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Risk Factors in the Norwegian Stock Market

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Abstract

This study investigates which risk factors are priced in the Norwegian stock market and which asset pricing model is superior among the CAPM, the Fama-French three-factor and five-factor model and a macroeconomic model. We estimate the models using the Fama-MacBeth methodology, and further compare the models based on their intercepts, R-squared statistics and stability in results. Our findings suggest that the factor portfolios SMB and RMW, in addition to the aggregate consumption, market and term structure variables are priced in the stock market. Moreover, we find that the Fama-French three-factor model is superior in explaining the cross-section of expected returns, based on the comparison of the models. Thus, the variables and factor portfolios are likely to proxy for systematic risk that is rewarded in the stock market.

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1.0 Introduction

The risk factors that are rewarded in the market and thus determines the prices and expected returns on assets is a debated topic within the area of financial economics. This study investigates which risk factors are rewarded in the Norwegian stock market. We will examine both macroeconomic factors and characteristic-based factors using prominent models such as the CAPM, the Fama-French three and five-factor models and a macroeconomic model. Moreover, we will compare which of the models is better in explaining expected returns.

The pioneering Capital Asset Pricing Model (CAPM) based on the work of Sharpe (1964), Lintner (1965) and Mossin (1966) established the foundation for modern financial theory. The CAPM is a single-factor model which describes a linear relation between the expected return on an asset and its covariance with the return on the market portfolio. Thus, the expected return for an asset increases as the exposure to the systematic risk inherent in the market portfolio increases.

Following the introduction of the CAPM, alternative asset pricing theories has developed, such as the Intertemporal CAPM (ICAPM) and the Arbitrage Pricing Theory (APT) introduced in Merton (1973) and Ross (1976), respectively. The ICAPM is a consumption-based asset pricing model, in which investors require compensation for changes in the investment opportunity set. Hence, state variables that influences the investment opportunity set are predicted to be rewarded in the market. Further, the APT predicts that general news or shocks that affect returns on all assets through systematic risk should be priced, such as macroeconomic variables.

In 1985, Chan, Chen and Hsiesh identified a set of macroeconomic variables and test whether these risks were rewarded in the US stock market. Their model included variables that a priori were expected to be priced such as changes in the term structure, growth in the industrial production, unexpected changes in inflation and bond spread. Their results support that unexpected changes in the inflation, the industrial production and the bond risk premium are significantly priced in the stock market. Similarly, Chen, Roll and Ross (1986) examined similar variables, however by including the oil price risk and the aggregate consumption to examine whether these are priced as well. Chen et al. (1986) conclude that several of the macroeconomic variables are rewarded in the US market. Nevertheless, neither the consumption nor the oil price risk was found to be separately rewarded in the stock market, in similarity to the market portfolio. Shanken and Weinstein (2006) suggest correcting the standard errors for measurement errors, which consequently will decrease the statistical significance reported in Chan et al. (1985) and Chen et al. (1986). Further, they report a lack of robustness in the results, and suggest an alternative procedure in forming the portfolios. Applying these changes, Shanken and Weinstein (2006) finds evidence that only the industrial production is priced in the US market. Moreover, Bodurtha, Cho and Senbet (1989) replicated and expanded the research of Chen et al. (1986) by considering international variables as well. In similarity to Shanken and Weinstein (2006), they find that only the industrial production is priced among the domestic variables. However, their findings indicate that the model is improved when including an international dimension. Recently, Benaković and Posedel (2010) examined whether macroeconomic factors are priced in the Croatian market and find a significant risk premium for the market and inflation.

Fama and French (1993) found that small company stocks tend to outperform large company stocks, and that value stocks tend to outperform growth stocks. Creating two factor mimicking portfolios SMB and HML to capture these anomalies, they extended the CAPM to a three-factor model (FF3). Thus, the FF3 explains the expected return on assets by combining a market factor, a size factor and a value factor. However, as researchers found that the FF3 fails to capture certain anomalies, alternative models were introduced. In particular, the FF3 did not capture the momentum effect as described in Jegadeesh and Titman (1993). Therefore, Carhart (1997) extended the FF3 to a four-factor model by including a momentum factor UMD. In 2012, Hou, Zue and Zhang introduced the Q-factor model as an alternative to the FF3 and Carhart's four-factor model. The Q-factor model includes a market factor, a size factor, an investment factor and a profitability factor, and Hou, Zue and Zhang (2015) argue that the performance of the Q-factor is in many cases better than the FF3 and Carhart's four-factor model. More recently, Fama and French (2015) extended their FF3 by including two additional factor portfolios for profitability (RMW) and investment (CMA), though with changes in the definitions of the profitability and investment factors from those of Hou et al. (2012). Further, Fama and French (2015) shows that the FF5 perform better in explaining expected returns than the FF3, however with an insignificant value (HML) factor.

Hence, a fundamental question in financial economics concerns which risks are rewarded in the stock market. There are competing asset pricing theories and empirical models that seek to help in identifying the priced risks, thus assist in understanding the risk-return relationship and pricing of financial assets. The conspicuous discrepancy is the motivation for this study. Therefore, we will identify which risk factors are priced in the Norwegian stock market and further which model is superior, based on several theories and empirical models. This will consequently enable investors to make better investment decisions.

In order to investigate which factors are priced in the Norwegian stock market and which of the models performs the best in our sample period, we identify macroeconomic and characteristic-based factors that are expected to be priced. Moreover, we identify four different models to test: the CAPM, the FF3, the FF5 and a macroeconomic model. We will estimate the models using the Fama-MacBeth (1973) procedure, as this allows us to examine the coefficients and statistical significance of risk premia estimates corrected for cross-sectional correlation. We will analyze the results obtained to examine which factors are priced and further compare the models based on their estimated intercepts, goodness of fit statistics and the stability in results in a robustness analysis.

We emphasize that our contributions to the field of finance are: i) constructing the factor portfolios RMW and CMA as described in Fama and French (2015) for the Norwegian stock market in our sample period and ii) identifying whether a macroeconomic model or a characteristic-based model is best in explaining the expected returns in the Norwegian stock market in our sample period.

The rest of this study is organized as follows. The second section comprise theories and empirical studies related to asset pricing models. In the third section, we present the models and factors we will examine. In the fourth section, we clarify the methodology we use in estimating the models and comparing them. Further, in the fifth section we describe the data used in the study. The sixth section contains the empirical results for the estimated models and a discussion part, in which the models are compared. In the seventh section we present our conclusion of the study based on our analysis of the obtained results.

2.0 Theory and Literature Review

In this section, we review essential asset pricing theories and empirical evidence in the literature that is helpful in establishing a framework in which we can analyze our obtained results and further conclude the study.

The theory section is divided into three subsections. Firstly, we consider the CAPM used to describe the relationship between expected returns and a market factor. Further, we review the theories of the APT and the ICAPM, which allows for multiple risk factors. In similarity, the literature review is divided into three subsections. Firstly, we review literature on factor models that apply macroeconomic risk factors to capture systematic risk of the economy. Further, we review literature on models that apply firm characteristics or investment strategies that are empirically found to outperform the market over time as factors. Lastly, we provide a short description of the dividend discount model used in deriving two factor portfolios in the recent FF5 model.

2.1 Theory

2.1.1 CAPM

The Capital Asset Pricing Model (CAPM) is a single-factor model built upon the work of Sharpe (1964), Lintner (1965) and Mossin (1966). The CAPM is an economic theory that describes the relationship between the equilibrium expected returns and risk on assets. The CAPM assume that all investors have homogeneous expectations, which consequently implies that all investors will hold the same risky portfolios. Therefore, all investors will hold the same portfolio, the market portfolio, which is a value-weighted portfolio of all assets in the investment universe. However, it is obviously not possible to observe the true market portfolio as it includes real estate and human capital, and it is therefore necessary to apply a proxy for the true market portfolio to test the CAPM. The implication of not considering all investment opportunities, as argued in e.g. Roll (1977), makes it impossible to test the CAPM. Obviously, this impairs the validity of the CAPM when testing it empirically.

The equilibrium expected return in the CAPM is dependent upon the market beta for asset i, β_i, which is the covariance of asset i's return, R_i, with the return on the market, R_M, divided by the variance of the return on the market:

$$\beta_i = \frac{cov(R_i, R_M)}{\sigma^2(R_M)}. \quad (1)$$

Then, the expected return for asset i, $E(R_i)$, can be computed by applying the security market line (SML) equation for an asset:

$$E(R_i) = R_f + \left[\mathrm{E}(R_M) - R_f\right] \beta_i \quad (2)$$

Where, R_f, is the risk-free rate and, $\left[E(R_M) - R_f\right]$, is the expected excess return on the market portfolio M. A fundamental concept in asset pricing theory is that investors require a compensation for the risk of investing in risky assets through a risk premium. This implies that risk-free assets should yield expected returns equal to the risk-free rates, whereas investors would require a higher compensation for risky assets. Further, eq. (2) can be rearranged to:

$$E(R_i) - R_f = \frac{\left[\mathrm{E}(R_M) - R_f\right]}{\sigma(R_M)} \beta_i \, \sigma(R_M) \quad (3)$$

where, in terms of a risk premium, $\frac{\left[\mathrm{E}(R_M) - R_f\right]}{\sigma(R_M)}$ is the price of risk, $\beta_i \, \sigma(R_M)$ is the quantity of risk and $E(R_i) - R_f$ is the risk premium for asset i. However, the quantity of risk is not equal to the total risk of the asset, because β_i only measures the systematic risk, i.e. the risk that cannot be reduced or eliminated through diversification. Thus, the non-systematic risk for an asset is not rewarded, and it is only the systematic risk of an asset that affect expected returns in the CAPM.

2.1.2 APT

The Arbitrage Pricing Theory (APT) introduced in Ross (1976) is an alternative approach in asset pricing theory to the CAPM in explaining an asset's expected returns. The APT was motivated by a lack of empirical success and strict underlying assumptions in the CAPM. The APT is based on the law of one price, which states that two assets that are identical in all economic aspects should have the same price. This implies that there are no arbitrage opportunities in the markets, because arbitrageurs will exploit mispricing in assets, such that the arbitrage opportunities are eliminated.

According to Cuthbertson (1996, p. 61), the return on an asset can be divided into an expected return component and an unexpected component. The unexpected component can be divided into news that affects either a particular asset (specific news), or all assets (general news). The general news could be macroeconomic changes such as an unexpected change in the term structure that cannot be diversified away (i.e. systematic), whereas specific news could be an innovation that affects only a specific firm or industry. The APT predicts that the general news will affect the return on all assets, however not by the same amount. Hence, in contrast to the CAPM, the APT opens for identifying the factors (e.g. macroeconomic such as in Chen et al. (1986)) that captures systematic risk that will consequently affect the returns.

In similarity to the CAPM, the APT predict a SML relating expected returns and risk, however with fewer and less restrictive assumptions relating to the distribution of the returns and utility functions of investors. Consequently, there are caveats concerning the implementation of the APT. Specifically, the APT does not specify which factors should be priced as it is an arbitrage theory and not an economic theory such as the CAPM. Thus, assuming that returns, R_i, can be described by a multifactor model with M factors:

$$R_i = \alpha_i + \beta_{i,1}F_1 + \beta_{i,2}F_2 + \cdots + \beta_{i,M}F_M + \epsilon_i \quad (4)$$

where α_i is a constant for asset i, $\beta_{i,M}$ is the risk for asset i associated with factor M, F_M is a systematic factor and ϵ_i is the non-systematic risk for asset i.

Then, the APT states that the expected return of asset i, $E(R_i)$, can be computed as:

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

where R_f is the risk-free rate and λ_M is the risk premium for factor M.

The APT does not specify which factors are priced in the market and determines the expected return of an asset in contrast to the CAPM. Theory does not yet describe any obvious and absolute path for choosing the factors in the APT. Therefore, the task of identifying the systematic factors that determines expected returns is under scrutiny in empirical research and might be motivated by rather simple economic intuition.

2.1.3 ICAPM

Merton (1973) argues that the CAPM assumptions are unrealistic to accomplish in real-world investing, because an investor often participates in the financial market for multiple years, and not a single year like the CAPM assume. The Intertemporal CAPM (ICAPM) introduced in Merton (1973) provides another alternative to the CAPM, however as a consumption-based asset pricing model in which investors require a compensation for changes in the investment opportunity set.

Following Bodie, Kane and Marcus (2014, pp. 435-436), the investors are assumed to maximize a utility function based on lifetime consumption rather than their wealth as such. Characteristics such as wealth, the risk-free rate, risk aversion, the amount of risk and risk premium affects the consumption each period. Thus, when assessing the risk of an asset, the ICAPM utilizes the covariance between the asset's return and aggregate consumption rather than the covariance between the asset's return and market's return such as in the CAPM.

In the ICAPM, wealth changes with the investment opportunity set, and an investor will therefore want to hedge the risk of changes in the investment opportunity set. It is possible to determine the expected return of an asset, $E(R_i)$, according to the ICAPM as:

$$E(R_i) = R_f + \beta_i^0\left[\mathrm{E}(R_M) - R_f\right] + \sum_{j=1}^{k}\beta_i^j\left[\mathrm{E}(R_j) - R_f\right] \quad (6)$$

where R_f is the risk-free rate, β_i^0 is the ordinary CAPM beta measuring the systematic risk of the asset to the market, $\mathrm{E}(R_M)$ is the expected return on the market, β_i^j is a beta for each factor measuring the volatility of the hedging security, $\mathrm{E}(R_j)$ is the expected return on the portfolio used to hedge the risk that arises from investing in asset i.

Hence, in the ICAPM framework, state variables that affect the investment opportunity set should be priced. However, in similarity to the APT, a caveat with empirical testing of the ICAPM is that the state variables that can be of hedging concerns and thus priced, are not identified.

2.2 Literature Review

2.2.1 Macroeconomic factor models

Following the APT framework, Chan, Chen and Hsieh (1985) investigate the firm size effect in the US stock market using a multifactor model estimated following a variant of the Fama-MacBeth (1973) procedure. On the basis of economic intuition, they include macroeconomic variables such as the market, changes in inflation, changes in slopes of the yield curve, growth in industrial production and changes in the risk premium. Chan et al. (1985) estimate the factor loadings on the macroeconomic variables applying twenty portfolios sorted by firm size as test assets. Their findings indicate that changes in the unexpected inflation variable, the industrial production variable and changes in the bond spread (risk premium) variable represent systematic risks that are significantly priced over their entire sample period.

In a similar study, Chen, Roll and Ross (1986) investigates whether changes in macroeconomic variables are risks that are rewarded in the US stock market. They use a set of similar variables to those in Chan et al. (1985), and estimate their models using the Fama-MacBeth procedure on twenty equal-weighted size portfolios. However, Chen et al. (1986) also test whether oil price risk and aggregate consumption (following the ICAPM) is separately rewarded in the market. Chen et al. (1986) argue that changes in general economic state variables representing systematic risk should influence stock prices and hence returns through changing the expected cash flow or discount rate for the stocks. Hence, Chen et al. (1986) identifies macroeconomic variables based on an a priori assumption that they will influence returns through either changing the expected cash flow or discount rate.

The findings in Chen et al. (1986) indicate that several variables are significantly priced in the US market, i.e. useful for explaining the expected stock returns. However, they did not find any significant relation between the consumption variable and the expected return, which is inconsistent with the prediction of the consumption-based ICAPM. In similarity, they did not find evidence that the risk from the oil price factor nor the market portfolio alone are rewarded in the stock market. Chen et al. (1986) concludes that stock returns are exposed to systematic economic news, and the five tested macroeconomic variables provides a description of the sources of systematic risk and priced risk.

Shanken and Weinstein (1990, 2006) revisited and reevaluated the models, procedures and conclusions in Chan et al. (1985) and Chen et al. (1986) using the same set of variables in the US stock market. They argue that the standard errors of the estimated risk premia from the Fama-MacBeth procedure applied in both studies are biased downward due to the errors-in-variables problem. Thus, they suggest correcting the standard errors and thus take into consideration the measurement error using a correction term introduced in Shanken (1992), which will consequently decrease the value of the reported t-statistics.

However, the main finding in Shanken and Weinstein (2006) indicate a lack of robustness in the results. In particular, they find that the results are very sensitive to the procedure in generating the portfolio returns and estimating the factor loadings. Chan et al. (1985) and Chen et al. (1986) form the size portfolios based on firm sizes at the end of the period, whereas Shanken and Weinstein (2006) suggest forming the portfolios at the beginning of each year and use the returns over the subsequent year to estimate the factor loadings. Thus, in contrast, Shanken and Weinstein (2006) use a post-ranking of returns rather than estimating the factor loadings using backward-looking returns. This results in remarkably different conclusions, as they find that only the industrial production variable is priced in the same sample period.

Bodurtha, Cho and Senbet (1989) replicated and expanded the research of Chen et al. (1986). When replicating the study, though with a shorter sample period, they find, in similarity to Shanken and Weinstein (2006), that only the industrial production is significantly priced. Further, they argue that because investors have the opportunity to participate in an international market, and there is an international economic interdependence in the real sector, international variables will influence segmented markets. Thus, they suggest that the Chen et al. (1986) model should be modified to include international variables in addition to the US domestic variables to better explain the cross-section of returns. Therefore, they estimated the models with international variables that are identified through an interbattery factor analysis. Whereas Chen et al. (1986) based their variables on an a priori expectation that they influence expected returns through either changing the stream of cash flows or discount rate, Bodurtha et al. (1989) employ an analytic procedure in identifying the variables. Their findings indicate that several international analogs of the variables used in Chen et al. (1986) are significant, supporting their suggestion of including an international dimension to the model. Nevertheless, as Bodurtha et al. (1989) argue, the power of their tests could be improved, for instance through using a set of portfolios sorted by other characteristics than size.

In 1991, Ferson and Harvey investigated the behavior of economic risk premia over time, applying state variables that are shown to influence asset returns in similar empirical research and theory. Following the CAPM, they include the market portfolio. Further, following the ICAPM, they include a variable for the growth in aggregate consumption and an interest rate variable to incorporate the state of the investment opportunity set. They also included variables for unexpected inflation, risk premium measured as the bond spread and a term spread. Their findings indicate that the most important factor for capturing predictable variations in the stock portfolio returns is the market risk premium.

More recently, Benaković and Posedel (2010) investigated whether macroeconomic risk factors are priced in the Croatian market in an APT framework. They estimate a model including variables for the inflation, industrial production, interest rates, oil prices and a Croatian market index using a similar approach to the Fama-MacBeth procedure. Their main findings are a significant risk premium for the market index and inflation, whereas the rest is found insignificant. The market has a positive risk premium, whereas the inflation yields dispersions in the signs. However, a major weakness in their study is the small sample size as they use monthly observations from January 2004 to October 2009. Another clear weakness is their test assets, which are only 14 stocks. The model does not take into consideration the estimation error of the factor loadings through adding a correction term following Shanken (1992) or alternatively grouping the stocks into portfolios such as Friend and Blume (1970) and Fama and MacBeth (1973).

We note that a substantial portion of the literature on macroeconomic models use economic variables that, according to theory, should proxy for systematic risks in the economy to describe the cross-section of expected returns. However, factor portfolios formed according to firm characteristics (or anomalies) as they are found to proxy for systematic risks, are frequently used following the introduction of the FF3. In contrary to the macroeconomic models, the factor portfolios are mainly based on empirical findings, and consequently several of the characteristic-based factor models we will assess in the following subsection are empirical models.

2.2.2 Characteristic-based factor models

In the CAPM, the market portfolio is predicted to be the only priced factor. Motivated by the empirical struggle for the CAPM, Fama and French (1993) extended the CAPM to a three-factor model (FF3). The FF3 extended the CAPM by including a factor mimicking portfolio for size, SMB, and a factor for value (book-to-market ratio), HML, to capture the size and value patterns in average stock returns. Hence, the FF3 model contains three factors to explain the expected return of a portfolio: the market factor, the size factor SMB and the value factor

HML. Applying the FF3 model on twenty-five size and book-to-market (B/M) sorted portfolios, Fama and French (1993) found statistically significant risk premia coefficients for the HML and SMB, as well as high R^2 statistics. Thus, they argue that these results indicate that the SMB and HML are significant in explaining the cross-section of returns and should be included in addition to the market factor as predicted by the CAPM.

Several researchers such as Jegadeesh and Titman (1993) and Chan, Jegadeesh and Lakonishok (1996) argue that the FF3 model fails to capture the momentum effect. To address this issue, Carhart (1997) introduced a model where a momentum factor *UMD* is added to the original FF3 model to better explain cross-sectional returns. The UMD factor portfolio is constructed by investing in past winners and selling past losers.

Chen, Novy-Marx and Zhang (2011) introduced an alternative three-factor model that consist of a market factor, a return on equity factor and an investment factor to explain the cross-section of expected returns. They argue that a firm's profitability and cost of capital determines the amount a firm would invest. For instance, a firm with low profitability and high cost of capital will have lower investments. Hence, investment should be negatively correlated with expected returns, when controlling for profitability, whereas profitability should be positively correlated with expected returns, when controlling for investment. Nevertheless, based on their findings the alternative three-factor model does not outperform the FF3 model.

Novy-Marx (2013) investigated the relationship between profitable firms and expected returns. In general, firms that earn higher returns are profitable firms, and vice versa. He argues that similar to book-to-market, the profitability (measured by gross profit-to-asset) can predict the average stock return. Investments in e.g. research and development or advertising reduces the current earnings without increasing the book value, despite expected higher profits. Moreover, as the dividend discount model states (which we further review in the next subsection), earnings reflect the true economic profitability. Therefore, Novy-Marx (2013) argue that earnings should be measured before these types of investments are made. Hence, they conclude that this makes gross profitability a better proxy than current earnings.

Hou, Xue and Zhang (2012, 2015) introduced a four-factor investment-based model. The expected return of an asset is characterized by the sensitivity of its return to four factors: market, investment, size and profitability. Their Q-factor model is developed upon Tobin's q theory (1969). Tobin (1969) argue that a firm's investment decision is based on a ratio, Q:

$$Q = \frac{Market\ value\ of\ firm\ capital}{Replacement\ cost\ of\ capital} \tag{7}$$

Eq. (7) implies that firms with higher cost of capital, ceteris paribus, have a lower Q, i.e low investments, and vice versa. Similarly, a higher market value, ceteris paribus, implies that the firm will have a higher Q, i.e high investments, and vice versa. The purpose of the Q-factor model is to capture the anomalies that the FF3 model and Carhart's four-factor model failed to, namely the impact of firm's investment behavior and profitability on expected average stock return from Tobin's q theory. Furthermore, the Q-factor model describes the momentum effect in addition to several average-return anomalies. Based on their results the Q-factor model outperforms the Carhart model in capturing stock market anomalies in the US market.

Acknowledging the new identified anomalies in the literature following the introduction of the FF3, Fama and French (2015) extended the FF3 model to a five-factor model (FF5). Based on the dividend discount model, the factor portfolios RMW and CMA are added to capture the profitability and investment anomalies, respectively. The factor portfolio RMW is the difference in returns between firms with high and low operating profitability, whereas CMA is the difference in returns between firms with conservative and aggressive investing. Interestingly, Fama and French (2015) found that after adding the profitability and investment factors, the value factor HML was redundant in explaining returns. Also, the FF5 models have trouble in explaining the average return for firms with low profitability but invest a lot. Further, they found that the FF5 model contain pricing errors, as all their tested models are rejected in an intercept test introduced in Gibbons, Ross and Shanken (1989). Nevertheless, they conclude that the FF5 model is adequate to explain 74% to 94% expected returns volatility. Hence, they conclude that the FF5 model captures the average stock returns better than their three-factor model.

Recently, Fama and French (2017) investigated the outcome of the FF5 model in North America, Japan and Europe. Their findings indicate that the FF5 model explained the average stock returns but with variability among the factors across the regions. In Japan the average returns show a weak link with the profitability and investment factors, whereas the value factor indicates a strong link. In contrast, the investment and profitability factor show a strong relation with average returns in North America. Fama and French (2017) further finds evidence that the investment factor, CMA, is redundant for both Europe and Japan. Hence, excluding the CMA factor from the FF5 does not have a large effect on the description for average returns in their sample period.

More recently, Hou, Xue and Zhang (2017) compared several asset pricing models, including the CAPM, the FF3, Carhart's model and the FF5 model in explaining stock return anomalies in the US. Their findings indicate that the two models that explained the anomalies best was the FF5 and the Q-factor model. Furthermore, the Q-factor model outperforms the FF5 model in explaining the profitability and momentum anomalies, whereas the FF5 explains the value-versus-growth anomalies better. Interestingly, they find that the investment and profitability anomalies are the most important in the cross-section of expected returns.

2.2.3 Dividend Discount Model

The Fama and French model is based on the dividend discount model (DDM). Gordon and Shapiro (1956) and Gordon (1962) argue that the price of a stock is the present value (PV) of all future dividend payments. The DDM can be expressed as:

$$P_0 = \frac{\sum_{t=1}^{\infty} E(d_t)}{(1+k)^t} \tag{8}$$

where P_0 is the current stock price, the expected dividend payment per stock at time t is denoted $E(d_t)$, and k is the internal rate of return. Further, the PV of a firm can be expressed as the difference in the total earnings that is reflected by the profitability of a firm and the retained earnings:

$$P_0 = \frac{\sum_{t=1}^{\infty} TE_t - RE_t}{(1+k)^t} \tag{9}$$

in which TE_t represents the total earnings in time t and RE_t represents the retained earnings. Furthermore, the retained earnings express the amount of earnings that is reinvested and can be denoted as the difference between the book value of equity that is reflected by a firm's investment. Thus, Miller and Modigliani (1961) argue that the market value of a firm can be represented as:

$$P_0 = \frac{\sum_{t=1}^{\infty} TE_t - (BV_t - BV_{t-1})}{(1+k)^t} \tag{10}$$

where, $(BV_t - BV_{t-1})$ represents the difference between the book value of equity at time t and $t-1$. Following eq. (10), increased total earnings yields increased profitability and hence an increase in the expected returns, whereas a higher growth in the equity yields increased investments and thus a decrease in the expected returns.

3.0 The Models and Factors

We use both theoretical and empirical models in this study. In this section, we outline the main models and factors that are used and the rationale behind the selections. In the models, we apply 28 portfolios sorted by industry, B/M and momentum characteristics as test assets.

There are two alternative theoretically based approaches often used in the selection of factors. According to Campbell, Lo and MacKinlay (1997, pp. 239), the first approach concerns specifying macroeconomic variables that are considered to capture systematic risks of the economy. This particular approach is for instance used in Chen, Roll and Ross (1986) and other macroeconomic models. Further, the second approach concerns specifying firm characteristics that are likely to capture the sensitivity to the systematic risks and then construct factor portfolios of stocks based on these characteristics (Campbell et al., 1997, pp. 239). This approach is for instance used in several characteristic-based factor models such as the empirical model introduced in Fama and French (1993). Because we estimate both characteristic-based factor models and a macroeconomic model, we employ both approaches. Further, we will obviously apply a market factor in the CAPM and the factor portfolios as described in Fama and French (1993, 2015) in the FF3 and the FF5. Moreover, we choose the variables with the objective of capturing systematic risks of the economy, as further described in section 3.4.

3.1 CAPM

The CAPM model has been a solid workhorse in the asset pricing literature for purposes such as describing the risk-return relationship of investments and thus the expected returns of assets. Since its introduction, the CAPM has been placed under scrutiny and tested empirically. Several studies (see e.g. Fama and French, 1993, 2015) and Hou, Xue and Zhang (2015)) proves that even though the CAPM is valid theoretically, it is not the best performing model empirically. Nonetheless, because the theory predicts that the market is the only factor that is priced and thus determines an asset’s expected return, it is a natural choice to include the model due to its theoretical foundation and genuine simplicity per se.

Following the CAPM model in eq. (11), it is necessary to include a factor to proxy for the expected return on the market portfolio $\mathrm{E}(R_M)$. Specifically, to test the CAPM and compute the expected return for the test assets $E(R_i)$, we include a factor $EMKT$ that represents the excess market return for the Norwegian stock exchange:

$$E(R_i) = R_f + EMKT_i \, \beta_{i,EMKT}. \tag{11}$$

where R_f is the risk-free rate and $\beta_{i,EMKT}$ is the factor loading for asset i to the market portfolio.

3.2 Fama-French three-factor model

Following its introduction in 1993, the characteristic-based factor model has become an important empirical model as an extension of the CAPM in explaining expected returns. The FF3 model has been shown to empirically outperform the

CAPM (see e.g. Fama and French (1993)) and thus indicate that the market factor in the CAPM alone is not necessarily sufficient. Hence, it is interesting to assess the performance of the FF3 model in Norway due to its relatively good empirical performance, and because the factors that are assumed to describe the returns are identified. In particular, to test the FF3 model, we include a market factor $EMKT$ similar to that of the CAPM in eq. (11), but also the factor portfolios as described in Fama and French (1993), SMB and HML as risk factors:

$$E(R_i) = R_f + EMKT_i\ \beta_{i,EMKT} + SMB_i\ \beta_{i,SMB} + HML_i\ \beta_{i,HML} \qquad (12)$$

where $\beta_{i,SMB}$ is the factor loading for asset i to the SMB factor and $\beta_{i,HML}$ is the factor loading for asset i to the HML factor.

3.3 Fama-French five-factor model

The FF5 model introduced in Fama and French (2015) has shown to perform better than the FF3 model, as an extension to the FF3 model with two additional factors. Although the FF5 model is rather recent compared to some of its peers such as the CAPM, the FF3 and the macroeconomic models introduced in Chen et al. (1986), it has captured interest in the asset pricing literature. The FF5 model has presented evidence that the five characteristic-based factors are better to determine expected returns than the CAPM and FF3. Thus, because the FF5 apparently is better than the CAPM and FF3 and due to its relatively recent introduction, we find it interesting to include the FF5 model in this study. Following Fama and French (2015), we extend eq. (12) by adding the two additional factor portfolios CMA and RMW:

$$E(R_i) = R_f + EMKT_i\ \beta_{i,EMKT} + SMB_i\ \beta_{i,SMB} + HML_i\ \beta_{i,HML} + CMA_i\ \beta_{i,CMA} + RMW_i\ \beta_{i,RMW} \qquad (13)$$

where $\beta_{i,CMA}$ is the factor loading for asset i to the CMA factor and $\beta_{i,RMW}$ is the factor loading for asset i to the RMW factor.

3.4 Macroeconomic model

Chen et al. (1986) introduced a well-known macroeconomic factor model consisting of macroeconomic variables as proxies for systematic factors. We primarily follow Chen et al. (1986) in their intuition and choice of the state variables that are a priori expected to capture systematic risk in the economy. Based on economic intuition, they are expected to have an effect on either cash flows or the discount rate and thus returns. This relation can for instance be seen in eq. (8) in the DDM. Moreover, we emphasize that the main reason for our theoretical approach rather than a factor (or principal component) analysis approach in selecting factors is that the factor analysis may yield results in which it is unknown what variables are found priced. Consequently, this may eliminate possible economic interpretations of the variables.

Following Chen et al. (1986), the discount rate is averaged over time, and consequently varies with the prevailing level of the interest rates, as well as the term spread with different maturities. Thus, changes in the interest rates will affect the discount rates. Further, industrial production is often seen as an indicator of the current state of the economy, and thus growth in the industrial production is expected to influence the current value of cash flows. Moreover, presuming that prices are in real terms, an unexpected change in the inflation will affect the pricing in a systematic manner. A rise in the inflation affects the purchasing power and thus the investment opportunity set for investors.

Although oil price risk is not found significantly priced in the US market in Chen et al. (1986), we have decided to test whether it is priced in this study. As noted in Bodurtha et al. (1989), oil price risk should be captured by the industrial production and inflation factors. Nevertheless, as our industrial production data excludes petroleum-related industries, the oil price variable might capture systematic risk that is in fact priced, however not captured by the industrial production variable.

In addition to the factors included in Chen et al. (1986), we include a foreign exchange rate factor in our model, motivated by the findings of Bodurtha et al. (1989) that supports using international variables. Bodurtha et al. (1989) argue that unexpected changes in international parity relations may influence stock returns. Further, they state that deviations from purchasing power parity (PPP) are often referred to as real exchange rate changes, which influence a country's relative competitiveness. Following their intuition, considering the demand side, a depreciation in the NOK against the USD leads to upward pressure on the inflation, as the cost of imports increase. Consequently, the demand and real income will decrease in Norway. This impact on the real sector, as a consequence of deviations from the PPP, will presumably influence the stock returns and thus be priced.

Moreover, asset pricing theory provides some suggestions. Following the CAPM, the market is assumed to capture all relevant factors, i.e. all the systematic risk that is rewarded is captured in the market portfolio. Further, changes in aggregate consumption may represent changes in the marginal utility of wealth, and thus influence returns following the ICAPM. Therefore, we include the market and consumption factors in our model.

Thus, motivated by theory, the macroeconomic model introduced in Chen et al. (1986) and the findings of Bodurtha et al. (1989), we will test a similar model in the Norwegian stock market. We apply a similar set of variables, however in a model comprising all factors:

$$E(R_i) = R_f + INF_i\, \beta_{i,INF} + CON_i\, \beta_{i,CON} + IP_i\, \beta_{i,IP} + FX_i\, \beta_{i,FX} + MKT_i\, \beta_{i,MKT} + OIL_i\, \beta_{i,OIL} + TS_i\, \beta_{i,TS} \quad (14)$$

where INF is a variable to proxy for the unexpected change in inflation, CON is a variable to proxy for the change in consumption, IP is a variable to proxy for the growth in industrial production, FX is a variable for the change in the USD/NOK exchange rate, MKT is a variable for the market return, OIL yields the change in oil prices while TS yields the term spread.

4.0 Methodology

In this study, we will apply the well-known procedure of Fama and MacBeth (1973) to find the determinants of expected return of the test assets. However, as the Fama-MacBeth procedure requires estimating numerous time-series and cross-sectional regressions, we have conformed a program to use in the statistical software EViews. The program is obtained through Brooks (2014, pp. 656-658) and adjusted to fit the dataset used in this study (Appendix A). Also, we modified the program to report the t-statistics for the intercept estimates from the time-series regressions in the first step. The Fama-MacBeth procedure is described in detail in the following subsection.

4.1 The Fama-MacBeth Procedure

Although factors affect cash-flows or the discount rate, they are not necessarily priced. Hence, it is necessary to compute estimates of the risk premium for the factors and their corresponding t-statistics to examine whether they are priced. The approach taken in our study is based upon the empirical methodology introduced in Fama and MacBeth (1973), where a two-pass regression method is applied to test the relationship between risk and expected return. This two-step procedure will ultimately yield estimates of each variable's factor loading and risk premium for each of the test assets. It will also enable us to examine the explanatory power of the models. Further, this procedure will correct the standard errors for cross-sectional correlation (Cochrane, 2000, p. 231). Using the obtained results, the expected returns of a portfolio can be computed simply as:

$$\mathrm{E}(R_i) = \alpha + \beta_{i,a}\lambda_{i,a} + \beta_{i,b}\lambda_{i,b} + \cdots \; , i = 1,2, \ldots N \qquad (15)$$

where $\mathrm{E}(R_i)$ is the expected excess return of portfolio i, $\beta_{i,a}$ is the exposure for portfolio i to a risk factor a, and $\lambda_{i,a}$ is the risk premium associated with risk factor a.

The first step of the procedure involves estimating the factor loading for each factor $F_{i,t}$ by running time-series regressions of each test asset's excess return,

$R_{i,t}$, on the M factors $F_{1,t}, F_{2,t} \dots, F_{M,t}$. Hence, for each test asset $i = 1, \dots N$, the following time-series regression is estimated using ordinary least squares:

$$R_{i,t} = \alpha_i + \beta_{i,F1} F_{1,t} + \beta_{i,F2} F_{2,t} + \dots + \beta_{i,FM} F_{M,t} + \varepsilon_{i,t} \ , t = 1, \dots T \quad (16)$$

where α_i is the intercept, $\beta_{i,F1}, \beta_{i,F2}, \dots, \beta_{i,FM}$ are the estimates of the factor loadings on the M factors, $\varepsilon_{i,t}$ is the error term, N is the number of test assets and T is the number of time-series observations. As the factor loadings are only estimates of the true factor loadings and are to be applied in the second step regressions, they are labeled in the following as $\hat{\beta}_{i,F1}, \hat{\beta}_{i,F2}, \dots, \hat{\beta}_{i,FM}$.

The second step of the procedure involves running cross-sectional regressions on the test assets by using the estimated factor loadings, $\hat{\beta}_{i,F1}, \hat{\beta}_{i,F1}, \dots, \hat{\beta}_{i,F1}$ from the first step, which will yield estimates of each factor's risk premium. The equation for the cross-sectional regressions are given in eq. (17):

$$R_{i,t} = \lambda_{0,t} + \lambda_{1,t} \hat{\beta}_{i,F1} + \lambda_{2,t} \hat{\beta}_{i,F2} + \dots + \lambda_{M,t} \hat{\beta}_{i,FM} + \varepsilon_{i,t} \ , i = 1, \dots N. \quad (17)$$

where $\lambda_{0,t}$ is the intercept and $\lambda_{1,t}, \lambda_{2,t}, \dots, \lambda_{M,t}$ are the risk premia for the M factors at time t. The cross-sectional regressions are estimated by ordinary least squares for each period, which yields a total of T estimates of the risk premium, that we further denote as $\hat{\lambda}_{1,t}, \hat{\lambda}_{2,t}, \dots, \hat{\lambda}_{m,t}$.

After obtaining the estimates of the risk premia, the average risk premium ($\overline{\hat{\lambda}_M}$) for each factor from $m = 1, \dots M$ is computed simply as the average of $\hat{\lambda}_{m,t}$:

$$\overline{\hat{\lambda}_m} = \frac{1}{T} \sum_{t=1}^{T} \hat{\lambda}_{m,t} \ , m = 1, \dots M. \quad (18)$$

Further, as we have obtained one estimate of the risk premia $\hat{\lambda}_{m,t}$ for each time period, we compute the t-ratio as:

$$t\left(\overline{\hat{\lambda}_m}\right) = \frac{\sqrt{T}\hat{\lambda}_m}{\hat{\sigma}_{\lambda m}} \quad (19)$$

where,

$$\hat{\sigma}_{\lambda,m} = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}\left(\hat{\lambda}_{m,t} - \hat{\lambda}_m\right)^2}\ . \qquad (20)$$

According to Brooks (2014, pp. 650-561), the computed t-statistic $t\left(\hat{\bar{\lambda}}_m\right)$ in eq. (19), as suggested by Fama and MacBeth (1973) follows a t-distribution with $T - 1$ degrees of freedom in finite samples, or is asymptotically standard normal. The test statistic implicitly assumes that the error terms in the cross-sectional regressions are independent and identically distributed. Nevertheless, according to Shanken (1992), the assumption of independence is not strictly satisfied, and the factor loadings are measured with errors. Hence, the estimates in the second step suffer an errors-in-variables (EIV) problem. This might cause a downward bias in the standard errors, which consequently contribute to an overestimation of the t-statistic (Shanken, 1992). We tackle the EIV problem by grouping stocks into portfolios, which is discussed in detail in the subsequent subsection.

4.2 Risk Factors

Following Chen et al. (1986), we extract the unpredictable component of the factor returns in the variables applied in the macroeconomic model. The procedure is simply to estimate an autoregressive model on each of the factor returns, and then use the residuals as the factor returns. Thus, we estimate an AR(1) model on each of the factor returns:

$$R_{t+1} = a + b \times R_t + e_{t+1} \qquad (21)$$

and then use the residuals, e_{t+1}, as the factor returns.

We also note that after transforming the macroeconomic data in levels to logarithmic changes, some of the variables exhibited serial correlation which was eliminated after performing our procedure. The transformations of the variables applied in the models are further described in the data section.

4.3 Test Assets

There is a discrepancy in the literature regarding which test assets are appropriate to apply in asset pricing models to minimize errors in estimation of the risk premia. Therefore, it is necessary to delicately select the appropriate test assets to apply in our models. As the second step in the Fama-MacBeth procedure use the estimated factor loadings from the first step, this introduces an EIV problem. Chen et al. (1986) argue that as a consequence of an EIV problem, the estimates of the factor loadings will be biased. Likewise, Cochrane (2000, p. 396) argue that because the factor loadings used in the cross-sectional regressions are estimated in time-series regressions, this will lead to underestimation of the standard errors, also asymptotically. However, this limitation can be tackled in different ways. For instance, following the correction in Shanken (1992), the measurement error is accounted for by multiplying the standard deviation in the t-statistic in eq. (19) by a factor (Brooks, 2014, p. 650). Alternatively, Friend and Blume (1970), Fama and MacBeth (1973) and several others tackle the EIV problem simply by grouping stocks into portfolios and use these as test assets. Fama and MacBeth (1973) argue that the estimated factor loadings of portfolios may be considerably more precise of the true factor loadings than for individual assets.

Ang, Liu and Schwarz (2017) argue that forming portfolios rather than stocks to reduce the estimation error in the factor loadings does not necessarily produce smaller estimation errors of the risk premia estimates. The rationale is that when forming portfolios, information captured by the single stocks are neglected as the dispersion in the factor loadings decrease. Their findings indicate that using portfolios rather than stocks may lead to a loss in efficiency in the risk premia estimates. Nevertheless, for the purpose of this study, we adopt the approach of grouping stocks into portfolios in an attempt to tackle the EIV problem.

It is also necessary to determine the characteristic the portfolios should be sorted according to, that further conceivably minimizes the estimation errors of the risk premia estimates. In the attempt to find some appropriate characteristics of the test assets for our models, we have collected several portfolios from Bernt Arne Ødegaard[2] that are sorted according to different characteristics, including size, B/M, momentum and industry. We will examine which characteristics yields the

[2] Bernt Arne Ødegaard have provided public asset pricing data for the Oslo Stock Exchange. Retrieved from: http://finance.bi.no/~bernt/financial_data/index.html

highest dispersion in the factor loadings and expected returns as this may lead to a lower estimation error. According to Ang et al. (2017), the higher the dispersion in betas – the more information is captured in the cross-section to estimate the risk premia. Thus, we consider dispersion in the betas as the most important, because the risk premia estimates are more sensitive to changes in the betas. Since, the estimation of the risk premium is essentially the difference in expected returns divided by the difference in betas. This is consistent with Lewellen, Nagel and Shanken (2010), who suggest that adding other factors than the size and B/M might improve empirical tests. They argue that the additional test asset portfolios can be useful provided that there is variation either in the expected returns on the left-hand-side or in risk on the right-hand-side.

Further, we follow Fama and French (2015) concerning the number of test portfolios. They apply several test assets consisting of between 25 and 32 portfolios. Thus, we will primarily focus a similar range of portfolios, although we consider a set of 20 B/M and size portfolios in the robustness analysis as well, mostly because these are commonly used in asset pricing models.

Lastly, we argue that it is interesting to examine test assets with different characteristics rather than simply applying the commonly used size and B/M in the Fama and French models. Lewellen et al. (2010) suggest expanding the set of test assets beyond the size and B/M portfolios, as this may consequently improve the power of the cross-sectional R^2. This is particularly interesting, because we will apply the cross-sectional R^2 in the comparison between the models.

4.4 Comparing models and robustness analysis

In the following, we will primarily focus on comparing the estimated models. We initially compare the models based on their estimated intercepts both in the time-series and cross-sectional regressions, as both intercept tests will indicate whether there are missing priced factors in the models, i.e. pricing errors. We should expect that a good model should produce an intercept equal to zero in both the time-series and cross-sectional regressions. Thus, an analysis of the estimated intercepts gives an indication of the relative performance of the models. Further, we have estimated the CAPM, the macroeconomic model, the FF3 and the FF5 model using four sets of new test assets, in addition to the main test asset we use. Moreover, we compare the explanatory power of each model by comparing the R^2 of the models. We then assess the stability in the results for each model, and ultimately conclude which model is superior in explaining the cross-section of expected returns based on its relative performance to the other models.

4.4.1 Intercept analysis

We will firstly examine the values of the estimated intercepts and the corresponding standard errors. Further, we compute the GRS test statistic introduced in Gibbons et al. (1989) that is commonly used in assessing the efficiency of asset pricing models. Moreover, we also assess the cross-sectional intercepts for all models and their corresponding t-statistics to test for cross-sectional pricing errors.

The GRS test can essentially be seen as an F-test to examine the null hypothesis that all intercepts are jointly equal to zero. Hence, a small GRS statistic indicate that the model is efficient. We use the GRS test rather than a χ^2-test, because the χ^2-test is asymptotically valid whereas the GRS statistic is valid for finite samples (Cochrane, 2000, p. 216). Moreover, Cochrane (2000, pp. 214-215) points out that the GRS statistic assumes that the residuals are normally distributed, uncorrelated and homoscedastic. Following Cochrane (2000, p. 216)[3], the GRS statistic is defined as:

$$GRS = \left(\frac{T-N-K}{N}\right)\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\bar{\mu}'\hat{\Sigma}_f^{-1}\bar{\mu}} \sim F_{N,T-N-K} \qquad (22)$$

where N is the number of test assets, K is the number of factors in the model and T is the number of periods in the time-series. Further, $\hat{\alpha}$ is a $N \times 1$ vector comprising the estimated intercepts from the time-series regressions, $\hat{\Sigma}$ is a $T \times N$ vector comprising the residual covariance matrix, $\hat{\Sigma}_f$ is a $K \times K$ covariance matrix of the factors and $\bar{\mu}$ is a $K \times 1$ factor matrix with the sample means.

We refer to Appendix B for a detailed description of how we compute the matrices $\hat{\alpha}, \hat{\Sigma}, \bar{\mu}$ and $\hat{\Sigma}_f$. Then, simply plugging $\hat{\alpha}, \hat{\Sigma}, \bar{\mu}$ and $\hat{\Sigma}_f$ into eq. (22) yields

[3] The notation for the GRS statistic is similar to those of Cochrane (2001) and Diether (2001).

an estimate of the GRS statistic. Since the GRS statistic follows the F distribution, the p-value of each statistic is calculated using the corresponding value and their respective degrees of freedom. The numerator and denominator degrees of freedom are respectively 28 and (329-28-K) for the CAPM, the FF3, whereas it is 28 and (276-28-K) for the FF5.

We note that because we examine models with different types of risk factors, i.e. factors of excess returns and macroeconomic factors, this has implications for the interpretation of the intercepts and consequently the GRS statistics. According to Cochrane (2000, p. 215), models with factors that are excess returns, such as the FF3 and the FF5 models and the CAPM, provides time-series intercepts that measure the degree of mispricing. Hence, a better model will yield a lower intercept estimate. However, as our estimated macrofactor model does not contain excess returns, then the time-series intercepts are not necessarily required to be equal to zero (Cochrane, 2000, p. 255). Following this, the GRS statistic can give an indication of which of the CAPM, FF3 and FF5 performs the best, but we can not conclude whether the macroeconomic model is better based solely on the GRS statistic. Thus, we have only reported the statistic for the CAPM, the FF3 and the FF5.

Therefore, we will further compare the models based on the intercept obtained from the cross-sectional regressions of the Fama-MacBeth procedure. This test is in some sense the equivalent of the GRS test on the time-series intercepts. An intercept estimate different from zero indicates that all the priced risk factors are not included in the model, i.e. the model is misspecified. Hence, we will assess the values of the estimated intercepts and the corresponding statistical significance, as this may indicate the extent to which the models encompass cross-sectional pricing errors. We expect that a good model will yield a relatively small intercept, and that it should be statistically insignificant (Adrian, Etula and Muir, 2014; Cochrane, 2000, p. 78).

4.4.2 Goodness of fit

There are several measures of “goodness of fit” for asset pricing models, such as the R^2 statistic and the HJ-distance introduced in Hansen and Jagannathan (1997).

We will compare the performance of the estimated models using the reported cross-sectional R^2 as a measure of the goodness of fit and explanatory power for each model. Kan, Robotti and Shanken (2013) argues that the R^2 can be used to assess the extent to which the estimated factor loadings account for the cross-sectional variation in average returns. Hence, a higher cross-sectional R^2 for one model relative to another can give an indication of whether the model explains the cross-section of returns better.

Nevertheless, Lewellen et al. (2010) argue that even though a model evidently has strong explanatory power, i.e. a high cross-sectional R^2, it can often yield misleading test results of asset pricing models. They further argue that a high cross-sectional R^2 can be obtained fairly easy provided that the factor returns line up with the expected returns. Hence, for the FF3 model, this only requires adding a factor that is weakly correlated with the SMB or the HML. We also note that one of their suggestions for improving the power of the test includes expanding the set of test assets beyond the commonly used size and B/M portfolios in the FF-models.

Lastly, we argue that although the R^2 statistic may give a rather simple and intuitive indication of the explanatory power of the models, it should be included only as a supplement to the other methods we use to compare the models. The critique disclosed in Lewellen et al. (2010) accentuate the fact that the R^2 statistic may produce incorrect conclusions when comparing models, because sample cross-sectional R^2 seems rather uninformative in describing the true performance of a model. Additionally, adding more risk factors to a model will always yield at least the same value of the R^2 statistic, even if it exists no relationship between the added risk factor and dependent variable (Brooks, 2014, p. 154). Hence, adding the two last factors in the FF5 model compared to the FF3 model will consequently give at least the same R^2 value for the FF5 model as for the FF3 model. We therefore interpret our R^2 statistics with caution, as we have a dispersion among the number of variables used in our models.

We estimate and save the R^2 of the models in the Fama-MacBeth program in EViews when running the Fama-MacBeth procedure. Following Brooks (2014, pp. 152-153), the R^2 can be computed as:

$$R^2 = \frac{\sum_t (\hat{y}_t - \bar{y})^2}{\sum_t (y_t - \bar{y})^2} \quad (23)$$

where y_t is the actual values of the dependent variable in the regression (given as $R_{i,t}$ in eq. 17), $\hat{y}$ is the fitted values of the dependent variable and $\bar{y}$ is the mean value of the dependent variable. Thus, the values of both y_t and $\bar{y}$ are known from our collected data, whereas we obtain the fitted values $\hat{y}_t$ from running the Fama-MacBeth program. The R^2 is calculated T times (for each cross-sectional regression as shown in eq. 17), and the final R^2 estimate for each model is then simply the average of the T estimated R^2 coefficients.

4.4.3 Robustness analysis

As a final indication of model performances in explaining expected returns, we will assess the robustness of the models applying different sets of test asset portfolios for each model. In particular, the new sets of test assets are BS (20 portfolios sorted according to B/M and size), ISM (28 portfolios sorted by industry, size and momentum), ISB (28 portfolios sorted by industry, size and B/M) and SBM (30 portfolios sorted by size, B/M and momentum). The procedure for estimating the models with the new test assets is obviously identical to the procedure applying the main test assets (sorted by industry, B/M and momentum).

We note that an alternative common approach is to remove or add factors in asset pricing models to examine the effect on the results. Nevertheless, we find remarkably low correlation among our factors – in particular between the macroeconomic variables. Therefore, it is reasonable to presume that to add or remove factors will not substantially affect the results.

Lewellen et al. (2010) suggests to expand the test assets in the FF-models simply beyond the commonly used size and B/M portfolios to improve the power of the R^2 statistic. The reasoning behind this is the strong factor structure of the two portfolios. They further argue that it is not necessarily legitimate to conclude that a model is successful in explaining expected returns if it works only on the two particular portfolios. Also, the factors in the FF-models might give an apparent advantage over the macroeconomic factors in explaining expected returns, as the FF factors are constructed to do so. Following this, we find it interesting to assess whether the performance of both the CAPM, the macroeconomic model and FF-models is similar across different test assets. Thus, we argue that a good model should provide fairly stable results regardless of the set of test assets used.

5.0 Data

The models in this study are primarily based upon the models introduced in Chen et al. (1986) and Fama and French (1993, 2015) and requires the use of both macroeconomic and characteristic-based variables. After completing the necessary transformations of variables from levels to changes and changes in returns using logarithmic differences and demeaning of variables, we end up with a total of 329 monthly observations spanning from August 1990 to December 2017. We provide a comprehensive description of the transformations of the variables in the subsequent subsection (see also Table 1 for a summary), whereas the procedure of demeaning the variables is previously described in the methodology section. Moreover, we have adopted the use of logarithmic returns in the macroeconomic variables following Chen et al. (1986).

We have not found a sufficient amount of financial data for Norwegian firms prior to 1995 and have therefore created the factors RMW and CMA for the Norwegian stock market only from January 1995 to December 2017. This results in a total of 276 observations for the CMA and RMW variables.

5.1 Test Assets

We have collected the monthly returns on twenty-eight value-weighted portfolios that are sorted by B/M, momentum and industry to apply as main test assets in the main models. Ten portfolios are sorted by book-to-market, ten portfolios are sorted by momentum, whereas eight portfolios are sorted by industry, due to lack of sufficient data for two of the industry portfolios. The test assets are collected in full through Ødegaard[4], and the portfolios are sorted by similar criteria used to generate the factor portfolios. Estimates of the monthly the risk-free rate RF_t in the whole sample period are also collected through Ødegaard, and is subtracted from the monthly test asset returns $r_{i,t}$ to obtain the monthly excess returns of the portfolios $R_{i,t}$:

$$R_{i,t} = r_{i,t} - RF_t. \tag{24}$$

We have also obtained the monthly returns on the portfolios used as test assets (BS, ISM, ISB and SBM) in the robustness analysis through Ødegaard.

5.2 Risk Factors

The basic time-series data required to create the macroeconomic factors are collected from various sources. The variables are collected and calculated without considering the growth in inflation, i.e. they are in nominal terms. In the following is a description of how each of the variables are constructed, and a summary of the definitions, sources and transformations of the factors are found in Table 1.

Table 1: Definitions of Series and Transformations

Variables	*Definitions of basic series and sources*
CPI	Natural logarithm of the Consumer Price Index (Statistics Norway).*
OILPRICE	Natural logarithm of the futures price of North Sea Brent Crude oil (LCOc1) (Macrobond).
MARKET	Natural logarithm of the closing price for the Oslo Børs All-share index (Macrobond).
USD/NOK	Natural logarithm of the USD/NOK exchange rate (Norges Bank).
10Y	Natural logarithm of the monthly average of daily quotes on Norwegian 10-year government bonds (Norges Bank).
3Y	Natural logarithm of the monthly average of daily quotes on Norwegian 3-year government bonds (Norges Bank).
INDPROD	Natural logarithm of the index of production, manufacturing ex. petroleum-related industries (Statistics Norway).*
CGI	Natural logarithm of the domestic trade, households consumption of goods index (Macrobond).*

[4] Bernt Arne Ødegaard have provided public asset pricing data for the Oslo Stock Exchange. Retrieved from: http://finance.bi.no/~bernt/financial_data/index.html

HML	Factor portfolio as calculated by Fama and French using Norwegian data (Ødegaard).
SMB	Factor portfolio as calculated by Fama and French using Norwegian data (Ødegaard).
RMW	Factor portfolio as calculated by Fama and French using Norwegian data. Construction of the factor is described in detail in section 5.3.
CMA	Factor portfolio as calculated by Fama and French using Norwegian data. Construction of the factor is described in detail in section 5.3.

***Seasonally adjusted series.**

Transformations	*Definitions of transformations*
$I_t = CPI_t - CPI_{t-1}$	Monthly inflation.
$INF_t = I_t - I_{t-1}$	Monthly change in inflation.
$OIL_t = OILPRICE_t - OILPRICE_{t-1}$	Monthly change in the price of North Sea Brent Crude oil.
$MKT_t = MARKET_t - MARKET_{t-1}$	Monthly return on the Oslo Børs All-share index.
$EMKT_t = MKT_t - RF_t$	Excess monthly return on the Oslo Børs All-share index.
$FX_t = USD/NOK_t - USD/NOK_{t-1}$	Monthly change in the USD/NOK exchange rate.
$3GB_t = 3Y_t - 3Y_{t-1}$	Monthly change in 3-year government bonds.
$10GB_t = 10Y_t - 10Y_{t-1}$	Monthly change in 10-year government bonds.
$TS_t = 10GB_t - 3GB_{t-1}$	Monthly term spread between the 10-year and 3-year bonds.
$CON_t = CGI_t - CGI_{t-1}$	Monthly change in consumption.
$IP_t = INDPROD_t - INDPROD_{t-1}$	Monthly growth rate of Norwegian industrial production.

5.2.1 Inflation

The consumer price index for Norway is collected through Statistics Norway and yields a monthly seasonally adjusted time series. After taking the natural logarithm of the prices, we obtain the series CPI. The monthly inflation, I_t is then computed as:

$$I_t = CPI_t - CPI_{t-1} \tag{25}$$

where the subscript t denotes the CPI value at the end of time t, whereas $t-1$ denotes the one-month antecedent CPI value. This subscript convention is adopted throughout the study.

Further, by taking the first difference of the inflation series:

$$INF_t = I_t - I_{t-1} \quad (26)$$

we obtain the series of unexpected monthly changes in inflation, as we assume that the expected value of INF_t at time $t-1$ is equal to INF_{t-1} i.e. $E[INF_t|INF_{t-1}] - INF_t = 0$. This expectation is also assumed for the following factors.

5.2.2 Oil price

The price series of LCOc1 oil futures contracts are collected through Macrobond and yields monthly closing prices for ICE Brent Crude oil denominated in US dollars (USD). We obtain the series $OILPRICE$ by taking the natural logarithm of the monthly prices. Furthermore, the monthly change in the price of crude oil is computed as:

$$OIL_t = OILPRICE_t - OILPRICE_{t-1}\ . \quad (27)$$

We follow the suggestion of Boyer and Filion (2007) that preserving this denomination will enable us to identify and isolate the impact of variations in the exchange rate independently of variations in the oil prices. Further, Brent Crude oil contracts are used rather than WTI, as European oil production tends to be priced relative to this oil (Bjørnland, 2009).

5.2.3 Market index

The series of monthly closing prices on the Oslo All-share index (OSEAX) are collected through Macrobond to proxy for the market return in Norway. The OSEAX is a value-weighted index that comprise all shares listed on Oslo Stock Exchange and it is adjusted for dividend payments (Oslo Børs, 2018). Firstly, we take the natural logarithm of the prices and obtain the series $MARKET$. Secondly, the monthly return on the market index is calculated as the first difference of the $MARKET$ series:

$$MKT_t = MARKET_t - MARKET_{t-1}. \quad (28)$$

Lastly, the monthly excess return on the market index is calculated by subtracting the risk-free rate:

$$EMKT_t = MKT_t - RF_t \quad (29)$$

where RF_t is the risk-free rate collected from Ødegaard.

5.2.4 Exchange rate

The monthly series of the exchange rate between the Norwegian krone and US dollar are collected through Norges Bank. The exchange rates are calculated by Norges Bank as monthly averages of the mid-points between bid and ask rates in the interbank market at a given time (Norges Bank, 2018). By taking the natural logarithm of the exchange rate series we obtain the series USD/NOK. The changes in the

USD/NOK exchange rates are then calculated as:

$$FX_t = USD_t/NOK_t - USD_{t-1}/NOK_{t-1}\ . \tag{30}$$

5.2.5 Term spread

We have collected the monthly average of daily quotes on government bonds from Norges Bank for bonds with a maturity of ten and three years. By taking the natural logarithm of the 3-year and 10-year bond quotes, we obtain the series $3Y$ and $10Y$, respectively. The logarithmic returns for the series are then generated as the first differences:

$$3GB_t = 3Y_t - 3Y_{t-1} \tag{31}$$

$$10GB_t = 10Y_t - 10Y_{t-1}\ . \tag{32}$$

The term spread variable is then calculated as:

$$TS_t = 10GB_t - 3GB_{t-1}\ . \tag{33}$$

We nevertheless note that although we calculate the term spread in similarity to Chen et al. (1986), we do not apply the yield on a treasury bill, but rather a 3-year government bond as the subtrahend. This is due to lack of treasury bills data from Norges Bank prior to February 2003.

5.2.6 Consumption

The households' consumption of goods index for the domestic trade in Norway is collected through Macrobond and yields a monthly seasonally adjusted time series. The consumption series CGI are constructed by taking the natural logarithm of the time series. Taking the first difference of the CGI series:

$$CON_t = CGI_t - CGI_{t-1} \tag{34}$$

yields the growth rates in nominal household consumption. However, the consumption figures are not disclosed until one month after the time of the observation. Therefore, to make the variable contemporaneous with the other variables we adopt the approach of Gjerde and Saettem (1999) to led the variable one period.

5.2.7 Industrial production

The index of production for Norway is collected through Statistics Norway and yields a monthly seasonally adjusted time series. The collected production index focuses primarily on the manufacturing industry and excludes petroleum-related industries. Taking the natural logarithm of the collected index of production, we obtain the series $INDPROD$. The industrial production factor is then constructed as:

$$IP_t = INDPROD_t - INDPROD_{t-1} \tag{35}$$

which yields the monthly growth rate in the Norwegian industrial production. In similarity to the consumption variable, we follow Chen et al. (1986) and Gjerde and Saettem (1999) and allow the subsequent statistical work to lead it by one month.

5.2.8 HML and SMB

We have collected monthly returns for the Fama and French benchmark factors HML and SMB through Ødegaard, which are calculated for the Norwegian stock market. Ødegaard constructs the HML and SMB factors by double sorting the stocks on the Norwegian stock market into six portfolios and further compute the factors as:

$$SMB = \frac{SV+SN+SG}{3} - \frac{BV+BN+BG}{3} \tag{36}$$

and

$$HML = \frac{SV+BV}{2} - \frac{SG+BG}{2} \tag{37}$$

where SV is Small Value, SM is Small Neutral, SG is Small Growth, BV is Big Value, BN is Big Neutral, and BG is Big Growth portfolios.

Thus, the SMB is the difference in returns between a portfolio consisting of small stocks and a portfolio consisting of large stocks, whereas the HML is the difference in returns between a portfolio with high book-to-market value stocks and a portfolio with low book-to-market growth stocks. The construction of the two last FF factors CMA and RMW is described in detail in the following subsection.

5.3 Construction of the CMA and RMW factors

In order to test the five-factor model introduced in Fama and French (2015) in Norway, we have constructed the operating profitability factor (RMW) and investment factor (CMA) for the Norwegian stock market. The RMW and CMA factors are acquired for the years 2003-2011 through former students[5] that have constructed the factors according to Fama and French (2015). Following the same procedure as the former students and Fama and French (2015), we have constructed the factors for the years 1995-2002 and 2012-2017 due to a substantial amount of missing data on firms listed on the OSE prior to 1995.

In constructing the operating profitability and investment factors, we started by collecting monthly returns for all stocks listed at the OSE in the periods 1995-2002 and 2012-2017 through OBI. We however note that stocks with presence on the OSE less than 12 months are excluded from the sample. Secondly, we obtained annual accounting data for all the listed firms from the Bloomberg Terminal, including each firm's market capitalizations, revenues, interest expenses, costs of goods sold, selling, general and administrative expenses, book equity and total assets.

Following Kenneth R. French[6], operating profitability is defined as:

$$OP = \frac{Revenues_t - COGS_t - Interest\ expenses_t - SG\&A_t}{Book\ Value_{t-1}} \tag{38}$$

whereas, investment is defined as:

$$INV = \frac{Total\ assets_{t-1} - Total\ assets\ _{t-2}}{\text{Total assets}\ _{t-2}}. \tag{39}$$

As the returns for the SMB and HML factors obtained through Ødegaard are calculated as value-weighted averages, we adopt this convention for the RMW

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[5] https://brage.bibsys.no/xmlui/bitstream/handle/11250/2442651/MSc0252016.pdf?sequence=1
[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

and CMA factors. Fama and French (2015) splitted the data for the US stock market into six portfolios using the 30th and 70th percentile as breakpoints to construct the portfolios. Due to the limited number of observations, we have utilized a 2x2 sorting, and used the median as breakpoints. Following Fama and French (1993), the financial data for $t-1$ for each of the returns in the corresponding portfolio is calculated as the value-weighted average of the constituent stocks from July of year t to June of $t+1$, and the portfolios are reformed in June of $t+1$.

To construct the operating profitability portfolio, we first defined the median as the breakpoints to be able to allocate the portfolios. Further, we ranked all the listed stocks on profitability, hence, we allocated the stocks into Robust and Weak portfolios. Then, by using the market capitalization median we grouped the stocks into Small and Big portfolios. Thus, we obtain four portfolios as seen in Table 2. A similar procedure was used to obtain the four portfolios for the investment factor by firstly ranking all the stocks on investment to obtain the Conservative and Aggressive portfolios. Finally, grouping the stocks into Small and Big portfolios, we obtained four portfolios as seen in Table 2. The factor Robust Minus Weak (RMW) is calculated as shown in eq. (40), i.e. as the average return of the Small Robust (SR) and Big Robust (BR) minus the average return of the Small weak (SW) and Big Weak (BW):

$$RMW = \frac{(SR+BR)}{2} - \frac{(SW+BW)}{2} \tag{40}$$

Similarly, the factor Conservative Minus Aggressive (CMA) is calculated as the average return of the Small Conservative (SC) and Big Conservative (BC) minus the average return of the Small Aggressive (SA) and Big Aggressive (BA):

$$CMA = \frac{(SC+BC)}{2} - \frac{(SA+BA)}{2} \tag{41}$$

Table 2: Portfolio characterization

Operating Profitability	Investment
Robust	**Conservative**
Small Robust (SR)	Small Conservative (SC)
Big Robust (BR)	Big Conservative (BC)
Weak	**Aggressive**
Small Weak (SW)	Small Aggressive (SA)
Big Weak (BW)	Big Aggressive (BA)

Thus, we obtain the operating profitability factor RMW and the investment factor CMA for the Norwegian stock market in the period 1995-2017. We emphasize that the construction of the factor portfolios for this period are among our contributions to the literature. Thus, we can share the factor data with students or whoever might be interested upon request.

5.4 Descriptive statistics and univariate analysis

After demeaning the macroeconomic variables following Chen et al. (1986), that is, extracting the unpredictable component of the returns, we obtained mean estimates close to zero as seen in Table 3. There is nevertheless some dispersion in the mean of the variables where FX has the lowest mean of -9.73E-09, whereas the SMB has the highest of 7.9E-00. Further, there are some dispersion in the standard deviations of the variables, where OIL has the highest of 8.6 and IP has the lowest of 1.5. We also note that several of the variables appear to be close to normally distributed as their skewness and kurtosis are near 0 and 3 respectively, and with low p-values for the Jarque-Bera test.

Table 3: Summary statistics of the variables

Variable	Mean	Median	Max	Min	St.dev.	Skewness	Kurtosis	Prob.
FX	-9.73E-09	-0.02	10.5	-6.1	2.4	0.31	3.84	0.06
IP	-5.63E-03	0.04	4.5	-5.3	1.5	-0.28	3.79	0.18
OIL	-3.13E-02	0.49	32.1	-36.0	8.6	-0.25	3.96	0.03
TS	-8.50E-04	-0.41	33.0	-30.8	7.2	0.57	6.05	0.00
INF	-7.66E-03	-0.03	1.9	-1.0	0.3	0.88	10.15	0.00
CON	-3.22E-02	0.06	4.7	-4.6	1.5	-0.02	3.40	33.6
MKT	2.82E-08	0.63	12.2	-27.9	5.9	-0.97	5.80	0.00
SMB	7.96E-00	0.84	22.1	-17.1	4.2	0.26	6.16	0.00
HML	7.62E-02	0.24	14.7	-16.6	4.8	-0.24	4.13	0.00
RMW	3.17E-01	0.11	11.4	-9.8	2.9	0.07	4.30	0.00
CMA	5.80E-01	0.27	16.6	-10.6	3.3	0.97	7.58	0.00
EMKT	3.29E-09	0.68	12.2	-28.1	5.9	-0.99	5.81	0.00

Note: All summary statistics in Table 3 are reported in percent, except for the skewness and kurtosis.

It is implicitly assumed when estimating using the OLS method that the explanatory variables are not correlated with one another. If the variables are highly correlated, the problem of multicollinearity may occur. Ignoring the presence of multicollinearity will affect the standard errors of the variables, which essentially will bias the significance and interpretation of the results of the coefficients. Additionally, multicollinearity among the variables will make the regression highly sensitive to minor changes in the variables, such that adding or removing an explanatory variable may lead to extensive changes in the coefficient values or significance of the other variables (Brooks, 2014, pp. 217-219).

From Panel A in Table 4, we see that the correlation among the macroeconomic variables are low overall. Hence, there are no show of multicollinearity among the variables. The highest correlation of 0.29 is between the market and oil variable, which is not completely unexpected as some of the largest companies in the market index are oil-related. Nevertheless, it is noteworthy that the correlation between the consumption variable and market variable is not higher, as the market tends to be a good proxy for the consumption. Further, from Panel B in Table 4, we see that the correlation between the variables are low as well, thus the variables are orthogonal to one another (Brooks, 2014, p. 217). The highest correlation of -0.47 in Panel B is between the excess return on the market and SMB variable. Thus, the low correlations between the variables overall does not indicate the presence of multicollinearity among the variables.

Table 4: Correlation between the variables

Panel A	CON	FX	INF	IP	MKT	OIL	TS
CON	1.00	-0.07	-0.04	0.10	0.15	0.07	-0.03
FX	-0.07	1.00	-0.01	-0.11	-0.10	-0.30	-0.08
INF	-0.04	-0.01	1.00	-0.02	-0.10	0.06	-0.04
IP	0.10	-0.11	-0.02	1.00	0.05	0.04	-0.01
MKT	0.15	-0.10	-0.10	0.05	1.00	0.29	0.04
OIL	0.07	-0.30	0.06	0.04	0.29	1.00	0.08
TS	-0.03	-0.08	-0.04	-0.01	0.04	0.08	1.00

Panel B	CMA	HML	EMKT	RMW	SMB
CMA	1.00	0.05	-0.03	-0.13	-0.01
HML	0.05	1.00	0.03	0.17	-0.13
EMKT	-0.03	0.03	1.00	-0.25	-0.47
RMW	-0.13	0.17	-0.25	1.00	0.00
SMB	-0.01	-0.13	-0.47	0.00	1.00

Note: Panel A report the correlation between the macroeconomic factors, whereas Panel B report the correlation between the characteristic-based factors.

According to Chen et al. (1986), autocorrelation in the variables implies the presence of an EIV problem. That is, the presence of significant fluctuations in the predictable component is captured by the factor loading if the predictable component is not removed and will thus bias the estimate of the factor loading. In our asset pricing study, we focus on the relation of the unpredictable components, i.e. the risk exposure.

In the original data we obtained, some of the macroeconomic variables exhibited significant autocorrelations. These results are however not reported, as extracting the unpredictable component of the returns following Chen et al. (1986) eliminated the significant autocorrelations. Further, variables such as CON and IP exhibited some seasonal autocorrelation at lag 12, which was eliminated when these were replaced with seasonally adjusted data. The results after demeaning the variables are found in Table 5, which displays the autocorrelations for the variables for their entire sample periods. The Ljung-Box statistic up to lag 12 with its corresponding p-value is also reported. The Ljung-Box test is a portmanteau test of linear dependence in time series, with a null hypothesis that all autocorrelation coefficients up to lag m are jointly zero (Brooks, 2014, p. 254). We however note that the HML has the lowest p-value of 0.10 for the Ljung-Box test, and hence indicate that there is no presence of significant autocorrelation among the variables.

Further, we have tested the variables for unit roots and non-stationarity. Non-stationarity in the data may lead to spurious regressions and hence impair the results of the model. For instance, unexpected changes in a variable in a stationary series will gradually disappear with time, whereas it will persist for infinity in a non-stationary series. Because it is inappropriate to simply examine the autocorrelation function to determine whether a series contains a unit root, we have conducted the Augmented Dickey-Fuller test for unit roots using the Akaike information criterion and the Kwiatkowski-Phillips-Schmidt-Shin test. The results from the tests are found in Appendix C. Thus, the results indicate the presence of neither unit roots nor non-stationarity in the variables

Table 5: Autocorrelations of the Variables

Symbol	ρ_1	ρ_2	ρ_3	ρ_4	ρ_5	ρ_6	ρ_7	ρ_8	ρ_9	ρ_{10}	ρ_{11}	ρ_{12}	LB*	Prob.**
CON	0.00	-0.01	0.00	-0.01	0.09	0.01	0.07	-0.09	-0.02	-0.01	-0.02	0.00	7.12	0.85
FX	0.04	-0.10	0.01	-0.02	-0.07	0.05	-0.06	-0.02	-0.06	0.03	0.02	-0.02	9.47	0.66
INF	0.00	0.01	0.01	-0.01	-0.06	0.01	0.06	0.08	0.00	0.04	-0.08	-0.12	12.20	0.43
IP	-0.02	0.00	-0.01	0.05	0.05	0.14	-0.01	-0.01	-0.07	0.02	0.03	-0.03	10.26	0.59
MKT	0.00	0.00	0.10	-0.02	-0.05	0.01	-0.02	-0.03	0.09	0.05	-0.02	-0.04	9.35	0.67
OIL	0.03	-0.02	-0.09	-0.05	0.03	0.05	-0.04	-0.05	-0.08	0.07	0.09	-0.04	12.43	0.41
TS	0.00	0.00	0.01	0.02	-0.05	-0.02	-0.05	-0.02	-0.05	0.01	-0.04	0.03	3.62	0.99
CMA	0.02	-0.02	-0.07	-0.03	-0.10	0.14	-0.14	-0.05	-0.04	0.04	-0.06	0.14	12.44	0.41
HML	0.09	-0.01	0.08	-0.05	-0.14	0.02	-0.01	-0.09	0.08	0.01	0.03	0.05	18.68	0.10
EMKT	-0.01	0.01	0.11	-0.01	-0.04	0.02	-0.02	-0.02	0.10	0.06	-0.02	-0.03	10.01	0.62
RMW	0.12	-0.06	-0.02	-0.02	0.03	0.01	0.04	-0.03	0.06	0.05	0.01	0.00	10.39	0.57
SMB	-0.09	0.03	-0.04	0.05	-0.11	-0.01	-0.01	-0.01	0.05	0.04	0.06	-0.02	10.83	0.54

Note: CON = monthly change in consumption; FX = monthly change in the USD/NOK exchange rate; INF = monthly change in inflation; IP = monthly growth rate of Norwegian industrial production; MKT = monthly return on the OSEAX; OIL = monthly change in the price of North Sea Crude oil; TS = monthly term spread between the 10-year and 3-year government bonds; HML, SMB, RMW and CMA = factor portfolios as calculated by Fama and French for the Norwegian stock market.
*Ljung-Box statistic calculated up to lag 12. **P-value for Ljung-Box statistic.

6.0 Main empirical results and discussion

In the first subsection we assess which test assets yields the highest dispersions in the expected returns and the factor loadings. These test assets are used in the main model in an attempt to obtain less estimation error in the factor loadings. In the second subsection, we examine which factors are priced in the Norwegian stock market using the main test assets. Further, we discuss the implications and interpretations of the results on the macroeconomic model in the third subsection. In the fourth, fifth and sixth subsections we compare the models by analysing the intercepts and the goodness of fit statistics of the models, in addition to a robustness analysis.

6.1 Dispersions in the expected returns and the factor loadings in the test assets

Lewellen et al. (2010) and Kan et al. (2013) suggest adding other portfolios such as industry portfolios in addition to the typical size and B/M portfolios as test assets in the FF models. Therefore, we have tested which of the collected industry, size, B/M and momentum portfolios yields the highest dispersions. The test assets with the highest dispersion will be applied as main test assets in the models.

Following that the estimates of the risk premia are a function of both the factor loadings and returns, the descriptive statistics for the set of test portfolios' returns are provided in Appendix D. We can see that the average maximum returns are largest in the industry and momentum portfolios of 0.56 and 0.33 in Panel A and C, whereas the B/M and size portfolios in Panel B and D both yields lower results of 0.30. Further, we see that the lowest average minimum returns of -0.32, -0.29 and -0.27 are found in the industry, B/M and momentum sorted portfolios respectively. Moreover, we find that the average standard deviation of the returns of 0.09, 0.08 and 0.08 are largest in the industry, B/M and momentum sorted portfolios respectively. Hence, considering the dispersion in the expected returns, the test portfolios that are currently favored are the industry, B/M and momentum sorted portfolios.

The descriptive statistics for the estimated factor loadings for each set of test portfolios in the four models are provided in Appendix E. The two largest average maximum factor loadings of 0.77 and 0.76 are found in Panel A and D, i.e. for the IBM and ISB portfolios respectively. These portfolios also yield the lowest factor loadings of -0.19. Moreover, the portfolios have the two highest average standard deviations of factor loadings of 0.24 and 0.23, respectively. Thus, we find that the IBM portfolios yields a marginally yet higher dispersion in factor loadings than the ISB portfolio.

6.2 Results from the Fama-MacBeth Procedure

Table 6 reports our results from the Fama-MacBeth procedure for the CAPM, the macroeconomic model, the FF3 model and the FF5 model.

Panel A shows the results for the CAPM. As we can see, the excess market factor is significant, which is consistent with the predictions of the CAPM that the market should be the only priced factor. Panel B shows that the consumption, market and term spread factors are significant for the macroeconomic model. Because we find multiple priced variables, including the market, this is more consistent with the predictions of the APT and the ICAPM rather than the CAPM. Also, we note that the intercept for the macroeconomic model is significant with a negative coefficient estimate. Furthermore, the R^2 for the macroeconomic model is the highest of 0.41. Panel C yields the results for the FF3 model. Interestingly, the only coefficient that yields a significant coefficient is the SMB factor, which is rather inconsistent with the findings in Fama and French (1993). By extending the FF3 model with the RMW and CMA factors, we obtained the results for the FF5 model in Panel D. Both RMW and SMB are found significant. This result is noteworthy, as adding the RMW and CMA factors to the FF3 only result in the RMW and SMB factor being significant. Thus, the market factor and HML is not found priced in neither the FF3 or FF5, whereas the CMA factor is not priced in the FF5.

An important finding in our result indicates that the importance of the value factor, HML, decreases by extending the FF3 model to the FF5 model, which is consistent with the findings in Fama and French (2015). Hence, the decrease in the HML factor indicates that the value factor might be redundant for describing the average returns in the Norwegian stock market. Further, we interestingly find that the CMA factor is not priced in the FF5. This is consistent with the recent findings in Fama and French (2017) indicating the CMA not being priced in Europe.

Table 6: Results from second-pass regressions. All coefficients x 10.

Panel A: CAPM

1990-2017	λ_0	λ_{EMKT}	R^2
Coeff.	-0.101	0.242	0.07
T-ratio	-1.043	2.220**	

Panel B: Macroeconomic model

1990-2017	λ_0	λ_{INF}	λ_{CON}	λ_{IP}	λ_{FX}	λ_{MKT}	λ_{OIL}	λ_{TS}	R^2
Coeff.	-0.180	0.004	0.165	-0.001	0.062	0.304	0.164	0.353	0.41
T-ratio	-1.815*	0.346	3.248***	-0.024	1.034	2.783***	0.610	1.837*	

Panel C: Fama French three factor

1990-2017	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	R^2
Coeff.	0.062	0.045	-0.015	0.161	0.22
T-ratio	0.648	0.417	-0.382	2.195**	

Panel D: Fama French five factor

1995-2017	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	λ_{RMW}	λ_{CMA}	R^2
Coeff.	0.116	-0.025	-0.003	0.148	-0.175	0.052	0.31
T-ratio	1.198	-0.231	0.075	2.060**	2.712***	0.641	

Note: Table 6 reports the results from the second-pass regressions using the Fama-MacBeth procedure. All coefficients are multiplied by 10. Panel A: the CAPM, Panel B: the macroeconomic model, Panel C: the FF3, Panel D: the FF5 model using the monthly excess return on the 28 IBM portfolios. Column (2) shows the intercept from the regressions, column (3-9) shows the risk premium estimates (λ_i) with the corresponding t-statistics and R^2 statistics. Asterisks *, ** and *** indicate the level of significance for the risk premium estimates at respectively the 10, 5 and 1 percent significance level.

Furthermore, the macroeconomic model in Panel B yields the highest explanatory power with an R^2 statistic of 0.41, whereas the second highest is the FF5 in Panel D with an R^2 of 0.31. These R^2 results are not surprising considering that the macroeconomic has a total of 7 explanatory variables, whereas the FF5 has 5 explanatory variables compared to only 3 and 1 in the FF3 and CAPM, respectively. We note that the FF5 does not consist of a subset of variables from the macroeconomic model, and hence the macroeconomic model is not bound to have a higher R^2 than the FF5 simply because it has 2 additional explanatory variables. Nonetheless, because the FF3 and the CAPM use a subset of the variables in the FF5, these are bound to have a lower R^2 than the FF5. Further, the intercept estimates are negative for both the CAPM and the macroeconomic model, whereas it is positive for the FF3 and FF5 models.

Interestingly, the macroeconomic model yields the highest intercept in absolute terms and is the only significant intercept estimate. As we expect that a good model will yield a small and insignificant intercept, this result does not favor the macroeconomic model. However, the FF3 and FF5 evidently has less pricing errors with positive and insignificant intercept estimates of 0.062 and 0.116, respectively.

Thus, we find that the FF5 model is the best of the four estimated models, based on its relatively high R^2 statistic and the positive insignificant intercept.

6.3 Implications and interpretations of the results in the macroeconomic model

If the expected risk premium (i.e. the risk premium coefficient) differs from zero, the economic variable is priced (Ferson and Harvey, 1991). The coefficients from the macroeconomic model in Table 6 shows that the consumption, foreign exchange rate, inflation, market, oil price and term structure are positive, while the industrial production and its intercept is negative. The consumption variable, intercept and market are the only coefficients found significant. In the following, we will discuss some possible implications and interpretations for the results.

We note that previous studies examining the US stock market such as Chan et al. (1985), Chen et al. (1986) and Ferson and Harvey (1991) reports negative inflation risk premia estimates of the same magnitude as our estimate. Their reported coefficients in percent are 0.09, 0.07, and 0.04, respectively. However, their findings are not consistent with ours due to differences in the signs. Moreover, following Chan et al. (1985), a negative risk premium is plausible in an economic aspect, provided that investors prefer assets that have returns positively correlated with inflation, and if this is a governing factor. Thus, our findings of a positive risk premium are rather surprising, as it might indicate that investors in the Norwegian stock market does not select assets based on its correlation with inflation, i.e. tendency to hedge against inflation. Nevertheless, we do emphasize that the inflation risk premium was found insignificant.

According to Lucas (1978), Breeden (1980) and Cox et al. (1985), in an intertemporal asset pricing model, an asset will be priced according to its covariance with aggregate consumption. Chen et al. (1986) did not find any significant portion of consumption, i.e. it is not a priced factor in the US. In contrast, our findings show a significant consumption coefficient. This may indicate that investors that participate in the Norwegian stock market require compensation for the uncertainty to their investment opportunity set related to investing in risky assets. Thus, we find that the consumption-based risk is priced as predicted in the ICAPM. Moreover, we find that the consumption beta is not the only priced risk, which is consistent with both the ICAPM and APT framework considering our findings indicates multiple risk factors.

The term spread in the macroeconomic model yields a significant risk premium coefficient. In contrary to the findings in Chen et al. (1986) that reports a negative risk premium for the term spread in the US, our findings yield a positive premium. This result is rather surprising, as it might indicate that the interest rate does not represent an alternative investment opportunity. Further, we note that the positive coefficient we find may indicate that stocks with returns that have an inverse relation to increases in the term spread are, other things equal, less valuable (Chen et al., 1986).

We find that both the oil price factor and exchange rate factor are positive and insignificant. Chen et al. (1986) present similar results for the oil risk premium, i.e. the oil price risk is not priced in the US market. Following the ICAPM, state variables that affect the investment opportunity set should be priced. Thus, our results may indicate that as neither the oil price nor exchange rate factor are priced, these risk factors do not represent systematic risk nor changes the investment opportunity set for investors participating in the Norwegian stock market.

We find that the risk premium of the market factor is both significant and positive. This is not a surprising result, and indicates that the market portfolio is priced, as predicted in the CAPM, ICAPM and APT. However, it is not the only priced factor as predicted by the CAPM. Considering the null hypothesis that the CAPM is true, the CAPM is not supported, as the results indicate that multiple risk factors are priced and might favor a framework such as the APT and ICAPM explaining expected returns based on multiple risk factors. We also note that the market factor in the macroeconomic model may capture, in an efficient market, the expected changes in other macroeconomic variables than those we have included in the model.

Typically, the industrial production factor is used to proxy for the level of real economic activity, and an increase in industrial production would yield economic growth. Chen et al. (1986) reports a significant and positive risk premium for the industrial production in which they suggest reflects the value of insuring against real systematic production risk. However, we obtain opposing results, that is, an insignificant and negative industrial production coefficient. Thus, an explanation for the negative premium might be that the investors participating in the Norwegian stock market does not value insurance against real systematic production risk. Further, we argue that an alternative explanation is that the negative risk premium might indicate that industrial production does not capture the development of value added in industries, and the factor does not reflect the state of the production level in Norway.

6.4 Intercept analysis

Table 7 reports the average alpha, the average of the absolute values for the alphas, the standard errors, the computed GRS statistic and its corresponding p-value for the time-series intercepts using the main test assets. We have reported the GRS statistic for the models, but we will not discuss the GRS results on the time-series intercepts for the macroeconomic model because the computed GRS statistic is only valid for models using portfolio returns such as the CAPM, the FF3 and the FF5 models.

Recalling that an intercept close to zero may indicate small pricing errors, we note that both the FF3 and the FF5 models has the lowest average time-series intercepts of 0.012. Nevertheless, the CAPM yields a marginally higher average intercept of 0.013. It is also noteworthy that the average of the absolute values for the intercepts in all models are equal to the average values, because all estimated time-series intercepts were positive. Further, Table 7 exhibit low standard errors for all models, however particularly both the FF3 and the FF5 models.

The computed GRS statistics for each model in Table 7 exhibit a relatively high GRS statistic and low p-value for all models. Thus, we reject the null hypothesis that all intercepts equal zero, which indicate that the models are missing priced factors. Interestingly, these GRS results are quite similar to those found in Fama and French (2015). Applying a set of different test assets, Fama and French (2015) reject the joint hypothesis that all their seven tested models comprising the excess return on the market, SMB, HML, RMW and CMA equal zero. Thus, Fama and French (2015) argue that their GRS statistics indicate that all their models are incomplete descriptions of expected returns, which is consistent with our findings on the CAPM, the FF3 and the FF5.

We emphasize that finding a good model to compute expected returns are among the objectives of this study, i.e. find the best model of the four specific models we test. Therefore, it is interesting to assess the GRS statistic not solely based on its absolute value, but rather its value relative to the other models. The CAPM yields the highest GRS statistic of 2.581. This is an expected result, taking the average intercepts into account and as the CAPM exhibited higher pricing errors and standard errors. Further, the GRS statistics for the FF3 and the FF5 models of 1.888 and 2.063, respectively, also yields an expected result, due to smaller errors.

Hence, the estimated time-series intercepts, their average values, standard errors and GRS statistics favor the efficiency of the FF3 model compared to the other models using the main test assets. The FF3 model has a similar estimated intercept and standard error as the FF5, however a smaller GRS statistic. Interestingly, this result is different from Fama and French (2015), who find that for six different sets of test assets, the FF5 produces a lower GRS statistic than the FF3. Thus, it is noteworthy that adding the two factors CMA and RMW in our models does not yield an improvement to the FF3. However, we do not use the same test portfolios as Fama and French (2015), which might be the rationale behind the differences.

Further, we stress the fact that we have not included the macroeconomic model in the analysis of time-series intercepts. Therefore, even though we find that the FF3 yields the best time-series intercept results, we cannot conclude that the FF3 is more efficient than the macroeconomic model and have less pricing errors based solely on these results. Therefore, we also assess the cross-sectional intercept estimates.

Table 7: Statistics for time-series intercept analysis

Panel A: CAPM

1990-2017	$\overline{\alpha}$	$\lvert\overline{\alpha}\rvert$	$\overline{SE}$	GRS	Prob. (GRS)
	0.013	0.013	0.001	2.581	0.000

Panel B: FF3

1990-2017	$\overline{\alpha}$	$\lvert\overline{\alpha}\rvert$	$\overline{SE}$	GRS	Prob. (GRS)
	0.012	0.012	0.000	1.888	0.005

Panel C: FF5

1995-2017	$\overline{\alpha}$	$\lvert\overline{\alpha}\rvert$	$\overline{SE}$	GRS	Prob. (GRS)
	0.012	0.012	0.000	2.063	0.001

Note: The first column shows for which model the data is reported for, and its corresponding sample years. The second column shows the average intercept of the estimated time-series intercept coefficients. The third column shows the average estimated intercept estimates. The fourth column shows the average standard errors of the models. The fifth column shows the GRS statistics, whereas the sixth column shows the corresponding p-values.

The results in Table 6 display that only the macroeconomic model yields a significant cross-sectional intercept. The intercept of the macroeconomic model is -0.180 and is the lowest intercept estimate. This indicates that the intercept in the macroeconomic model is significantly different from zero and thus the model is missing priced factors. In comparison, the CAPM exhibit a negative cross-sectional intercept as well, however insignificant. Moreover, both the FF3 and FF5 in Panel C and Panel D exhibit insignificant and positive intercepts of 0.062 and 0.116 respectively. The FF3 yields the lowest absolute value of the cross-sectional intercepts. Because the models are not significantly equal to zero, we cannot conclude that neither the CAPM, FF3 nor FF5 are missing priced factors. Nevertheless, because we expect that a good model will have a relatively small intercept that should be statistically insignificant (Adrian, Etula and Muir, 2014; Cochrane, 2000, p. 78), we find that the cross-sectional intercept estimates favor the FF3.

6.5 Analysis of goodness of fit

For the CAPM, the R^2 statistics obtained in the different test portfolios are quite similar, where the highest R^2 of 0.10 is obtained in the BS test asset (Appendix F, Table F.1.) and the lowest R^2 is obtained in the SBM portfolio (Appendix F, Table F.4.) of 0.06. Further, in the macroeconomic model, the BS portfolio yields the highest R^2 of 0.67, while the SBM portfolio yields the lowest R^2 of 0.39.

Applying the different test assets in the FF3 model, we obtain quite similar R^2 results. The BS portfolio yields the highest R^2 of 0.29. In comparison, our main test asset, IBM, reports a R^2 of 0.22. Further, the SBM yields the lowest R^2 of 0.19. In the FF5 model the highest R^2 of 0.48 is reported in the BS portfolio, while the lowest R^2 of 0.29 is reported in the SBM portfolio. As expected, the R^2 of the CAPM is consistently outperformed by the R^2 of the FF3, whereas the R^2 of the FF3 is consistently outperformed by the R^2 of the FF5. Because both the CAPM and FF3 are obtained using a subset of the FF5 factors, however fewer factors, this consequently always yields a higher R^2 for the FF5 model.

As our results indicate, comparing the performance of the estimated models based merely on the reported cross-sectional R^2 as a measure of the goodness of fit or explanatory power may yield misleading conclusions. Yet, we do find that the R^2 of the macroeconomic model is consistently higher than the other models. Thus, the macroeconomic model is favored in terms of its cross-sectional explanatory power of returns on all compositions of the test assets.

6.6 Robustness analysis

We have estimated the models using a set of different test assets to examine the stability in results. The results are reported in full in Appendix F, and a summary for each model is given in Table 8. We have argued that a good model will show less dispersion in the results when estimating the models using the same factors but with different sets of test portfolios.

The results for the CAPM model are shown in Table 8, and reports a negative intercept for the IBM portfolio, whereas it is positive for the remaining test assets. Thus, IBM yields the lowest estimate of -0.101, whereas the highest is 0.351 for the ISB portfolio. The intercept is significant only for the BS, ISM and ISB portfolio. Further, the market factor is found negative in three of the five different test assets, and significant in three as well. It is found positive only using the IBM and SBM test assets. Moreover, the highest R^2 statistic of 0.12 is obtained in the ISM and ISB test assets, whereas SBM yields the lowest of 0.06. Thus, there is some dispersion in the estimates of the intercept and market, both in terms of the signs, their values and significance. The R^2 statistic is however quite similar for the different test assets.

In Table 8, the macroeconomic model yields a negative intercept in three of the models. Three of the intercepts are also found significant. The lowest intercept coefficient of -0.180 is found for the IBM test asset, whereas the highest of 0.433 is in the ISM test asset. For the inflation factor, it is found negative and significant only in the ISM, whereas it is positive in the other models. The highest inflation coefficient of 0.008 is found in the BS. Similar to the inflation factor, the consumption factor is found negative in only one model. It is however found significant only with positive coefficients. The highest estimate of 0.195 is found in the SBM, whereas the lowest of -0.008 is found in the ISB. Further, the industrial production factor yields three negative coefficients, where two of these are found significant. The coefficients range from -0.129 to 0.045 in the ISM and BS, respectively. The foreign exchange factor is consistently positive, however not significant. The highest estimate is 0.120, whereas the lowest is 0.026. Moreover, we find that the market factor is significant in four of the five models. It is found negative in the ISM and ISB test assets, and positive in the rest. The lowest coefficient of -0.315, and the highest of 0.304 are respectively found in the ISM and IBM. We further find that the oil factor has some changes across the models, with the lowest estimate of -0.649 in the BS, and the highest of 0.164 in the IBM. The oil factor is significant in only one instance, and it is negative in three of the models. The term spread factor is found significant in three models, and positive in only two. The term spread factor ranges from a significant coefficient of -0.377 using the ISB to a significant coefficient of 0.468 in the SBM.

Further, there are more dispersions in the R^2 statistics for the macroeconomic model than found in the CAPM. The highest R^2 statistic of 0.66 is found in the BS, whereas the lowest of 0.39 is found in the SBM. This gives a difference between the highest and lowest R^2 of 0.27, which is remarkably higher than the difference of 0.06 for the CAPM.

The intercept estimates for the FF3 model is consistently found positive in all models, with a range from 0.062 in the IBM to 0.231 in the BS test asset. The intercept is found significant in three instances. Further, the market is found positive using the IBM, whereas it is found negative in the remaining test assets. Obviously, the highest coefficient of 0.045 is found in the IBM, whereas the lowest of -0.124 is found in the BS. In similarity, the HML factor is found negative in four of the models. HML ranges from -0.011 in the ISB to 0.004 in the BS. Moreover, the SMB is found both significant and positive in all five models. The SMB has a narrow range of 0.066 between the highest and lowest coefficient. Lastly, the R^2 is found to be 0.22 in the IBM and SBM, whereas it is 0.29 for the remaining test assets. Thus, the FF3 model yields a marginally higher dispersion of 0.01 between the highest and lowest R^2 than the CAPM.

In similarity to the FF3, the intercept estimates for the FF5 model are found positive in all five models, and significant in three. The highest coefficient of 0.313 is obtained using the SB, whereas the lowest of 0.116 is obtained in the IBM. In some similarity to the FF3, the market factor is found negative in all instances, but also significant in one of the models. The market factor ranges from -0.229 using the SBM to -0.025 using the IBM. The HML coefficient is negative in three of the models. In similarity to the FF3, none of the HML coefficients are found significant. The highest HML coefficient is 0.029, whereas the lowest is -0.060. Moreover, all SMB coefficients are found positive and significant, as in the FF3. The difference between the highest and lowest SMB estimate is 0.031. For the RMW factor, all coefficients are negative and significant, with a range from -0.124 to -0.179 using the ISM and SBM test assets respectively. The CMA factor is found positive in all instances, yet insignificant. The CMA factor has a dispersion of 0.087. Lastly, the reported R^2 for the FF5 models are consistently higher than for the CAPM and FF3, however significantly more spread. The difference between the highest and lowest R^2 is 0.19, which is remarkably higher than 0.06 and 0.07 for the CAPM and FF3, respectively.

Table 8: Summary of the second-pass regression results for all models using the different test assets. All coefficients x 10.

Panel A: CAPM

	λ_0	λ_{EMKT}	R^2
IBM	-0.101	0.242**	0.07
SB	0.181*	-0.052	0.10
ISM	0.334***	-0.189***	0.12
ISB	0.351***	-0.208***	0.12
SBM	0.024	0.113	0.06

Panel B: Macroeconomic model

	λ_0	λ_{INF}	λ_{CON}	λ_{IP}	λ_{FX}	λ_{MKT}	λ_{OIL}	λ_{TS}	R^2
IBM	-0.180*	0.004	0.165***	-0.001	0.062	0.304***	0.164	0.353*	0.41
SB	-0.081	0.008	0.121	0.045	0.104	0.185	-0.649	-0.214	0.66
ISM	0.433***	-0.034**	0.106	-0.129**	0.120	-0.315***	-0.516*	-0.214	0.44
ISB	0.405***	0.019*	-0.008	-0.108**	0.026	-0.207***	-0.329	-0.377*	0.46
SBM	-0.115	0.003	0.195***	0.032	0.070	0.229**	0.058	0.468**	0.39

Panel C: FF3

	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	R^2
IBM	0.062	0.045	-0.015	0.161**	0.22
SB	0.231**	-0.124	0.004	0.227***	0.22
ISM	0.175***	-0.074	-0.060	0.192***	0.29
ISB	0.171***	-0.057	-0.011	0.173***	0.29
SBM	0.122	-0.018	-0.012	0.195***	0.29

Panel D: FF5

	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	λ_{RMW}	λ_{CMA}	R^2
IBM	0.116	-0.025	-0.003	0.148**	-0.175***	0.052	0.31
SB	0.313**	-0.229	0.029	0.162*	-0.179**	0.135	0.48
ISM	0.205***	-0.117	-0.060	0.179***	-0.124**	0.059	0.38
ISB	0.212***	-0.119*	0.004	0.159***	-0.176***	0.052	0.37
SBM	0.156	-0.066	-0.002	0.168***	-0.158***	0.048	0.29

Note: Table 8 reports a summary from the second-pass regression using the Fama-MacBeth procedure with all sets of test assets. All coefficients are multiplied by 10. Column (1) shows the test asset applied, where IBM = 28 industry, B/M and momentum portfolios, SB = 20 size and B/M portfolios, ISM = 28 industry, size and momentum portfolios, ISB = 28 industry, size and B/M portfolios and SBM = 30 size, B/M and momentum portfolios. Panel A yields the result for CAPM, Panel B for the macroeconomic model, Panel C for the FF3 and Panel D for the FF5. Column (2-10) shows the estimated risk premia λ_i for each factor i, for each test asset in column (1). Asterisks *, ** and *** indicate the level of significance for the risk premium estimates at respectively the 10, 5 and 1 percent significance level.

Examining the models in terms of deviation in the signs of each coefficient applying different test assets, we see that both the FF3 and the FF5 models only have two coefficients that are not equal as the majority for each factor. Further, we see that it is consistently the same factors that are significant in both models, except for the excess return on the market in one instance in the FF5. Nevertheless, the CAPM has a small difference in the R^2 amongst the models of 0.06, whereas the FF3 closely follows with a difference of 0.07. However, both the CAPM and macroeconomic model deviates more in both the signs and significance of the factors than the FF3 and FF5. Thus, considering the low deviation in the R^2 of the FF3, it is concluded that the FF3 yields the most stability in results of the four estimated models when applying a set of different test portfolios.

7.0 Conclusion

This study investigates which risk factors are rewarded in the Norwegian stock market. In particular, we examine the macroeconomic variables motivated by Chen et al. (1986) in an APT framework: changes in inflation, changes in the oil price, return on the market portfolio, changes in the USD/NOK exchange rate, the term spread between 10-year and 3-year bonds, the growth rate in Norwegian industrial production and changes in consumption as proxies for systematic risk. In addition, we examine the characteristic-based factors HML, SMB, RMW and

CMA as introduced in Fama and French (1993, 2015). Moreover, we compare which of the CAPM, the FF3, the FF5 and macroeconomic model is superior in explaining expected returns.

To minimize estimation errors in the risk premia estimates, we firstly determine the set of test asset portfolios that yields the lowest dispersions in returns and factor loadings to use as main test assets. Further, the main test assets are applied when running the Fama-MacBeth procedure to examine which risk factors are priced in the stock market. Furthermore, we compare the performance of the four models based on an analysis of the intercepts, goodness of fit statistics and a robustness analysis.

Our findings indicate that exposure to the market portfolio is rewarded in the stock market, which is consistent with the prediction of the CAPM. Nevertheless, we find that the consumption and term structure variables are priced as well, with positive risk premia coefficients, which is consistent with the ICAPM as these are expected to affect the investment opportunity set for investors. Also, our findings indicate multiple priced factors which is also consistent with the APT framework. Surprisingly, the findings of a positive risk premium for the term spread variable might indicate that the interest rate does not represent an alternative investment opportunity for investors participating in the Norwegian stock market. In addition, the term spread variable may indicate that stocks with returns that have an inverse relation to increases in the term spread are considered, other things equal, less valuable.

Furthermore, the SMB and RMW factor mimicking portfolios are found to be priced in the stock market, which is consistent with the findings of Fama and French (2015). However, the market, HML and CMA factor mimicking portfolios are not priced in the Norwegian stock market, which deviates from the findings of Fama and French (2015). Moreover, it is interesting that our insignificant CMA factor is consistent with the findings in Fama and French (2017) that the CMA is redundant for Europe. Thus, excluding the market, HML and CMA factors from the FF5 model might not have a large effect on the description for average returns.

Moreover, we initially found that the FF5 model outperformed the other models in explaining the cross-section of expected returns based on its relatively high R^2 statistic and positive insignificant intercept applying the main test assets IBM. However, the analysis of time-series intercept estimates based on each model's average value, standard errors and GRS statistic favored the FF3 model. It is noteworthy that the time-series intercepts of the macroeconomic model were not considered, and consequently the FF3 was only shown to have less pricing errors than the CAPM and FF5. However, analyzing the cross-sectional intercepts yields the same conclusion. We cannot conclude that neither the CAPM, FF3 nor FF5 are missing priced factors, but as the FF3 yields the lowest insignificant absolute value of the cross-sectional intercept, the FF3 is favored. Furthermore, analysing the goodness of fit statistic, R^2 for a set of different test portfolios, we found that macroeconomic model consistently had higher cross-sectional explanatory power than the remaining models. This result was rather expected, considering the macroeconomic model consist of more variables than the other models. Lastly, examining the robustness of the models in terms of consistency in the significance of the coefficients, in the coefficient signs and R^2 statistics, our results indicate that the FF3 yields the most stability in results when applying different sets of test assets. Consequently, our findings support that the FF3 outperforms the CAPM, the FF5 and the macroeconomic model in explaining returns in the Norwegian stock market.

For future research, it would be interesting to assess whether a set of other macroeconomic variables proxy for systematic risk and thus are rewarded in the Norwegian stock market. For instance, including variables to add an international dimension to the model. Further, there are some noteworthy weaknesses to the methodology applied in this study. In particular, we emphasize that adjusting the standard errors of the coefficient estimates following Shanken (1992) could lead to less measurement error in the coefficient estimates. Moreover, we suggest extending the methods for comparing the asset pricing models in this study, for instance by including measures of goodness of fit such as the HJ-distance introduced in Hansen and Jagannathan (1997). Lastly, it would be interesting to compare the CAPM, the FF3 and FF5 used in this study with the recent Q-factor model.

8.0 Bibliography

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. (2017). Using individual stocks or portfolios in tests of factor models. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1106463

Asad, H. (2017). An Empirical Assessment of the Q-Factor Model: Evidence from the Karachi Stock Exchange Humaira Asad and Faraz Khalid Cheema. *Lahore Journal of Economics*, *22*(2), 117-138.

Asness, C. S. (1994). Variables that explain stock returns: simulated and empirical evidence. Ph.D. Dissertation, University of Chicago. Retrieved from http://www.worldcat.org/title/variables-that-explain-stock-returns-simulated-and-empirical-evidence/oclc/383860488

Azeez, A. A., & Yonezawa, Y. (2006). Macroeconomic factors and the empirical content of the Arbitrage Pricing Theory in the Japanese stock market. *Japan and the World Economy*, *18*(4), 568-591.

Benaković, D., & Posedel, P. (2010). Do macroeconomic factors matter for stock returns? Evidence from estimating a multifactor model on the Croatian market. *Business systems research journal: international journal of the Society for Advancing Business & Information Technology (BIT)*, *1*(1-2), 39-46.

Bjørnland, H. C. (2009). Oil price shocks and stock market booms in an oil exporting country. *Scottish Journal of Political Economy*, 56(2), 232-254.

Bodie, Z., Kane, A. & Marcus, A. (2014). *Investments* (10th Global Edition). Berkshire: McGraw-Hill Education.

Bodurtha, J.N., Cho, D.C., Senbet, L.W. (1989). Economic Forces and the Stock Market: An international Perspective. *The Global Finance Journal*, 1(1), 21-46.

Boyer, M. M., & Filion, D. (2007). Common and fundamental factors in stock returns of Canadian oil and gas companies. *Energy Economics*, 29(3), 428-453.

Breeden, D. T. (1980). Consumption risk in futures markets. *The Journal of Finance*, 35(2), 503-520.

Breeden, D., 1979, "An Intertemporal Asset Pricing Model with Stochastic Consumption and Investment Opportunities," *Journal of Financial Economics*, 7, 265-296.

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

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). *The econometrics of financial markets*. Princeton, NJ: princeton University press.

Carhart, M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, 52 (1): 57-82.

Chan, K. C., Chen, N. F., & Hsieh, D. A. (1985). An exploratory investigation of the firm size effect. *Journal of Financial Economics*, *14*(3), 451-471.

Chan, L. K., Jegadeesh, N., & Lakonishok, J. (1996). Momentum strategies. *The Journal of Finance*, 51(5), 1681-1713.

Chen, L., Novy-Marx, R., & Zhang, L. (2011). An alternative three-factor model. Retrieved from https://ssrn.com/abstract=1418117

Chen, N. F. (1991). Financial investment opportunities and the macroeconomy. *The Journal of Finance*, 46(2), 529-554.

Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business*, 383-403.

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

Cochrane, J.H. (2001). Empirical methods notes. [PDF file]. Retrieved from: https://faculty.chicagobooth.edu/john.cochrane/teaching/35150_advanced_investments/week_5_notes.pdf

Cox, J. C., Ingersoll Jr, J. E., & Ross, S. A. (1985). An intertemporal general equilibrium model of asset prices. *Econometrica: Journal of the Econometric Society*, 363-384.

Cuthbertson, K. (1996). Quantitative Financial Economics: Stocks, Bonds and Foreign Exchange. Chichester: John Wiley & Sons Ltd.

Diether, K. (2001). GRS Review [PDF file]. Retrieved from: http://faculty.chicagobooth.edu/eugene.fama/teaching/Reading%20List%20and%20Notes/GRS.pdf

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. (2015). “A five-factor asset pricing model.” *Journal of Financial Economics*, 116:1-22.

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.

Ferson, W. E., & Harvey, C. R. (1991). The variation of economic risk premiums. *Journal of Political Economy*, *99*(2), 385-415.

Flannery, M. J., & Protopapadakis, A. A. (2002). Macroeconomic factors do influence aggregate stock returns. *The Review of Financial Studies*, 15(3), 751-782.

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.

Gjerde, Ø., & Saettem, F. (1999). Causal relations among stock returns and macroeconomic variables in a small, open economy. *Journal of International Financial Markets, Institutions and Money*, 9(1), 61-74.

Gordon, M. J. (1962). *The investment, financing, and valuation of the corporation*. RD Irwin.

Gordon, M. J., & Shapiro, E. (1956). Capital equipment analysis: the required rate of profit. *Management science*, *3*(1), 102-110.

Hansen, L. P., & Jagannathan, R. (1997). Assessing specification errors in stochastic discount factor models. *The Journal of Finance*, 52(2), 557-590.

Hou, K., Xue, C., & Zhang, L. (2012). Digesting anomalies: An investment approach (Working Paper No. 18435). Cambridge, MA: National Bureau of Economic Research.

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. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2520929

Jarrow, R.A., Maksimovic, V., Ziemba, W.T. (1995). Handbooks in Operations Research and Management Science: Finance (vol. 9). Amsterdam: Elsevier BV.

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.

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.

Kaul, G. (1987). Stock returns and inflation: The role of the monetary sector. *Journal of Financial Economics*, 18(2), 253-276.

King, B. F. (1966). Market and industry factors in stock price behavior. *The Journal of Business*, *39*(1), 139-190.

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*, 47 (1): 13-37.

Lucas Jr, R. E. (1978). Asset prices in an exchange economy. *Econometrica: Journal of the Econometric Society*, 1429-1445.

Merton, R. (1973). An Intertemporal Capital Asset Pricing Model. *Econometrica*, 41, 867-887.

Miller, M. H., & Modigliani, F. (1961). Dividend policy, growth, and the valuation of shares. *the Journal of Business*, *34*(4), 411-433.

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

Norges Bank. (2018). US dollar (USD). Retrieved from https://www.norges-bank.no/en/Statistics/exchange_rates/currency/USD

Novy-Marx, R. (2013). The other side of value: The gross profitability premium. *Journal of Financial Economics*, *108*(1), 1-28.

Oslo Børs. (2018). Oslo Børs All-share index. Retrieved from: https://www.oslobors.no/ob_eng/markedsaktivitet/#/details/OSEAX.OSE/overview

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.

Ross, S. A. (1976). The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory*, 13, 341-360.

Schwert, G. W. (1989). Why does stock market volatility change over time?. *The Journal of Finance*, 44(5), 1115-1153.

Shanken, J. (1992). On the estimation of beta-pricing models. *The Review of Financial Studies*, 5(1), 1-33.

Shanken, J., & Weinstein, M. I. (1990). *Macroeconomic variables and asset pricing: Further results*. William E. Simon Graduate School of Business Administration, University of Rochester.

Shanken, J., & Weinstein, M. I. (2006). Economic forces and the stock market revisited. *Journal of Empirical Finance*, *13*(2), 129-144.

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.

Wongbangpo, P., & Sharma, S. C. (2002). Stock market and macroeconomic fundamental dynamic interactions: ASEAN-5 countries. *Journal of Asian Economics*, *13*(1), 27-51.

9.0 Appendices

Appendix A: The Fama-MacBeth Program

Note: we have provided the code used to estimate the macroeconomic model with the main variables and main test assets. To estimate the CAPM, FF3 and FF5, the variables shown in the code are simply replaced with the variables in the respective model. For instance, applying the code to the FF3 requires the user to change all occurrences of INF to EMKT, OIL to HML, FX to SMB and to delete the parts of the code containing the remaining variables TS, MKT, IP and CON. In similarity, to change the test asset portfolios for the models, the 28 test assets (I10, I15,…,M10) in the code are replaced with the new test asset. The program is obtained through Brooks (2014, pp. 656-658).

```
'OPEN EVIEWS WORKFILE WITH TRANSFORMED VARIABLES AND RETURNS, EXCEPT THE
'TEST ASSETS RETURNS
LOAD F:\PRICESANDRETURNS
'TRANSFORM TEST ASSET RETURNS INTO EXCESS RETURNS
I10=I10-RF
I15=I15-RF
I20=I20-RF
I25=I25-RF
I30=I30-RF
I35=I35-RF
I40=I40-RF
I45=I45-RF
B1=B1-RF
B2=B2-RF
B3=B3-RF
B4=B4-RF
B5=B5-RF
B6=B6-RF
B7=B7-RF
B8=B8-RF
B9=B9-RF
B10=B10-RF
M1=M1-RF
M2=M2-RF
M3=M3-RF
M4=M4-RF
M5=M5-RF
M6=M6-RF
M7=M7-RF
```

```
M8=M8-RF
M9=M9-RF
M10=M10-RF

'DEFINE THE NUMBER OF TIME SERIES OBSERVATIONS
!NOBS=329

'CONSTRUCT SERIES TO PUT FACTOR LOADINGS AND T-STATISTICS ON THE
'INTERCEPTS FROM STEP 1 AND RISK PREMIA FROM STAGE 2 INTO
SERIES BETA_C
SERIES BETA_T_C
SERIES BETA_INF
SERIES BETA_OIL
SERIES BETA_FX
SERIES BETA_TS
SERIES BETA_MKT
SERIES BETA_IP
SERIES BETA_CON
SERIES LAMBDA_C
SERIES LAMBDA_INF
SERIES LAMBDA_OIL
SERIES LAMBDA_FX
SERIES LAMBDA_TS
SERIES LAMBDA_MKT
SERIES LAMBDA_IP
SERIES LAMBDA_CON
SERIES LAMBDA_R2
SCALAR LAMBDA_C_MEAN
SCALAR LAMBDA_C_TRATIO
SCALAR LAMBDA_INF_MEAN
SCALAR LAMBDA_INF_TRATIO
SCALAR LAMBDA_OIL_MEAN
SCALAR LAMBDA_OIL_TRATIO
SCALAR LAMBDA_FX_MEAN
SCALAR LAMBDA_FX_TRATIO
SCALAR LAMBDA_TS_MEAN
SCALAR LAMBDA_TS_TRATIO
SCALAR LAMBDA_MKT_MEAN
SCALAR LAMBDA_MKT_TRATIO
SCALAR LAMBDA_IP_MEAN
SCALAR LAMBDA_IP_TRATIO
SCALAR LAMBDA_CON_MEAN
SCALAR LAMBDA_CON_TRATIO
SCALAR LAMBDA_R2_MEAN

'FOR LOOP CONSTRUCTS SERIES TO PUT THE CROSS-SECTIONAL DATA INTO
```

```
FOR !M = 1 TO 329
SERIES TIME{!M}
NEXT

'RUN TIME-SERIES REGRESSIONS FOR EACH PORTFOLIO IN WHOLE SAMPLE PERIOD
'AND SAVE BETA ESTIMATES AND T-STATISTICS FOR INTERCEPT ESTIMATES IN THE
'CONSTRUCTED SERIES
SMPL 1990:08 2017:12
!J=1
FOR %Y I10 I15 I20 I25 I30 I35 I40 I45 B1 B2 B3 B4 B5 B6 B7 B8 B9 B10 M1
M2 M3 M4 M5 M6 M7 M8 9 M10
EQUATION EQ1.LS {%Y} C INF OIL FX TS MKT IP CON
BETA_C(!J)=@COEFS(1)
BETA_T_C(!J)=@TSTATS(2)
BETA_INF(!J)=@COEFS(2)
BETA_OIL(!J)=@COEFS(3)
BETA_FX(!J)=@COEFS(4)
BETA_TS(!J)=@COEFS(5)
BETA_MKT(!J)=@COEFS(6)
BETA_IP(!J)=@COEFS(7)
BETA_CON(!J)=@COEFS(8)
!J=!J+1
NEXT

'RESORT THE DATA SO EACH COLUMN IS A MONTH AND EACH ROW IS RETURNS ON
'TEST ASSETS
FOR !K=1 TO 329
TIME!K(1)=I10(!K)
TIME!K(2)=I15(!K)
TIME!K(3)=I20(!K)
TIME!K(4)=I25(!K)
TIME!K(5)=I30(!K)
TIME!K(6)=I35(!K)
TIME!K(7)=I40(!K)
TIME!K(8)=I45(!K)
TIME!K(9)=B1(!K)
TIME!K(10)=B2(!K)
TIME!K(11)=B3(!K)
TIME!K(12)=B4(!K)
TIME!K(13)=B5(!K)
TIME!K(14)=B6(!K)
TIME!K(15)=B7(!K)
TIME!K(16)=B8(!K)
TIME!K(17)=B9(!K)
TIME!K(18)=B10(!K)
TIME!K(19)=M1(!K)
```

```
TIME!K(20)=M2(!K)
TIME!K(21)=M3(!K)
TIME!K(22)=M4(!K)
TIME!K(23)=M5(!K)
TIME!K(24)=M6(!K)
TIME!K(25)=M7(!K)
TIME!K(26)=M8(!K)
TIME!K(27)=M9(!K)
TIME!K(28)=M10(!K)
NEXT

'RUN THE SECOND STEP CROSS-SECTIONAL REGRESSIONS USING THE ESTIMATED
'BETAS
FOR !Z = 1 TO !NOBS
EQUATION EQ1.LS TIME!Z C BETA_INF BETA_OIL BETA_FX BETA_TS BETA_MKT
BETA_IP BETA_CON
LAMBDA_C(!Z)=@COEFS(1)
LAMBDA_INF(!Z)=@COEFS(2)
LAMBDA_OIL(!Z)=@COEFS(3)
LAMBDA_FX(!Z)=@COEFS(4)
LAMBDA_TS(!Z)=@COEFS(5)
LAMBDA_MKT(!Z)=@COEFS(6)
LAMBDA_IP(!Z)=@COEFS(7)
LAMBDA_CON(!Z)=@COEFS(8)
LAMBDA_R2(!Z)=@R2
NEXT

'ESTIMATION OF THE MEANS AND T-RATIOS FOR THE RISK PREMIA ESTIMATES FROM
'THE CROSS-SECTIONAL REGRESSIONS
LAMBDA_C_MEAN=@MEAN(LAMBDA_C)
LAMBDA_C_TRATIO=@SQRT(!NOBS)*@MEAN(LAMBDA_C)/@STDEV(LAMBDA_C)
LAMBDA_INF_MEAN=@MEAN(LAMBDA_INF)
LAMBDA_INF_TRATIO=@SQRT(!NOBS)*@MEAN(LAMBDA_INF)/@STDEV(LAMBDA_INF)
LAMBDA_OIL_MEAN=@MEAN(LAMBDA_OIL)
LAMBDA_OIL_TRATIO=@SQRT(!NOBS)*@MEAN(LAMBDA_OIL)/@STDEV(LAMBDA_OIL)
LAMBDA_FX_MEAN=@MEAN(LAMBDA_FX)
LAMBDA_FX_TRATIO=@SQRT(!NOBS)*@MEAN(LAMBDA_FX)/@STDEV(LAMBDA_FX)
LAMBDA_TS_MEAN=@MEAN(LAMBDA_TS)
LAMBDA_TS_TRATIO=@SQRT(!NOBS)*@MEAN(LAMBDA_TS)/@STDEV(LAMBDA_TS)
LAMBDA_MKT_MEAN=@MEAN(LAMBDA_MKT)
LAMBDA_MKT_TRATIO=@SQRT(!NOBS)*@MEAN(LAMBDA_MKT)/@STDEV(LAMBDA_MKT)
LAMBDA_IP_MEAN=@MEAN(LAMBDA_IP)
LAMBDA_IP_TRATIO=@SQRT(!NOBS)*@MEAN(LAMBDA_IP)/@STDEV(LAMBDA_IP)
LAMBDA_CON_MEAN=@MEAN(LAMBDA_CON)
LAMBDA_CON_TRATIO=@SQRT(!NOBS)*@MEAN(LAMBDA_CON)/@STDEV(LAMBDA_CON)
LAMBDA_R2_MEAN=@MEAN(LAMBDA_R2)
```

Appendix B: Details in computing the GRS statistic

When running the Fama-MacBeth program in EViews, we save all estimated intercepts from the time-series regressions in a $N \times 1$ vector as shown in the following equation:

$$\hat{\alpha} = \begin{matrix} \hat{\alpha}_1 \\ \hat{\alpha}_2 \\ \vdots \\ \hat{\alpha}_N \end{matrix} \quad \text{(B.1)}$$

Further, we calculate the residuals for each test asset from the time-series regressions as:

$$\hat{\varepsilon}_{it} = (R_{it} - R_{ft}) - \hat{\alpha}_i - \sum_{j=1}^{K} \hat{\beta}_{ij} F_{jt} \quad \text{(B.2)}$$

where $(R_{it} - R_{ft})$ is the excess return on test asset i in period t, $\hat{\alpha}_i$ is the estimated intercept for test asset i, $\hat{\beta}_{ij}$ is the estimated factor loading for test asset i to factor $j = 1, \dots, K$ and F is the return on factor $j = 1, \dots K$ in period t. When we have obtained the estimates of the residuals $\hat{\varepsilon}_{it}$, the residual covariance matrix $\hat{\Sigma}$ is calculated as:

$$\hat{\Sigma} = \frac{\hat{\varepsilon}\prime\hat{\varepsilon}}{T} \quad \text{(B.3)}$$

where,

$$\hat{\varepsilon} = \begin{matrix} \hat{\varepsilon}_{11} & \hat{\varepsilon}_{12} & \dots & \hat{\varepsilon}_{1N} \\ \hat{\varepsilon}_{21} & \hat{\varepsilon}_{22} & \dots & \hat{\varepsilon}_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{\varepsilon}_{T1} & \hat{\varepsilon}_{T2} & \dots & \hat{\varepsilon}_{TN} \end{matrix}. \quad \text{(B.4)}$$

Further, the factor matrix $\bar{\mu}$ is simply the sample means of the factors formed in a $K \times 1$ vector:

$$\bar{\mu} = \begin{matrix} \bar{F}_1 \\ \bar{F}_2 \\ \vdots \\ \bar{F}_K \end{matrix}. \quad \text{(B.5)}$$

Lastly, we compute an unbiased covariance matrix of the factors $\hat{\Sigma}_f$ as:

$$\hat{\Sigma}_f = \frac{(F-\bar{F})\prime(F-\bar{F})}{T}, \quad \text{(B.6)}$$

where,

$$F = \begin{matrix} F_{11} & F_{12} & \dots & F_{1K} \\ F_{21} & F_{22} & \dots & F_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ F_{T1} & F_{T2} & \dots & F_{TK} \end{matrix} \quad \text{(B.7)}$$

and,

$$\bar{F} = \begin{matrix} \bar{F}_1 & \bar{F}_2 & \dots & \bar{F}_K \\ \bar{F}_1 & \bar{F}_2 & \dots & \bar{F}_K \\ \vdots & \vdots & \ddots & \vdots \\ \bar{F}_1 & \bar{F}_2 & \dots & \bar{F}_K \end{matrix}. \quad \text{(B.8)}$$

Appendix C: Unit root and stationarity tests

Table C.1: Tests for Unit Root and Stationarity in the Variables in the Macroeconomic model

Part A: Augmented Dickey Fuller test (Schwarz information criterion with a maximum lag of 16).

	CON		FX		INF		IP		MKT		OIL		TS	
	i	i+t	i	i+t	i	i+t	i	i+t	i	i+t	i	i+t	i	i+t
T-stat.	-18.13	-18.10	-17.53	-17.51	-18.12	-18.10	-18.38	-18.37	-18.26	-18.25	-17.67	-17.64	-18.12	-18.10
1% Crit. Value	-3.45	-3.99	-3.45	-3.99	-3.45	-3.99	-3.45	-3.99	-3.45	-3.99	-3.45	-3.99	-3.45	-3.99
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Part B: Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

	CON		FX		INF		IP		MKT		OIL		TS	
	i	i+t	i	i+t	i	i+t	i	i+t	i	i+t	i	i+t	i	i+t
LM-stat.	0.08	0.08	0.09	0.08	0.07	0.06	0.13	0.08	0.06	0.05	0.07	0.07	0.06	0.03
1% Asym. Crit. Value	0.74	0.22	0.74	0.22	0.74	0.22	0.74	0.22	0.74	0.22	0.74	0.22	0.74	0.22

Note: we have also tested the variables for unit roots and stationarity using the Augmented Dickey Fuller test with Akaike information criterion with a maximum lag of 16 and the Phillips-Perron test. The results are not included, as all tests report that there is no unit root in the variables.

Table C.2: Tests for Unit Root and Stationarity in the Variables in the CAPM, the FF3 and FF5 models

Part A: Augmented Dickey Fuller test (Schwarz information criterion with a maximum lag of 16).

	CMA		HML		EMKT		RMW		SMB	
	i	i+t	i	i+t	i	i+t	i	i+t	i	i+t
T-stat.	-12.21	-12.20	-16.74	-16.75	-18.29	-18.32	-17.87	-17.90	-19.87	-20.06
1% Crit. Value	-3.45	-3.99	-3.45	-3.99	-3.45	-3.99	-3.45	-3.99	-3.45	-3.99
Prob.	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Part B: Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test.

	CMA i	CMA i+t	HML i	HML i+t	EMKT i	EMKT i+t	RMW i	RMW i+t	SMB i	SMB i+t
LM-stat.	0.08	0.07	0.04	0.48	0.14	0.05	0.17	0.03	0.48	0.04
1% Asym. Crit. Value	0,74	0.22	0.74	0.22	0.74	0.22	0.74	0.22	0.74	0.22

Note: we have also tested the variables for unit roots and stationarity using the Augmented Dickey Fuller test with Akaike information criterion with a maximum lag of 16 and the Phillips-Perron test. The results are not included, as all tests report that there is no unit root in the variables.

Appendix D: Descriptive statistics for returns for test assets

Panel A: Industry sorted portfolios

	i10	i15	i20	i25	i30	i35	i40	i45	**Avg.**
Max.	0.20	1.49	0.17	0.66	0.29	0.42	0.28	1.01	**0.56**
Min.	-0.28	-0.45	-0.26	-0.35	-0.30	-0.28	-0.25	-0.37	**-0.32**
Avg.	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.03	**0.02**
St.dev	0.07	0.13	0.07	0.11	0.07	0.08	0.07	0.11	**0.09**

Panel B: B/M sorted portfolios

	b1	b2	b3	b4	b5	b6	b7	b8	b9	b10	**Avg.**
Max.	0.28	0.38	0.33	0.20	0.21	0.32	0.25	0.41	0.26	0.38	**0.30**
Min.	-0.39	-0.20	-0.35	-0.33	-0.28	-0.32	-0.26	-0.24	-0.27	-0.28	**-0.29**
Avg.	0.02	0.02	0.01	0.02	0.01	0.02	0.02	0.02	0.02	0.02	**0.02**
St.dev	0.09	0.07	0.08	0.07	0.07	0.08	0.08	0.08	0.08	0.08	**0.08**

Panel C: Momentum sorted portfolios

	m1	m2	m3	m4	m5	m6	m7	m8	m9	m10	**Avg.**
Max.	0.43	0.44	0.26	0.24	0.33	0.25	0.31	0.27	0.29	0.46	**0.33**
Min.	-0.22	-0.41	-0.27	-0.28	-0.23	-0.22	-0.25	-0.27	-0.28	-0.31	**-0.27**
Avg.	0.03	0.03	0.02	0.01	0.02	0.02	0.01	0.01	0.01	0.02	**0.02**
St.dev	0.08	0.10	0.08	0.07	0.07	0.06	0.07	0.07	0.07	0.08	**0.08**

Panel D: Size sorted portfolios

	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10	**Avg.**
Max.	0.30	0.37	0.29	0.28	0.26	0.30	0.20	0.55	0.25	0.15	**0.30**
Min.	-0.16	-0.12	-0.17	-0.17	-0.15	-0.16	-0.23	-0.21	-0.24	-0.23	**-0.18**
Avg.	0.03	0.03	0.03	0.02	0.03	0.03	0.02	0.02	0.02	0.01	**0.02**
St.dev	0.07	0.07	0.07	0.07	0.07	0.07	0.06	0.07	0.07	0.06	**0.07**

Note: Panel A display the descriptive statistics for the 8 industry sorted portfolios, Panel B display the descriptive statistics for the 10 B/M sorted portfolios, Panel C display the descriptive statistics for the 10 momentum portfolios and Panel D display the descriptive statistics for the 10 size portfolios. The portfolios are value-weighted and collected in full from Ødegaard as described in the data section. For Panel A: i10 corresponds to GICS code 10 (Energy), i15 to GICS code 15 (Materials), i20 to GICS code 20 (Industrials), i25 to GICS code 25 (Consumer discretionary), i30 to GICS code 30 (Consumer staples), i35 to GICS code 35 (Health care), i40 to GICS code 40 (Financials) and lastly i45 to GICS code 45 (Information technology). Further, in Panels A-D: b1, m1 and s1 describes the lowest B/M, momentum and smallest size, whereas b10, m10 and s10 describes the highest B/M, momentum and largest size.

In the first column, we describe the content in the 8 (Panel A) and 10 (Panel B-D) next columns. Max display the maximum return for each portfolio, Min display the minimum return, Avg display the average return and St.dev display the standard deviation of returns. The last column in each panel yields the average maximum return, minimum return, average return and standard deviation of return for all portfolios respectively. Thus, it is the last column that is assessed in the discussion of which test assets yield most dispersion in returns.

Appendix E: Descriptive statistics for factor loadings for test assets

Panel A: IBM portfolios

	CAPM	Macrofactor model							FF3			FF5					
	β_{EMKT}	β_{CON}	β_{FX}	β_{INF}	β_{IP}	β_{MKT}	β_{OIL}	β_{TS}	β_{HML}	β_{EMKT}	β_{SMB}	β_{HML}	β_{SMB}	β_{RMW}	β_{CMA}	β_{EMKT}	**Avg.**
Max.	1.49	0.57	0.44	2.15	0.48	1.26	0.16	0.11	0.48	1.37	0.88	0.48	0.88	0.09	0.20	1.22	**0.77**
Min.	0.46	-0.28	-0.38	-1.59	-0.48	0.67	-0.27	-0.08	-0.63	0.36	-0.13	-0.59	-0.12	-0.40	-0.10	0.59	**-0.19**
Avg.	0.95	0.07	0.01	0.34	0.02	0.98	-0.05	0.02	0.02	1.00	0.13	0.03	0.13	-0.07	0.08	0.99	**0.29**
St.dev.	0.34	0.21	0.17	1.01	0.29	0.11	0.08	0.05	0.26	0.32	0.15	0.26	0.15	0.13	0.09	0.14	**0.24**

Panel B: B/M and size portfolios

	CAPM	Macrofactor model							FF3			FF5					
	β_{EMKT}	β_{CON}	β_{FX}	β_{INF}	β_{IP}	β_{MKT}	β_{OIL}	β_{TS}	β_{HML}	β_{EMKT}	β_{SMB}	β_{HML}	β_{SMB}	β_{RMW}	β_{CMA}	β_{EMKT}	**Avg.**
Max.	1.06	0.48	0.25	2.08	0.42	1.10	0.05	0.11	0.48	1.13	0.88	0.48	0.88	0.07	0.19	1.11	**0.67**
Min.	0.38	-0.29	-0.22	-1.59	-0.35	0.39	-0.10	-0.08	-0.42	0.59	-0.13	-0.41	-0.12	-0.31	-0.04	0.59	**-0.14**
Avg.	0.86	0.10	0.01	0.23	0.07	0.87	-0.02	0.03	0.04	0.96	0.30	0.05	0.30	-0.10	0.08	0.95	**0.30**
St.dev.	0.19	0.22	0.13	0.76	0.18	0.20	0.04	0.04	0.22	0.13	0.31	0.22	0.11	0.08	0.07	0.11	**0.20**

Panel C: ISM portfolios

	CAPM	Macrofactor model							FF3			FF5					
	β_{EMKT}	β_{CON}	β_{FX}	β_{INF}	β_{IP}	β_{MKT}	β_{OIL}	β_{TS}	β_{HML}	β_{EMKT}	β_{SMB}	β_{HML}	β_{SMB}	β_{RMW}	β_{CMA}	β_{EMKT}	**Avg.**
Max.	1.21	0.57	0.44	2.15	0.31	1.26	0.16	0.10	0.46	1.38	0.64	0.45	0.88	0.14	0.22	1.32	**0.67**
Min.	0.38	-0.29	-0.38	-0.90	-0.41	0.39	-0.27	-0.04	-0.63	0.59	-0.13	-0.59	-0.12	-0.40	-0.10	0.59	**-0.14**
Avg.	0.87	0.10	0.02	0.38	0.01	0.89	-0.04	0.02	0.03	0.96	0.28	0.03	0.27	-0.08	0.08	0.95	**0.30**
St.dev.	0.17	0.21	0.15	0.75	0.16	0.18	0.08	0.04	0.19	0.16	0.29	0.19	0.29	0.13	0.09	0.15	**0.20**

Panel D: ISB portfolios

	CAPM	Macrofactor model							FF3			FF5					
	β_{EMKT}	β_{CON}	β_{FX}	β_{INF}	β_{IP}	β_{MKT}	β_{OIL}	β_{TS}	β_{HML}	β_{EMKT}	β_{SMB}	β_{HML}	β_{SMB}	β_{RMW}	β_{CMA}	β_{EMKT}	**Avg.**
Max.	1.21	0.57	0.44	2.15	0.42	1.26	0.16	0.11	0.48	1.38	0.88	0.48	0.88	0.14	0.22	1.32	**0.76**
Min.	0.38	-0.29	-0.38	-1.59	-0.41	0.39	-0.27	-0.08	-0.63	0.59	-0.13	-0.59	-0.12	-0.40	-0.10	0.59	**-0.19**
Avg.	0.88	0.09	0.02	0.35	0.04	0.90	-0.04	0.03	0.03	0.96	0.25	0.03	0.24	-0.08	0.08	0.95	**0.30**
St.dev.	0.18	0.23	0.16	0.94	0.19	0.19	0.08	0.04	0.26	0.15	0.29	0.25	0.29	0.13	0.08	0.15	**0.23**

Panel E: SBM portfolios

	CAPM	Macrofactor model							FF3			FF5					
	β_{EMKT}	β_{CON}	β_{FX}	β_{INF}	β_{IP}	β_{MKT}	β_{OIL}	β_{TS}	β_{HML}	β_{EMKT}	β_{SMB}	β_{HML}	β_{SMB}	β_{RMW}	β_{CMA}	β_{EMKT}	**Avg.**
Max.	1.08	0.48	0.25	2.08	0.42	1.10	0.04	0.11	0.48	1.24	0.88	0.48	0.88	0.09	0.20	1.22	**0.69**
Min.	0.38	-0.29	-0.22	-1.59	-0.35	0.39	-0.10	-0.08	-0.42	0.59	-0.13	-0.41	-0.12	-0.32	-0.09	0.59	**-0.14**
Avg.	0.89	0.09	0.01	0.24	0.05	0.90	-0.02	0.02	0.04	0.97	0.27	0.05	0.26	-0.09	0.08	0.96	**0.30**
St.dev.	0.16	0.20	0.12	0.86	0.18	0.17	0.04	0.04	0.19	0.12	0.28	0.19	0.28	0.10	0.07	0.12	**0.20**

Panel A display the descriptive statistics for the 28 IBM portfolios, Panel B the descriptive statistics for the 20 B/M and size portfolios, Panel C the descriptive statistics for the 28 ISM portfolios, Panel D the descriptive statistics for the 28 ISB portfolios and Panel E the descriptive statistics for the 30 SBM portfolios. For Panel A-E: the first column displays the content in the next 16 columns. The 2nd column display the maximum value, minimum value, average value and standard deviation for estimated factor loadings for the CAPM. The 3rd to the 9th column display similar values for the factor loadings for the macrofactor model. The 10th to the 12th column display the values for the factor loadings for the FF3 model, whereas the 13th to 17th column display the values for the FF5 model. The last column shows the average of the maximum value, minimum value, average value and standard deviation for all 16 factor loadings. The last column in each panel yields the average maximum return, minimum return, average return and standard deviation of return for all portfolios respectively. Thus, it is the last column that is assessed in the discussion of which test assets yield most dispersion in factor loadings.

Appendix F: Results from Fama-MacBeth procedure using different test assets

Table F.1.: VW B/M & Size portfolios - Results from cross-sectional regressions. All coefficients x 10.

Panel A: CAPM

1990-2017	λ_0	λ_{EMKT}	R^2
Coeff.	0.181	-0.052	0.10
T-ratio	1.682*	-0.447	

Panel B: Macroeconomic model

1990-2017	λ_0	λ_{INF}	λ_{CON}	λ_{IP}	λ_{FX}	λ_{MKT}	λ_{OIL}	λ_{TS}	R^2
Coeff.	-0.081	0.007	0.121	0.045	0.104	0.185	-0.649	-0.214	0.66
T-ratio	-0.547	0.478	1.432	0.926	1.460	1.218	-1.554	-0.605	

Panel C: Fama French three factor

1990-2017	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	R^2
Coeff.	0.231	-0.124	0.004	0.227	0.22
T-ratio	2.075**	-1.031	0.088	2.863***	

Panel D: Fama French five factor

1995-2017	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	λ_{RMW}	λ_{CMA}	R^2
Coeff.	0.313	-0.229	0.029	0.162	-0.179	0.135	0.48
T-ratio	2.459**	-1.614	0.641	1.903*	-2.319**	0.846	

Note: Table F.1. reports the results from the second-pass regression using the Fama-MacBeth procedure with the BS test asset. All coefficients are multiplied by 10. Panel A yields the result for CAPM, Panel B for the macroeconomic model, Panel C for the FF3 and Panel D for the FF5. Column (2-10) shows the estimated risk premia λ_i for each factor i, for each test asset in column (1). Asterisks *, ** and *** indicate the level of significance for the risk premium estimates at respectively the 10, 5 and 1 percent significance level.

Table F.2.: VW ISM portfolios - Results from cross-sectional regressions. All coefficients x 10.

Panel A: CAPM

1990-2017	λ_0	λ_{EMKT}	R^2
Coeff.	0.334	-0.189	0.12
T-ratio	7.932***	-3.435***	

Panel B: Macroeconomic model

1990-2017	λ_0	λ_{INF}	λ_{CON}	λ_{IP}	λ_{FX}	λ_{MKT}	λ_{OIL}	λ_{TS}	R^2
Coeff.	0.433	-0.034	0.106	-0.129	0.120	-0.315	-0.516	-0.214	0.44
T-ratio	7.644***	-2.240**	1.432	-2.123**	1.412	-4.693***	-1.993*	-0.395	

Panel C: Fama French three factor

1990-2017	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	R^2
Coeff.	0.175	-0.074	-0.060	0.192	0.29
T-ratio	2.715***	-0.992	-0.866	6.316***	

Panel D: Fama French five factor

1995-2017	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	λ_{RMW}	λ_{CMA}	R^2
Coeff.	0.205	-0.117	-0.060	0.179	-0.124	0.059	0.38
T-ratio	3.091***	-1.507	-0.786	5.938***	-2.032**	0.672	

Note: Table F.2. reports the results from the second-pass regression using the Fama-MacBeth procedure with the ISM test asset. All coefficients are multiplied by 10. Panel A yields the result for CAPM, Panel B for the macroeconomic model, Panel C for the FF3 and Panel D for the FF5. Column (2-10) shows the estimated risk premia λ_i for each factor i, for each test asset in column (1). Asterisks *, ** and *** indicate the level of significance for the risk premium estimates at respectively the 10, 5 and 1 percent significance level.

Table F.3.: VW ISB portfolios - Results from cross-sectional regressions. All coefficients x 10.

Panel A: CAPM

1990-2017	λ_0	λ_{EMKT}	R^2
Coeff.	0.351	-0.208	0.12
T-ratio	8.401***	-3.882***	

Panel B: Macroeconomic model

1990-2017	λ_0	λ_{INF}	λ_{CON}	λ_{IP}	λ_{FX}	λ_{MKT}	λ_{OIL}	λ_{TS}	R^2
Coeff.	0.405	0.019	-0.008	-0.108	0.026	-0.207	-0.329	-0.377	0.46
T-ratio	8.161***	1.830*	-0.192	-2.197**	0.407	-4.513***	-1.389	-1.671*	

Panel C: Fama French three factor

1990-2017	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	R^2
Coeff.	0.171	-0.057	-0.011	0.173	0.29
T-ratio	3.278***	-0.910	-0.281	5.708***	

Panel D: Fama French five factor

1995-2017	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	λ_{RMW}	λ_{CMA}	R^2
Coeff.	0.212	-0.119	0.004	0.159	-0,.176	0.052	0.37
T-ratio	4.008***	-1.899*	0.109	5.262***	-2.826***	0.516	

Note: Table F.3. reports the results from the second-pass regression using the Fama-MacBeth procedure with the ISB test asset. All coefficients are multiplied by 10. Panel A yields the result for CAPM, Panel B for the macroeconomic model, Panel C for the FF3 and Panel D for the FF5. Column (2-10) shows the estimated risk premia λ_i for each factor i, for each test asset in column (1). Asterisks *, ** and *** indicate the level of significance for the risk premium estimates at respectively the 10, 5 and 1 percent significance level.

Table F.4.: VW SBM portfolios - Results from cross-sectional regressions. All coefficients x 10.

Panel A: CAPM

1990-2017	λ_0	λ_{EMKT}	R^2
Coeff.	0.024	0.113	0.06
T-ratio	0.263	1.102	

Panel B: Macroeconomic model

1990-2017	λ_0	λ_{INF}	λ_{CON}	λ_{IP}	λ_{FX}	λ_{MKT}	λ_{OIL}	λ_{TS}	R^2
Coeff.	-0.115	0.003	0.195	0.032	0.070	0.229	0.058	0.468	0.39
T-ratio	-1.128	0.233	4.138***	0.835	1.220	2.062**	0.228	2.530**	

Panel C: Fama French three factor

1990-2017	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	R^2
Coeff.	0.122	-0.018	-0.012	0.195	0.29
T-ratio	1.397	-0.182	-0.289	3.374***	

Panel D: Fama French five factor

1995-2017	λ_0	λ_{EMKT}	λ_{HML}	λ_{SMB}	λ_{RMW}	λ_{CMA}	R^2
Coeff.	0.156	-0.066	-0.002	0.168	-0.158	0.048	0.29
T-ratio	1.644	-0.609	-0.051	2.989***	-2.618***	0.480	

Note: Table F.4. reports the results from the second-pass regression using the Fama-MacBeth procedure with the SBM test asset. All coefficients are multiplied by 10. Panel A yields the result for CAPM, Panel B for the macroeconomic model, Panel C for the FF3 and Panel D for the FF5. Column (2-10) shows the estimated risk premia λ_i for each factor i, for each test asset in column (1). Asterisks *, ** and *** indicate the level of significance for the risk premium estimates at respectively the 10, 5 and 1 percent significance level.