36	0.00
MKT SMB HML RMW CMA WML	2.49	0.00	1.33	0.00

*Panel B. 5 x 5 Size-OP portfolios for US and UK for June 1991 to December 2021, 354 months***.**

	The US		**The UK**	
Model factors	**GRS**	**p(GRS)**	**GRS**	**p(GRS)**
MKT SMB HML RMW CMA	1.53	0.05	1.16	0.00
MKT SMB HML RMW CMA WML	1.43	0.09	1.14	0.00

*Panel C. 5 x 5 Size-INV portfolios for US and UK for June 1991 to December 2021, 354 months***.**

	The US		**The UK**	
Model factors	**GRS**	**p(GRS)**	**GRS**	**p(GRS)**
MKT SMB HML RMW CMA	1.90	0.01	1.01	0.00
MKT SMB HML RMW CMA WML	1.78	0.01	1.00	0.00

*Panel D. 5 x 5 Size-MOM portfolios for the US and UK for June 1991 to December 2021, 354 months***.**

	The US		**The UK**	
Model factors	**GRS**	**p(GRS)**	**GRS**	**p(GRS)**
MKT SMB HML RMW CMA	1.75	0.02	1.30	0.00
MKT SMB HML RMW CMA WML	1.22	0.02	1.27	0.00

6.4 Risk Premiums

Building upon the results found in the sections for time-series regression and intercept analysis, we find that the six-factor model fail to explain average excess returns in both the US and the UK. Therefore, the analysis is advanced by estimating risk premiums by the second step of the Fama-MacBeth regression based on cross-sectional data. The risk premiums are presented in table 17, where Panel A illustrate the risk premiums for portfolios sorted on size-BM, Panel B present the sorts on size-OP, Panel C the sorts on size-INV, and Panel D presents the sorts on size-MOM.

The cross-sectional regression on size-BM obtains statistically significant risk premiums only for the size factor, the profitability factor, and the investment factor at a 10% significance level. For regression on size-OP, however, all factors except for the market factor are statistically significant in explaining average excess returns in the US at a 10% significance level. For the size-INV sorts, the investment and momentum factor are exclusively in describing average excess returns and only the market factor explain excess returns for the US on the size-MOM sorted portfolios. For the UK market, the cross-sectional regression on size-BM obtains statistically significant risk premiums only for the size and value factor with 99% confidence. For regression on size-OP, the size, profitability, and momentum factor are significant risk premiums. The risk premium of the investment factor is significant at a 10% level for portfolios sorted on size-INV, and the market and momentum factor are significant in describing risk premiums for portfolios sorted on size-MOM.

Despite significant results of the intercepts in the first step Fama-MacBeth regression for the UK market, table 18 shows that the second step of the methodology conclude bad model fit due to nonzero intercepts. Overall, the results amplify the conclusions of the previous analyses that both the five-factor and the six-factor models are insufficient in describing average excess returns in the US and the UK. Moreover, none of the US or UK models shows good model fit.

Table 17.

The risk premiums related to one unit of additional exposure to the RHS factors. The risk premiums are estimated by the cross-sectional second step Fama-MacBeth regression:

$$R_{i,t} = \lambda_{0,t} + \lambda_{1,t}\hat{b}_{i,1} + \lambda_{2,t}\hat{s}_{i,2} + \lambda_{3,t}\hat{h}_{i,3} + \lambda_{4,t}\hat{r}_{i,4} + \lambda_{5,t}\hat{c}_{i,5} + \lambda_{6,t}\hat{w}_{i,6} + u_{i,t} \quad i = 1, \dots, N \qquad \textbf{(8)}$$

The sorts on size-BM are presented in Panel A, sorts on size-OP in Panel B, sorts on size-INV in Panel C, and sorts on size-MOM in Panel D.

Panel A. 5 x 5 size-BM portfolios for the US

	λ^{α}	λ^{MKT}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}	λ^{WML}	*Adj* R^2
Coeff	0.06	0.15	0.16*	0.05	0.44*	0.48*	1.04	0.46
t-stat	(1.13)	(0.34)	(2.57)	(0.67)	(2.67)	(2.41)	(0.90)	

Panel B. 5 x 5 size-OP portfolios for the US

	λ^{α}	λ^{MKT}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}	λ^{WML}	*Adj* R^2
Coeff	0.09*	0.30	0.13*	0.47**	0.23***	0.32*	1.76*	0.81
t-stat	(2.33)	(0.08)	(2.64)	(2.93)	(4.47)	(2.28)	(2.43)	

Panel C. 5 x 5 size-INV portfolios for the US

	λ^{α}	λ^{MKT}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}	λ^{WML}	*Adj* R^2
Coeff	0.07	0.06	0.07	0.29	-0.02	0.23**	2.05*	0.43
t-stat	(1.46)	(0.12)	(0.88)	(1.06)	(-0.05)	(3.37)	(2.61)	

Panel D. 5 x 5 size-MOM portfolios for the US

	λ^{α}	λ^{MKT}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}	λ^{WML}	*Adj* R^2
Coeff	0.08**	0.25	0.10*	0.50	-0.24	0.05	0.61**	0.74
t-stat	(3.47)	(0.87)	(2.12)	(1.8)	(-1.31)	(0.34)	(1.06)	

Table 18.

The risk premiums related to one unit of additional exposure to the RHS factors. The risk premiums are estimated by the cross-sectional second step Fama-MacBeth regression:

$$R_{i,t} = \lambda_{0,t} + \lambda_{1,t}\hat{b}_{i,1} + \lambda_{2,t}\hat{s}_{i,2} + \lambda_{3,t}\hat{h}_{i,3} + \lambda_{4,t}\hat{r}_{i,4} + \lambda_{5,t}\hat{c}_{i,5} + \lambda_{6,t}\hat{w}_{i,6} + u_{i,t} \quad i = 1, \dots, N \qquad \textbf{(8)}$$

The sorts on size-BM are presented in Panel A, sorts on size-OP in Panel B, sorts on size-INV in Panel C, and sorts on size-MOM in Panel D.

Panel A. 5 x 5 size-BM portfolios for the UK

	λ^{α}	λ^{MKT}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}	λ^{WML}	*Adj R^2*
Coeff	0.09	-0.79	0.84***	0.97***	0.30	0.77	0.44	0.69
t-stat	(0.19)	(-1.20)	(5.47)	(4.48)	(0.64)	(1.38)	(0.75)	

Panel B. 5 x 5 size-OP portfolios for the UK

	λ^{α}	λ^{MKT}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}	λ^{WML}	*Adj R^2*
Coeff	0.28	-0.72	0.88***	0.33	1.43**	0.94	1.02*	0.55
t-stat	(0.64)	(-1.49)	(4.35)	(0.84)	(3.80)	(1.63)	(2.02)	

Panel C. 5 x 5 size-INV portfolios for the UK

	λ^{α}	λ^{MKT}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}	λ^{WML}	*Adj R^2*
Coeff	-0.17	-0.30	0.61**	-1.19	1.85	0.39	0.17	0.35
t-stat	(-0.31)	(-0.41)	(2.93)	(-1.55)	(1.80)	(1.01)	(0.31)	

Panel D. 5 x 5 size-MOM portfolios for the UK

	λ^{α}	λ^{MKT}	λ^{SMB}	λ^{HML}	λ^{RMW}	λ^{CMA}	λ^{WML}	*Adj R^2*
Coeff	-0.75**	0.74	0.72*	-0.25	-0.79	0.52	1.49***	0.46
t-stat	(3.47)	(1.72)	(2.39)	(-0.30)	(-0.88)	(0.46)	(4.03)	

7 Conclusion

7.1 Main Findings and Implications

This study tests the Fama-French five-factor model as a benchmark, and a six-factor model, adding momentum to the US and UK markets from June 1990 to December 2021. The result of the factor spanning tests led to mixed evidence in the US and the UK markets for the six-factor model. In the US, the regressions revealed redundancy of the size and value factors. Concurrently, in the UK, the value, profitability, and investment are redundant in describing monthly excess returns. Thus, the explanatory power of the factors is fully absorbed by the other factors in their regressions. To investigate these observations further, the regression approach of Fama and MacBeth (1973) was conducted. The test results on the six-factor model suggest that the market and size factors are essential in describing average excess returns for both equity markets. However, there is no evidence of profitability, investment, or momentum premium in the corresponding markets. The two tests give different conclusions regarding factor redundancy, emphasizing the importance of running the Fama-MacBeth regression. Further tests infer that the six-factor model does not sufficiently improve the explanatory power of excess returns relative to the five-factor model in the US and the UK.

The factor exposures constructed by the first step of the Fama-MacBeth regression suggest that small growth stocks are unfavorable based on their insignificant results in both the US and the UK. This outcome is also established by Fama and French (2015a). The impediment is not restricted to this stock group, as the six-factor models complicate the returns of several other portfolios regardless of their sorts. Moreover, the cross-sectional regression from the second step regression methodology concludes that most factors do not price the market. The tests suggest that the six-factor model is an insufficient asset pricing model for all four portfolio sorts. The GRS test assesses the performance of the models in the two separate markets. Due to lower GRS statistics, the six-factor outperforms the five-factor of Fama and French (2015a, 2017) in the US and the UK.
Moreover, the GRS test's outcome supports the other tests' conclusion that the factor models are inadequate. This implies that neither the five-factor model nor the six-

factor model explains returns in the US and the UK. To conclude, the application of the Fama-MacBeth regressions shows that an introduction of a momentum factor is not convincing, nor is the implementation of the six-factor model in the US and UK stock markets.

To take the analysis one step further implications of the results on investors are discussed. Factor models are often used to evaluate portfolio performance and create factor funds. The appeal of an exemplary asset pricing model that captures risk is its adaptability to predict stock returns. By constructing portfolios based on risk factors instead of more common asset classes, investors can focus on risk drives across the portfolio. The six-factor model implemented in the US and the UK markets can be used in applications, although it did not pass all the robustness tests. However, the findings did suggest a better fit of the six-factor model and significant factors through factor-spanning regressions. These factors should, thus, be implemented in the real-time market and tested for adaptability.

7.2 Limitations and Further Research

The essence of our results is susceptible to discussions, and criticism can be pointed out at the fundamentals and implementations of our approach. Researchers raise questions about the adequacy of the empirical results of risk factors. Lo and MacKinlay (1990) classify the pursuit of risk factors as pure data mining, whereas other researchers find that redundant factors can have explanatory power (Ferson and Harvey, 1991). Additionally, Lakonishok et al. (1994) claim that factor premiums result from irrational investor behavior instead of compensation for systematic risk. However, since the applicability of a six-factor model is inspected, it is automatically assumed that factor models are valuable in explaining average excess returns. Because of limitations in the thesis, possible improvements of the analysis will be evaluated in a three-step discussion.

Firstly, a limitation of the analysis can be the construction of the test portfolios. The consideration of value-weighted and equal-weighted returns has been largely debated. In our analysis, value-weighted returns have been applied to construct the portfolios.

The reasoning behind this choice is the major impact a company's market capitalization has on return. Fama and French (1993) argue that the size-effect in the portfolio construction is redundant. Therefore, equally-weighted returns could be an acceptable approach to portfolio construction. Additionally, equivalently to Fama and French (2017), the risk-free rate used to calculate excess returns is restricted to the 1-month US Treasury Bill for the US and the UK model. A better analysis, which could contribute to a more reliable result, is to use country-specific risk-free rates.

Secondly, there are redundant factors in the pricing model. The well-known phenomenon of "factor-zoo" should be considered, distinguishing between useful and redundant factors in the model. As the number of factors grow systematical tests and examinations of factors become increasingly important. Therefore, the models could be improved by eliminating redundant factors from the six-factor model. Another approach could be to change the fundamentals of the existing factors. Fama and French (2018) discuss issues of factor choices in the six-factor model and discuss alternative methods to calculate the profitability factor.

Finally, several major crises in our sample period, from 1990 to 2015, have impacted the level of globalization and productivity. The crisis can be classified as either financial or external. In 2000, NASDAQ dropped nearly 80% due to the "Dotcom bubble" burst (Ponciano, 2022). Another crisis known as "the Great Recession" hit the markets in 2008, leading to a significant fall in both the US and the UK economies (Ponciano, 2022). These global crises are categorized as financial or economic crises driven by market forces. Thus, they should be, to some extent, detected by the pricing model. One could expect the value and momentum factor to capture some of these variations. However, external crises are more challenging to predict. The Covid-19 pandemic is a good proxy that devastated several aspects of the global economy. It is almost insurmountable to create asset pricing models factoring in this crisis as it is categorized as an external shock on the market. Thus, further research should be conducted on this phenomenon and whether another factor can capture these sudden market volatilities.

Appendix

Appendix 1

The RHS factors are the six explanatory variables for the LHS portfolios that are constructed from 2 x 3 sorts on *Size* and *B/M*, *OP*, *Inv*, and *MOM*. Moreover, the size sorts are assigned into two groups, small (*S*) and big (*B*) stocks, whereas the stocks are further sorted based on combinations of book to market (*B/M*), operating profitability (*OP*), annual growth rate (*Inv*), and momentum (*MOM*).

We construct six portfolios for size formed on *B/M*: SG (small growth), SN (small neutral), SV (small value), BG (big growth), BN (big neutral), and BV (big value). Further, we construct six portfolios from size formed on *OP*: SR (small robust), SN (small neutral), SW (small weak), BR (big robust), BN (big neutral), and BW (big weak). We also construct six portfolios for size formed on *Inv*: SC (small conservative), SN (small neutral), SA (small aggressive), BC (big conservative), BN (big neutral), and BA (big aggressive). Finally, we construct six portfolios for size formed on *MOM*: SW (small winners), SN (small neutral), SL (small losers), BW (big winners), BN (big neutral), and BL (big losers):

$$SMB_{B/M} = 1/3 * (SV + SN + SG) - 1/3 * (BV + BN + BG)$$
$$SMB_{OP} = 1/3 * (SR + SN + SW) - 1/3 * (BR + BN + BW)$$
$$SMB_{Inv} = 1/3 * (SC + SN + SA) - 1/3 * (BC + BN + BA)$$
$$SMB_{MOM} = 1/3 * (SW + SN + SL) - 1/3 * (BW + BN + BL)$$

The *Size* factor (SMB) is calculated by the average of the three size factors formed on *B/M*, *OP*, and *Inv*: $SMB = 1/3 * (SMB_{B/M} + SMB_{OP} + SMB_{Inv} + SMB_{MOM})$

The final factors, *HML*, *RMW*, *CMA*, and *MOM* are then calculated as:

$$HML = 1/2 * (SV + BV) - 1/2 * (SG + BG)$$
$$RMW = 1/2 * (SR + BR) - 1/2 * (SW + BW)$$
$$CMA = 1/2 * (SC + BC) - 1/2 * (SA + BA)$$
$$MOM = 1/2 * (SW + BW) - 1/2 * (SL + BL)$$

Appendix 2

Replication evaluation.

$$SMB = SMB_{rep} + \varepsilon = \underset{(-0.87)}{0.00} + \underset{(145.66)}{0.99}\ SMB_{rep}$$

$$HML = HML_{rep} + \varepsilon = \underset{(0.92)}{0.00} + \underset{(76.56)}{0.96}\ HML_{rep}$$

$$RMW = HML_{rep} + \varepsilon = \underset{(0.47)}{0.00} + \underset{(44.58)}{0.93}\ RMW_{rep}$$

$$CMA = HML_{rep} + \varepsilon = \underset{(1.20)}{0.00} + \underset{(88.74)}{0.98}\ CMA_{rep}$$

Appendix 3

Regression equations of descriptive statistics for the replication study.

$$SMB = \alpha + \beta\ SMB_{rep} + u_i = \underset{(-0.87)}{0.00} + \underset{(145.66)}{0.99}\ SMB_{rep}$$

$$HML = \alpha + \beta\ HML_{rep} + u_i = \underset{(0.92)}{0.00} + \underset{(76.56)}{0.96}\ HML_{rep}$$

$$RMW = \alpha + \beta\ RMW_{rep} + u_i = \underset{(0.47)}{0.00} + \underset{(44.58)}{0.93}\ RMW_{rep}$$

$$CMA = \alpha + \beta\ CMA_{rep} + u_i = \underset{(1.20)}{0.00} + \underset{(88.74)}{0.98}\ CMA_{rep}$$

Appendix 4

Regression equation of factor spanning test where one factor is tested on the five other. .

$$Mkt_t = a_i + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + w_i WML_t + \varepsilon_i$$

$$SMB_t = a_i + b_i Mkt_t + h_i HML_t + r_i RMW_t + c_i CMA_t + w_i WML_t + \varepsilon_i$$

$$HML_t = a_i + b_i Mkt_t + s_i SMB_t + r_i RMW_t + c_i CMA_t + w_i WML_t + \varepsilon_i$$

$$RMW_t = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + c_i CMA_t + w_i WML_t + \varepsilon_i$$

$$CMA_t = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + r_i RMW_t + w_i WML_t + \varepsilon_i$$

$$WML_t = a_i + b_i Mkt_t + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + \varepsilon_i$$

List of Tables

Table 11. *Average monthly excess returns for value-weighted portfolios for the US from June 1990 to December 2021, 354 months, on four different sort portfolios. All values are in percentage (%).*

Panel A. 5 x 5 Size-BM portfolios for the US

	Low BM	**2**	**3**	**4**	**High BM**
Small	0.48	0.99	0.94	1.11	1.34
2	0.72	0.92	0.97	0.95	0.98
3	0.77	0.94	0.92	0.90	1.12
4	0.94	0.94	0.96	0.88	0.86
Big	0.86	0.76	0.79	0.68	0.76

Panel B. 5 x 5 Size-OP portfolios for the US

	Low OP	**2**	**3**	**4**	**High OP**
Small	0.78	1.17	1.27	1.44	1.10
2	0.68	0.96	0.93	1.03	1.17
3	0.82	0.83	1.05	0.80	1.08
4	0.59	1.06	0.92	0.89	0.91
Big	0.64	0.65	0.76	0.80	0.94

Panel C. 5 x 5 Size-INV portfolios for the US

The US					
	Low INV	**2**	**3**	**4**	**High INV**
Small	1.22	1.14	1.10	0.93	0.55
2	0.90	0.95	1.03	1.02	0.62
3	0.97	0.89	0.89	0.89	0.73
4	0.90	0.90	0.92	0.96	0.84
Big	0.92	0.76	0.76	0.90	0.81

Panel D. 5 x 5 Size-MOM portfolios for the US

The US					
	Low MOM	**2**	**3**	**4**	**High MOM**
Small	0.96	1.12	1.12	1.10	0.99
2	0.84	0.93	0.97	1.07	0.91
3	0.75	0.89	0.93	0.95	0.98
4	0.70	1.07	0.93	0.91	0.98
Big	0.63	0.73	0.85	0.84	0.92

Table 12. *Average monthly excess returns for value-weighted portfolios for the UK from June 1990 to December 2021, 354 months, on four different sort portfolios. All values are in percentage (%).*

Panel A. 5 x 5 Size-BM portfolios for the UK

The UK					
	Low BM	**2**	**3**	**4**	**High BM**
Small	0.56	0.55	0.48	1.82	2.18
2	0.76	0.66	1.03	1.18	2.34
3	0.31	0.67	0.50	1.02	1.20
4	0.23	0.51	0.70	0.66	0.72
Big	0.41	0.32	0.30	0.21	0.37

Panel B. 5 x 5 Size-OP portfolios for the UK

The UK					
	Low OP	**2**	**3**	**4**	**High OP**
Small	1.27	0.25	0.63	0.58	2.07
2	0.78	0.20	0.68	1.63	1.83
3	0.50	0.87	0.05	0.92	1.19
4	0.35	0.53	0.45	0.94	1.39
Big	0.16	0.53	0.44	0.40	0.32

Panel C. 5 x 5 Size-Inv portfolios for the UK

The UK					
	Low INV	**2**	**3**	**4**	**High INV**
Small	1.05	0.23	0.46	0.90	1.70
2	1.87	0.47	0.70	0.70	1.20
3	0.39	0.36	0.58	0.34	0.99
4	0.99	0.39	0.34	0.25	0.96
Big	0.66	0.28	0.40	0.12	0.73

Panel A. 5 x 5 Size-MOM portfolios for the UK

The UK					
	Low MOM	**2**	**3**	**4**	**High MOM**
Small	0.28	0.80	0.33	1.73	2.31
2	0.48	0.35	0.93	1.62	1.87
3	0.07	0.47	0.90	1.43	1.22
4	0.49	0.11	0.47	1.23	1.63
Big	0.69	0.07	0.39	0.50	1.17

Table 15.

Factor exposures of US size-BM, size-OP, size-INV, and size-MOM portfolios. Results from the N first-step Fama-MacBeth time-series regressions model (6):

$$R_{i,t} = \alpha_i + b_{i,1}MKT_{1,t} + s_{i,2}SMB_{2,t} + h_{i,3}HML_{3,t} + r_{i,4}RMW_{4,t} + c_{i,5}CMA_{5,t} + w_{i,6}WML_{6,t} + u_{i,t}$$

Panel A. 5 x 5 size-BM portfolios for the US and UK from June 1990 to December 2021, 354 months.

	US					UK				
	$\hat{\alpha}$					$\hat{\alpha}$				
BM →	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.002	0.001	0.001	0.002**	0.004*	-0.004**	-0.003***	-0.002**	-0.002**	-0.001**
	(-1.88)	(1.45)	(1.28)	(2.68)	(2.34)	(-7.51)	(-4.84)	(-2.79)	(-5.54)	(-3.81)
2	0.000	0.000	0.000	0.000	-0.001	-0.003**	-0.002***	-0.002*	-0.001*	-0.002**
	(-0.51)	(0.46)	(0.198)	(-0.27)	(-1.40)	(-3.62)	(-7.04)	(-2.71)	(-2.52)	(-3.12)
3	0.000	0.001	0.000	0.000	0.001	-0.002**	-0.002***	-0.001**	-0.002**	-0.001**
	(0.08)	(0.63)	(0.12)	(-1.23)	(0.78)	(3.16)	(-8.42)	(-3.08)	(-3.66)	(-3.41)
4	0.002*	0.000	0.000	-0.001	-0.001	-0.001**	-0.002***	-0.001**	-0.001**	-0.001*
	2.21	(0.27)	(0.14)	(-0.84)	(-0.79)	(-3.58)	(-6.87)	(-3.78)	(-3.35)	(-2.54)
Big	0.001	0.000	0.001	-0.001	-0.001	-0.004**	-0.005***	-0.007**	-0.007**	-0.007**
	(1.54)	(0.04)	(0.82)	(-1.40)	(-0.43)	(-3.09)	(-3.67)	(-2.71)	(-2.68)	(-3.31)

	$\hat{b}$					$\hat{b}$				
BM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	0.98***	0.89***	0.87***	0.85***	0.95***	0.77***	0.83***	0.43***	0.62***	0.68***
	(28.37)	(32.10)	(42.69)	(38.59)	(24.02)	(7.50)	(6.31)	(3.34)	(8.60)	(8.51)
2	0.99***	0.94	0.96***	0.95***	1.08***	0.67***	0.73***	0.62***	0.62***	0.71***
	(43.64)	(40.50)	(50.69)	(44.92)	(49.04)	(8.93)	(10.88)	(11.80)	(10.43)	(12.46)
3	1.00***	1.01***	0.97***	1.02***	1.05***	0.73***	0.72***	0.87***	0.70***	0.64***
	(44.50)	(40.50)	(39.70)	(42.31)	(35.10)	(13.89)	(14.30)	(17.80)	(15.10)	(13.56)
4	1.02***	1.04***	01.07***	1.03***	1.08***	0.74***	0.66***	0.67***	0.78***	0.76***
	(46.24)	(41.75)	(42.17)	(40.19)	(36.59)	(13.82)	(15.64)	(12.09)	(13.94)	(14.6)
Big	1.01***	0.95***	0.94***	1.00***	0.99***	0.37***	0.66***	0.74***	0.78***	0.67***
	(79.74)	(49.15)	(41.30)	(46.34)	(30.91)	(11.67)	(21.34)	(22.92)	(19.05)	(17.65)

	$\hat{s}$					$\hat{s}$				
BM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	1.27***	1.22***	1.05***	1.02***	1.02***	1.29***	1.02***	1.19***	1.16***	0.63***
	(27.43)	(32.79)	(38.49)	(34.70)	(19.19)	(8.73)	(5.42)	(6.51)	(11.26)	(5.2)
2	1.01***	0.95***	0.80***	0.84***	0.91***	1.08***	0.86***	0.87	0.92***	0.85***
	(33.33)	(37.59)	(31.98)	(30.20)	(30.96)	(10.08)	(8.87)	(11.56)	(10.73)	(10.49)
3	0.76***	0.53***	0.45***	0.46***	0.55***	0.74***	0.76***	0.79***	0.72***	0.60***
	(25.21)	(16.08)	(13.94)	(14.52)	(13.88)	(9.84)	(10.53)	(11.35)	(10.77)	(8.92)
4	0.41	0.27***	0.21***	0.27***	0.23***	0.31***	0.56***	0.47***	0.42***	0.51***
	(14.11)	(8.19)	(6.08)	(7.89)	(5.87)	(4.06)	(9.25)	(5.93)	(5.26)	(6.68)
Big	-0.19**	-0.20**	-0.17**	-0.11	-0.09*	-0.15***	-0.08	-0.01	-0.09	-0.07
	(-3.47)	(-3.56)	(-3.52)	(-3.79)	(-1.99)	(-3.43)	(-1.76)	(-0.04)	(-1.47)	(-1.32)

	$\hat{h}$					$\hat{h}$				
BM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.47*	-0.24*	0.05	0.29***	0.42***	-0.02	0.38**	0.65***	0.31**	0.48***
	(-2.17)	(-2.14)	(1.57)	(8.01)	(6.30)	(-0.13)	(1.89)	(3.32)	(2.86)	(3.95)
2	-0.41*	-0.06	0.23***	0.44***	0.63***	-0.54***	0.15	0.40***	0.66***	0.74***
	(-2.80)	(-1.84)	(7.43)	(12.41)	(17.04)	(-4.74)	(1.43)	(5.04)	(7.23)	(8.52)
3	-0.39**	0.11**	0.40***	0.52***	0.64***	-0.05	-0.17*	0.44***	0.41***	0.55***
	(-10.39)	(2.78)	(9.66)	(12.78)	(12.78)	(-0.62)	(-2.21)	(5.85)	(5.80)	(7.62)
4	-0.38**	0.15***	0.42***	0.44***	0.83***	0.13	0.07	0.41***	0.41***	0.37***
	(-10.44)	(3.59)	(9.74)	(10.48)	(17.09)	(1.56)	(1.01)	(4.80)	(4.84)	(4.58)
Big	-0.32**	0.09**	0.33***	0.74***	0.76***	-0.20***	-0.03	0.21***	0.32***	0.52***
	(-15.04)	(2.85)	(8.63)	(20.50)	(14.09)	(-4.05)	(-0.62)	(4.19)	(5.13)	(9.03)

	$\hat{r}$					$\hat{r}$				
BM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.50***	-0.34**	-0.06	-0.01	-0.17*	-0.06	-0.53**	0.16	0.02	0.19
	(-8.31)	(-2.96)	(-1.55)	(-0.26)	(-2.49)	(-0.37)	(-2.69)	(0.82)	(0.23)	(1.56)
2	-0.26***	0.10	0.09**	0.15***	0.08*	0.20	-0.07	-0.07	-0.20*	0.07
	(-6.63)	(2.92)	(3.01)	(4.03)	(2.21)	(1.84)	(-0.67)	(-0.86)	(-2.26)	(0.80)
3	-0.15***	0.10*	-0.17**	0.12**	0.11*	-0.07	-0.18*	0.23**	-0.09	-0.01
	(-3.88)	(2.30)	(3.94)	(2.90)	(2.08)	(-0.85)	(-2.45)	(3.11)	(-1.27)	(-0.02)
4	-0.14***	0.13**	0.13**	0.11*	0.00	-0.09	-0.10	0.12	0.10	-0.07
	(-3.61)	(3.11)	(2.96)	(2.43)	(-0.08)	(-1.01)	(-1.49)	(1.49)	(1.21)	(-0.84)
Big	0.18***	0.06***	-0.06	0.02	-0.22*	-0.01	-0.01	0.04	-0.05	-0.12*
	(8.18)	(1.86)	(-1.52)	(0.50)	(-3.94)	(-0.20)	(-0.30)	(0.82)	(-0.79)	(-2.05)

	$\hat{c}$					$\hat{c}$				
BM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.03	0.15*	0.06	0.07	0.38***	0.06	-0.52*	-0.19	0.02	0.15
	(-0.31)	(2.16)	(1.21)	(1.26)	(3.92)	(0.33)	(-2.42)	(-0.92)	(0.20)	(1.14)
2	-0.14*	0.01**	0.14**	0.07	0.03	-0.30	-0.21	-0.06	-0.13	-0.10
	(-2.54)	(-0.15)	(2.95)	(0.14)	(0.48)	(-2.43)	(-1.88)	(-0.70)	(-1.35)	(-1.09)
3	-0.28**	-0.07	-0.07	0.10	0.00	-0.10	0.00	-0.15	-0.11	-0.07
	(-3.13)	(-1.18)	(-1.13)	(1.76)	(0.04)	(-0.05)	(-1.87)	(-1.33)	(-0.89)	(0.46)
4	-0.11*	0.10	0.04	0.14*	-0.06	0.04	-0.10	-0.04	-0.04	-0.05
	(-2.05)	(1.58)	(0.70)	(2.21)	(-0.84)	(1.08)	(-0.55)	(-0.41)	(-0.60)	(-0.16)
Big	0.00	0.19***	0.04	-0.17**	-0.08	-0.01	-0.18***	-0.18***	-0.02	-0.22***
	(0.31)	(4.07)	(0.70)	(3.25)	(-0.98)	(-0.24)	(-3.52)	(-3.34)	(-0.26)	(-3.59)

	$\hat{w}$					$\hat{w}$				
BM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.05	0.06**	0.00	0.04*	-0.02	0.05	-0.19	0.08	0.07	-0.27
	(-1.79)	(2.64)	(0.254	(2.41)	(-0.69)	(0.26)	(-0.77)	(0.34)	(0.54)	(-1.75)
2	-0.02	-0.03	0.01	-0.01	-0.03	-0.02	-0.01	0.22*	0.15	0.13
	(-1.16)	(-1.91)	(0.52)	(-0.55)	(-1.89)	(-0.17)	(-0.04)	(2.21)	(1.32)	(1.18)
3	-0.01	-0.03	-0.04	0.00	-0.08**	0.21*	0.02	-0.02	0.02	-0.05
	(-0.64)	(1.28)	(-1.76)	(-0.20)	(-3.12)	(2.05)	(0.22)	(-0.17)	(0.22)	(-0.54)
4	0.02	-0.4*	-0.05	-0.02	-0.10**	0.06	0.10	0.14	-0.14	0.09
	(1.11)	(-2.02)	(-2.60)	(-0.76)	(-3.24)	(0.62)	(1.25)	(1.35)	(-1.33)	(0.88)
Big	-0.02	-0.01	-0.04	-0.07	0.0	0.08	0.16**	0.06	-0.11	0.07
	(-1.46)	(-0.90)	(-2.14)	(-3.78)	(0.83)	(1.40)	(2.74)	(0.95)	(-1.44)	(0.99)

Note: Significance levels: p < 0.1 *, p < 0.05 **, p < 0.01 ***

Panel B. 5 x 5 size-OP portfolios for the US and UK from June 1990 to December 2021, 354 months.

	US					**UK**				
	$\hat{\alpha}$					$\hat{\alpha}$				
OP→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	0.000	0.002*	0.002	0.003	0.000	-0.034**	-0.016***	-0.016**	-0.013**	-0.026**
	(0.28)	(2.04)	(1.48)	(0.06)	(0.087)	(-3.49)	(-4.07)	(-3.43)	(-2.92)	(-3.89)
2	-0.001	-0.001	0.000	0.001	0.000	-0.028**	-0.079***	-0.019**	-0.012**	-0.019**
	(-0.73)	(-0.63)	(-0.17)	(1.03)	(-0.26)	(-2.95)	(-7.26)	(-3.56)	(-3.12)	(-6345)
3	-0.001	-0.001	0.000	-0.002	-0.001	-0.024**	-0.020***	-0.011**	-0.017**	-0.015**
	(-0.54)	(-0.95)	(0.07)	(-1.49)	(-0.52)	(-3.44)	(-7.97)	(-3.97)	(-7.56)	(-3.12)
4	0.000	0.001	0.000	0.000	-0.001	-0.022**	-0.016***	-0.013**	-0.014**	-0.015**
	(0.05)	(1.09)	(-0.20)	(-034)	(-0.55)	(-3.23)	(-5.66)	(-3.29)	(-2.81)	(-5.63)
Big	0.002*	0.001	0.001	0.001	0.001	-0.004	-0.010***	-0.007**	-0.007**	-0.004**
	(1.99)	(1.07)	(1.05)	(0.80)	(.091)	(-1.11)	(-4.06)	(-3.17)	(-3.07)	(-3.21)

	$\hat{b}$					$\hat{b}$				
OP→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	0.96***	0.93***	0.98***	0.99***	1.05***	0.69***	0.59***	0.57***	0.56***	0.72***
	(31.24)	(31.25)	(22.58)	(7.52)	(30.82)	(7.35)	(7.01)	(8.93)	(6.06)	(6.47)
2	1.01***	1.03***	0.98***	0.97***	1.17***	0.65***	0.61***	0.72***	0.62***	0.72***
	(43.70)	(47.82)	(45.46)	(20.45)	(28.78)	(13.01)	(7.66)	(11.96)	(12.11)	(11.79)
3	1.10***	1.04***	1.03***	1.04***	1.12***	0.95***	0.82***	0.69***	0.65***	0.68***
	(34.38)	(35.46)	(22.72)	(37.53)	(35.10)	(11.79)	(15.47)	(17.14)	(13.31)	(15.25)
4	1.11***	1.10***	1.05***	1.02***	1.05***	0.95***	0.86***	0.75***	0.58***	0.67***
	(30.08)	(32.87)	(37.24)	(38.09)	(38.33)	(11.33)	(14.39)	(17.12)	(13.87)	(15.86)
Big	1.04***	0.92***	0.99***	0.95***	0.97***	0.24*	0.84***	0.62***	0.76***	0.56***
	(33.08)	(28.00)	(35.97)	(44.73)	(57.54)	(2.54)	(15.95)	(19.97)	(21.35)	(20.25)

	$\hat{s}$					$\hat{s}$				
OP→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	1.19***	1.13***	1.09***	1.30***	1.16***	1.14***	0.96***	0.78***	0.86***	1.04***
	(28.71)	(23.38)	(18.91)	(7.39)	(25.34)	(8.40)	(7.92)	(8.76)	(6.41)	(6.56)
2	0.98***	0.95***	0.93***	1.05***	1.18***	0.77***	1.03***	0.91***	0.80***	0.92***
	(30.59)	(33.36)	(32.31)	(32.53)	(28.78)	(10.89)	(9.03)	(10.48)	(10.96)	(10.57)
3	0.64***	0.71***	0.77***	0.72***	0.77***	0.83***	0.85**	0.79***	0.62***	0.72***
	(15.04)	(18.10)	(22.72)	(19.48)	(18.14)	(10.58)	(11.20)	(13.64)	(8.89)	(11.27)
4	0.35***	0.54***	0.45***	0.36***	0.41***	0.61***	0.73***	0.49***	0.54***	0.50***
	(7.09)	(11.94)	(12.00)	(10.15)	(11.20)	(5.04)	(3.52)	(7.79)	(8.86)	(8.25)
Big	-0.24**	-0.02	-0.18**	-0.09**	-0.14**	0.24	0.84	0.62	0.76*	0.56*
	(-3.81)	(-0.46)	(-3.93)	(-3.07)	(-2.29)	(-1.87)	(-0.64)	(-1.57)	(-2.14)	(-2.27)

	$\hat{h}$					$\hat{h}$				
OP→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.16**	0.11*	0.12	0.26	0.22***	-0.37*	0.55***	0.39***	0.11	-0.13
	(-3.07)	(2.11)	(1.65)	(1.17)	(3.88)	(-2.57)	(4.28)	(4.06)	(0.79)	(-0.78)
2	-0.15**	0.11**	0.18***	0.09*	0.19***	-0.08	0.71***	0.47***	0.44***	0.04
	(-3275)	(3.12)	(4.84)	(2.36)	(3.70)	(-1.09)	(5.80)	(5.12)	(5.75)	(0.38)
3	-0.12*	0.11*	0.09*	0.14**	0.20***	0.08	0.49***	0.33***	0.12	0.20**
	(-2.39)	(2.21)	(2.20)	(3.04)	(3.81)	(0.38)	(6.11)	(5.36)	(1.56)	(2.87)
4	-0.18**	-0.08	0.09	0.08	0.09 (1.95)	0.51***	0.23*	0.23***	0.28***	0.11
	(-2.81)	(-1.44)	(1.82)	(1.81)		(4.00)	(2.54)	(3.41)	(4.39)	(1.61)
Big	0.22***	0.08	-0.13**	-0.11**	-0.27**	-0.59***	0.37***	0.29***	0.18***	-0.12**
	(4.17)	(1.43)	(-2.85)	(-3.26)	(-2.62)	(-4.18)	(4.64)	(6.27)	(3.39)	(-2.94)

	$\hat{r}$					$\hat{r}$				
OP→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.59**	0.06	0.21**	-0.04	0.31***	-0.19	0.15	0.08	0.00	-0.09
	(-11.06)	(1.24)	(2.76)	(-0.16)	(5.13)	(-1.33)	(1.18)	(0.83)	(0.00)	(-0.57)
2	-0.62**	0.19***	0.23***	0.38***	0.54***	-0.33***	-0.11	0.22*	0.18*	0.33***
	(-2.74)	(4.99)	(6.20)	(9.02)	(10.11)	(-4.41)	(-0.94)	(2.47)	(2.47)	(3.56)
3	-0.65**	-0.11*	0.29***	0.33***	0.56***	-0.11***	-0.03	0.12*	0.09	0.02
	(-2.64)	(2.12)	(6.60)	(6.80)	(10.17)	(3.57)	(-0.34)	(1.97)	(1.24)	(0.34)
4	-0.72**	-0.15*	0.15**	0.38***	0.29***	-0.11	-0.02	-0.04	0.04	-0.01
	(-3.35)	(-2.53)	(3.06)	(8.10)	(6.05)	(-0.90)	(-0.17)	(-0.53)	(0.66)	(-0.08)
Big	-0.82**	-0.42**	-0.23**	0.16***	0.39***	-0.85***	-0.40***	0.03	0.04	0.03
	(-2.18)	(-3.34)	(-4.84)	(4.29)	(13.20)	(-6.11)	(-5.09)	(0.61)	(0.83)	(0.77)

	$\hat{c}$					$\hat{c}$				
OP→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	0.14	0.07	0.17	0.70*	-0.09	-0.07	0.09	-0.10	-0.25	0.07
	(1.87)	(0.92)	(1.58)	(2.18)	(-1.02)	(-0.45)	(0.67)	(-0.97)	(-1.66)	(0.38)
2	0.07	0.06	-0.12*	-0.19**	-0.28**	0.03	-0.57***	-0.02	-0.08	-0.19
	(1.14)	(1.108)	(-2.26)	(-3.23)	(-3.69)	(0.40)	(-4.34)	(-0.15)	(-0.97)	(-1.94)
3	-0.21**	-0.08	-0.01	-0.12	-0.23**	0.13	-0.14	-0.01	-0.10	-0.01
	(-2.61)	(-1.08)	(-0.24)	(-1.85)	(-1.93)	(-1.94)	(-1.66)	(-0.09)	(-1.29)	(-0.18)
4	-0.10	0.07	0.02	-0.02	-0.01	-0.02	-0.14	-0.10	-0.04	-0.06
	(-1.07)	(0.81)	(0.31)	(-0.27)	(-0.11)	(-0.16)	(-1.44)	(-1.38)	(-0.58)	(-0.85)
Big	-0.32**	-0.08	0.08	-0.16**	0.15***	0.28	-0.24**	-0.07	-0.19**	-0.08
	(-3.15)	(-0.99)	(1.19)	(-3.10)	(3.73)	(1.81)	(-2.79)	(-1.33)	(-3.18)	(-1.74)

	$\widehat{w}$					$\widehat{w}$				
OP→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.02	-0.06*	-0.04	0.05	0.10***	-0.13	-0.42*	0.10	0.31	0.17
	(-0.86)	(-2.25)	(-1.08)	(0.45)	(3.79)	(-0.70)	(-2.56)	(0.82)	(1.73)	(0.80)
2	0.00	-0.03	0.07***	0.08***	0.08***	-0.09	0.08	0.16	0.14	0.08
	(--0.15)	(-1.73)	(4.20)	(4.17)	(3.34)	(-0.95)	(0.53)	(1.39)	(1.46)	(0.72)
3	-0.06*	-0.07**	0.00	0.15***	-0.05	-0.30	-0.10	0.14	-0.04	0.10
	(-2.27)	(-2.69)	(-0.16)	(6.57)	(-1.93)	(0.72)	(-0.97)	(1.79)	(-0.38)	(1.23)
4	-0.10**	0.04	0.00	0.14***	-0.04	0.00	-0.20	0.12	0.22**	-0.03
	(-3.36)	(1.42)	(-0.05)	(6.32)	(-1.71)	(-0.01)	(-1.75)	(1.45)	(2.70)	(-0.33)
Big	-0.05*	-0.10**	-0.05	0.001	0.02	0.38*	0.01	0.04	-0.12	0.12*
	(-2.01)	(-3.69)	(-2.37)	(0.45)	(1.61)	(2.11)	(0.11)	(0.64)	(-1.75)	(2.23)

Note: Significance levels: $p < 0.1$ *, $p < 0.05$ **, $p < 0.01$ ***

Panel C. 5 x 5 size-OP portfolios for the US and UK from June 1990 to December 2021, 354 months.

	US					UK				
	$\hat{\alpha}$					$\hat{\alpha}$				
INV→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.002*	0.001	0.002*	0.002*	0.002	-0.027**	-0.013**	-0.014**	-0.021**	-0.031**
	(-2.18)	(0.53)	(2.34)	(2.54)	(1.52)	(-3.45)	(-3.14)	(-3.49)	(-3.56)	(-3.48)
2	-0.002*	0.001	0.000	0.000	-0.001	-0.028**	-0.015**	-0.018**	-0.019**	-0.023**
	(-2.16)	(1.03)	(0.34)	(-0.73)	(-1.44)	(-2.15)	(-2.98)	(-2.91)	(-3.25)	(-2.99)
3	0.000	-0.001	0.000	-0.001	0.000	-0.013**	-0.015***	-0.015**	-0.021**	-0.019**
	(-0.09)	(-0.68)	(-0.43)	(-0.97)	(0.33)	(-2.61)	(-6.51)	(-3.68)	(-3.52)	(-3.24)
4	0.001	0.001	0.000	0.000	0.000	-0.019**	-0.009***	-0.012**	-0.011**	-0.019**
	(0.67)	(1.05)	(0.15)	(-0.36)	(-0.45)	(-2.99)	(-3.74)	(-2.63)	(-3.26)	(-3.15)
Big	0.002*	0.001	0.000	-0.001	0.000	-0.010**	-0.005**	-0.006**	-0.005**	-0.009**
	(2.18)	(1.35)	(-1.16)	(-0.88)	(0.43)	(-2.24)	(-3.25)	(-3.50)	(-3.59)	(-2.74)

	$\hat{b}$					$\hat{b}$				
INV→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	0.94***	0.88***	0.83***	0.89***	1.03***	0.42**	0.60***	0.52***	0.55***	0.80***
	(34.90)	(37.64)	(34.16)	(40.83)	(24.91)	(3.29)	(6.91)	(7.98)	(5.86)	(9.23)
2	0.99***	0.96***	0.94***	0.97***	1.09***	1.08***	0.83***	0.77***	0.85***	0.91***
	(52.93)	(53.63)	(44.45)	(44.71)	(53.55)	(10.95)	(10.87)	(10.87)	(10.15)	(14.38)
3	1.03***	1.01***	0.97***	0.98***	1.07***	0.71***	0.67***	0.77***	0.81***	0.73***
	(44.20)	(43.77)	(44.11)	(43.51)	(40.21)	(11.75)	(16.63)	(14.41)	(14.93)	(10.11)
4	1.08***	0.97***	1.01***	1.04***	1.10***	0.81***	0.27***	0.55***	0.45***	0.57***
	(40.30)	(38.19)	(47.34)	(44.66)	(45.63)	(14.31)	(10.89)	(18.51)	(16.46)	(12.79)
Big	1.05***	1.01***	0.97***	0.95***	1.02***	0.04***	-0.14***	-0.13***	-0.04***	-0.18***
	(53.62)	(54.43)	(59.08)	(56.30)	(45.26)	(12.43)	(19.17)	(20.01)	(19.54)	(8.50)

	$\hat{s}$					$\hat{s}$				
INV→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	1.14***	1.00***	1.02***	1.03***	1.34***	1.29***	0.89***	0.78***	0.83***	1.08***
	(31.41)	(32.28)	(31.53)	(35.51)	(24.38)	(6.99)	(6.99)	(8.45)	(6.23)	(8.63)
2	1.02***	0.92***	0.92***	0.76***	0.97***	0.84***	0.77***	0.85***	0.91***	0.71***
	(40.47)	(38.81)	(32.58)	(26.18)	(35.56)	(9.07)	(10.24)	(9.23)	(11.81)	(12.83)
3	0.67***	0.65***	0.47***	0.60***	0.59***	0.67***	0.77**	0.81***	0.73***	0.59***
	(21.38)	(21.26)	(15.91)	(20.19)	(16.65)	(6.16)	(10.80)	(10.89)	(9.65)	(9.37)
4	0.48***	0.35***	0.21***	0.22***	0.22***	0.59***	0.27***	0.55***	0.45***	0.57***
	(13.44)	(10.34)	(7.49)	(7.16)	(6.96)	(7.26)	(3.52)	(9.53)	(6.98)	(7.01)
Big	-0.23***	-0.21***	-0.12***	-0.13***	0.22***	0.04	-0.14**	-0.13**	-0.04	-0.18
	(-8.79)	(-8.50)	(-5.58)	(-5.66)	(-7.18)	(0.52)	(-2.86)	(-2.72)	(-0.85)	(-1.64)

INV→	$\hat{h}$ Low	2	3	4	High	$\hat{h}$ Low	2	3	4	High
Small	-0.09*	0.12**	0.17***	0.17***	-0.16*	0.21	0.44**	0.45***	0.28	0.27*
	(-2.05)	(3.22)	(4.17)	(4.60)	(-2.38)	(1.07)	(3.24)	(4.61)	(1.97)	(2.05)
2	-0.11*	0.26***	0.09*	0.26***	0.03	0.07	0.34***	0.61***	0.69***	0.03
	(-2.62)	(8.84)	(2.45)	(6.91)	(0.99)	(0.72)	(4.31)	(6.21)	(8.54)	(0.34)
3	-0.04	0.17***	0.26***	0.22***	0.13**	0.18	0.33***	0.12	0.47***	0.15
	(-0.95)	(4.31)	(6.93)	(5.91)	(2.82)	(1.50)	(5.09)	(1.59)	(5.36)	(1.86)
4	-0.19***	0.16***	0.27***	0.24***	0.23***	0.03	0.55***	0.35***	0.00	0.17*
	(-4.17)	(3.78)	(7.54)	(6.28)	(5.80)	(0.32)	(6.74)	(5.84)	(0.00)	(2.02)
Big	-0.06	0.00	0.10***	0.05	-0.11**	0.16*	0.05	0.14**	0.14**	-0.06
	(-1.92)	(-0.01)	(3.78)	(1.63)	(-2.91)	(2.12)	(0.87)	(2.85)	(2.92)	(-0.52)

INV→	$\hat{r}$ Low	2	3	4	High	$\hat{r}$ Low	2	3	4	High
Small	-0.25***	-0.01	0.09*	-0.03	-0.53***	-0.03	-0.04	0.03	-0.10	-0.09
	(-5.21)	(-0.15)	(2.03)	(-0.67)	(-7.40)	(-0.14)	(-0.31)	(0.29)	(-0.74)	(-0.73)
2	-0.20***	0.19***	0.19***	0.13***	-0.24***	-0.10	0.07	0.22*	-0.09	-0.04
	(-6.13)	(6.21)	(5.28)	(3.54)	(-6.93)	(-1.07)	(0.85)	(2.29)	(-1.12)	(-0.58)
3	-0.19***	0.16	0.14	0.13**	-0.15**	0.16	0.08	0.04	0.04	-0.22**
	(-4.66)	(3.87)	(3.76)	(3.23)	(-3.19)	(1.32)	(1.28)	(0.58)	(0.49)	(-2.74)
4	-0.26***	0.07	0.14***	0.13**	-0.09*	-0.03	0.18*	0.09	-0.10	-0.12
	(-5.67)	(1.67)	(3.80)	(3.26)	(-2.24)	(-0.39)	(2.24)	(1.57)	(-1.49)	(-1.48)
Big	-0.06	0.10**	0.17***	0.06*	0.00	-0.08	-0.09	0.06	-0.01	-0.15
	(-1.69)	(3.12)	(5.78)	(2.16)	(0.08)	(-1.12)	(-1.81)	(1.22)	(-0.32)	(-1.39)

INV→	$\hat{c}$ Low	2	3	4	High	$\hat{c}$ Low	2	3	4	High
Small	-0.25***	0.10	0.09	0.26***	0.60***	-0.29	-0.26	-0.12	0.08	0.14
	(-3.85)	(1.77)	(1.60)	(4.92)	(5.87)	(-1.40)	(-1.77)	(-1.12)	(0.50)	(0.96)
2	-0.42***	-0.16***	0.23***	0.16**	0.46***	-0.61***	-0.02	-0.17	0.04	0.09
	(-9.07)	(-3.69)	(4.42)	(2.93)	(9.16)	(-5.79)	(-0.23)	(-1.61)	(0.40)	(1.12)
3	-0.53***	-0.11	0.08	0.23***	0.30***	-0.14	-0.14*	-0.13	0.02	0.26**
	(-9.34)	(-1.94)	(1.50)	(4.24)	(4.68)	(-1.95)	(-2.06)	(-1.73)	(0.17)	(2.92)
4	-0.35***	-0.08	0.10	0.22***	0.35***	-0.12	-0.19*	-0.08	0.07	0.06
	(-5.36)	(-1.29)	(1.96)	(3.94)	(5.84)	(-1.23)	(-2.13)	(-1.24)	(0.96)	(0.64)
Big	-0.65***	-0.04	0.20***	0.34***	0.83***	-0.51***	-0.29***	-0.04	0.08	0.37**
	(-13.52)	(-0.80)	(5.03)	(8.24)	(14.87)	(-6.43)	(-5.23)	(-0.81)	(1.66)	(3.03)

	$\widehat{w}$					$\widehat{w}$				
INV→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.03 (-1.21)	0.00 (-0.04)	0.01 (0.33)	0.00 (-0.16)	0.05 (1.45)	-0.13 (-0.53)	0.11 (0.63)	-0.07 (-0.53)	0.27 (1.52)	-0.01 (-0.07)
2	-0.02 (-1.71)	-0.03 (-1.73)	0.01 (0.64)	0.01 (0.37)	-0.03 (-1.55)	-0.06 (-0.50)	0.13 (1.39)	0.08 (0.65)	0.29** (2.81)	-0.13 (-1.32)
3	-0.04 (-1.91)	0.01 (0.56)	0.02 (0.91)	0.01 (0.31)	-0.04 (-1.76)	-0.44** (-2.83)	0.04 (0.50)	-0.12 (-1.30)	-0.12 (-1.08)	0.39*** (3.72)
4	0.04 (1.70)	0.04 (1.79)	-0.02 (-1.13)	-0.06** (-3.36)	-0.04* (-2.07)	-0.16 (-1.49)	0.08 (0.77)	0.09 (1.21)	0.06 (0.69)	0.09 (0.81)
Big	0.01 (0.50)	0.03 (1.81)	-0.02 (-1.66)	0.00 (0.34)	-0.07** (-3.88)	0.13 (1.42)	0.06 (0.90)	0.05 (0.88)	0.09 (1.57)	-0.36* (-2.53)

Note: Significance levels: $p < 0.1$ *, $p < 0.05$ **, $p < 0.01$ ***

Panel D. 5 x 5 size-MOM portfolios for the US and UK from June 1990 to December 2021, 354 months.

	US					**UK**				
	$\widehat{\alpha}$					$\widehat{\alpha}$				
MOM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	0.001 (0.80)	0.003* (2.03)	0.002** (2.62)	0.002* (2.39)	0.000 (0.27)	-0.035** (-3.43)	-0.029*** (-9.45)	-0.015** (-3.70)	-0.018** (-2.63)	-0.014 (-1.71)
2	-0.001 (-0.79)	0.000 (-0.34)	0.000 (0.29)	0.001 (1.46)	0.000 (-0.47)	-0.026** (-3.73)	-0.029*** (-12.99)	-0.021** (-3.50)	-0.015** (-3.69)	-0.014** (-3.34)
3	-0.001 (-0.85)	0.001 (0.47)	0.000 (-0.09)	0.000 (0.34)	0.000 (0.19)	-0.019** (-3.45)	-0.026*** (-11.18)	-0.021** (-3.69)	-0.015** (-3.60)	-0.010* (-2.25)
4	-0.002 (-1.24)	0.002 (1.79)	0.000 (0.48)	0.000 (0.34)	0.001 (0.55)	-0.016** (-2.23)	-0.022*** (-8.59)	-0.014** (-3.07)	-0.011** (-3.40)	-0.010** (-2.40)
Big	-0.002 (-0.76)	0.000 (0.16)	0.001 (1.28)	0.000 (0.28)	0.000 (0.68)	-0.004 (-1.25)	-0.007* (-2.50)	-0.008** (-3.54)	-0.005** (-2.65)	0.008** (-2.61)

	$\widehat{b}$					$\widehat{b}$				
MOM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	1.03*** (28.65)	0.85*** (25.66)	0.83*** (33.52)	0.97*** (33.97)	1.12*** (30.63)	0.81*** (6.95)	0.70*** (10.80)	0.67*** (12.12)	0.53*** (9.06)	0.35* (1.97)
2	0.94*** (39.08)	0.92*** (46.90)	0.90*** (46.15)	1.03*** (41.09)	1.17*** (42.99)	0.59*** (9.32)	0.71*** (15.08)	0.65*** (9.40)	0.58*** (14.21)	0.48*** (7.05)
3	0.96*** (29.94)	0.94*** (38.27)	0.93*** (43.89)	1.07*** (38.44)	1.23*** (36.75)	0.51*** (9.32)	0.89*** (18.14)	0.78*** (17.36)	0.65*** (17.25)	0.64*** (7.12)
4	1.01*** (29.53)	0.95*** (35.19)	0.96*** (44.15)	0.95*** (36.79)	1.09*** (34.20)	0.31*** (3.77)	0.96*** (17.76)	0.86*** (20.25)	0.71*** (19.30)	0.36*** (7.22)
Big	1.15*** (19.50)	0.97*** (33.70)	0.93*** (45.70)	0.95*** (44.16)	1.07*** (35.54)	-0.49*** (-7.14)	1.17*** (19.62)	0.80*** (21.94)	0.65*** (22.90)	0.27*** (5.75)

	$\hat{s}$					$\hat{s}$				
MOM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	1.31***	1.03***	1.00***	0.91***	1.16***	1.16***	0.98***	0.92***	0.89***	1.08***
	(27.23)	(23.42)	(30.27)	(28.52)	(27.55)	(7.04)	(10.55)	(11.57)	(10.57)	(4.21)
2	1.12***	0.90***	0.79***	0.78***	0.95***	0.65***	0.99***	1.03***	0.84***	0.71***
	(29.03)	(33.85)	(29.84)	(26.66)	(29.57)	(7.06)	(14.68)	(10.33)	(14.24)	(7.07)
3	0.81***	0.58***	0.50***	0.49***	0.67***	0.57***	0.88***	0.84***	0.74***	0.64***
	(15.73)	(17.41)	(17.58)	(15.34)	(17.36)	(7.28)	(12.41)	(12.92)	(13.55)	(4.96)
4	0.51***	0.31***	0.27***	0.18***	0.37***	-0.04	0.55***	-0.55***	0.60***	0.35***
	(9.29)	(8.17)	(9.28)	(5.30)	(8.75)	(-0.37)	(7.08)	(8.99)	(11.41)	(4.77)
Big	0.19*	-0.08*	-0.10***	-0.16***	-0.14***	-0.42**	-0.29***	-0.05	-0.09*	-0.08
	(2.48)	(-2.22)	(-3.97)	(-5.88)	(-3.69)	(-3.21)	(-3.42)	(-0.95)	(-2.13)	(-1.09)

	$\hat{h}$					$\hat{h}$				
MOM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.04	0.14**	0.13**	0.10*	-0.12*	0.35	0.47*	0.19*	0.32***	0.43
	(-0.72)	(2.61)	(3.07)	(2.54)	(-2.27)	(1.96)	(4.75)	(2.29)	(3.61)	(1.59)
2	0.07	0.19***	0.24***	0.13***	-0.09*	0.27*	0.51***	0.00***	0.42***	0.26*
	(1.53)	(5.85)	(7.24)	(3.75)	(-2.33)	(2.08)	(7.04)	(0.04)	(6.71)	(2.44)
3	0.21**	0.31***	0.28***	0.22***	-0.06	0.23**	0.46***	0.15*	0.15**	0.09
	(3.24)	(3.37)	(7.75)	(5.36)	(-1.41)	(2.81)	(6.07)	(2.10)	(2.61)	(0.67)
4	0.17*	0.37***	0.21***	0.25***	-0.10	0.26*	0.27**	0.28***	0.16**	0.12
	(2.44)	(7.79)	(5.83)	(5.77)	(-1.84)	(2.05)	(3.31)	(4.28)	(2.90)	(1.54)
Big	0.29**	0.31**	0.26***	0.013***	-0.05	-0.16	0.33***	0.29***	0.10*	-0.12
	(2.94)	(2.35)	(7.52)	(3.67)	(-1.05)	(1.55)	(3.59)	(5.29)	(2.31)	(-1.63)

	$\hat{r}$					$\hat{r}$				
MOM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.44***	-0.11*	-0.06	-0.04	-0.22***	0.26	-0.05	0.02	0.08	-0.25
	(-7.10)	(-1.97)	(-1.38)	(-1.03)	(-4.17)	(1.54)	(-0.57)	(0.21)	(0.96)	(-0.97)
2	-0.11*	0.17***	0.19***	0.14***	-0.18***	-0.15	-0.08	0.20*	0.03	-0.10
	(-2.12)	(4.73)	(5.59)	(3.61)	(-4.29)	(-1.56)	(-1.09)	(1.99)	(0.41)	(-0.96)
3	-0.05	0.12***	0.24***	0.23***	-0.09	-0.02	-0.04	-0.04	0.01	0.10
	(-0.76)	(2.86)	(6.46)	(5.32)	(-1.81)	(-0.24)	(-0.53)	(-0.35)	(0.23)	(0.78)
4	-0.19**	0.17***	0.21***	0.19***	-0.12*	0.20	-0.08	0.01	0.01	0.03
	(-2.64)	(3.35)	(5.56)	(4.20)	(-2.26)	(1.27)	(-1.06)	(0.24)	(0.16)	(0.39)
Big	0.09	0.12*	0.18***	0.21***	0.04	-0.12	-0.13	0.04	-0.02	-0.14*
	(0.89)	(2.40)	(5.00)	(5.57)	(0.81)	(1.25)	(-1.46)	(0.72)	(-0.39)	(-2.04)

	$\hat{c}$					$\hat{c}$				
MOM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	0.30***	0.32***	0.14*	0.14*	0.04	0.00	0.01	-0.07	-0.07	-0.20
	(3.36)	(3.95)	(2.37)	(2.36)	(0.49)	(0.00)	(0.11)	(-0.76)	(-0.72)	(-0.69)
2	0.16*	0.13**	0.02	0.12*	-0.11	-0.17	-0.12	-0.37**	-0.08	-0.18
	(2.19)	(2.71)	(0.32)	(2.14)	(-1.82)	(-1.61)	(-1.52)	(-3.27)	(-1.17)	(-1.56)
3	-0.08	-0.03	0.04	-0.03	-0.24**	-0.06	-0.18*	-0.01	-0.01	-0.03
	(-0.82)	(-0.53)	(0.87)	(-0.47)	(-3.29)	(-0.65)	(-2.22)	(-0.07)	(-0.24)	(-0.25)
4	0.17	-0.01	0.14**	0.01	-0.18*	0.17	-0.04	-0.12	-0.08	-0.05
	(1.74)	(0.86)	(2.72)	(0.21)	(-2.36)	(1.27)	(-0.46)	(-1.66)	(-1.38)	(-0.57)
Big	-0.06	0.01	0.02	0.03	-0.4***	0.21	-0.08	-0.12*	-0.11*	-0.17*
	(-0.46)	(0.17)	(0.37)	(0.50)	(-5.39)	(1.88)	(-0.78)	(-1.99)	(-2.38)	(-2.21)

	$\widehat{w}$					$\widehat{w}$				
MOM→	**Low**	**2**	**3**	**4**	**High**	**Low**	**2**	**3**	**4**	**High**
Small	-0.18***	-0.03	0.10***	0.15***	0.20***	-0.58**	-0.21	0.06	0.03	0.16
	(-6.14)	(-0.97)	(4.78)	(7.73)	(7.86)	(-2.63)	(-1.68)	(0.57)	(0.31)	(0.46)
2	-0.33	-0.08***	0.00	0.03***	0.20***	-0.32	0.11	0.34*	0.32***	0.28*
	(-14.07)	(-4.97)	(1.64)	(4.72)	(9.01)	(-2.60)	(1.24)	(2.53)	(4.00)	(2.11)
3	-0.31***	-0.13***	-0.03	0.03	0.20***	-0.17	-0.20*	-0.07	0.25***	0.13
	(-11.54)	(-6.62)	(-0.25)	(1.56)	(8.33)	(-0.58)	(-2.15)	(0.79)	(3.39)	(0.77)
4	-0.31***	-0.13	-0.02	0.03	0.17***	-0.49**	-0.22*	-0.02	0.30***	0.25
	(-9.01)	(-5.72)	(-1.68)	(1.19)	(6.55)	(-2.11)	(-2.11)	(-0.23)	(4.17)	(-2.52)
Big	-0.42***	-0.26***	-0.11***	0.04*	0.20***	-0.52***	-0.97***	-0.16*	0.33***	0.20*
	(-8.58)	(-10.78)	(-6.89)	(2.52)	(8.30)	(-3.88)	(-8.40)	(-2.33)	(5.95)	(2.16)

Note: Significance levels: p < 0.1 *, p < 0.05 **, p < 0.01 ***

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