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A comparison of Asset Pricing Models in the Norwegian Stock Market

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Abstract

This master thesis tests and evaluates different asset pricing models for the Norwegian stock market. The models are made to explain the cross-section of expected stock returns, and we apply them to real-world data and compare their performance.

This paper applies four models to the Norwegian stock market; CAPM, Fama and French Three-Factor Model (FF3), Fama and French Five-Factor Model (FF5), and the Carhart Four-Factor Model (C4). We evaluate their performance using the Fama and MacBeth (1973) procedure with both time-series and cross-sectional regressions and compare the models based on intercept analysis, explanatory power, and stability in results. The purpose of the comparison is to find a superior model that should be applied when analysing the Norwegian stock market.

The Fama-French three-factor model is the most preferred amongst our models. We find no evidence that adding more factors, either the Momentum or the RMW and CMA factor, explain the cross-section of expected returns better than the three-factor model. Further, all models yield a significant intercept which entails that the models are missing priced risk factors for the Norwegian stock market. Other models with different risk factors should, therefore, be considered when conduction analysis in the Norwegian market. However, we find that the Fama-French three-factor model is a relatively stable and applicable model.

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1. Introduction

Asset pricing models are applied daily all over the world and have an extensive list of purposes. From estimating expected future returns and the cost of equity for a company, to measuring and evaluating portfolio performance. Its vast usage is reflected in all the literature and models created over the years. Despite this, studies conducting empirical tests of different models have not yet concluded which model best describes the data.

The Capital Asset Pricing Model (CAPM) of William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966) was a pioneering break-through for modern financial economics. The single-factor model describes the relationship between systematic risk and expected return for assets and is used in finance to determine a theoretically appropriate required return of an asset. The CAPM has been exposed to much criticism because of poor empirical results and unrealistic assumptions. Over the years, additional asset pricing models have been developed, such as the Intertemporal CAPM (Merton, 1973) and Arbitrage Pricing Theory (Ross, 1976). Also, researchers observed several “anomalies” in the US stock market. Banz (1981) found that small market cap stocks seemed to outperform large market cap stocks, and Basu (1983) found evidence that value stocks (high book-to-market ratio) tend to outperform growth stocks (low book-to-market ratio). These observations led to the development of the Fama and French three-factor model. Fama and French (1993) extended the CAPM and added two additional factors, small minus big (SMB) and high minus low (HML), to capture the size and B/M “anomalies”. Since then, researchers have found many new “anomalies” that the three-factor model fails to capture, which has resulted in the development of alternative models. In 1997, Carhart presented a four-factor model which captures the momentum “anomaly” from Jegadeesh and Titman (1993). He took the three-factor model of Fama and French and added a momentum risk factor. More recently, Fama and French (2012) introduced a five-factor model, another extension of their three-factor model, where they add a profitability (robust minus weak, RMW) and an investment (conservative minus aggressive, CMA) factor.

Moreover, Fama and French (2015) show that the five-factor model outperforms the three-factor model in explaining expected returns.

Many more explanations, theories, and models have arisen, yet, there is no consensus on a common model that is superior in explaining the cross-section of returns. Researchers and investors keep finding new strategies superior to the performance predicted by the pricing models. Hence, a central question in financial economics is to find an asset pricing model which includes all priced risk.

In this study we evaluate four established asset pricing models and, to some degree, find the model best suited to explain expected returns in the cross-section in the Norwegian market. We do not believe that any model is perfect. However, we want to find the superior amongst the models tested. Hence, the research questions can be formulated as follows:

Which asset pricing model is best suited to explain the cross-section of expected returns in the Norwegian stock market?

The four models we compare are the CAPM, the Fama-French three-factor model, the Carhart four-factor model, and the Fama-French five-factor model. The three latter are all developed to capture “anomalies” that CAPM fails to do and thus leads one to believe that they will perform better than CAPM. However, we want to include CAPM in our study because the easy and intuitive model is still in use.

We estimate the models using the methodology of Fama and MacBeth (1973), where the first step is to run time-series regressions followed by cross-sectional regressions. Further, we analyse and compare the models based on intercept analysis, explanatory power, and stability in results.

We find that the Fama-French three-factor model is the most preferred amongst our models. No evidence suggests that adding more factors, either the Momentum or the RMW and CMA factor, explains the cross-section of expected returns better than the three-factor model. Further, all models yield a significant intercept which entails that the models are missing priced risk factors for the Norwegian stock market. Other models with different risk factors should, therefore, be considered when conduction analysis in the Norwegian market. These findings are consistent with the research of Næs, Skjæltorp and Ødegaard (2009). They find that a three-factor model containing the market, a size factor, and a liquidity factor provides a reasonable fit for the cross-section of stock returns in Norway. However, we find that the Fama-French three-factor model is a relatively stable and applicable model to explain the cross-section of expected returns in the Norwegian market.

This paper has the following outline: Section two briefly introduce the theory of asset pricing models, section three reviews literature, section four presents the models, section five describes the methodology, section six explains the data and includes descriptive statistics, section seven contains empirical results and discussion, and in section eight we conclude.

2. Theory

2.1 CAPM

The Capital Asset Pricing Model is a single-factor model that was introduced by William Sharpe (1964) and John Lintner (1965) and was the birth of asset pricing theory. The theory is still being used and taught to this day, five decades later. The advantages with the model are its simple logic and intuitively pleasing predictions about how to measure risk and about the relationship between expected return and risk.

The model assumes that all investors have homogenous expectations, and optimally will hold mean-variance efficient portfolios. In a frictionless market, this implies that all investors will hold the market portfolio, which is a value-weighted portfolio of all assets available in the financial market.

CAPM, as mentioned, is still popular today due to its simplicity. However, the empirical record of the model is poor, mainly because it is not possible to observe the true market portfolio. Therefore, we need to apply a proxy for the true market portfolio to empirically test CAPM.

The Sharpe and Lintner version of the CAPM assumes that investors can borrow and lend at a risk-free rate. For this version we have expected return for asset *i*:

$$E(R_i) = R_f + \beta_{im}\left[E(R_m) - R_f\right] \tag{1}$$

Where,

$$\beta_{im} = \frac{Cov[R_i, R_m]}{Var[R_m]} \tag{2}$$

$E(R_i)$ is the expected return on asset i, $E(R_m)$ is the expected return of the market portfolio, and R_f is the risk-free return. β_{im} is the regression coefficient between the asset and the market and is a risk measure that gives the amount of market risk of the asset. A beta higher than one implies that the asset is expected to earn a higher return than the market (given that the market is expected to yield positive return), but with a higher risk. Investors require compensation in the form of a risk premium for holding a risky asset. This implies that a risk-free asset should yield an expected return equal to the risk-free rate, and a risky asset is expected to yield a higher return.

In CAPM, only systematic risk, the risk that cannot be reduced or eliminated through diversification, is rewarded with a higher expected return. β_{im} only capture the asset´s systematic risk, which implies that the total risk of the asset does not equal the quantity of risk. The expected excess return on any asset is the price of risk times the quantity of risk. By rearranging equation (1) we get:

$$E(R_i) - R_f = \frac{E(R_m) - R_f}{\sigma_m} * \sigma_m \beta_{im} \tag{3}$$

Where $E(R_i) - R_f$ is the risk premium, $\frac{E(R_m)-R_f}{\sigma_m}$ is the price of risk and $\sigma_m \beta_{im}$ is the quantity of risk of asset i.

2.2 APT

Stephen Ross (1976) developed the Arbitrage Pricing Theory. The APT predicts a security market line, linking risk and expected return, and it allows for multiple risk factors. Also, the APT is anchored in observable portfolios such as the market index and does not require identification of the unobservable market portfolio.

APT relies on three fundamental propositions:

- Security returns can be described by a factor model.
- There are sufficient securities to diversify away idiosyncratic risk.
- Well-functioning security markets do not allow for the persistence of arbitrage opportunities. If any arbitrage opportunities were to exist, then investors will exploit the mispricing, bringing assets back to fair value.

Assume returns can be described by the following K-factor model:

$$R_i = \alpha_i + \beta_{i,1} F_1 + \beta_{i,2} F_2 + \cdots + \beta_{i,K} F_K + \varepsilon_i \tag{4}$$

Where α_i is a constant, $\beta_{i,K}$ is the risk for asset *i* associated with factor K, F_K is the systematic risk factor, and ε_i is the unsystematic risk component of asset *i*. Then, APT suggests that the expected return for an investment with no non-systematic risk can be computed as:

$$E(R_i) = R_f + \beta_{i,1}\lambda_1 + \beta_{i,2}\lambda_2 + \cdots + \beta_{i,K}\lambda_K \quad (5)$$

Where λ_k, k = 1,…K is the risk premia (expected return) for factor k.

APT, in contrast to CAPM, does not define the factors that determine the expected return of an asset. "The currently dominant approach to specifying factors as candidates for relevant sources of systematic risk uses firm characteristics that seem on empirical grounds to proxy for exposure to systematic risk. The factors chosen are variables that on past evidence seem to predict average returns well and therefore may be capturing risk premiums" (Bodie, Kane & Marcus, 2014, p. 340). One example of this approach is the Fama and French three-factor model.

3. Literature review

3.1 CAPM

There are several studies on the empirical performance of CAPM. Friend and Blume (1970) conducted one of the first studies which questioned the validity of CAPM. In the paper "Measurement of Portfolio Performance Under Uncertainty" (1970), they examine the relationship of one-parameter performance measures to risk for 200 random portfolios. The portfolios were selected from 788 stocks on the New York Stock Exchange through the period January 1960 to June 1968. The performance measures were Jensen, Treynor, and Sharpe, while the risk measure was beta. They found a bias in the performance measures relative to beta as the results show that performance and risk are strongly inversely correlated, where the risky portfolios perform poorer than the less risky portfolios. Friend and Blume (1970) also question the assumptions of CAPM, and they try to explain the bias through the unrealistic assumption that investors can borrow and lend unlimited quantities at the same risk-free rate. CAPM has been modified and extended numerous times in order to make a more realistic approach towards asset pricing. Fischer Black (1972) developed a new version where the risk-free rate is replaced with a zero-beta portfolio, which serves as the risk-free rate. Douglas Breeden (1979) developed the Consumption CAPM, which relies on the aggregate real consumption growth rather than the market portfolio´s return, to estimate the expected return of an asset. Merton (1983) introduced the Intertemporal Capital Asset Pricing Model (ICAPM) as an extension to CAPM that also accounts for time-varying factors such as inflation and future returns.

Numerous empirical tests of the CAPM have been done. Some studies support the CAPM, such as Black, Jensen and Scholes (1972) and Fama and MacBeth (1973), who empirically find a relationship between risk (beta) and returns. However, other studies have challenged the CAPM and find no relationship between betas and returns. Banz (1981) suggests that CAPM is missing a factor. He finds that the size of a firm explains variation in return, where the average return of small firms was substantially higher than the average return of larger firms, after adjusting for risk. Fama and French (1992) support Banz (1981) and find that other explanatory variables, such as firm size and book to market equity ratio, seem to explain the cross-section of stock returns better than beta. Based on this evidence, Fama and French introduced the three-factor model in 1993.

Some studies also challenge the challengers, where they argue that the poor empirical results are caused by a fault in the market proxy. Roll (1977) argues that the CAPM never has or will be empirically tested due to the unobservable true market portfolio.

3.2 Fama-French three-factor model

Fama and French (1993) make an extension of the CAPM by adding two additional risk factors related to firm size and book-to-market ratio. They find that this expanded model captures much of the variation in returns among stocks in the U.S. (Fama & French, 1996). The choice of factors is motivated by empirical evidence, which makes it difficult to interpret in a theoretical manner. They found that, on average, firms with high book-to-market equity ratio (B/M) tend to have persistently poor earnings, and firms with low B/M have persistently high earnings. Also, small firms tend to be more profitable than large firms. Fama and

French (1998) found that the three-factor model outperforms CAPM in explaining the cross-section of stock returns in 13 major markets.

However, Fama and French (1996) admit that the main embarrassment of the three-factor model is its failure to capture the continuation of short-term returns documented by Jegadeesh and Titman (1993) and Asness (1995). Jegadeesh & Titman (1993) found evidence that buying past winners and selling past losers gave significant abnormal returns, as the performance of a stock, good or bad, tend to persist over several months. Carhart (1997) purposed a solution to this problem, as he added momentum as an additional risk factor to the Fama-French three-factor model.

3.3 Carhart four-factor model

Carhart (1997) investigated mutual funds and found that the momentum factor was statistically significant alongside the value and size factors. Many other studies also examine momentum returns of firm value and firm size (Jagadeesh and Titman, 1993; Nijman, Swinkels & Verbeek, 2004), and the results show that the momentum effect is more substantial on small-cap growth stocks.

3.4 Hou, Xue, Zhang's q-factor model

Hou. Xue and Zhang (2015) introduced a new four-factor model. They propose that the expected return of an asset is described by the sensitivities of its return to the market excess return, investment, size, and profitability (ROE). Their q-factor model is partly inspired by investment-based asset pricing, which in turn is built upon Tobin's (1969) q-theory of investments. Tobin's Q is calculated as the market value of a company divided by the replacement value of the firm's assets. The Q measures if a firm or market is relatively over- or under-valued. Hou, Xue and Zhang (2015) argue that "firms invest more when their marginal q (the net present value of future cash flows generated from an additional unit of assets) is high. Given expected profitability or cash flows, low discount rates imply high marginal q and high investment, and high discount rates imply low marginal q and low investment" and that expected returns decrease with investment-to-assets. The purpose of the model is to capture "anomalies" that the Fama-French three-factor model was unable to, especially the impact of a firm´s investment behaviour and profitability on expected stock return. They tested the model on 80 "anomalies" in the U.S. market and concluded that the q-factor model outperforms both the Fama-French three-factor model and Carhart´s four-factor model in capturing many of the significant "anomalies".

3.5 Fama-French five-factor model

Fama and French (2015) published the five-factor model in 2015 where they include operating profitability (RMW) and investment (CMA) as two additional factors to the three-factor model (Fama & French, 1993). Evidence shows that the three-factor model does not explain the variance in returns related to profitability and investment. Hence, they include them as factors in a new model (Fama-French, 2015). Fama and French (2015) used U.S. data and argued that the five-factor model performs better than the three-factor model on capturing patterns in the average stock return. However, they reject the GRS-test on the five-factor model, which implies that the model is not perfect. Nevertheless, it was still able to explain between 71 and 94 % of the variance in returns of the examined portfolios. Thus, they conclude that the five-factor model is superior between the two models.

Fama and French (2017) also studied how the five-factor model performs in international markets (North America, Europe, Japan, and Asia Pacific). They find that "average stock returns for North America, Europe, and Asia Pacific increase with the book-to-market ratio and profitability and are negatively related to investment. For Japan, the relation between average returns and B/M is strong, but average returns show little relation to profitability or investment" (Fama & French, 2017). For the sample period 1990-2015, their findings indicate that all five factors have unique information about average returns in North America. However, CMA, the investment factor, is redundant for Japan and Europe. Hence, dropping CMA from the five-factor model has little effect on the explanation of average returns in those regions.

3.6 Similar studies

The paper “Evaluating asset pricing model in the Korean stock market” by Kim, Kim and Shin (2012) evaluates and compares asset pricing models in the Korean stock market. The models which are evaluated and compared are the CAPM, several APT-motivated models, the CCAPM, and several ICAPM-motivated models. In the study, they conduct time-series tests and cross-sectional regression tests. They find that the Fama-French five-factor model performs best among the tested models. Then the Fama-French three-factor model and the Campbell model are next on explaining cross-sectional stock returns in Korea.

In 2017, Hou, Xue and Zhang (2017) investigated and compared the performance of several empirical asset pricing models in explaining hundreds of significant “anomalies” in the broad cross-section. Their study includes the classical models such as CAPM, Fama-French three-factor model, and Carhart four-factor model. In addition to some newer models, such as Hou, Xue and Zhang q-factor model and Fama-French five-factor model. Their findings indicate that the q-factor model and the five-factor model are the two best performing models in explaining stock return “anomalies” in New York Stock Exchange (NYSE). Moreover, the q-factor model outperforms the five-factor model in explaining momentum and profitability “anomalies”, but the five-factor model is better in explaining value-versus-growth “anomalies”. Furthermore, they find that investment and profitability “are the key driving forces in the broad cross-section of expected return” (Hou et al., 2017).

Despite a large amount of international empirical asset pricing studies, there are to our knowledge, just a few studies regarding the Norwegian stock market. Næs et al. (2009) have done substantial research on which factors affect the Oslo Stock Exchange. In their paper, they analyse return patterns in the Norwegian stock market in the period 1980-2006 and find that a three-factor model containing the market, a size factor and a liquidity factor provides a reasonable fit for the cross-section of stock returns in Norway.

4. The models

In this section, we outline the four models that are used in this study. Also, we explain why these particular models were selected.

4.1 CAPM

The Capital Asset Pricing Model is a centrepiece of modern financial economics and asset pricing literature. Although the CAPM does not adequately withstand empirical test, it is widely used because it is simple, gives good insight and because its accuracy is considered acceptable for essential applications (Bodie et al., 2014, p. 291). Thus, it is natural to include the model in this study.

As mentioned earlier, to test the CAPM empirically, it is necessary to include a factor as a proxy for the unobservable market portfolio. We will use the factor *ERM*, the excess return for the Norwegian stock market, as a proxy to compute the expected return of the test assets. Hence, we obtain the CAPM model:

$$E(R_i) - R_f = \beta_{i,ERM}(ERM_i) \tag{6}$$

where $E(R_i) - R_f$ is the expected excess return of the test assets, R_f is the risk-free rate, and $\beta_{i,ERM}$ is the coefficient loading for asset *i* to the excess return of the Norwegian stock exchange.

4.2 Fama-French three-factor model

Empirical research shows that returns are related to firm characteristics like size (Banz, 1981), earning/price (Basu, 1983), cash flow/price (Lakonishok, Shleifer & Vishny, 1994), book-to-market equity (Rosenberg, Reid & Lanstein, 1985), past sales growth, long-term past return, and short-term past return. As the CAPM does not explain these patterns, Fama and French introduced the three-factor model to take care of this problem. In addition to the excess return on market portfolio, $(E(R_m) - R_f)$, they introduced two new factors which are HML and SMB. HML is the difference between the return on a portfolio of high-book-to-market stocks and the return on a portfolio of low-book-to-market stocks and SMB is the difference between the return on a portfolio of small stocks and the return on a portfolio of large stocks. The equation derives the expected excess return on asset i:

$$E(R_i) - R_f = \beta_{i,ERM}(ERM_i) + \beta_{i,SMB}(SMB_i) + \beta_{i,HML}(HML_i) \qquad (7)$$

(Fama & French, 1996)

where, $\beta_{i,SMB}$ and $\beta_{i,HML}$ are the sensitivities of asset *i* to risk factors SMB and HML.

4.3 Carhart four-factor model

The Carhart four-factor model was constructed using the Fama and French (1993) three-factor model plus an additional factor capturing Jegadeesh and Titman's (1993) one-year momentum "anomaly". Næs et al. (2009) state that "momentum strategies have also been shown to work outside the U.S. Rouwenhorst (1998) documents momentum strategies in 12 European stock markets over the period 1980-95, while Chan, Hameed, and Tong (2000) find support for momentum strategies in 23 international stock indices, of which 9 Asian, 11 European, two North-American and one South-African". Further, the four-factor model has shown to perform better than the Fama-French three-factor model (Hou et al., 2017). Thus, it would be interesting to include the model in our study and assess its performance in Norway:

$$E(R_i) - R_f = \beta_{i,ERM}(ERM_i) + \beta_{i,SMB}(SMB_i) + \beta_{i,HML}(HML_i) + \beta_{i,PR1YR}(PR1YR_t) \qquad (8)$$

(Carhart, 1997)

where PR1YR are the returns on value-weighted, zero-investment one-year momentum in stock returns and $\beta_{i,PR1YR}$ is the sensitivity of asset *i* to the risk factor PR1YR.

4.4 Fama-French five-factor model

The five-factor model is an extension of the three-factor model with a profitability and investment factor added. We find it interesting to include the five-factor model as it is a relatively new model compared to CAPM, Fama-French three-factor model, and Carhart four-factor model. Also, several studies have presented evidence that it is better than CAPM and the three-factor model to determine expected returns. The model:

$$E(R_i) - R_f = \beta_{i,ERM}(ERM_i) + \beta_{i,SMB}(SMB_i) + \beta_{i,HML}(HML_i) + \beta_{i,RMW}(RMW_i) + \beta_{i,CMA}(CMA_i) \tag{9}$$

(Fama & French, 2015)

Where RMW_i is the difference between returns on diversified stocks with robust and weak profitability and CMA_i is the difference in return on diversified portfolios of the stocks of low and high investment firms. $\beta_{i,RMW}$ and $\beta_{i,CMA}$ are the sensitivities of asset *i* to risk factors RMW and CMA.

5. Methodology

Throughout this study, we apply the Fama and MacBeth (1973) procedure to determine which of the suggested asset pricing models is superior in explaining the cross-section of expected returns in the Norwegian stock market. We use test assets consisting of 28-30 portfolios. Further, intercept analysis, stability analysis, and explanatory power is evaluated and used as arguments to determine if there is a superior model.

5.1 Fama and MacBeth – two-step regression

The methodology applied by Fama and MacBeth (1973) is a two-step regression which enables us to see the relationship between risk and expected return. From the two-step regressions, we obtain estimates of loading’s and risk premiums for each factor, and we apply several tests to determine the best model in explaining the cross-section of expected returns.

The first step of the methodology is to do a time-series regression of the test assets on the factors to obtain estimates of beta for each factor in the different models. In these estimations we assume constant coefficients and constant expected returns. The regression is estimated using ordinary least squares, and we run the regression for all the test assets, $i = 1, \dots N$, where N is the number of portfolios we use as test assets:

$$R_{i,t} = \alpha_i + \beta_{i,1}F_{1,t} + \beta_{i,2}F_{2,t} + \cdots + \beta_{i,K}F_{K,t} + \varepsilon_{i,t} \quad , t = 1, \dots T \tag{10}$$

From the regressions, α_i is the intercept, $\beta_{i,1}, \beta_{i,2}, \dots ,\beta_{i,K}$ are the factor loadings on each of the K factors, $\varepsilon_{i,t}$ is the error term, and T is the number of time steps observations. The factor loadings are only estimations of the true factor loadings. Therefore, we label the estimates of the factor loadings $\hat{\beta}_{i,1}, \hat{\beta}_{i,2}, \dots ,\hat{\beta}_{i,K}$.

The second step of the methodology is to regress return on the estimated factor loadings $\hat{\beta}_{i,1}, \hat{\beta}_{i,2}, \dots ,\hat{\beta}_{i,K}$ for each cross-sectional observation. This yields the estimated risk premium for each of the K factors. The cross-sectional regression is:

$$R_{i,t} = \lambda_{0,t} + \lambda_{1,t}\hat{\beta}_{i,1} + \lambda_{2,t}\hat{\beta}_{i,2} + \cdots + \lambda_{K,t}\hat{\beta}_{i,K} + \varepsilon_{i,t} \quad , i = 1, \dots N \tag{11}$$

Where $\lambda_{0,t}$ is the intercept, $\lambda_{1,t}, \lambda_{2,t}, \dots ,\lambda_{K,t}$ is the estimate of the risk premium (in period t) for the K factors, and $\varepsilon_{i,t}$ is the error term. From the OLS regressions for each cross-section, we obtain T estimates of the risk premium for each factor. Because they are estimates we name them $\hat{\lambda}_{1,t}, \hat{\lambda}_{2,t}, \dots ,\hat{\lambda}_{K,t}$.

Further, we calculate the average risk premium, $\overline{\hat{\lambda}_k}$, for each factor $k = 1, \dots K$:

$$\overline{\hat{\lambda}_k} = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_{k,t} \quad , k = 1, \dots K \tag{12}$$

After obtaining the average risk premium for each factor we can compute the t-ratio as:

$$t\left(\overline{\hat{\lambda}_k}\right) = \frac{\sqrt{T} * \overline{\hat{\lambda}_k}}{\hat{\sigma}_{\lambda,k}} \quad , k = 1, \dots K \tag{13}$$

where,

$$\hat{\sigma}_{\lambda,k} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(\hat{\lambda}_{k,t} - \overline{\hat{\lambda}_k}\right)^2} \quad , k = 1 \dots K \tag{14}$$

According to Brooks (2019, p. 589), the test statistic is asymptotically normal, implying that it follows a t-distribution with T-1 degrees of freedom in finite samples. The t-statistics will give insight into whether the risk premiums are statistically significant or not. Noteworthy, according to Shanken (1992), the Fama and MacBeth approach with rolling window betas cause the series of estimates not to be independent, which is a criterion for the t-distribution. Moreover, he explains that if a single beta is estimated, which is the approach in this study, measurement error in beta decline as the sample size increases. In this case, he states that the second-pass estimator is T-consistent.

5.2 Test assets

The appropriate test assets to apply in an asset pricing model depends on how one can minimize errors in the estimation of the risk premia. As the cross-sectional regression in the Fama-MacBeth method uses estimated factor loadings from the time-series regression, this introduces an EIV (errors in variables) problem. One widely used method to tackle this problem is to group stocks in portfolios, which Blume (1970) initially gave the idea to do. Fama and MacBeth (1973) argue that using portfolios rather than individual stocks reduces the EIV problem significantly. An alternative approach that Litzenberger and Ramaswamy (1979) and others apply to reduce the EIV problem is to use the entire universe of stocks to estimate the cross-sectional risk premium.

Further, in a study by Ang, Liu and Schwarz (2017) they find that the motivation for using portfolios instead of stocks is empirically wrong. The motivation being that the betas are estimated with errors and this estimation error is diversified away by aggregating stocks into portfolios. They find that the reduced uncertainty of the factor loadings does not translate to lower standard errors for risk premium estimates. Reason being that portfolios diversify away information contained in individual stocks factor loadings, and therefore reduces the dispersion of the cross-sectional betas. However, we will use portfolios in this study to try to tackle the EIV problem, and high dispersion in the cross-sectional betas between the portfolios will be an important criterion.

We collect several portfolios from Bernt Arne Ødegaard (2019). He uses different characteristics to sort assets and creates portfolios based on this sorting. One of the suggestions of Lewellen, Nagel and Shanken (2010) is to include other characteristics than the commonly used size-B/M portfolios due to problems tied to the strong covariance structure. Therefore, we collect portfolios sorted according to five different characteristics: Size, B/M, Momentum, Industry, and Spread. The Spread portfolios are according to Næs et al. (2009) "calculated as the difference between the closing bid and ask prices, relative to the midpoint price. Portfolio 1 contains the stocks with the lowest spread, i.e. the most liquid companies, while portfolio 10 contains companies with the biggest spread". Following Fama and French (2015), who uses test assets consisting of 25-32 portfolios, we construct test assets with a similar range of portfolios. Since the data from Ødegaard contains up to ten portfolios for each characteristic, this implies that we group the five characteristics in sets of three, to obtain ten sets of test assets (e.g., one set of test assets includes the ten portfolios of Size, B/M, and Momentum, which entails that the test assets hold 30 portfolios).

To find the appropriate test assets to use in our models, we want these test assets to minimize the errors in the estimation of the risk premia. We evaluate the different characteristics of dispersion in expected returns to get an indication of which characteristics might give a higher dispersion of the cross-sectional betas. The reason we want high dispersion in the cross-sectional betas is motivated by the logic of Ang et al. (2017), that higher dispersion in betas entails that more information is captured in the cross-section to estimate the risk premia. Thus, we believe that the estimation of the risk premia will be more accurate. Further, we examine the ten sets of test assets to see which test assets yield the highest dispersion of the cross-sectional betas and apply these test assets to our models.

5.3 Model comparison

To answer our research question, if one asset pricing model is superior to the others, we need to compare the models. For this, we need appropriate tests/analyses, which allows us to evaluate a model's relative performance.

Intercept analysis is a commonly used method to determine if an asset pricing model includes all priced risks. If the intercept is statistically different from zero, this implies that the model does not include all priced risk factors. We analyse the intercept from both the time-series and the cross-sectional regressions to determine if the model includes all priced risk factors. If one model yields a zero-intercept, we conclude that this model performs better as it seems to include all priced risk factors. Further, we compare the models based on the cross-sectional adjusted-R^2, which indicates how much of the variation in the cross-section of expected return the model explains, adjusted for the number of parameters. The motivation to use adjusted-$R^{2,}$ in addition to R^2, is that some of the models are just an extension of another model, such as FF5 includes the factors of FF3 and two additional factors. This implies that the five-factor model's R^2, by definition, will be equal to, or higher, than that of the three-factor model. Therefore, we use adjusted-R^2 as it corrects for the number of factors in the model. We show in Appendix A how the R^2 and adjusted R^2 are calculated. Lastly, we will test the models using different sets of test assets, in addition to our main test assets, to measure the stability of the results. Hopefully, these tests/analyses give us enough insight to compare and determine which model is superior.

5.3.1 Intercept analysis

For the cross-sectional regressions, we estimate the average risk premium by averaging the T number of risk premiums for any factor. We also show how we calculate the t-ratio in equation (13). The same logic is applied for the intercept, $\lambda_{0,t}$. The null hypothesis is $\lambda_{0,t} = 0$, which implies that if the null hypothesis is rejected, the intercept is statistically significantly different from zero, and the model has cross-sectional pricing errors.

For the time-series regressions, the intercept analysis is different. Reason being that we run N regressions, which results in N different alphas, one for each test asset. It is hard to evaluate a model's performance based on 28-30 alphas, which is why we apply the GRS-test proposed by Gibbons, Ross and Shanken (1989). The GRS-test, similar to an F-test, examines the hypothesis that all the alphas from a set of time-series regressions are jointly equal to zero. The GRS-statistic is defined, following Cochrane (2000, p.217), as:

$$GRS = \left(\frac{T - N - K}{N}\right) \frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1 + E_T(f)'\hat{\Omega}^{-1}E_T(f)} \sim F_{N,T-N-K} \tag{15}$$

Where T is the number of cross-sectional periods, N is the number of test assets, K is the number of factors in the model. $\hat{\alpha}$ is an N × 1 vector with the estimated intercepts from the regressions, $\hat{\Sigma}$ is an N × N unbiased estimate of the residual covariance matrix, $E_T(f)$ is a K × 1 vector of the factor portfolios means, and $\hat{\Omega}$ is an unbiased estimate of the factor portfolios covariance matrix. Further descriptions on how we calculate the GRS-statistic is shown in Appendix A. The motivation for using GRS-test rather than a χ^2-test is that according to Cochrane (2000, p.216) the χ^2-test is asymptotically valid whereas the GRS-test is valid for finite samples.

The GRS-statistic follows the F-distribution with numerator and denominator degrees of freedom equal to N and T-N-K, respectively. Calculating the GRS-statistic as in equation (15) and finding the associated F-statistic will enable us to determine if the model's intercepts are jointly statistically significantly different from zero. We again emphasise that the performance of the model is better if the intercepts are not significantly different from zero, as this entails that the model captures all the priced risks factors.

5.3.2 Explanatory power

As a practical matter, models are at best approximations of reality. It is therefore desirable to have a measure of "goodness of fit". R^2 is such a measure which describes how much of the variation in the dependent variable is explained by the independent variables. A high cross-sectional R^2 should imply that the model captures most of the variation in expected return.

However, according to Kan, Robotti and Shanken (2013), the cross-sectional R^2 has been treated mainly as a descriptive statistic in asset pricing research. Thus, we do not interpret R^2 to be the realistic explanatory power of the model in the cross-section. Therefore, we solely use R^2 to compare the performance of the different models against each other. Further, Kan et al. (2013) state that the R^2 for average returns should be employed rather than the average of monthly R^2s. Therefore, we will adjustment the cross-sectional regression to obtain R^2 and adjusted-R^2 for average returns:

$$E(R_i) = \lambda_0 + \lambda_1\hat{\beta}_{i,1} + \lambda_2\hat{\beta}_{i,2} + \cdots + \lambda_K\hat{\beta}_{i,K} + \varepsilon_i \quad i = 1 \ldots N \qquad (16)$$

Where $E(R_i)$ is the average return on test asset i, λ_0 is the intercept for the sample period and $\lambda_1, \lambda_2, \ldots, \lambda_K$ are the factors risk premia for the sample period.

Both R^2 and adjusted R^2 are default outputs in MATLAB. Comparing the values gives insight into which model might be superior. However, we do this with caution as there are many critics to the cross-sectional R^2.

5.3.3 Stability analysis

The test results from our models are evaluated based on our main test assets. However, an interesting approach is to change the test assets to determine if the results are stable, or differs, with the change applied. We want a good asset pricing model to work for any portfolio or stock, given that the estimation of the factor loadings is correct. Thus, stability in results will be an important analysis to determine the relative performance of the models. As previously mentioned, and explained in section "6.1 Main test assets", we acquire ten sets of test assets which differs in the characteristics of the portfolios retained as test assets. We choose the set of assets that yields the highest dispersion in the cross-sectional betas as our main test assets, whereas the remaining nine sets are used in the stability analysis. Further, we apply some changes to the collected test assets, where we reduce the sample length for all models to equal the sample length collected for FF5. We also perform the analysis with equally-weighted test assets.

Of course, the process is the same for every set of test assets, and the model that produces the most stable results will be favoured in terms of the stability analysis.

6. Data

The models compared in this study are the Fama-French three-factor model (FF3), Fama-French five-factor model (FF5), CAPM, and the Carhart four-factor model (C4). Thus, we need the factors for all models, where most of them are collected through Bernt Arne Ødegaard (2019). A description of the collected data is presented later in this section. Test assets are created based on five sets of portfolios which differ in characteristics: Industry, B/M, Momentum, Size, and Spread. For the CAPM, FF3, and C4 factor model, we have monthly data from July 1981 to December 2018, implying 450 observations. However, due to the lack of data for Norwegian firms before 1995, the collected RMW and CMA only contain monthly data from January 1995 to December 2017. Hence, we have 276 observations for the FF5 model.

6.1 Main test assets

Appendix B1 shows the descriptive analysis of the excess return for the five different characteristics sets of portfolios. As previously discussed, we favour the characteristics which yield the highest dispersion in expected returns as this may imply higher dispersion in the cross-sectional betas and therefore more information captured to estimate the risk premia. From Appendix B1, which includes the minimum, maximum, average, and standard deviation of excess return for the different characteristics portfolios, we observe that the highest average monthly returns of 2.7% and 2.2% are for the Size and Spread characteristic portfolios, respectively. The lowest of the average of minimum return is for the Industry characteristic portfolios with -32.9% and the highest of the average maximum return is also in the Industry portfolios with 58.7%. Further, the average standard deviation is the highest for the Industry, B/M and Momentum portfolio, with an average standard deviation of 0.089, 0.081, and 0.078, respectively. As high standard deviation might imply higher dispersion in the cross-sectional beta, these portfolios are currently favoured.

The most preferred test assets are the test assets with the highest dispersion in the cross-sectional betas. The test assets contain 28-30 portfolios and are sorted in the following way:

First, we have five sets of characteristics portfolios, which are:

Industry (I)	– 8 portfolios
B/M (B)	– 10 portfolios
Momentum (M)	– 10 portfolios
Spread (Sp)	– 10 portfolios
Size (Si)	– 10 portfolios

Lastly, we gather the characteristics in sets of three to create test assets, and with five characteristics, this implies ten sets of test assets:

IBM – 28 portfolios
IBSp – 28 portfolios
IBSi – 28 portfolios
IMSp – 28 portfolios
IMSi – 28 portfolios
ISpSi – 28 portfolios
BMSp – 30 portfolios
BMSi – 30 portfolios
BSpSi – 30 portfolios
MSpSi – 30 portfolios

Further, Appendix B2 shows the descriptive analysis of the cross-sectional betas. The highest of the average of the maximum betas are in the IMSi, IBSi, and ISpSi portfolios. The lowest of the average of the minimum betas are also in portfolio IMSi, IBSi, and ISpSi. Moreover, the highest average standard deviation of the cross-sectional betas using the four asset pricing models is the test asset IBSi with an average standard deviation of 0.19. Thus, IBSi will be used as main test assets in the main models due to the high dispersion in cross-sectional betas, which we believe will lower the estimation error of the risk premia.

6.2 HML, SMB, and PR1YR

We collect monthly data for the Fama-French factors HML and SMB and Carhart momentum factor (PR1YR) through Bernt Arne Ødegaard (2019), which has calculated the factor portfolios using Norwegian data. Ødegaard has constructed the HML and SMB factors as follows: "First companies at the OSE are sorted into three B/M portfolios (H,M,L). Thereafter companies in each B/M portfolio are sorted into two size portfolios (S,B). Finally, HML and SMB are constructed from the size cross-sorted portfolios (SH, SM, SL, BH, BM, BL) in such a manner that they are zero investments" (Næs et al., 2009):

$$HML = \left(\frac{SH + BH}{2}\right) - \left(\frac{SL + BL}{2}\right) \tag{17}$$

$$SMB = \left(\frac{SH + SM + SL}{3}\right) - \left(\frac{BH + BM + BL}{3}\right) \tag{18}$$

where SH is Small-High, SM is Small-Medium, SL is Small-Low, BH is Big-High, BM is Big-Medium, and BL is Big-Low portfolios.

The PR1YR factor is constructed by sorting stocks into three portfolios at the end of each month, based on their previous 11-month return. The portfolios are losers (low return stocks), medium and winners (high return stocks), and are rebalanced each month. The PR1YR factor is the difference in return of portfolio three (winners) and one (losers).

6.3 Market risk premium

The market risk premium is the return of the market in excess of risk-free return:

$$ERM_t = R_{market,t} - R_{f,t} \tag{19}$$

Estimates of the monthly market return and risk-free rate are collected from Ødegaard (2019) for the entire sample period. We use the value-weighted market index, which is constructed from most of the stocks at Oslo Stock Exchange.

6.4 CMA and RMW

The last factors in the FF5 model are collected through former students, Kristiansen and Mahmood (2018), that have performed a similar study. With collected data from the Bloomberg terminal, they have created:

- Operating Profitability (Revenue minus COGS, SGA and interest expenses, all divided by book equity)

- Investments (Total assets from year t-1 minus total assets from year t-2, divided by total assets from year t-2)

They use a 2x2 sorting and the median of either operating profitability (OP) or investments (In) as breaking points. From OP, they obtain robust (R) and weak (W), and from In they obtain conservative (C) and aggressive (A). Splitting each of these four portfolios into small and big allows them to calculate RMW and CMA:

$$RMW = \frac{SR + BR}{2} - \frac{SW + BW}{2} \tag{20}$$

Where SR, BR, SW, and BW are small-robust, big-robust, small-weak, and big-weak, respectively.

$$CMA = \frac{SC + BC}{2} - \frac{SA + BA}{2} \tag{21}$$

Where SC, BC, SA, and BA are small-conservative, big-conservative, small-aggressive, and big-aggressive, respectively.

6.5 Descriptive statistics for the factors

Table 1 shows the descriptive statistics of the exogenous variables. We see from the table that there is some dispersion in the mean estimates, where ERM (excess market return) has the highest estimated mean of 1.35 %, and RMW has the lowest estimated mean of 0.35 %. ERM is also the most volatile independent variable, with an estimated standard deviation of 5.99 %, whereas RMW has the lowest standard deviation of 3.12%.

Table 1 Summary statistics of the factors

Table 1 shows statistics for monthly excess returns for the factors

Variable	Mean	Max	Min	Std. Dev.	Skewness	Kurtosis	Observations
ERM	1.35 %	18.61 %	-25.06 %	5.99 %	-0.57	4.84	450
SMB	0.79 %	22.22 %	-17.08 %	4.30 %	0.45	6.28	450
HML	0.40 %	18.44 %	-16.65 %	4.83 %	-0.11	4.16	450
PR1YR	0.95 %	15.43 %	-16.78 %	4.81 %	-0.41	4.31	450
RMW	0.35 %	11.36 %	-9.76 %	3.12 %	0.04	3.87	276
CMA	0.61 %	16.57 %	-10.64 %	3.41 %	0.91	7.24	276

When using the Ordinary Least Squared estimation method, it is an implicit assumption that the explanatory variables are not correlated with one another. If the variables are highly correlated with each other, we have multicollinearity. Ignoring the presence of multicollinearity will impact the standard errors of the coefficients. Further, the regression will become very sensitive to small changes, so adding or removing an explanatory variable leads to substantial changes in the other variables' significances and coefficient estimates. Lastly, significance tests may give inappropriate conclusions as the confidence intervals for the variables become very wide (Brooks, 2019, p. 215).

Table 2 Correlation between the factors

Panel A shows the correlations between the factors in the Fama-French three-factor model and the Carhart's four-factor model for the time period 1981-2018

Panel B shows the correlations between the factors in the Fama-French five-factor model for the time period 1995-2017.

Panel A	ERM	SMB	HML
ERM	1.00		
SMB	-0.41	1.00	
HML	0.05	-0.12	1.00
PR1YR	-0.12	0.12	-0.03

Panel B	ERM	SMB	HML	RMW
ERM	1.00			
SMB	-0.47	1.00		
HML	-0.20	-0.05	1.00	
RMW	-0.32	0.00	0.21	1.00
CMA	0.03	0.00	0.09	-0.12

Table 2, panel A, shows the correlations between the variables in the Fama-French three-factor model and Carhart four-factor model for the time period 1981-2018, and table 2, panel B, reports the correlations between the variables in the Fama-French five-factor model, for the time period 1995-2017. We see from the table that the correlation between the explanatory variables is low overall. Hence, there is no indication of multicollinearity among the variables. The highest absolute correlation is between ERM and SMB in both panel A and B, with correlations of -0.41 and -0.47, respectively.

When doing time-series analyses, it is important that the variables are stationary. Use of non-stationary data can lead to spurious regressions. Hence, provide misleading statistical evidence and impact our results. We are only working with asset returns, which are unit-free and stationary (Brooks, 2014, p. 7). Thus, spurious regressions are not an issue in this study.

7. Main results and discussion

This section shows and describes the results of the tests for the selected asset pricing models. For the main analysis, we use value-weighted portfolios. To get a more thorough comparison, we also estimate each model for equally-weighted portfolios and value-weighted portfolios with sample length equal to the Fama-French five-factor model (1995-2017). These results are reported in Appendix C2 and Appendix C3, respectively.

In the first subsection, we examine the risk premia of the risk factors from the Fama-Macbeth regressions. In the second and third subsection, we compare the models by analysing the intercepts and the coefficients of determination. The fourth subsection contains a stability analysis where we estimate the models using other sets of test assets.

7.1 Fama-MacBeth cross-sectional regressions

Table 3 presents the results from the Fama-MacBeth two-pass regressions, where we have tested the CAPM, Fama-French three-factor model (FF3), Carhart´s four-factor model (C4) and Fama-French five-factor model (FF5) in the cross-section of our main test assets, IBSi.

Table 3 Results from cross-sectional regressions

Table 3 reports the results from the cross-sectional regressions using the Fama and MacBeth procedure. All models are estimated using monthly excess return on the 28 IBSi portfolios. Column 2 reports the intercept, columns 3-7 show the estimated risk premia and the corresponding t-statistic for each factor, and columns 8-9 show the R^2 and adjusted R^2 for the estimated model. *, ** and *** indicate the significance for the risk premia estimates at the 10, 5 and 1 percent level, respectively.

Panel A: CAPM

1981-2018	λ_0	λ_{ERM}	R^2	R^2_{adj}
CAPM	0.040	-0.025	0.466	0.445
T-ratio	(-10.193)***	(-5.227)***		

Panel B: Fama French three factor model

1981-2018	λ_0	λ_{SMB}	λ_{HML}	λ_{ERM}	R^2	R^2_{adj}
FF3	0.025	0.016	0.000	-0.012	0.727	0.693
T-ratio	(4.956)***	(6.235)***	(0.060)	(-2.138)**		

Panel C: Carhart four factor model

1981-2018	λ_0	λ_{SMB}	λ_{HML}	λ_{PR1YR}	λ_{ERM}	R^2	R^2_{adj}
C4	0.027	0.017	0.000	-0.005	-0.015	0.737	0.691
T-ratio	(4.982)***	(6.249)***	(-0.097)	(-0.563)	(-2.386)**		

Panel D: Fama French five factor model

1995-2017	λ_0	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{ERM}	R^2	R^2_{adj}
FF5	0.015	0.017	0.000	-0.009	0.005	-0.002	0.773	0.722
T-ratio	(3.441)***	(5.623)***	(0.018)	(-1.314)	(0.533)	(-0.336)		

Panel A shows the results for the estimated CAPM using value-weighted portfolios. In this subsection, we will focus on the second column, which shows the estimated risk premium for the market factor (value-weighted) and the associated t-statistic. We find that the market factor is significantly different from zero at the 1% level. Hence, the market portfolio is a priced risk factor, and the CAPM is a reasonably well-specified model for our main test assets. However, we did not expect the λ_{ERM} to be negative. Modern Portfolio Theory argues that, in a market of risk-averse investors, higher risk should be associated with a higher expected return. So, the expected value of the risk premia, λ_{ERM}, which is the slope of $E(R_{market}) – E(R_f)$, is positive (Fama & Macbeth, 1973). Our findings are not consistent with this theory, as the results show a negative trade-off between risk and return on average. However, Asness, Frazzini, and Pedersen (2012) show that “leverage aversion changes the predictions of modern portfolio theory: It implies that safer assets must offer higher risk-adjusted returns than riskier assets because leverage-averse investors tilt their portfolio toward riskier assets to achieve high unleveraged returns, thus pushing up the prices of risky assets and reducing the expected return on those assets”. Also, Frazzini and Pedersen (2014) find that a betting against beta factor, which is long leveraged low-beta assets and short high-beta assets, produces significant positive risk-adjusted returns.

Panel B shows the results from the estimation of the Fama-French three-factor model. We find that SMB yields a significant risk premia at the 1% level, and the market factor is priced and significant at 5%. However, HML is insignificant and not a priced risk factor. Hence, our results from the Norwegian stock market are not consistent with the findings of Fama and French (1993) for the U.S.

Panel C shows the results for Carhart´s four-factor model. Adding the PR1YR factor to the three-factor model do not result in any change of the significance of the other risk factors. The momentum factor is found insignificant and not priced in the Norwegian stock market.

Looking at the five-factor model in panel D, we can see that the size factor is the only significant risk factor. Hence, when extending the three-factor model with RMW and CMA, the market factor becomes insignificant. Also, both the new risk factors seem not to be priced, which is inconsistent with what Fama and French (2015) found in the U.S., but somewhat consistent with Fama and French (2017) which finds that the investment factor is redundant for describing average returns in Europe. Interestingly, the profitability factor obtains a negative risk premia, which indicates that during the sample period, 1995-2017, there are no significant excess returns obtainable by investing in the RMW factor.

7.2 Intercept analysis

7.2.1 Time-series intercept

Table 4 reports the average absolute alpha, the standard deviation, and the computed GRS-statistics and its corresponding p-value, for the time-series intercept. The GRS-test is applied to test the null hypothesis that all intercepts are jointly equal to zero. Thus, if the null hypothesis is not rejected, the model seems to include all priced risk factors as the intercept is not significantly different from zero. However, if the null is rejected, the model has unexplained abnormal return, which implies that the model does not include all the priced risk factors.

Table 4 Statistics for the time-series intercept

The first column shows the sample years used for the models. The second column shows which model the data is reported for. The third column presents the average of absolute estimated time-series alphas. The fourth column presents the standard deviation of the estimated time-series intercepts. The fifth column reports the GRS-statistics, whereas the last column reports the corresponding p-value.

		$\lvert\bar{\alpha}\rvert$	σ_{α}	GRS	p-GRS
1981-2018	CAPM	0.006	0.008	5.467	0.000
	FF3	0.004	0.005	3.904	0.000
	C4	0.003	0.005	3.391	0.000
1995-2017	FF5	0.004	0.005	2.948	0.000

Similar to the results of Fama and French (2015) in the U.S., table 4 reports high GRS-statistics for all models. The p-value states, for all models, that the test rejects the null hypothesis on all commonly used significant levels. Thus, like Fama and French (2015), we conclude that all our models are incomplete descriptions of expected return. However, the GRS-test does not reject the null hypothesis for the IBM test assets, and this is discussed in the “Stability in results” subsection.

Although the models are incomplete, the purpose of this paper is to evaluate the model’s relative performance to each other. Not surprisingly, CAPM has the highest GRS-statistic of 5.467. CAPM also has the highest value for the average absolute alpha and the standard errors, which is expected because it is the simplest of all our models. Further, FF3 has the second highest GRS-statistic of 3.904, while C4 and FF5 have the lowest GRS-statistic of 3.391 and 2.948, respectively.

Moreover, we see from table 4 that the average absolute intercept is lower for C4 compared to FF5, and the standard deviation is marginally lower as well. Thus, we compute the GRS-statistic again, but this time, the sample length is reduced to that of FF5 for all models. The reason being that the GRS-statistic increases in T, and we, therefore, want to compare the models using the same sample length.

Table 5 Statistics for the time-series intercept - equal sample length

The first column shows the sample years used for the models. The second column shows which model the data is reported for. The third column presents the average of absolute estimated time-series alphas. The fourth column presents the standard deviation of the estimated time-series intercepts. The fifth column reports the GRS-statistics, whereas the last column reports the corresponding p-value.

		$\lvert\bar{\alpha}\rvert$	σ_α	GRS	p-GRS
1995-2017	CAPM	0.006	0.008	4.053	0.000
	FF3	0.004	0.005	2.925	0.000
	C4	0.004	0.005	2.532	0.000
	FF5	0.004	0.005	2.948	0.000

Table 5 reports the GRS-statistics for all the models, with a reduction in sample length to that of FF5. Now, both FF3 and C4 has a lower GRS-statistic than FF5, with a GRS-statistic of 2.925 and 2.532, respectively. Still, the test rejects the null hypothesis, with high values for the GRS-statistics for all models. We conclude that, according to the time-series intercept analysis, no model appears superior, as the models fail to include all the priced risk factors. Thus, the factors included in our models are not sufficient to explain the cross-section of expected return for the Norwegian stock market, and it seems to be missing priced risk factors.

7.2.2 Cross-sectional intercept

Table 3 provides the statistics for the intercepts, λ_0, from the cross-sectional regressions. Noteworthy, the cross-sectional intercept is statistically significantly different from zero for all models. This implies, again, that all priced risk factors are not included to explain the cross-section of expected returns. According to Adrian, Etula and Muri (2014), a good pricing model features an economically small and statistically insignificant intercept. As all our intercepts are significantly different from zero, we favour a small intercept.

In table 3, we find that the largest intercept is for the CAPM and C4 model, with an intercept of 0.04 and 0.027, respectively. FF3 has an intercept of 0.025, and FF5 has the smallest estimated intercept of 0.015. However, these values are high, as the smallest intercept has an effect of 1.5% on expected monthly returns. Still, FF5 is favoured in terms of cross-section intercept as the model has the smallest cross-section intercept with the lowest t-ratio.

Moreover, the estimation is conducted reducing the sample length so that each model has the same number of observations as FF5, and the results are shown in table 6. With the same sample length, we observe that both FF3 and C4 yields a marginally lower intercept than FF5. C4 yields the lowest intercept of 0.0146.

Table 6 Results from cross-sectional regressions – equal sample length

Table 6 reports the results from the cross-sectional regressions using the Fama and MacBeth procedure. All models are estimated using monthly excess return on the 28 IBSi portfolios. Column 2 reports the intercept, columns 3-7 show the estimated risk premia and the corresponding t-statistic for each factor, and columns 8-9 show the R^2 and adjusted R^2 for the estimated model. *, ** and *** indicate the significance for the risk premia estimates at the 10, 5 and 1 percent level respectively.

Panel A: CAPM

1995-2017	λ_0	λ_{ERM}	R^2	R^2_{adj}
CAPM	0.027	-0.011	0.167	0.135
T-ratio	(7.786)***	(-2.289)**		

Panel B: Fama French three factor model

1995-2017	λ_0	λ_{SMB}	λ_{HML}	λ_{ERM}	R^2	R^2_{adj}
FF3	0.015	0.017	0.000	-0.001	0.757	0.727
T-ratio	(3.409)***	(5.912)***	(-0.075)	(-0.233)		

Panel C: Carhart four factor model

1995-2017	λ_0	λ_{SMB}	λ_{HML}	λ_{PR1YR}	λ_{ERM}	R^2	R^2_{adj}
C4	0.015	0.017	0.000	0.004	-0.001	0.758	0.716
T-ratio	(3.111)***	(5.866)***	(-0,015)	(0.488)	(-0.129)**		

Panel D: Fama French five factor model

1995-2017	λ_0	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{ERM}	R^2	R^2_{adj}
FF5	0.015	0.017	0.000	-0.009	0.005	-0.002	0.773	0.722
T-ratio	(3.441)***	(5.623)***	(0.018)	(-1.314)	(0.533)	(-0.336)		

Based on the analysis of the cross-sectional intercept, we conclude that FF3 is the most favoured model. The first argument is that both the FF3 and C4 models produced a lower intercept relative to FF5 with the same sample length as the FF5. The second argument is that FF3 has a smaller intercept than C4 when using the full sample length. However, we emphasise that the differences are marginal and that FF3 did not produce a cross-sectional intercept that was extremely superior to the other models, except for the CAPM.

7.3 Explanatory power

The R^2 and adjusted R^2 estimates are also presented in table 3. We again emphasise that R^2 for the cross-sectional regressions are solely used for comparison purposes, and not interpreted as the true explanatory power of the model (Kan et al., 2013). CAPM has a low R^2 (0.466) relative to the other models. C4 has a slightly higher R^2 of 0.737 than FF3 with 0.727. However, as C4 includes all factors of FF3 plus an additional factor, the R^2 measure must be higher. Thus, comparing the adjusted R^2, which corrects for the number of parameters, we observe that FF3 yields a higher adjusted R^2 (0.693) than C4 (0.691). Further, FF5 has the largest R^2 and adjusted R^2 of the models of 0.773 and 0.722, respectively.

However, using the same sample length for all models, we see in table 6 that FF3 has a higher adjusted R^2 than FF5. This implies that we find no evidence that adding more factors, either the momentum factor or the RMW and CMA factors, improves the model's explanatory power. Thus, this analysis favours the FF3 model.

7.4 Stability in results

In this subsection, we present the most interesting results from our varying model estimation. In addition to our main test assets, we estimate the models using nine different sets of test assets. Further, we do the estimation on the full sample size obtained for each model and estimations where all models have the same sample size, due to lack of data for the factors in FF5. Moreover, we originally obtain value-weighted portfolios to use as test assets, but we also estimate the models with equally-weighted portfolios as test assets. The portfolio characteristics are the same for both value- and equally-weighted.

7.4.1 Discussion of risk premia

In the CAPM (Appendix C1), the market factor is negative and significant for all test assets except for IBM, which yields an insignificant, but positive, coefficient of 0.010. The market factor in IBM is both positive and significant when using equally-weighted portfolios (Appendix C2) and value-weighted portfolios with a shorter sample length (Appendix C3). The lowest coefficient of -0.030 is obtained for MSpSi, which mean that there is a dispersion of 0.041.

In Appendix C1, the estimates for SMB in FF3 are consistently positive and significant for all sets of test assets. The factor has low dispersion and ranges from 0.012 in BSpSi to 0.018 in IMSi. HML is positive in half of the sets, where BSpSi has the highest value of 0.007, and MSpSi has the lowest of -0.008. Only HML in BSpSi is significant at 10%. Further, the market factor is positive only in IBM and BMSp and negative in the remaining sets, where five of the negative estimates are significant. The market factor ranges from -0.019 in BSpSi to 0.004 in IBM. Thus, FF3 has a lower dispersion in the market factor than the CAPM. For equally-weighted portfolios (Appendix C2) both SMB and HML are priced risk factors and statistically significant at 5%. The market factor is not at priced factor when using equally-weighted portfolios.

In similarity to FF3, the SMB factor in C4 (Appendix C1) is positive and significant for all sets. BSpSi has the lowest value of 0.012, and IMSi has the highest value of 0.018. HML ranges from -0.010 in MSpSi to 0.007 in BSpSi and has negative estimates in six sets. As in FF3, HML in BSpSi is the only significant at 10% level. Moreover, PR1YR is negative in four sets and positive in four sets; none are significant. PR1YR ranges from -0.007 in BSpSi to 0.009 in IBSp. Further, the market factor is negative in six sets and ranges from -0.021 in BSpSi to 0.005 in BMSp.

In some similarity to FF3 and C4, SMB in FF5 (Appendix C1) is stable and positive for all sets, but not significant for IBM. SMB ranges from 0.011 in IBM to 0.017 in BSpSi. As in FF3, HML is positive in five sets, but not significant in any of the sets. HML has low dispersion and with the lowest value of -0.003 in BSpSi and the highest value of 0.003 in MSpSi. RMW is negative in all sets, with a dispersion of 0.008. RMW in BMSi is the only significant at 10% level. When using equally-weighted portfolios (Appendix C2), RMW is positive in nine of the ten sets of test assets. CMA and the market factor are both negative in six sets, has dispersions of 0.010 and 0.012, and no significant estimates.

Interestingly, HML is more stable in terms of the sign when using equally-weighted portfolios (Appendix C2). This is the case for all three models, where nine of the ten sets of test assets gave positive estimates.

Comparing the models using the same sample length as in FF5 (Appendix C3), we can see that SMB is equal in terms of signs and with low dispersion in all three models. HML has a lower dispersion for FF5. However, in terms of signs, FF3 and C4 are more stable with eight negative estimates against five negative and five positive estimates for FF5. Further, it is consistently the same factors that are significant in FF3, C4, and FF5, except SMB in one test asset in FF5. The market factor has the highest dispersion of 0.033 in CAPM and the lowest dispersion of 0.010 in FF3.

Consequentially, all the models, except the CAPM, are pretty stable in terms of significance. However, C4 and FF3 have lower dispersions between the sets of test assets and are more stable in terms of risk premia signs.

Further, the estimated risk premia for a factor should equal the expected return of that factor, e.g. $E(\lambda_{SMB}) = E(SMB_t)$ (Fama and MacBeth, 1973). Comparing the mean returns for the factors from table 1 with the estimated risk premia's in Appendix C1, we see that this is seldom the case. It appears that the risk premia, on average, is overestimated for the most often significant factor SMB, while underestimated for other factors.

7.4.2 Discussion of intercept and explanatory power

Table 7 reports the average absolute alpha, the standard deviation, and the computed GRS-statistics and its corresponding p-value, for the time-series intercept for the IBM portfolio. All models keep the null hypothesis at the normal significance levels. Keeping the null hypothesis implies that all the time-series intercepts are not statistically significantly different from zero, which again means that the intercepts, when using the IBM test assets, are zero and that the model includes all the priced risk factors. This result suggests that the models include all factors explaining returns for the set of portfolio characteristics: Industry, B/M, and Momentum. However, this is not the result for any other set of test assets and not the result when using the equally-weighted portfolios for IBM. Thus, we believe that the stand-out observation for the IBM test assets is related to the composition of the characteristics and the value-weighted returns for the portfolios. Further research is required to explain this.

Table 7 Statistics for the time-series intercept for IBM - equal sample length

The first column shows the sample years used for the models. The second column shows which model the data is reported for. The third column presents the average of absolute estimated time-series alphas. The fourth column presents the standard deviation of the estimated time-series intercepts. The fifth column reports the GRS-statistics, whereas the last column reports the corresponding p-value.

		$\lvert\bar{\alpha}\rvert$	σ_α	GRS	p-GRS
1995-2017	CAPM	0.003	0.004	1.382	0.102
	FF3	0.003	0.003	1.050	0.402
	C4	0.003	0.004	0.986	0.490
	FF5	0.003	0.004	1.261	0.179

Moreover, Appendix C1 reports, amongst other results, the estimated cross-sectional intercept for the IBM test assets. Like the result for the time-series intercept, the cross-sectional estimates also yield non-significant intercepts for IBM. The results are believed to be connected since the conclusion for this observation is in both cases that the models include all priced risk factors to explain expected return on the test assets IBM. Further, no such observation for all models is found for any of the other sets of test assets.

The conclusion is the same as in the subsection "7.3 Explanatory power" regarding the explanatory power for all ten sets of value-weighted test assets. However, when equally-weighted test assets are applied, there is a rather large decline in R^2. From Appendix C1 & C2, we calculated the average R^2 for all ten sets of test assets, both value- and equally-weighted. The average R^2 for the value-weighted test assets is 0.35, 0.63, 0.64, and 0.60 for CAPM, FF3, C4, and FF5, respectively. Note that the average R^2 can be lower for FF5 relative to FF3 due to the difference in sample length. Moreover, the average R^2 for the equally-weighted test assets are 0.20, 0.41, 0.43, and 0.44 for CAPM, FF3, C4, and FF5, respectively. This indicates a decline in the explanatory power of around 0.2 for all the models.

Although R^2 is not interpreted as the true explanatory power of the model, the decline is rather substantial and worth discussing. One explanation might be that the returns for smaller stock are more volatile, thus giving these smaller stocks a higher weight makes the portfolio more volatile. As the returns of the portfolios vary more in the cross-section, the models seem to weaken its explanatory power. However, one could argue that an asset pricing model is designed to explain expected returns for all stock/portfolios. Therefore, these results indicate that the models perform poorly when smaller stocks are given more weight, and suggests that the models are not as efficient in explaining the cross-section of expected returns for small and volatile stocks.

From Appendix C1, we want to highlight that the R^2 is higher for all sets of test assets that includes the portfolio characteristic Size. This is also believed to be connected to the usage of value-weighted portfolios, as we do not see this difference for the equally-weighted portfolios.

8. Conclusion

This thesis compares the performance of the CAPM, Fama-French three-factor model, Carhart four-factor model, and Fama-French five-factor model and questions which model is superior in explaining the cross-section of expected returns in the Norwegian Stock market.

We analyse value- and equally-weighted portfolios sorted on five characteristics which are grouped into sets of test assets. To minimize the errors in the estimation of the risk premia, we create ten sets of test assets composed of the different portfolios based on characteristics and apply the set which yields the highest dispersion in cross-sectional betas as our main test assets. Then, we assess the Fama-Macbeth two-pass regression to determine which risk factors that are priced in the Norwegian stock market. Further, we compare the models based on intercept analysis, explanatory power, and stability in results.

Our results show that the market portfolio is a priced risk factor in CAPM, but with a negative risk-return relationship, which is not consistent with Modern Portfolio Theory. Thus, there seems to be a betting against beta effect in the Norwegian stock market, similar to the findings of Frazzini and Pedersen (2014) in the U.S. Further, we find that SMB seems to be a risk factor which demands risk compensation in the Norwegian stock market. However, the other empirically motivated factors linked to B/M, momentum, profitability, and investment do not seem relevant in the Norwegian stock market, as we find them insignificant.

The time-series intercept estimates are not jointly zero for any model. Hence, the models are incomplete descriptions of expected return. Additionally, in terms of cross-sectional intercepts, the Fama-French three-factor model is marginally superior even though all the models have a significant cross-sectional intercept. However, the factors in our models are not sufficient as the models seem to be missing priced risk factors for the Norwegian stock market. Different models should be tested and evaluated to asses if other risk factors are priced.

Moreover, the Fama-French three-factor model is also superior in terms of explanatory power, as it has the highest adjusted-R^2 amongst the models. However, when equally-weighted test assets are applied the R^2 drops significantly for all models. This result indicates that the models explain less of the variation in the cross-section of expected returns when the smaller stocks are given more weight. The result is believed to be an effect of the more volatile returns for small stocks, thus reducing the explanatory power. This implies that the models struggle to explain volatile returns.

Furthermore, analysing the stability of the models in terms of coefficients signs and significance, our results indicate that all the models are relatively stable, but C4 and FF3 are more favourable.

Interestingly, we find that both the time-series and the cross-sectional intercepts are insignificant in all models when using IBM as test assets. Hence, the models include all priced risk factors when the portfolio characteristics Industry, B/M, and Momentum are applied. However, the conclusion is that there are missing priced risk factors since this is the result for nine out of ten sets of test assets, but further research should be done to examine why the results are like this for the IBM test assets.

Consequently, our findings indicate that amongst the tested models, Fama-French three-factor is best suited to explain the cross-section of expected returns in the Norwegian stock market. SMB is a priced risk factor, and the excess market returns seem to be significant as this is the result for most of the observations using value-weighted test assets. However, it appears to be missing priced risk factors as the intercept is different from zero. These findings are consistent with the research of Næs et al. (2009). They find that a three-factor model containing the market, a size factor, and a liquidity factor provides a reasonable fit for the cross-section of stock returns in Norway. However, we find that the Fama-French three-factor model is a relatively stable and applicable model to explain the cross-section of expected returns in the Norwegian market.

As all of the investigated models are missing priced risk factors, it would be interesting to include other models such as a macroeconomic model, the q-factor model, and a model containing a liquidity factor. Another suggestion for future research might be to look for one or a few factors which can account for several “anomalies” since adding a factor for each “anomaly” might add noise to the model. Finally, some weaknesses in our study should be pointed out.

In this study we try to tackle the EIV problem, that arises when estimated factor loadings are used as independent variables in the cross-sectional regressions, by grouping the stocks in portfolios. However, Ang et al. (2017) find that the reduced uncertainty of the factor loadings, by using portfolios, does not translate to lower standard errors for risk premia estimates. Other methods to reduce the EIV problem could, therefore, be used to obtain more accurate estimates. Further, Fama and MacBeth (1973) use rolling window estimates of the factor loadings, thus allowing for time-varying betas. In this thesis, we estimate constant factor loadings. Using time-varying betas is therefore recommended for future research.

9. References

Adrian, T., Etula, E., & Muir, T. (2014). Financial intermediaries and the cross-section of asset returns. *The Journal of Finance*, *69*(6), 2557-2596.

Ang, A., Liu, J., & Schwarz, K. (2018, August). Using stocks or portfolios in tests of factor models. In *AFA 2009 San Francisco Meetings Paper*.

Asness, C. S. (1995). The power of past stock returns to explain future stock returns. *Available at SSRN 2865769*.

Asness, C. S., Frazzini, A., & Pedersen, L. H. (2012). Leverage aversion and risk parity. *Financial Analysts Journal*, *68*(1), 47-59.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of financial economics*, 9(1), 3-18.

Basu, S. (1983). The relationship between earnings' yield, market value and return for NYSE common stocks: Further evidence. *Journal of financial economics*, *12*(1), 129-156.

Black, F. (1972). Capital market equilibrium with restricted borrowing. *The Journal of business*, 45(3), 444-455.

Black, F., Jensen, M. C., & Scholes, M. S. (1972). The capital asset pricing model: Some empirical tests.

Blume, M. E. (1970). Portfolio theory: a step toward its practical application. *The Journal of Business*, *43*(2), 152-173.

Bodie, Z., Kane, A., & Marcus, A. (2014). Investments (10th ed.). New York: McGraw-Hill.

Breeden, D. T. (1979). An intertemporal asset pricing model with stochastic consumption and investment opportunities. *Journal of Financial Economics*, *7*(3), 265-296.

Brooks, C. (2014). *Introductory Econometrics for Finance*. Cambridge: Cambridge University Press.

Brooks, C. (2019). *Introductory Econometrics for Finance*. Cambridge: Cambridge University Press.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, *52*(1), 57-82.

Cochrane, J. H. (2000). *Asset Pricing*. Princeton university press. Retrieved from: http://ecsocman.hse.ru/data/018/648/1219/finbook.pdf

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance,* 47(2), 427-465.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), 3-56.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The journal of finance*, *51*(1), 55-84.

Fama, E. F., & French, K. R. (1998). Value versus growth: The international evidence. *The journal of finance*, *53*(6), 1975-1999.

Fama, E. F., & French, K. R. (2015a). A five-factor asset pricing model. *Journal of Financial Economics*, 116 1-22.

Fama, E. F., & French, K. R. (2016). Dissecting anomalies with a five-factor model. *The Review of Financial Studies*, *29*(1), 69-103.

Fama, E. F., & French, K. R. (2017). International tests of a five-factor asset pricing model. *Journal of financial Economics*, *123*(3), 441-463.

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, 81(3), 607-636.

Frazzini, A., & Pedersen, L. H. (2014). Betting against beta. *Journal of Financial Economics*, *111*(1), 1-25.

Friend, I., & Blume, M. (1970). Measurement of portfolio performance under uncertainty. *The American Economic Review*, 60(4), 561-575.

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society*, 1121-1152.

Hou, K., Xue, C., & Zhang, L. (2015). Digesting anomalies: An investment approach. *The Review of Financial Studies*, 28(3), 650-705.

Hou, K., Xue, C., & Zhang, L. (2017). A comparison of new factor models. *Fisher College of Business Working Paper, (2015-03),* 05.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, *48*(1), 65-91.

Jegadeesh, N., & Titman, S. (2011). Momentum. *Annu. Rev. Financ. Econ.*, *3*(1), 493-509.

Kan, R., Robotti, C., & Shanken, J. (2013). Pricing model performance and the two-pass cross-sectional regression methodology. *The Journal of Finance*, *68*(6), 2617-2649.

Kim, S. H., Kim, D., & Shin, H. S. (2012). Evaluating asset pricing models in the Korean stock market. *Pacific-Basin Finance Journal*, 20(2), 198-227.

Kristiansen, M. S. & Mahmood, R. (2018). *Risk Factors in the Norwegian Stock Market* (Master Thesis). Handelshøyskolen BI, Oslo. Retrieved from https://biopen.bi.no/bi-xmlui/handle/11250/2580080

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment, extrapolation, and risk. *The journal of finance*, *49*(5), 1541-1578.

Lewellen, J., Nagel, S., & Shanken, J. (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial economics*, *96*(2), 175-194.

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, 13-37.

Litzenberger, R. H., & Ramaswamy, K. (1979). The effect of personal taxes and dividends on capital asset prices: Theory and empirical evidence. *Journal of financial economics*, *7*(2), 163-195.

Merton, R. C. (1973). An intertemporal capital asset pricing model. *Econometrica*, *41*(5), 867-887.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica: Journal of the econometric society*, 768-783.

Nijman, T., Swinkels, L., & Verbeek, M. (2004). Do countries or industries explain momentum in Europe?. *Journal of Empirical Finance*, *11*(4), 461-481.

Næs, R., Skjeltorp, J. A., & Ødegaard, B. A. (2009). What factors affect the Oslo Stock Exchange?. Norges Bank.

Roll, R. (1977). A critique of the asset pricing theory's tests Part I: On past and potential testability of the theory. *Journal of financial economics*, *4*(2), 129-176.

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. *The Journal of Portfolio Management*, *11*(3), 9-16.

Shanken, J. (1992). On the estimation of beta-pricing models. *The review of financial studies*, *5*(1), 1-33.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, *19*(3), 425-442.

Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of money, credit and banking*, 1(1), 15-29.

Ødegaard, B. A. (2019). Asset pricing data at OSE. Retrieved from: http://www1.uis.no/ansatt/odegaard/financial_data/ose_asset_pricing_data/index.html

10. Appendices

10.1 Appendix A: Computing GRS-statistic and (adjusted)-R^2

GRS-statistic:

From the time-series regressions we save all the intercepts in a N×1 vector, $\hat{\alpha}$. We obtain the residuals from each regression, which we store in a T×N matrix, $\hat{\varepsilon}$.

Further, $\hat{\Sigma}$ is calculated as:

$$\hat{\Sigma} = \frac{\hat{\varepsilon}'\varepsilon}{T}$$

Let F be a T×K matrix with all the factor returns. $E_T(f)$ is a K×1 matrix with each factor mean. And $\hat{\Omega}$ is calculated as:

$$\hat{\Omega} = \frac{(F - E_T(f)')'(F - E_T(f)')}{T}$$

Lastly, inserting all calculated variables gives the GRS-statistic:

$$GRS = \left(\frac{T - N - K}{N}\right)\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1 + E_T(f)'\hat{\Omega}^{-1}E_T(f)} \sim F_{N,T-N-K}$$

R^2

R^2 is calculated from the cross-sectional regression for average returns:

$$E(R_i) = \lambda_0 + \lambda_1\hat{\beta}_{i,1} + \lambda_2\hat{\beta}_{i,2} + \cdots + \lambda_K\hat{\beta}_{i,K} + \varepsilon_i \quad i = 1 \ldots N$$

From Brooks (2014, pp. 152-155), R^2 is defined as:

$$R^2 = \frac{\sum_{i=1}^{N}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}$$

Where $\hat{y}_i$ is the fitted values of the dependent variable i, y_i is the actual value for the dependent variable ($E(R_i)$ in our case), and $\bar{y}$ is the mean value of the dependent variable.

Further, adjusted R^2 can be calculated as follows:

$$R^2_{adj} = 1 - \left[\frac{N-1}{N-K}(1 - R^2)\right]$$

Where N is the number of test assets and K is the number of parameters.

10.2 Appendix B1: Descriptive statistic of the excess return for the five characteristic sets of portfolios

Panel A-D shows the descriptive statistics for the B/M, Momentum, Size and Spread portfolios respectively, where portfolio 1 indicates that stocks with the lowest values for the characteristic is sorted in this portfolio and portfolio 10 indicates that stocks with the highest value for the characteristic is stored in this portfolio. Panel E shows the descriptive statistics for the Industry sorted portfolios where the number of the portfolios: 10, 15, 20, 25, 30, 35, 40 and 45, is the GICS code for Energy, Material, Industry, Consumer discretionary, Consumer staples, Health, Finance and IT, respectively. The first columns display the calculated properties of the portfolios, where min (max) is the minimum (maximum) excess return for the portfolios, mean is the average excess return for the portfolios and Std.Dev is the standard deviation of excess return for the portfolios. The last column reports the average of the min, max, mean and Std.Dev for all the characteristic sorted portfolios. The last column is assessed in the discussion of which test assets should be applied as main test assets.

Panel A: B/M sorted portfolios

1981-2018	1	2	3	4	5	6	7	8	9	10	**Average**
Min	-0.393	-0.203	-0.368	-0.331	-0.281	-0.317	-0.263	-0.257	-0.271	-0.283	**-0.297**
Max	0.650	0.381	0.325	0.275	0.341	0.323	0.261	0.506	0.435	0.380	**0.388**
Mean	0.017	0.018	0.016	0.018	0.016	0.021	0.024	0.022	0.024	0.020	**0.020**
Std.Dev	0.091	0.073	0.080	0.071	0.075	0.082	0.078	0.090	0.086	0.083	**0.081**

Panel B: Momentum sorted portfolios

1981-2018	1	2	3	4	5	6	7	8	9	10	**Average**
Min	-0.285	-0.412	-0.268	-0.277	-0.262	-0.322	-0.247	-0.281	-0.275	-0.307	**-0.294**
Max	0.427	0.437	0.265	0.258	0.331	0.252	0.306	0.380	0.604	0.465	**0.373**
Mean	0.022	0.027	0.018	0.015	0.018	0.019	0.017	0.017	0.015	0.024	**0.019**
Std.Dev	0.084	0.102	0.078	0.075	0.070	0.067	0.070	0.073	0.080	0.081	**0.078**

Panel C: Size sorted portfolios

1981-2018	1	2	3	4	5	6	7	8	9	10	**Average**
Min	-0.267	-0.121	-0.263	-0.212	-0.170	-0.158	-0.234	-0.211	-0.250	-0.279	**-0.217**
Max	0.698	0.371	0.403	0.332	0.354	0.303	0.278	0.554	0.252	0.219	**0.376**
Mean	0.040	0.035	0.028	0.026	0.028	0.029	0.024	0.024	0.019	0.016	**0.027**
Std.Dev	0.090	0.076	0.075	0.070	0.068	0.069	0.066	0.070	0.073	0.063	**0.072**

Panel D: Spread sorted portfolios

1981-2018	1	2	3	4	5	6	7	8	9	10	**Average**
Min	-0.261	-0.283	-0.228	-0.228	-0.189	-0.215	-0.208	-0.179	-0.150	-0.206	**-0.215**
Max	0.276	0.205	0.407	0.530	0.318	0.308	0.402	0.425	0.872	0.381	**0.413**
Mean	0.018	0.017	0.022	0.019	0.022	0.021	0.022	0.022	0.028	0.033	**0.022**
Std.Dev	0.066	0.069	0.079	0.074	0.067	0.068	0.075	0.066	0.084	0.071	**0.072**

Panel D: Industry sorted portfolios

1981-2018	10	15	20	25	30	35	40	45	**Average**
Min	-0.282	-0.447	-0.259	-0.347	-0.299	-0.351	-0.245	-0.402	**-0.329**
Max	0.273	1.490	0.278	0.658	0.288	0.420	0.283	1.007	**0.587**
Mean	0.017	0.017	0.018	0.023	0.021	0.019	0.015	0.022	**0.019**
Std.Dev	0.078	0.120	0.070	0.101	0.072	0.084	0.068	0.114	**0.089**

10.3 Appendix B2: Descriptive statistic for factor loadings with different test assets

Panel A-J display the descriptive statistic for the different sets of test assets described in “Data” in the subsection “Main test assets” (e.g. IBM is the test assets including the Industry, B/M and Momentum portfolios). The second column reports the minimum, maximum, average and standard deviation for the factor loading for CAPM. The third to fifth column presents values for the factor loadings for FF3. Sixth to ninth column for C4, and the tenth to fourteenth column for FF5. The last column presents the average of the minimum value, maximum value, average value and standard deviation for all the 13 factor loadings.

Panel A: IBM portfolios

1981-2018	**CAPM**	**FF3**			**C4**				**FF5**					
	β_{ERM}	β_{SMB}	β_{HML}	β_{ERM}	β_{SMB}	β_{HML}	β_{PR1YR}	β_{ERM}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{ERM}	**Average**
Min	0.74	-0.12	-0.54	0.73	-0.13	-0.54	-0.49	0.73	-0.12	-0.72	-0.37	-0.19	0.62	**-0.03**
Max	1.20	0.36	0.44	1.29	0.41	0.44	0.19	1.28	0.45	0.38	0.16	0.19	1.44	**0.63**
Mean	0.99	0.10	0.02	1.02	0.11	0.02	-0.08	1.02	0.07	0.00	-0.06	0.03	1.01	**0.33**
Std.Dev	0.11	0.13	0.24	0.13	0.14	0.24	0.15	0.12	0.13	0.26	0.13	0.09	0.16	**0.16**

Panel B: IBSp portfolios

1981-2018	**CAPM**	**FF3**			**C4**				**FF5**					
	β_{ERM}	β_{SMB}	β_{HML}	β_{ERM}	β_{SMB}	β_{HML}	β_{PR1YR}	β_{ERM}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{ERM}	**Average**
Min	0.58	-0.12	-0.54	0.73	-0.13	-0.54	-0.27	0.73	-0.12	-0.72	-0.31	-0.19	0.62	**-0.02**
Max	1.20	0.65	0.44	1.29	0.66	0.44	0.14	1.28	0.59	0.38	0.15	0.19	1.44	**0.68**
Mean	0.94	0.18	0.02	0.99	0.18	0.02	-0.05	0.99	0.16	0.01	-0.07	0.03	0.97	**0.34**
Std.Dev	0.15	0.22	0.23	0.13	0.22	0.23	0.10	0.13	0.21	0.25	0.13	0.09	0.17	**0.18**

Panel C: IBSi portfolios

1981-2018	**CAPM**	**FF3**			**C4**				**FF5**					
	β_{ERM}	β_{SMB}	β_{HML}	β_{ERM}	β_{SMB}	β_{HML}	β_{PR1YR}	β_{ERM}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{ERM}	**Average**
Min	0.56	-0.18	-0.54	0.72	-0.18	-0.54	-0.27	0.71	-0.14	-0.72	-0.31	-0.19	0.48	**-0.05**
Max	1.20	0.79	0.44	1.29	0.79	0.44	0.14	1.28	0.95	0.38	0.15	0.19	1.44	**0.73**
Mean	0.94	0.21	0.02	1.00	0.22	0.02	-0.05	1.00	0.19	0.00	-0.07	0.03	0.97	**0.35**
Std.Dev	0.16	0.28	0.23	0.13	0.28	0.23	0.10	0.13	0.29	0.26	0.13	0.09	0.18	**0.19**

Appendix B2 (continued)

Panel D: IMSp portfolios

1981-2018	**CAPM**	**FF3**			**C4**				**FF5**					
	β_{ERM}	β_{SMB}	β_{HML}	β_{ERM}	β_{SMB}	β_{HML}	β_{PR1YR}	β_{ERM}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{ERM}	**Average**
Min	0.58	-0.09	-0.54	0.73	-0.09	-0.54	-0.49	0.73	-0.09	-0.72	-0.37	-0.19	0.62	**-0.04**
Max	1.20	0.65	0.42	1.29	0.66	0.42	0.19	1.28	0.59	0.38	0.16	0.19	1.44	**0.68**
Mean	0.93	0.20	0.03	0.98	0.21	0.02	-0.07	0.98	0.19	0.00	-0.07	0.03	0.96	**0.34**
Std.Dev	0.14	0.21	0.17	0.12	0.21	0.17	0.15	0.12	0.20	0.20	0.14	0.10	0.17	**0.16**

Panel E: IMSi portfolios

1981-2018	**CAPM**	**FF3**			**C4**				**FF5**					
	β_{ERM}	β_{SMB}	β_{HML}	β_{ERM}	β_{SMB}	β_{HML}	β_{PR1YR}	β_{ERM}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{ERM}	**Average**
Min	0.56	-0.18	-0.54	0.72	-0.18	-0.54	-0.49	0.71	-0.14	-0.72	-0.37	-0.19	0.48	**-0.07**
Max	1.20	0.79	0.42	1.29	0.79	0.42	0.19	1.28	0.95	0.38	0.16	0.19	1.44	**0.73**
Mean	0.92	0.24	0.02	0.99	0.24	0.02	-0.06	0.99	0.22	-0.01	-0.07	0.03	0.96	**0.35**
Std.Dev	0.15	0.27	0.16	0.13	0.27	0.16	0.15	0.12	0.28	0.20	0.14	0.09	0.18	**0.18**

Panel F: ISiSp portfolios

1981-2018	**CAPM**	**FF3**			**C4**				**FF5**					
	β_{ERM}	β_{SMB}	β_{HML}	β_{ERM}	β_{SMB}	β_{HML}	β_{PR1YR}	β_{ERM}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{ERM}	**Average**
Min	0.56	-0.18	-0.54	0.72	-0.18	-0.54	-0.27	0.71	-0.14	-0.72	-0.31	-0.19	0.48	**-0.05**
Max	1.20	0.79	0.42	1.29	0.79	0.42	0.14	1.28	0.95	0.38	0.15	0.19	1.44	**0.73**
Mean	0.87	0.31	0.03	0.96	0.32	0.03	-0.04	0.96	0.31	0.00	-0.08	0.03	0.92	**0.36**
Std.Dev	0.16	0.29	0.16	0.12	0.29	0.16	0.09	0.12	0.28	0.19	0.14	0.09	0.18	**0.17**

Panel G: BMSp portfolios

1981-2018	**CAPM**	**FF3**			**C4**				**FF5**					
	β_{ERM}	β_{SMB}	β_{HML}	β_{ERM}	β_{SMB}	β_{HML}	β_{PR1YR}	β_{ERM}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{ERM}	**Average**
Min	0.58	-0.12	-0.42	0.77	-0.13	-0.42	-0.49	0.77	-0.12	-0.48	-0.37	-0.12	0.66	**0.01**
Max	1.14	0.65	0.44	1.24	0.66	0.44	0.19	1.21	0.59	0.36	0.16	0.19	1.25	**0.65**
Mean	0.94	0.19	0.03	1.00	0.20	0.03	-0.06	0.99	0.17	0.01	-0.09	0.03	0.96	**0.34**
Std.Dev	0.13	0.21	0.19	0.11	0.21	0.19	0.14	0.10	0.20	0.18	0.12	0.08	0.14	**0.15**

Appendix B2 (continued)

Panel H: BMSi portfolios

1981-2018	CAPM	FF3			C4				FF5					
	β_{ERM}	β_{SMB}	β_{HML}	β_{ERM}	β_{SMB}	β_{HML}	β_{PR1YR}	β_{ERM}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{ERM}	Average
Min	0.56	-0.18	-0.42	0.72	-0.18	-0.42	-0.49	0.71	-0.14	-0.48	-0.37	-0.12	0.48	**-0.03**
Max	1.14	0.79	0.44	1.24	0.79	0.44	0.19	1.21	0.95	0.36	0.16	0.14	1.25	**0.70**
Mean	0.94	0.23	0.03	1.00	0.23	0.03	-0.05	1.00	0.20	0.00	-0.09	0.03	0.97	**0.35**
Std.Dev	0.14	0.27	0.18	0.11	0.27	0.18	0.14	0.11	0.27	0.18	0.12	0.07	0.15	**0.17**

Panel I: BSpSi portfolios

1981-2018	CAPM	FF3			C4				FF5					
	β_{ERM}	β_{SMB}	β_{HML}	β_{ERM}	β_{SMB}	β_{HML}	β_{PR1YR}	β_{ERM}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{ERM}	Average
Min	0.56	-0.18	-0.42	0.72	-0.18	-0.42	-0.14	0.71	-0.14	-0.48	-0.31	-0.11	0.48	**0.01**
Max	1.13	0.79	0.44	1.19	0.79	0.44	0.08	1.18	0.95	0.36	0.11	0.19	1.16	**0.68**
Mean	0.89	0.30	0.04	0.97	0.30	0.04	-0.03	0.97	0.28	0.01	-0.09	0.03	0.93	**0.36**
Std.Dev	0.16	0.29	0.18	0.11	0.29	0.18	0.07	0.11	0.28	0.17	0.12	0.08	0.15	**0.17**

Panel J: MSpSi portfolios

1981-2018	CAPM	FF3			C4				FF5					
	β_{ERM}	β_{SMB}	β_{HML}	β_{ERM}	β_{SMB}	β_{HML}	β_{PR1YR}	β_{ERM}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	β_{ERM}	Average
Min	0.56	-0.18	-0.17	0.72	-0.18	-0.17	-0.49	0.71	-0.14	-0.16	-0.37	-0.12	0.48	**0.04**
Max	1.14	0.79	0.21	1.24	0.79	0.21	0.19	1.21	0.95	0.14	0.16	0.19	1.25	**0.65**
Mean	0.87	0.32	0.04	0.97	0.32	0.04	-0.04	0.96	0.31	0.00	-0.10	0.03	0.92	**0.36**
Std.Dev	0.15	0.27	0.08	0.10	0.27	0.08	0.13	0.10	0.26	0.08	0.13	0.08	0.15	**0.14**

10.4 Appendix C1: Fama-Macbeth for different value-weighted sets of test assets

Results for Fama-Macbeth second-pass regressions for ten different sets of test assets. All portfolios are value-weighted. The first column shows the different set of test assets (see section "6.1 Main test assets" for a description of each test asset). Second to seventh column shows the estimated risk premia for each factor. *, ** and *** indicate the level of significance at respectively 10%, 5% and 1%.

Panel A: CAPM

1981-2018	λ_0	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.040***	-0.025***	0.466	0.445
IBM	0.004	0.01	0.123	0.089
IBSP	0.025***	-0.011**	0.202	0.171
IMSp	0.025***	-0.011**	0.152	0.119
IMSi	0.04***	-0.026***	0.404	0.381
ISpSi	0.042***	-0.028***	0.570	0.554
BMSp	0.024***	-0.010**	0.111	0.079
BMSi	0.042***	-0.027***	0.405	0.384
BSpSi	0.042***	-0.027***	0.564	0.549
MSpSi	0.044***	-0.03***	0.523	0.506

Panel B: Fama-French three-factor model

1981-2018	λ_0	λ_{SMB}	λ_{HML}	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.025***	0.016***	0.000	-0.012**	0.727	0.693
IBM	0.008	0.013**	-0.001	0.004	0.399	0.323
IBSP	0.015***	0.012***	0.000	-0.002	0.544	0.486
IMSp	0.013**	0.015***	-0.005	-0.002	0.581	0.528
IMSi	0.025***	0.018***	-0.007	-0.012**	0.720	0.685
ISpSi	0.029***	0.015***	-0.006	-0.017***	0.701	0.664
BMSp	0.008	0.015***	0.001	0.004	0.576	0.527
BMSi	0.023***	0.017***	0.002	-0.011*	0.694	0.659
BSpSi	0.033***	0.012***	0.007*	-0.019***	0.710	0.676
MSpSi	0.026***	0.016***	-0.008	-0.014**	0.659	0.620

Appendix C1 (continued)

Panel C: Carhart four-factor model

1981-2018	λ_0	λ_{SMB}	λ_{HML}	λ_{PR1YR}	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.027***	0.017***	0.000	-0.005	-0.015**	0.737	0.691
IBM	0.007	0.014**	-0.001	0.004	0.005	0.410	0.308
IBSP	0.012*	0.013***	0.001	0.009	0.001	0.565	0.489
IMSp	0.013**	0.015***	-0.005	0.003	-0.001	0.582	0.509
IMSi	0.027***	0.018***	-0.008	-0.001	-0.015**	0.729	0.682
ISpSi	0.031***	0.015***	-0.007	-0.003	-0.019***	0.708	0.658
BMSp	0.007	0.015***	0.001	0.003	0.005	0.581	0.514
BMSi	0.024***	0.017***	0.002	-0.001	-0.012**	0.699	0.651
BSpSi	0.034***	0.012***	0.006*	-0.007	-0.021***	0.722	0.677
MSpSi	0.028***	0.016***	-0.01	-0.002	-0.016**	0.668	0.614

Panel D: Fama-French five-factor model

1995-2017	λ_0	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.015***	0.017***	0.000	-0.009	0.005	-0.002	0.773	0.722
IBM	0.007	0.011	-0.001	-0.01	0.001	0.006	0.492	0.377
IBSP	0.011**	0.012***	-0.001	-0.004	-0.002	0.003	0.497	0.383
IMSp	0.011**	0.013***	-0.002	-0.005	-0.005	0.003	0.524	0.416
IMSi	0.015***	0.017***	0.000	-0.009	0.000	-0.002	0.748	0.691
ISpSi	0.017***	0.015***	-0.002	-0.003	-0.006	-0.003	0.686	0.615
BMSp	0.011**	0.013***	0.000	-0.007	-0.003	0.002	0.375	0.244
BMSi	0.018***	0.016***	0.001	-0.01*	0.004	-0.004	0.703	0.641
BSpSi	0.02***	0.013***	0.003	-0.003	-0.004	-0.006	0.631	0.554
MSpSi	0.018***	0.015***	-0.003	-0.006	-0.005	-0.005	0.603	0.520

10.5 Appendix C2: Fama-Macbeth for different equally-weighted sets of test assets

Results for Fama-Macbeth second-pass regressions for ten different sets of test assets. All portfolios are equally-weighted. The first column shows the different set of test assets (see section "6.1 Main test assets" for a description of each test asset). Second to seventh column shows the estimated risk premia for each factor. *, ** and *** indicate the level of significance at respectively 10%, 5% and 1%.

Panel A: CAPM (EW)

1981-2018	λ_0	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.020***	-0.011***	0.161	0.129
IBM	0.003	0.009*	0.085	0.049
IBSP	0.017***	-0.008*	0.077	0.042
IMSp	0.014***	-0.004	0.035	-0.003
IMSi	0.016***	-0.007*	0.105	0.071
ISpSi	0.021***	-0.014***	0.398	0.374
BMSp	0.018***	-0.01**	0.074	0.041
BMSi	0.022***	-0.013***	0.163	0.133
BSpSi	0.027***	-0.020***	0.454	0.435
MSpSi	0.024***	-0.017***	0.430	0.410

Panel B: Fama-French three factor model (EW)

1981-2018	λ_0	λ_{SMB}	λ_{HML}	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.014***	0.007**	0.007**	-0.007	0.420	0.347
IBM	0.001	0.009	0.006*	0.006	0.339	0.257
IBSP	0.010***	0.008**	0.007**	-0.003	0.359	0.279
IMSp	0.007*	0.010**	0.001	-0.001	0.195	0.094
IMSi	0.011***	0.008***	0.000	-0.004	0.234	0.138
ISpSi	0.019***	0.005*	0.003	-0.012***	0.421	0.349
BMSp	0.001	0.016***	0.008**	0.003	0.509	0.452
BMSi	0.009***	0.011***	0.008**	-0.003	0.462	0.400
BSpSi	0.024***	0.005*	0.010***	-0.017***	0.663	0.624
MSpSi	0.021***	0.009***	-0.009	-0.015***	0.504	0.447

Appendix C2 (continued)

Panel C: Carhart four-factor model (EW)

1981-2018	λ_0	λ_{SMB}	λ_{HML}	λ_{PR1YR}	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.014***	0.007**	0.007**	0.003	-0.006	0.420	0.319
IBM	-0.002	0.011*	0.007**	0.008*	0.009	0.413	0.311
IBSP	0.007	0.010**	0.008**	0.011	0.001	0.378	0.270
IMSp	0.006	0.011***	0.002	0.005	0.001	0.214	0.077
IMSi	0.010***	0.008***	0.001	0.002	-0.003	0.236	0.103
ISpSi	0.022***	0.005	0.001	-0.008	-0.015***	0.440	0.343
BMSp	-0.001	0.017***	0.008***	0.006	0.005	0.532	0.457
BMSi	0.008**	0.011***	0.008**	0.004	-0.002	0.468	0.383
BSpSi	0.026***	0.004	0.010***	-0.014*	-0.021***	0.688	0.638
MSpSi	0.023***	0.009***	-0.011*	-0.001	-0.017***	0.512	0.434

Panel D: Fama-French five-factor model (EW)

1995-2017	λ_0	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.008**	0.013***	0.006	0.01	0.002	0.001	0.529	0.422
IBM	0.001	0.013*	0.006	0.005	-0.004	0.008	0.547	0.444
IBSP	0.007**	0.011**	0.006	0.002	-0.001	0.001	0.229	0.054
IMSp	0.005*	0.011**	0.003	0.002	-0.003	0.003	0.356	0.209
IMSi	0.006**	0.012***	0.003	0.012	-0.001	0.003	0.559	0.459
ISpSi	0.010***	0.009***	0.002	0.007	0.001	-0.001	0.386	0.247
BMSp	0.005**	0.014***	0.006	-0.002	0.005	0.001	0.355	0.221
BMSi	0.006***	0.014***	0.007*	0.010	0.004	0.002	0.534	0.437
BSpSi	0.013***	0.008***	0.006	0.006	0.003	-0.005	0.453	0.339
MSpSi	0.011***	0.01***	-0.009	0.003	0.004	-0.002	0.452	0.338

10.6 Appendix C3: Fama-Macbeth for different value-weighted sets of test assets with shorter sample length

Results for Fama-Macbeth second-pass regressions for ten different sets of test assets. All portfolios are value-weighted and have sample length 1995-2017. The first column shows the different set of test assets (see section "6.1 Main test assets" for a description of each test asset). Second to seventh column shows the estimated risk premia for each factor. *, ** and *** indicate the level of significance at respectively 10%, 5% and 1%.

Panel A: CAPM

1995-2017	λ_0	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.027***	-0.011**	0.167	0.135
IBM	-0.001	0.016**	0.299	0.272
IBSP	0.017***	-0.002	0.007	-0.031
IMSp	0.016***	0.000	0.000	-0.038
IMSi	0.026***	-0.010**	0.108	0.073
ISpSi	0.027***	-0.010**	0.172	0.140
BMSp	0.021***	-0.006	0.050	0.016
BMSi	0.033***	-0.017***	0.280	0.255
BSpSi	0.032***	-0.016***	0.404	0.383
MSpSi	0.032***	-0.015***	0.280	0.255

Panel B: Fama-French three-factor model

1995-2017	λ_0	λ_{SMB}	λ_{HML}	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.015***	0.017***	0.000	-0.001	0.757	0.727
IBM	0.008	0.014*	-0.001	0.005	0.458	0.391
IBSP	0.01**	0.013***	-0.001	0.003	0.494	0.431
IMSp	0.011**	0.013***	-0.003	0.003	0.508	0.446
IMSi	0.015***	0.018***	-0.002	-0.002	0.730	0.697
ISpSi	0.016***	0.015***	-0.003	-0.002	0.675	0.635
BMSp	0.011**	0.013***	-0.001	0.003	0.350	0.275
BMSi	0.017***	0.017***	0.001	-0.003	0.674	0.636
BSpSi	0.019***	0.013***	0.002	-0.005	0.623	0.580
MSpSi	0.018***	0.015***	-0.005	-0.005	0.584	0.536

Appendix C3 (continued)

Panel C: Carhart four-factor model

1995-2017	λ_0	λ_{SMB}	λ_{HML}	λ_{PR1YR}	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.015***	0.017***	0.000	0.004	-0.001	0.758	0.716
IBM	0.008	0.016**	-0.001	0.004	0.006	0.470	0.378
IBSP	0.01**	0.013***	-0.001	0.003	0.004	0.496	0.408
IMSp	0.01**	0.013***	-0.003	0.003	0.004	0.513	0.428
IMSi	0.015***	0.018***	-0.002	0.005	-0.001	0.735	0.689
ISpSi	0.016***	0.015***	-0.002	0.004	-0.002	0.677	0.621
BMSp	0.011**	0.013***	-0.001	0.002	0.003	0.352	0.248
BMSi	0.017***	0.017***	0.001	0.004	-0.003	0.676	0.624
BSpSi	0.019***	0.013***	0.002	0.001	-0.005	0.624	0.563
MSpSi	0.018***	0.015***	-0.005	0.004	-0.004	0.586	0.519

Panel D: Fama-French five-factor model

1995-2017	λ_0	λ_{SMB}	λ_{HML}	λ_{RMW}	λ_{CMA}	λ_{ERM}	R^2	R^2_{adj}
IBSi	0.015***	0.017***	0.000	-0.009	0.005	-0.002	0.773	0.722
IBM	0.007	0.011	-0.001	-0.01	0.001	0.006	0.492	0.377
IBSP	0.011**	0.012***	-0.001	-0.004	-0.002	0.003	0.497	0.383
IMSp	0.011**	0.013***	-0.002	-0.005	-0.005	0.003	0.524	0.416
IMSi	0.015***	0.017***	0.000	-0.009	0.000	-0.002	0.748	0.691
ISpSi	0.017***	0.015***	-0.002	-0.003	-0.006	-0.003	0.686	0.615
BMSp	0.011**	0.013***	0.000	-0.007	-0.003	0.002	0.375	0.244
BMSi	0.018***	0.016***	0.001	-0.01*	0.004	-0.004	0.703	0.641
BSpSi	0.02***	0.013***	0.003	-0.003	-0.004	-0.006	0.631	0.554
MSpSi	0.018***	0.015***	-0.003	-0.006	-0.005	-0.005	0.603	0.52