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Systematic Risk Factors at Oslo Stock Exchange

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Sammendrag

Vi konstruerer fem systematiske risikofaktorer for Oslo Børs i perioden fra 1991 til 2010: en markedsfaktor, og faktorer relatert til selskapsstørrelse, bokverdi av egenkapital dividert på markedsverdien til egenkapital, momentum, og belånings- og finansieringsbegrensninger. Vi finner bevis for en momentumeffekt på kortsiktig avkastning og signifikant positiv avkastning for faktoren tilknyttet bokverdi dividert på markedsverdi. Det er lite som tyder på at det er noen positiv sammenheng mellom estimert beta og påfølgende avkastning, noe som er motstridende til CAPM. Det er ingen indikasjon på høyere abnormal avkastning knyttet til selskapets størrelse. Denne rapporten gir nye bevis knyttet til belånings- og finansieringsbegrensninger for Oslo Børs, som ikke viser seg å gi noen signifikant positiv risikojustert avkastning. En standard firefaktormodell som inneholder markedsfaktoren, størrelsesfaktoren, bok-til-markedsverdifaktoren og en momentumfaktor gir best beskrivelse av det norske aksjemarkedet.

Abstract

We construct five systematic risk factors for the Oslo Stock Exchange over the sample period of 1991 to 2010: an overall market factor, and factors related to firm size, book-to-market equity, momentum, and leverage and margin constraints. We find evidence of a continuation of short-term returns and significant positive differential returns for book-to-market equity. There appears to be no positive relationship between beta estimated and subsequent returns, which is contradictory to CAPM. Also, there is no indication of higher abnormal returns related to firm size. This paper provides new evidence related to leverage and margin constraints, which is found to not yield any positive risk-adjusted returns for the Norwegian stock market. The standard four-factor model containing the market factor, size-factor, book-to-market factor, and a momentum factor provides a reasonable fit for the cross-section of Norwegian stock returns.

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Abstract

We construct five systematic risk factors for the Oslo Stock Exchange over the sample period of 1991 to 2010: an overall market factor, and factors related to firm size, book-to-market equity, momentum, and leverage and margin constraints. We find evidence of a continuation of short-term returns and significant positive differential returns for book-to-market equity. There appears to be no positive relationship between beta estimated and subsequent returns, which is contradictory to CAPM. Also, there is no indication of higher abnormal returns related to firm size. This paper provides new evidence related to leverage and margin constraints, which is found to not yield any positive risk-adjusted returns for the Norwegian stock market. The standard four-factor model containing the market factor, size-factor, book-to-market factor, and a momentum factor provides a reasonable fit for the cross-section of Norwegian stock returns.

*The School of Business, Oslo (HiOA), e-mail: fredrik.korneliussen@sb1markets.no and christer.rasmussen@nordea.no. We thank Knut Nygaard for encouragement, valuable academic support and feedback as our supervisor. We acknowledge Kristian Heggen, Senior Sales Manager at Nordea Markets, for practical advice. Also, we appreciate the quick response from Bernt Arne Ødegaard and Andrea Frazzini related to factor construction. This study is conducted as our Master's thesis at the department of Economics at School of Business, Oslo (HiOA). We both have specialization in Finance and Financial Management. Structuring of our data and the construction of the factors has been a demanding process, which also has required a depth study in programming. A major portion of this Master's thesis is exercised in MATLAB, which has been a time consuming process. Also, a significant amount of time has been spent learning and mastering R and LaTeX for this study.

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1 Introduction

One of the most discussed topics in finance is the relationship between risk and return. The behavior and understanding of asset prices is important for professional investors, and of fundamental importance for the macro economy as it provides crucial information for key economic decisions. Most people in their daily life are influenced by the asset prices, when deciding between saving in the form of cash, bank deposits, portfolios or stocks. The decision depends on what people think of the risk and return associated with these options.

Asset pricing theory is concerned with explaining prices of financial assets in an uncertain world. It tries to clarify why some assets give more compensation than others. The theoretical and empirical asset pricing literature is internationally very extensive. In spite of this there are few analyses that especially study the Oslo Stock Exchange (OSE). Such an extensive empirical analysis of the Oslo Stock Exchange has to our knowledge just been completed by Bernt Arne Ødegaard, using different assumptions than we have in this analysis. An understanding of what risk factors that are essential for stock prices, the magnitude of realized risk premiums, and to what extent the cross-section of returns at the OSE is different from other stock markets is of interest to investors and companies raising capital through the exchange. In our research we investigate whether the factors typically used internationally for such purposes also are relevant in the Norwegian setting. This includes an overall market factor, and factors related to firm size, book-to-market equity, and momentum.

Previously it has been argued that the security market line is too flat relative to the Capital Asset Pricing Model (CAPM) (Black, Jensen, and Scholes, 1972), and that it is better explained by the CAPM with restricted borrowing (Black, 1972). Many investors are in fact constrained in the leverage that they can take, and they therefore overweight risky securities instead of using leverage, causing those assets to offer lower returns. A behavior of tilting toward high-beta assets suggests that more risky high-beta assets require lower risk-adjusted returns than low-beta assets, which require leverage. Pursuing this line of thinking, Frazzini and Pedersen (2013) present a model with leverage and margin constraints that vary across investors and time. They also introduce a betting against beta (BAB) factor, which they believe can exploit this effect. This paper is probably the first paper that examines these conditions for the Norwegian market, by constructing a market-neutral BAB-factor which is long leveraged low-beta assets and short high-beta assets.

The purpose of our analysis is to investigate whether the factors affecting the stock prices at Oslo Stock Exchange can be explained using standard financial theory, and to what extent the results from other international stock markets are also found in the Norwegian stock market. We use a dataset including all stocks listed on the Oslo Stock Exchange in the period 1991 – 2010 and a second dataset consisting of accounting numbers for the period 1980 – 2011. For any model and data set combination, the Black, Jensen and Scholes (1972) time series average absolute pricing error test, and the Fama MacBeth (1973) cross-sectional test are conducted. Our results document that in addition to the local market, empirically motivated factors related to book-to-market equity, and momentum seem to be factors demanding risk compensation at the Oslo Stock Exchange. The size effect appears to have a slight negative effect, but the results are not significant. We also present evidence related to leverage and margin constraints, which is found to not yield any positive risk-adjusted returns for the Norwegian stock market.

In the next section we give an overview of related literature for this research. Section 3 contains development of the asset pricing theory, starting with Markowitz Portfolio Theory. The section provides a deeper understanding of where asset-pricing models comes from, diverse factor models, and different characteristics which the standard benchmark asset pricing model, CAPM, not can explain. In section 4 we give a brief description of the Oslo Stock Exchange, our data and sample selection, how asset returns are calculated and a detailed description of how stock prices are calculated. Section 5 give an advanced understanding of how all the potential risk factors are constructed, and the main results from our empirical investigation are presented in section 6. First, we see whether some of the factors give significant returns, then we show a sort approach where we examine the returns on sets of deciles formed from sorts on different firm characteristics, before we present results from the cross-sectional Fama MacBeth (1973) regressions. The final section provides a brief conclusion of our study, and we also propose what could be an interesting approach in further studies.

2 Related literature

The classical CAPM was for a long time considered a basic framework for explaining differences in returns across assets. It asserts that assets that correlate more strongly with the market as a whole carry more risk and thus require a higher return in compensation. In a large number of international studies researchers have attempted to test this proposition, and although early CAPM tests seemed promising, the empirical support for the model was increasingly questioned towards the end of the 1970s. As the CAPM seemed to be failing, a number of studies found that the cross-sectional variation in average returns across securities could not be explained by the market beta alone. Fundamental variables such as size (Banz, 1981), ratio of book-to-market value (Rosenberg, Reid and Lanstein, 1985; Chan, Hamao and Lakonishok, 1991), macroeconomic variables and the price to earnings ratio (Basu, 1983) where found to account for a sizeable portion of the cross-sectional variation in expected returns. Others show that a firm's average stock return can be explained by a reversal in long-term returns (DeBondt and Thaler, 1985); stocks with low long-term previous returns tend to have higher future returns. Jagadeesh and Titman (1993) found, on the contrary, that short-term returns tend to continue; stocks with higher returns in the previous twelve months tend to have higher future returns.

The body of work discussed above was eventually synthesized into a three-factor model constructed by Fama and French (1993). The three-factor model captures the size and value patterns in average returns and has shown to greatly improve the explanatory power relative to the CAPM model. Return momentum was still left unexplained, therefore Carhart (1997) later proposed a four-factor model including a momentum factor. Both models are commonly used in applications, but most notably to evaluate portfolio performance. More recently, Frazzini and Pedersen (2013) presented a model with leverage and margin constraints that vary across both investors and time. Because constrained investors bid up high-beta assets, high beta is associated with low alpha. A betting against beta (BAB) factor, which is long leveraged low-beta assets and short high-beta assets, was introduced and was showed to yield significant positive risk-adjusted returns.

Despite the extensive theoretical and empirical international asset pricing literature, there are just a few analyses concerning the Norwegian stock market. Randi Næs, Johannes A. Skjeltorp and Bernt Arne Ødegaard (2009) have done considerable research on this topic and found that a three-factor model containing the market, a size factor and a liquidity factor provides a reasonable fit for the cross-section of Norwegian stock returns.

3 Asset Pricing Theory

Asset pricing theory is concerned with explaining prices of financial assets in an uncertain world. It tries to clarify why some assets give more compensation than others. A central insight, dating back to the portfolio model of Markowitz (1952), is that investors should only demand compensation for systematic risk, i.e., risk that can not be eliminated by holding a well diversified portfolio. But which systematic risks drive stock returns, and to what extent are investors compensated for them in terms of higher expected returns? The uncertainty, or compensation for risk is what makes asset pricing interesting and complicated.

A simple way of looking at the asset pricing theory is to state that it all stems from the simple concept that price equals expected discounted payoff. However, there are elaborations to this statement. Generally we can differentiate between what is called absolute pricing and relative pricing (Cochrane, 2001). Absolute pricing base prices on economic theory, such as assumptions about preferences of economic agents and supply and demand. Absolute pricing does not take into consideration other prices quoted in the market, and most absolute pricing models are what are known as equilibrium pricing models. They calculate at what prices a market will reach equilibrium - where supply and demand balance and the market clears. A shortcoming of many equilibrium models is the fact that they calculate hypothetical equilibrium prices that not necessarily match actual prices currently observed in the market. This violates the law of one price, described below. The Capital Asset Pricing Model (CAPM) by Sharpe (1964), Lintner (1965) and Mossin (1966), and other equilibrium models are examples of this approach.

In relative pricing, on the other hand, we learn of an assets value given the prices of some other assets, determined by the market. Most relative pricing models are based on the theory of absence of arbitrage opportunities. Prices are determined relative to other prices quoted in the market in such a manner as to preclude any arbitrage opportunities. An arbitrage opportunity is a "money pump", which makes it possible to make arbitrary amounts of money without taking on any risk. The Law of One Price states that if two assets are equivalent in all economically relevant respects, then they should have the same market price. If the law is violated, it will cause arbitrageurs to simultaneously buy the asset where it is cheap and selling it where it is expensive, and in the process force the prices in equilibrium so that the arbitrage opportunity is eliminated (Cochrane, 2001). The idea that market prices will move to rule out arbitrage opportunities is perhaps the most fundamental concept in capital market theory. The Arbitrage Pricing Theory (APT) by Ross (1976) is an example of this approach.

3.1 The Markowitz portfolio theory

The framework of Markowitz (1952) is commonly known as the Mean Variance model, due to the fact that it is based on expected value (mean) and the variance of the various portfolios. The model provides a method to analyze how good a given portfolio is, based on only these measures. Markowitz stated that an investor does (or should) consider expected return a desirable thing and variance of return an undesirable thing (Markowitz, 1952). Thus, an investor will always strive to switch from one investment to another which has the same expected return but less risk, or one which has the same risk but greater expected return, or one which has both greater expected return and less risk. To prove his point, Markowitz used mathematical statistics.

Suppose we have a portfolio with n different assets, where R_i is the return on the i_{th} asset. Let μ_i and σ_i^2 be the related mean and variance, and let $\sigma_{i,j}$ $(= p_{i,j}\sigma_i\sigma_j)$ be the covariance between R_i and R_j. Suppose that the relative value of the portfolio invested in asset i is x_i. If R is the return on the portfolio as a whole, then:

$$\mu = E[R] = \sum_{i=1}^{n} x_i \mu_i \tag{3.1.1}$$

$$\sigma^2 = Var[R] = \sum_{i=1}^{n} x_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j \sigma_{ij} \tag{3.1.2}$$

$$\sum_{i=1}^{n} x_i = 1 \tag{3.1.3}$$

$$x_i \geq 0, i = 1, 2, ..., n \tag{3.1.4}$$

Condition 3.1.4 excludes negative values of the x_i, meaning that only long positions are allowed. To include also short sales, this condition has to be omitted. The investor has a choice of various combinations of μ and σ^2 depending on his choices of $x_1, ..., x_n$. The set of all achievable combinations of σ^2 and μ is called the attainable set. An investor can state which combination is desired, and the portfolio that gives the desired combination can be found. Based on the assumption that the investor is motivated to maximize μ and minimize σ^2, he would select a portfolio which gives a (σ^2, μ) combination in the efficient set (or efficient frontier). See appendix 8.1 for further description.

Investors should diversify funds amongst securities which give maximum expected return. By combining assets that are not perfectly correlated, the risk (variance) embedded in a portfolio is lowered and the higher risk-adjusted returns can be achieved. This is implicit by looking at the covariance coefficient in 3.1.2. The lower the covariance between assets, the greater the reduction in risk that can be derived. To illustrate, if we suppose that the assets are all independent and uncorrelated, then:

$$Var[R] = \sum_{i=1}^{n} x_i^2 \sigma_i^2 \tag{3.1.5}$$

Suppose further that the portfolio is equally weighted, so $x_i = x = 1/n \; \forall i$, and that the average variance is:

$$\overline{\sigma^2} = \frac{1}{n} \sum_{i=1}^{n} \sigma_i^2$$

then portfolio variance can be written as:

$$Var[R] = \sum_{i=1}^{n} \frac{1}{n_i^2} \sigma_i^2 = \frac{1}{n} \sum_{i=1}^{n} \frac{\sigma_i^2}{n} \longrightarrow 0 \tag{3.1.6}$$

as $n \longrightarrow \infty$. Hence, as we acquire more and more assets, the risk moves to 0. It is, however, not enough only to invest in many securities to reduce the variance. It is also necessary to avoid investing in securities that are highly correlated. Thus, we can diversify across industries with different economic characteristics, because it is more likely for firms within the same industry to do poorly at the same time then for firms in unrelated industries[46]. Suppose now that the portfolio is still equally weighted, but this time the assets are not necessarily uncorrelated. And, consider the average covariance as:

$$\overline{\sigma_{ij}} = \frac{1}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_{ij}$$

then the portfolio variance from equation 3.1.2 simplifies to:

$$
\begin{aligned}
Var[R] &= \sum_{i=1}^{n} \frac{1}{n^2}\sigma_i^2 + \sum_{i=1}^{n}\sum_{j=1}^{n} \frac{1}{n^2}\sigma_{ij} \\
&= \frac{1}{n^2}\sum_{i=1}^{n}\sigma_i^2 + \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\sigma_{ij} \\
&= \frac{n\overline{\sigma^2}}{n^2} + \frac{n(n-1)}{n^2}\overline{\sigma_{ij}} \\
&= \frac{\overline{\sigma^2}}{n} + (1-\frac{1}{n})\overline{\sigma_{ij}}
\end{aligned} \tag{3.1.7}
$$

Thus, as n $\longrightarrow \infty$, the portfolio variance σ^2 converges to $\sigma^2 = \overline{\sigma_{ij}}$. That is, as the number of assets in the portfolio increases, the variance of individual assets become negligible, and its the covariance term that dominate. This is our measure of the undiversifiable, systematic, risk (Markowitz, 1959).

3.2 Factor models

The mean-variance theory by Markowitz (1952) requires knowledge of the mean, variance and covariance for all n assets, making the computation heavy as more assets are included. In 1958 James Tobin showed that when a risk-free investment is included, the efficient frontier must be a straight line (Tobin, 1958)(see appendix 8.1 for details). Based on both Markowitz and Tobin, William Sharpe (1963) showed that the computing time could be greatly reduced by his Diagonal Model, commonly known as the Single Factor Model. The model of Sharpe is the first simplified factor model, where only one factor is being considered. All that is required is parameter estimation of how the security will behave relative to the market. The model is described by:

$$
R_i = E[R_i] + \beta_i F + \epsilon_i \tag{3.2.1}
$$

Where $E[R_i]$ is the expected return on stock i. F is the deviation of the common factor from its expected value, and β_i is the sensitivity of the firm i to that factor. ϵ_i is the firm specific disturbance.

As noted in the model, the uncertainty in asset returns has two sources: a common or macroeconomic factor, and a firm specific factor. As described above, Markowitz showed that the firm specific risk becomes negligible when combining assets that are less than perfectly correlated in order to reduce portfolio risk, without sacrificing portfolio return. Thus, risk is limited to an undiversifible level in a well-diversified portfolio. Investors only worry about variation in their total wealth and consumption rather than variations in the value of each single stock in their portfolio. Thus, the only relevant risk for decision is the systematic risk. Diversifiable, non-systematic risk is not priced.

3.2.1 Capital Asset Pricing Model

The CAPM is an equilibrium model that results from Markowitz work. The model is a special case of the Single Factor Model, and was developed simultaneously in three papers by Sharpe in 1964, Lintner in 1965, and Mossin in 1966. CAPM tells us how investors determine expected returns and asset prices, as function of one risk factor, the market portfolio. According to CAPM, the expected return $E[R_i]$ of a given financial asset i is given by:

$$E[R_i] = r_f + \beta_i(E[R_m] - r_f) \tag{3.2.2}$$

where r_f is the risk-free rate, $E[R_m]$ is the expected return on the market portfolio, and β_i measures the covariability between the return on stock i and the market portfolio. In the CAPM model, β_i is the key measure of systematic risk that requires a risk premium for holding. But how good is actually CAPM when it comes to explaining the cross-section of asset prices? If we assume rational market expectations, meaning that observed returns $R_{i,t}$ are equal to expected returns plus a random error $\epsilon_{i,t}$, CAPM can be tested based on this equation:

$$R_{i,t} - r_f = \alpha + \beta_i(R_m - r_f) + \epsilon_{i,t} \tag{3.2.3}$$

Early tests performed by Douglas (1969), Black and Scholes (1973) and Black, Jensen and Scholes (1972) found a positive relation in accordance with the theory. However, the estimated coefficient implied an implausibly high value for the riskless rate of return, and they did not account for cross-sectional correlation in stock returns. This led to biased inference. Fama and MacBeth (1973) found substantial support of the model with their alternative approach (described in section 6.4), and their approach has become a standard method for testing cross-sectional asset pricing models.

However, the CAPM is based on very simplified assumptions (see appendix 8.2) and although the early tests seemed promising, the empirical support for the model was questioned toward the end of 1970s. In his influential paper from 1977, Richard Roll criticized tests of CAPM arguing that the theory is not testable unless the exact composition of the true market portfolio was known and used in the tests. However, the market portfolio contains every individual asset in the economy, including human capital, and is therefore inherently unobservable. Using a proxy for the market portfolio, which previous tests had done, would therefore lead to biased and misleading results. Later on, using the methodologies developed in the earlier tests, several other studies tested for the determinants of cross-sectional differences in returns. These led to the discovery of a number of CAPM "anomalies" (described in more detail in section 3.4), where firm specific characteristics seemed related to differences in return. In 1992, Fama and French wrote a paper where they integrated most of these results and at the same time established that the CAPM beta have practically no additional explanatory power once book-to-market and firm size have been accounted for.

However, if we assume that the CAPM is true, we can expect that returns will be increasing in beta. We should thus expect to observe that securities with higher beta have higher returns. Following Sharpe and Cooper (1972), we can test these implications of CAPM by first estimating betas, and then see if the portfolios with higher estimated betas have higher subsequent returns. This is done in section 6.2.

3.3 Multi-factor models

It has been shown that different strategies can result in high average returns without large betas. Thus, there is not necessarily a strong tendency for the strategies return to move up and down with the market as a whole. Multi-factor models can be useful in this context. These models introduce uncertainty stemming from multiple sources, whereas the CAPM, in principle, limits risk to one source - covariance with the market portfolio.

3.3.1 Arbitrage Pricing Theory

In 1976 Stephen Ross developed the Arbitrage Pricing Theory (APT), which can be viewed as an extension of the CAPM. From a purely statistical characterization of realized return, and simple arbitrage arguments, Ross (1976) showed how expected returns could be priced by multiple factors. The return is thus given by a factor structure:

$$R_i = E[R_i] + \Sigma \beta_i F + \epsilon_i \tag{3.3.1}$$

Where F is a systematic risk factor, and β_i is a constant giving the loading of asset i on the factor F. An asset is mispriced under the APT if its current price diverges from the price predicted by the model. The price should equal the sum of all future cash flows discounted at the APT rate. Nevertheless, the theory cannot guarantee that all assets will satisfy the equation at all time, since it is not an equilibrium condition anymore, but rather a no-arbitrage condition.

Unlike the CAPM, the APT does not tell us which are the systematic factors driving returns, and it gives no guidance of where to look for factors. However, there are two principles that can be used as guidance when specifying a reasonable list of factors. First, we wish to restrict ourselves to a limited number of systematic factors with considerable ability to explain security returns. Second, we wish to choose factors that seem likely to be important risk factors that concern investors sufficiently that they will demand meaningful risk premiums to bear exposure to those sources of risk. Chen, Roll, and Ross (1986) chose an approach with a set of factors based on the ability of these factors to paint a broad picture of the macro economy, which is one of many possibilities that can be considered.

However, there have been identified many patterns in average stock returns. DeBondt and Thaler (1985) found that stocks that had over-performed over longer horizons tend to underperform over subsequent years (and vice versa). Jagadesh and Titman (1993) found, on the contrary, that a short-term return tends to continue; i.e.

stocks with higher returns in the previous 12 months tend to have higher future returns. Furthermore, firms average stock returns have been found related to its book-to-market equity (BE/ME)(Statman, 1980, Rosenberg, Reid and Landstein, 1985), earnings/price (E/P)(Basu, 1977, 1983), cash flow/price (C/P), past sales growth (Lakonishok, Schleifer and Vishny, 1994), and firm size (Banz, 1981). Findings like the ones mentioned were positively related to expected returns, even after the CAPM beta had been controlled for; they are typically called anomalies.

3.3.2 Fama-French Three-Factor model

Fama-French three-factor model (Fama and French, 1993) is one of the most popular current multi-factor models. The model is composed of the work mentioned above, and Fama and French (1993) argue that many of the anomalies associated to CAPM are related, and that the three-factor model captures them. The three-factor model extends the CAPM model by two new factors. In addition to the market portfolio, the model includes a portfolio of "small-minus-big" market value stocks (SMB), and a portfolio of "high-minus-low" book-to-market value stocks (HML). Fama and French justify their model on empirical grounds, arguing that SMB and HML not necessarily are obvious candidates for relevant risk factors. However, these variables may proxy for yet-unknown more fundamental variables for which investors demand compensation. Explicitly, the expected return given by the three-factor-model is:

$$E(R_i) - r_f = b_i[E(R_m) - r_f] + s_i E(SMB) + h_i E(HML) \tag{3.3.2}$$

Where $E(R_m) - r_f$, $E(SMB)$, and $E(HML)$ are expected premiums, and the factor sensitivities or loadings, b, s and h are the slopes in the time-series regression:

$$R_i - r_f = a_i + b_i(R_m - r_f) + s_i SMB + h_i HML + \epsilon_i \tag{3.3.3}$$

In support for their argument, Fama and French (1995) showed that book-to-market equity and slopes on HML could be interpreted as compensation for distress risk. They found that weak firms with persistently low earnings tend to have high BE/ME and positive slopes on HML. In the opposite case, strong firms with persistently high earnings have low BE/ME and negative slopes on HML.

The three-factor model, in accordance to DeBondt and Thaler (1985), is also shown to capture reversals of long-term returns. Stocks with low long-term past returns tend to have positive SMB and HML slopes, and higher future average returns. In the opposite case, long-term winners tend to have negative slopes and low future returns. However, the three-factor-model comes up short related to explain the continuation of short-term returns recognized by Jagadesh and Titman (1993).

Apart from explaining differences in expected returns across stocks, Fama and French also showed that their factors could explain a significant amount of variation in time-series. In other words, stocks with similar exposure to these factors move together. In light of the model's empirical success, Fama and French argue that SMB and HML are priced risk factors and that this makes the three-factor-model an equilibrium-pricing model.

Despite their effective way to simplify and unify the immense literature on the cross-section of stock returns, Fama and French (1993) interpretations have produced reasonable scepticism, much centered on HML, argued to be the premium for distress. Kothari, Shanken, and Sloan (1995) argue that a substantial part of the premium is due to survivor bias, so the average return for high BE/ME firms is overstated. Another view, pointed out by Black (1993), is that researchers that focus on finding variables that are related to average return eventually may uncover past "patterns" purely by chance (called data-snooping). A third view is that distress premium is irrational in the way investors overreact and underprice distressed stocks, and overprice growth stocks.

3.3.3 Carhart Four-Factor model

Although Fama-French Three-Factor-Model (1993) has been shown to improve on average CAPM pricing errors, the model comes up short related to explain the continuation of short-term returns recognized by Jagadeesh and Titman (1993). Jagadeesh and Titman (1993) show that simple strategies that rank stocks based on their past 3-12 monthly returns, predict relative performance over the next 3-12 months. That is, recent winners will continue to be winners over the next 3-12 months and recent losers will continue to be losers over the next 3-12 months. After 12 months, the effect disappears and there is a sharp drop in momentum profitability. As you reach 3 to 5 years of past data, mean reversion becomes strong, giving the opposite effect of momentum (Asness, 1994). Based on the observation by Jagadesh and Titman (1993), Carhart (1997) constructs a Four-Factor-Model using Fama and Frenchs model plus an additional factor, prior one-year (PR1YR), capturing Jagadesh and Titmans (1993) one-year momentum anomaly. Carhart (1997) states that the resulting model is consistent with a market equilibrium model with four risk factors, or it can be interpreted as a performance attribution model where the coefficients and premia on the factor-mimicing portfolios indicate the proportion of mean return attributable to four elementary strategies. The four-factor model can be shown by:

$$E(R_i) - r_f = b_i[E(R_m) - r_f] + s_iE(SMB) + h_iE(HML) + p_iE(PR1YR) \quad (3.3.4)$$

where PR1YR is the difference in return between a portfolio of past winners and a portfolio of past losers. In the same manner as the three-factor model, b_i, s_i, h_i and p_i specifies the factor loadings which are the slopes in the time-series regression:

$$R_i - r_f = a_i + b_i(R_m - r_f) + s_iSMB + h_iHML + p_iPR1YR + \epsilon_i \quad (3.3.5)$$

Based on numerous findings, a number of behavioral-finance papers have built theories based on investor psychology to explain both the book-to-market and momentum effects, e.g., based on investor underreaction to news in the short-run, leading to momentum. Also psychology based on overreaction in the longer run, leading to reversals, or book-to-market effects (Economic Sciences Prize Committee of the Royal Swedish Academy of Sciences, 2013).

Lakonishok et al. (1991) and Lakonishok, Shleifer, and Vishny(1992) explain the effect as what they call "window dressing". This is when fund managers prepare for clients regular progress reports on their portfolios, they tend to visualize their skills by keeping shares that are rising and selling those that are falling. This type of behavior is further encouraged by the common practice of fund selection in the business. Fund managers who recently beat the market can attract more capital flows from their sponsors, and the managers will invest more in the winning stocks that they hold, giving the momentum effect an extra boost.

Grundy and Martin (2001) provide an explanation related to firm's specific component of returns. Lee and Swaminathan (2000) explain the effect by trading volume. George and Hwang (2004) state that a large portion of the momentum effect can be obtained by using the 52-week high price. Characteristics like small size and low analyst coverage (Hong, Lim, and Stein, 2000), high market-to-book ratios (Daniel and Titman, 1999) and high analyst forecast dispersion (Zhang, 2006) are related to stocks with momentum profits. All these type of characteristics are explained through the concept of information uncertainty Zhang (2006). The anomaly derived from the momentum profits poses a challenge to the efficient market hypothesis. The market hypothesis in its weak work states that past price movements should not provide any guide to future price movements. This is clearly not the case with the trading strategy that prefers past winners and makes profit of the strategy. With an efficient market, it is wasteful to time trading because all information is already reflected in the price.

Literature on the momentum strategy is massive but research on assessing whether a stock is running out of momentum is untouched. Investors hardly have sufficient information to determine whether the stock price of a winning stock has exceeded its equilibrium to a level where the risk incurred from dropping is imminent.

Kelsey, Kozhan, and Pang (2011) demonstrate that momentum is more likely to continue for downward trends in a highly uncertain market. Daniel and Moskowitz (2012) document that the losses of momentum portfolios are due to the highly skewed returns of the momentum strategies. In particularly bad conditions, the past losers of the momentum strategy usually have a very high premium. The strong profits that come along with the market recovery lead to a "momentum crash". Investors who implemented the momentum strategy would experience series of negative returns especially after a market collapse.

3.3.4 Betting Against Beta

Recently, Journal of Financial Economics published the highly influential research paper "Betting Against Beta" by Andrea Frazzini and Lasse Pedersen (2013), where a dynamic model with leverage and margin constraints that vary across investors and time is presented. Frazzini and Pedersen integrate and extend multiple aspects from the earlier work by Black (1972, 1993), related to CAPM with restricted borrowing, and Black, Jensen, and Scholes (1972) which argued that the "Capital Market Line" (CML)[1] is flatter than assumed by CAPM. Frazzini and Pedersen construct a Betting Against Beta (BAB) factor that they argue rival HML, SMB and momentum in terms of economic magnitude, statistical significance, and robustness across time periods, sub-samples of stocks, and global asset classes.

While CAPM assumes that all investors invest in the portfolio with the highest expected excess returns per unit of risk (Sharpe ratio[2]), and leverage or de-leverage according to their willingness to take on risk, Frazzini and Pedersen acknowledge that a large number of investors – such as individuals, pension funds, and mutual funds – are unable to use leverage, and therefore overweight risky securities instead of using leverage. Hence, these constrained investors need to purchase assets riskier than would be optimal in order to reach their required expected return. This suggests that risky high-beta assets require lower risk-adjusted returns, meaning that investors are not rewarded efficiently for taking risk because they bid up high-beta assets. This can be seen in conjunction with the relative flatness of the CML, outlined by Black, Jensen, and Scholes (1972). For unconstrained investors this can present an appealing strategy, and Frazzini and Pedersen (2013) find empirically that portfolios of high-beta assets have lower alphas and Sharpe ratios than portfolios of low-beta assets.

To capture the asset-pricing effect of the funding friction, Frazzini and Pedersen (2013) construct a market-neutral BAB-factor. The BAB factor is a portfolio that goes long low-beta assets and short-sells high-beta assets. To illustrate, let w_L be the relative portfolio weights for a portfolio of low-beta assets with return $R^L_{t+1} = R'_{t+1} w_L$ and consider similarly a portfolio of high-beta assets with return R^H_{t+1}. The portfolio betas are denoted β^L_t and β^H_t, where $\beta^L_t < \beta^H_t$. The BAB factor is then constructed as follows:

$$R^{BAB}_{t+1} = \frac{1}{\beta^L_t}(R^L_{t+1} - r_f) - \frac{1}{\beta^H_t}(R^H_{t+1} - r_f) \tag{3.3.6}$$

The portfolio has a beta of zero, which makes it market neutral. Meaning that the long side has been leveraged to a beta of 1, and the short side has been de-leveraged to a beta of 1.

3.4 Identifying anomalies

The name, anomaly, has been given because the CAPM, often seen as the standard benchmark asset pricing model, could not explain them. The anomalies show links

[1] The Capital Market Line specifies the return an individual investor expects to receive on a portfolio. This is a linear relationship between risk and return on efficient portfolios. See appendix 8.1

[2] Sharpe ratio is a measure of risk-adjusted returns. It says how great returns a portfolio has given relative to its risk. Sharpe Ratio is based on the difference between a portfolio's return and the risk-free rate divided by the standard deviation of the portfolio(Sharpe, 1994).

between the cross-section of asset prices and observable characteristic of the stock in question. Generally, there are two approaches used to identify anomalies. The first approach, examines returns on sets of portfolios formed from sorts on anomaly variables. The second approach is a cross-sectional related regression presented by Fama and MacBeth (1973) that use anomaly variables to explain the cross-section of average returns.

3.4.1 Sorts

The sorts approach, done by Lakonishok, Shleifer, and Vishny (LSV, 1994), and later done by Fama and French (2008), examine the returns on sets of deciles formed from sorts on different anomalies. The approach is simple, and gives a picture of how average returns vary across the spectrum of an anomaly variable. Following the LSV procedure, Fama and French (2008) produced a strong positive relation between average return and the anomalies in question. Firm size, BE/ME and return momentum have all shown remarkable persistence across markets and over time. In section 6.3 we follow the sort procedure, and investigate whether these characteristics also seem relevant for returns in the Norwegian stock market. However, just looking at the realized portfolio returns like this does not constitute a formal test of a model. Thus, we perform a more formal test of the relationship between CAPM anomalies and risk-adjusted returns in section 6.4.

3.4.2 Cross-section regression

To answer which anomalies are distinct and which have little marginal ability to explain returns, we use the cross-section related regression approach of Fama and MacBeth (1973). Based on insights from earlier tests done by Douglas (1969), Black and Scholes (1973), and Black, Jensen and Scholes (1972), Fama and MacBeth (1973) presented an alternative procedure for running cross-sectional regressions, and for producing standard errors and test statistics. Their approach uses anomaly variables in a regression to explain the cross-section of average returns. The advantage is that the multiple regressions slopes provide direct estimates of marginal effects, meaning that we can measure marginal effects for many explanatory variables with our dataset from the Oslo Stock Exchange. The approach gives us the opportunity to conduct straightforward diagnostics on the regression residuals. This will allow us to judge whether the relation between average returns and the variables, implied by the regression slopes, show up across the full range of the variables. The Fama and MacBeth (1973) is done in the following two steps:

The first step in the method is to perform a set of time-series regressions of each portfolio return to find the beta estimates. Assume we have n portfolio returns over T periods with a specific portfolio's excess return in a particular time denoted $R_{i,t}$. The number of regressions equals the number of portfolios one is testing:

$$
\begin{aligned}
R_{1,t} &= \alpha_1 + \beta_{1,F_1} F_{1,t} + \beta_{1,F_{2,t}} F_{2,t} + ... + \beta_{1,F_{m,t}} F_{m,t} + \epsilon_{1,t} \\
R_{2,t} &= \alpha_2 + \beta_{2,F_1} F_{1,t} + \beta_{2,F_{2,t}} F_{2,t} + ... + \beta_{2,F_{m,t}} F_{m,t} + \epsilon_{2,t} \\
R_{n,t} &= \alpha_n + \beta_{n,F_1} F_{1,t} + \beta_{n,F_{2,t}} F_{2,t} + ... + \beta_{1,F_{m,t}} F_{m,t} + \epsilon_{n,t}
\end{aligned}
\tag{3.4.1}
$$

The step gives us information about to what extent each portfolio's return is affected by each factor, and provides us with estimates of the $\beta' s$ required for the next step. In the second step a cross-sectional regression is performed, to calculate the premiums for each factor. $\hat{\beta}_{i,F_m}$ is defined as the estimated $\beta' s$ for each portfolio for factor F_m. The estimated coefficients from step one are used as explanatory variables, and the regression is run for every month in the sample, to calculate a single risk premium for each factor:

$$
\begin{aligned}
R_{i,1} &= \alpha_1 + \gamma_{1,1}\hat{\beta}_{i,F_1} + \gamma_{2,1}\hat{\beta}_{i,F_2} + ... + \gamma_{m,1}\hat{\beta}_{i,F_m} + \epsilon_1 \\
R_{i,2} &= \alpha_2 + \gamma_{1,2}\hat{\beta}_{i,F_1} + \gamma_{2,2}\hat{\beta}_{i,F_2} + ... + \gamma_{m,2}\hat{\beta}_{i,F_m} + \epsilon_2 \\
R_{i,T} &= \alpha_T + \gamma_{1,T}\hat{\beta}_{i,F_1} + \gamma_{2,T}\hat{\beta}_{i,F_2} + ... + \gamma_{m,T}\hat{\beta}_{i,F_m} + \epsilon_T
\end{aligned}
\tag{3.4.2}
$$

The $\gamma_{j,T}$ terms are regression coefficients. The only variation between the regressions is in the dependent variables, which is different for each time period. The independent $\hat{\beta}_{i,F_m}$ terms, on the other hand, will be exactly the same for every regression. Further, Fama and MacBeth (1973) suggests to estimate γ and α as the average of the cross-sectional regression estimates:

$$
\hat{\gamma} = \frac{1}{T}\sum_{t=1}^{T}\hat{\gamma}_t, \qquad \hat{\alpha}_i = \frac{1}{T}\sum_{t=1}^{T}\hat{\alpha}_{i,t} \tag{3.4.3}
$$

and to test if these averages deviate significantly from the expected values according to the theory. The correct standard error for the test is calculated from the time-series standard deviation of the coefficients from the cross-sectional regressions:

$$
\sigma^2(\hat{\gamma}) = \frac{1}{T^2}\sum_{t=1}^{T}(\hat{\gamma}_t - \hat{\gamma})^2, \qquad \sigma^2(\hat{\alpha}_i) = \sum_{t=1}^{T}(\hat{\alpha}_{i,t} - \hat{\alpha}_i)^2 \tag{3.4.4}
$$

Both the sorting and Fama and MacBeth (1973) approach face some potential pitfalls and problems. For example it can encounter problems related to domination by microcaps where microcaps often consist of a large portion, and tend to have more extreme values. To avoid the problem related to sorting, the average returns can be examined from separate sorts of microcaps, small stocks, and big stocks on each variable. Related to the regression one can estimate separate regressions for microcaps, small stocks, and big stocks, as well as for a sample that includes all except microcap stocks. Also, the return on individual stocks can be extreme and therefore it has potential for influential observation problems.

4 Data, calculation, and sample selection

4.1 Oslo Stock Exchange

Before a detailed description of the data used in our analysis and the related calculation, we give a brief introduction about the Oslo Stock Exchange, its development, and its composition, acquired from their website . Hopefully this will grant the reader with a more comprehensive insight into our analysis.

Oslo Stock Exchange goes all the way back to September 1818 when it was established. However, the trading did not begin until April 1819. Since that time there have been a number of changes to the market place, also in the period from 1991 to 2010. One of the main changes in the period took place in 1991, when a new electronic trading system (ASTS) was introduced, which made it possible to trade via the Internet. This led brokers to move out of the stock exchange building, and to the establishment of a number of specialized Internet brokers. To create a common Nordic/Baltic platform for the exchanges and market participants, Oslo Stock Exchange joined the NOREX alliance in 2000. Along with the other NOREX exchanges, Oslo Stock Exchange in 2002 moved to a common platform (SAXESS). The platform has simplified and automated trading on the Oslo Stock Exchange as all changes get updated in real time, and the transactions are completed automatically when price, volume and other order characteristics coincide. These changes, combined with an adaptation of the opening hours to harmonize the Norwegian securities market with the other Nordic markets, have led to improved liquidity for many companies during the period.

Oslo stock exchange has grown rapidly during the last decades. In 1980 there were 93 listed companies on the Oslo stock exchange with a market value of NOK 16,5 billions. At the end of 2010, the number of listed companies on the exchange had increased to 239 companies and had a total market value of NOK 1 806 billions(Kili, 1996).

Historically, a few very large companies have dominated the Oslo stock exchange. In the early 1980s, Norsk Hydro accounted for over fifty percent of the market value, while the IPOs of the state-owned companies Telenor and Statoil in 2000 and 2001 respectively, have a major impact on the stock exchange today(Kili, 1996).

4.2 Data and sample selection

The data used for empirical investigation in this article is provided by the Oslo Stock Exchange[3], and includes daily observations of all equities traded at the Oslo Stock Exchange in the period from 1991 to 2010. The data contains end of day bid and

[3]Both accounting and price data are provided by the OSE data service (oslo børsinformasjon (OBI)).

offer prices, as well as the last trade price of the day, if there was any trading. The data provided from Oslo Stock Exchange seems complete but we have found some missing stocks in the dataset. We also have accompanying accounting information for the equities, although this information is somewhat lacking. This leads to a rather reduced data set where this information is used. To visualize this incomplete data, table 1 shows how many stocks that are missing in the accounting information that exist in our dataset with daily prices. These missing values will affect our results where accounting information is used to construct factors like SMB and HML. In empirical asset pricing investigation, it is common to filter the data before calculating representative returns for the exchange. The reason is that securities that are seldom traded, or those defined as penny stocks, are challenging and can give exaggerated returns (Ødegaard, 2014). In the following, we have therefore made three different filters of preconditions that need to be fulfilled before a security is included in the analysis. All our analyses is done with each of these filters to make our results more robust. With our dynamic algorithm we adjust the preconditions to analyze the results.

Our choice of filter is a result of practical advice from Kristian Heggen, where we use more realistic preconditions than earlier papers. Calculations require that stocks have a minimum number of 50 trading days during the previous year to enter the sample pool. Stocks with market capitalization under NOK 50 million are excluded, and we don't use any preconditions regarding penny stocks at all. The second filter is similar to the one used by Bernt Arne Ødegaard (2009), where calculations require that stocks have a minimum number of 20 trading days to enter the sample pool. Also, calculations require that the stock have a price above NOK 10 and a total value outstanding of minimum NOK 1 million to be considered. Finally, in our third filter we have chosen to adjust all the prerequisites down to zero, using all the data we have available. The three different filters are illustrated in table 2, while we in table 1 provide some descriptive statistics for our filtering of the sample. Generally, all results presented in this paper will be based on our preconditions, and results of the remaining filter criteria are shown in appendix.

Table 1: Filtering and exclusions

Filtering the dataset

Year-end	Total stocks	Missing stocks	Penny stocks	Micro caps.	Iliquid stocks
1991	143	20	0	14	0
1992	157	11	0	26	2
1993	162	18	0	9	11
1994	173	14	0	8	2
1995	177	14	0	8	10
1996	187	18	0	3	7
1997	236	18	0	5	17
1998	251	15	0	18	3
1999	229	40	0	10	1
2000	226	33	0	15	7
2001	223	28	0	18	0
2002	212	27	0	30	0
2003	187	36	0	7	2
2004	196	17	0	3	4
2005	229	22	0	1	18
2006	235	23	0	1	11
2007	273	23	0	1	11
2008	265	29	0	13	2
2009	241	32	0	10	1

The table provides some descriptive statistics for the sample of equities traded on the Oslo Stock Exchange in the period 1991 to 2010. The first column lists the year. The second column lists the number of stocks available in our dataset with daily prices. The third column lists how many stocks that are missing in our accounting information. The fourth column lists how many stocks that are excluded for having to low stock price. The fifth column lists how many stocks that are excluded regarding market capitalization. The final column lists how many stocks that are excluded based on trading days.

Table 2: The three filters used in this paper

	Our preconditions	Ødegaards preconditions	No preconditions
Market Cap (MNOK)	50	1	0
Stock Price (NOK)	0	10	0
Minimum trading days	50	20	0

4.3 Asset return calculations

There are generally two methods used to calculate returns from a series of prices, simple returns and continuously compounded returns. The different returns are calculated as follows:

$$\text{Simple returns: } R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \text{ x } 100\% \tag{4.3.1}$$

$$\text{Continuously compounded returns: } r_t = 100\% \text{ x } ln(\frac{P_t}{P_{t-1}}) \tag{4.3.2}$$

where R_t denotes the simple return at time t, r_t denotes the continuously compounded return at time t, P_t denotes the asset price at time t, and ln denotes the natural logarithm(Brooks, 2008).

If the asset under consideration is a stock or a portfolio of stocks, the total return due to holding it is the sum of the capital gain and any dividends paid during the holding period (Brooks, 2008). Ignoring dividend payments is unfortunate, and will lead to an underestimation of the total returns that accrue to investors. For short holding periods this is likely to be negligible, but over investment horizons of several years this will have a severe impact on cumulative returns. Ignoring dividends also has an effect of distortion on the cross-sections of stock returns. For example, growth stocks with large capital gains will be inappropriately favored over income stocks, such as utilities and mature industries that pay high dividends. We take this into account and make several adjustments to the stock prices, see section 4.4 below. By adjusting the stock prices, either of the two formulae presented above generate returns that provide a measure of the total return that will accrue to a holder of the asset during time t. However, we are using log-return, which is most commonly used in financial modeling. Part of the reason for this is that the relationship between multi-period continuously compounded returns and one-period continuously compounded returns is simpler than the relationship between multi-period simple returns and one-period simple returns. The multi-period simple returns becomes a geometric sum of the one-period simple returns, meaning that adding simple one-period returns to arrive at a multi-period returns can lead to misleading results. Continuously compounded multi-period returns, on the other hand, is just the sum of the continuously compounded one-period returns. This makes continuously compounding better suited for financial modeling (Brooks, 2008). To illustrate this, consider a two-month continuously compounded return defined as:

$$r_t(2) = ln(1 + R_t(2)) = ln(\frac{P_t}{P_{t-2}}) = p_t - p_{t-2}$$

taking exponentials of both sides shows that:

$$P_t = P_{t-2}e^{rt(2)}$$

so that $r_t(2)$ is the continuously compounded growth rate of prices between months $t-2$ and t. Using $\frac{P_t}{P_{t-2}} = \frac{P_t}{P_{t-1}}$ x $\frac{P_{t-1}}{P_{t-2}}$ and the fact that $\ln(xy) = \ln(x) + \ln(y)$ it follows that:

$$\begin{aligned} r_t(2) &= ln(\frac{P_t}{P_{t-1}} \text{ x } \frac{P_{t-1}}{P_{t-2}}) \\ &= ln(\frac{P_t}{P_{t-1}}) + ln(\frac{P_{t-1}}{P_{t-2}}) \\ &= r_t + r_{t-1} \end{aligned}$$

4.4 Adjusting stock price

When calculating returns we make several adjustments to the stock prices. This is done to better handle problems related to dividends, splits and no-trade. If a stock is traded during the day, we use the closing price adjusted for splits and adjusted for dividend distributions. Dividends reduce the total assets of the company causing the share price to fall once the dividend is paid out to the investors. Furthermore, a company can perform a stock split or a reverse split. The number of outstanding shares increases (decreases) by the multiple corresponding to the split (reversed split), but the total market value of common equity is unchanged. Hence, using unadjusted stock prices leads to very inaccurate measurement of the single-day change in price. Related to stocks that have not been traded during a day, we use the mean value of the bid price and ask price, adjusted for splits and dividends. Our opinion is that even if there is no actual trading during a day, the bid and ask prices give valuable information about the hypothetical direction of the prices, reflecting what potential buyers and sellers actually want to pay and sell the stocks for. In cases where there is no trading during the day, and either the ask price or bid price is missing, we use the previous actual close price. Clearly, this is a problem related to illiquid stocks, and you can debate whether to use other calculations of the price than the previous close price. One solution is to exclude stocks with poor liquidity, or to use an interpolation method between trade dates. We use the generic adjusted price, which is the last closing price adjusted for splits and dividends.

In cases where we don't have a closing price for the actual day, bid price, ask price or a previous closing price, we use the nearest price to calculate returns. This is the case where a stock gets listed but starts trading after a period. For example, if a company is listed October the $2st$, and the first trading takes place October $4th$, the actual closing price on the $4th$ is used for the previous days. This adjustment occurs very rarely, and the return for the few days without trading are set to zero. This means that as far as the company is listed at Oslo Stock Exchange, we always use an adjusted price for every trading day. As the identifier of a security, we are using the International Securities Identification Number (ISIN). If stocks are missing ISIN, they are excluded from our data. Similarly, if a stock is listed and de-listed later with just one or zero trades, the stock is excluded because of the impossibility to calculate the stocks returns.

5 Method

5.1 Estimation of Market Beta

The betas are estimated by the slope of a regression line, where return on a security is related to the return on the market, consisting of all the securities in our data[4].

$$\beta_{it} = \frac{Cov(R_{it}, R_{mt})}{Var(R_{mt})} \tag{5.1.1}$$

where $Cov(R_{it}, R_{mt})$ is the covariance between R_{it} and R_{mt}, and $Var(R_{mt})$ is the variance of R_{mt}. In order to implement the calculation, we need to choose a time period for the estimation.

This measurement of a security's instantaneous and possibly time-varying riskiness in terms of its market exposure (beta) is something that has increased in importance lately. This is based on the increase in high frequency trading and the reduction in investment horizons. The stock's market exposure is in fact not the same when measured across different return frequencies. Gilbert, Hrdlicka, Kalodimos and Siegel (2014) showed that sorting stocks based on the difference between low- and high-frequency betas yields large mispricing relative to the CAPM at high frequencies, but smaller mispricing at lower frequencies. They also documented a robust relationship between the frequency dependence of betas and proxies for the uncertainty about the effect of systematic news on firm value. Their research shows empirically that the frequency dependence of betas is associated with firm- and industry-level proxies of opacity (uncertainty about the effect of systematic news on firm value). Their expectations model, free from microstructure, trading frictions and behavioral biases, shows how opacity can generate differences in unconditional betas across frequencies. The apparent mispricing at high frequencies relative to CAPM reflects the unconditional CAPM's failure to capture opaque and transparent firm's risk exposure properly at high frequencies, while the unconditional CAPM does so correctly at low frequencies. They also document that conditional high-frequency betas vary with systematic news and that the conditional CAPM is not able to price assets correctly. By sorting stocks based on the difference between their quarterly and daily beta estimates, $\Delta\beta$, they find that a portfolio that is long high stocks, $\Delta\beta$, and short low stocks, $\Delta\beta$, yields large positive CAPM alphas when using daily returns but significantly lower alphas when using quarterly returns. Their study states that the effect of opacity can confound asset pricing models and distort risk measurements at high frequencies, while opacity has little impact at low frequencies.

Asset pricing models such as the CAPM or the Fama- French-Carhart model that might be appropriate at low frequencies will not price assets correctly when applied at high frequencies, as the effect of opacity-induced uncertainty is not captured by betas. Bearing this in mind we have chosen to use monthly data and both five (60 months) and three (36 months) years of data in our estimation (a security would not

[4]Calculations use the securities satisfying the filter criteria discussed in section 4.2.

be included if a full 36 or 60 months of data were not available). Also, based on our rolling regression, we rebalance our beta estimates each month. Finally, we define our proxy for the market factor in stock returns as the excess market return, $R_m - r_f$. r_f is the one month NIBOR-rate at the beginning of the month, while R_m is the returns on the equally-weighted portfolio of the stocks.

5.2 Construction of SMB & HML

In this section we will give a comment on the methodology, the forming of six portfolios sorted on stocks ME and BE/ME, used in our study of economic fundamentals. To construct both the SMB-factor and the HML-factor, we are using some preconditions relative to penny stocks, micro caps and trading days described in our filtering of securities in section 4.2. The method used when constructing the factors is similar to the method used by Fama and French (1992). At the end of June each year t (1992 – 2010), stocks that meet our preconditions is allocated into two groups, small (S) or big (B), based on whether their June market equity (price time shares) is below or above the median market value for OSE stocks.

The stocks are also broken into an independent sort to three book-to-market equity groups; low, medium or high (L, M or H). This is based on the breakpoints for the bottom 30 percent (*low*), middle 40 percent (*medium*), and top 30 percent (*high*) of the ranked values of BE/ME for the OSE stocks. When constructing low, medium and high we use a round function for low and high. Medium is defined as the sum of low and high subtracted by the total numbers of stocks. This will give approximately 30 percent for low and high, and 40 percent for the medium. Book equity, BE, is defined as the OBI book value of stockholders equity. Book equity for the fiscal year ending in calendar year *t-1*, divided by market equity at the end of December of *t-1* corresponds to Book-to-market equity, BE/ME. Firms with negative BE are included in our sample. However, this only applies to very few companies and will only have a marginal effect. Fama and French (1992) exclude these firms from their sample when constructing the factors.

The six size portfolios (S/L, S/M, S/H, and B/L, B/M, B/H) are defined as the intersections of the two ME and the three BE/ME groups. For instance, the S/H portfolio contains the stocks in the small-ME group that also were in the high-BE/ME group, and the B/L portfolio contains the big-ME stocks that also had low BE/MEs. The construction of these portfolios is illustrated in table 3.

The monthly value-weighted returns on the six portfolios are calculated from July of year t to the following June of *t+1*, were the portfolios are reformed. Firms need to have both stock prices for December of year *t-1* and June of t and OBI book equity for year *t-1* to be included in the sample. Also, since the portfolios are reformed every year stocks might be both listed and de-listed between the reformations. These listings or de-listings are excluded. This means that if S/H consists of 20 stocks when formed and 2 stocks de-lists during the year, we will compute the average return based on the 18

Table 3: The construction of the six size portfolios

	Median ME	
Top 30 percent BE/ME	S/H	B/H
Middle 40 percent BE/ME	S/M	B/M
Bottom 30 percent BE/ME	S/L	B/L

remaining stocks. Furthermore, if a company gets listed during the year, the company will not be included in one of the portfolios until June year $t+1$, when the portfolios are reformed. Table 22 in the appendix shows the six different portfolios where returns are calculated as the value-weighted average.

The SMB-factor is defined as the difference, each month, between the average of the returns on the three small-stock portfolios (S/L, S/M, and S/H) and the average of the returns on the three big-stock portfolios (B/L, B/M, and B/H). Thus, SMB is the difference between the returns on small- and big-stock portfolios with about the same weighted-average book-to-market equity. This makes the influence of BE/ME trivial, focusing instead on the different return behaviors of small and big stocks. HML, on the other hand, are defined as the difference, each month, between the simple average returns on the two high-BE/ME portfolios (S/H and B/H) and the average of the returns on the two low-BE/ME portfolios (S/L and B/L). As the two components of HML are returns on high- and low-BE/ME portfolios with about the same weighted average size, the two returns should be largely free of the size factor in returns. Meaning the focus will be on different return behaviors of high- and low-BE/ME firms.

$$SMB = average(S/L, S/M, S/H) - average(B/L, B/M, B/H) \tag{5.2.1}$$

$$HML = average(S/H, B/H) - average(S/L, B/L) \tag{5.2.2}$$

5.3 Construction of PR1YR

To capture short-term past performance, we follow Carhart's (1997) method related to construction of the momentum factor. Each month, t, we examine how well a momentum strategy is by going long the previous winners, and short-selling the previous losers. On a monthly basis, we rank stocks at the end of the month $t-1$ based on their cumulative logarithmic returns from $t-12$ to $t-2$ to identify the winners and the losers. To avoid the 1-month reversal in stock returns, which may be related to liquidity or microstructure issues (Jagadeesh (1990), Lo and MacKinaly (1990), Boudoukh, Richardson, and Whitelaw (1994), Grinblatt and Moskowitz (2004)), the most recent month, $t-1$, is skipped. This is standard in the momentum literature.

Before the securities are included in the portfolios, they need to fulfill the preconditions determined in our filtering described in section 4.2. Also, a security must have had monthly returns for the previous $t-12$ to $t-2$. This means that the security has to be listed at the exchange for all the 11 months to be included. If a security is listed in month $t-11$ and gets traded for the rest of the period, it will be excluded from the portfolio. Securities can fulfill this precondition and still be de-listed in month $t-1$, which also leads to exclusion. In month t we obviously only include securities that still are listed, and when using our filter[5] securities with a total value outstanding below NOK 50 million will be excluded. Whether or not to include a security based on its market capitalization is determined the last trading day of period $t-1$. Regarding the requirement related to minimum number of trading days, a security must have fulfilled this requirement during the 11 months $t-12$ to $t-2$ to be included. A security with only a few actual trades less than 50 during the period, will be excluded regardless of extremely high or low returns.

Stocks fulfilling the described requirements are then split into three portfolios based on their cumulative logarithmic returns from $t-12$ to $t-2$: the top 30 percent, the median 40 percent, and the bottom 30 percent. When constructing the top and bottom 30 percent, we use a round function.To finalize the PR1YR-factor the equal-weighted average portfolio return is calculated for the top and the bottom portfolios in each of the subsequent months. The return of the momentum strategy, which buys the winner portfolio and sells the loser portfolio, is then the return of the winner portfolio minus the return of the loser portfolio, in each month. If a company gets de-listed in period t, we exclude this security and compute the average return with the rest of the securities. There are several reasons why a security might de-list during a month, for example in case of bankruptcy, mergers and acquisitions. During our time sample there are few months with more than one de-listing, and ignoring one security has a minimal marginal effect on the average simple return of this month.

5.4 Construction of BAB

With respect to the construction of the BAB-factor, we have for the most part chosen to follow Frazzini and Pedersen's (2013) method. Our method differs from theirs when estimating market betas. Frazzini and Pedersen (2013) estimate pre-ranking betas from rolling regressions of excess returns on market excess returns using daily data (if available). We have chosen the same approach but we exclusively use monthly data(see section 5.1 where we justify our choice of data). The choice of estimation period is a trade-off between a short period reflecting structural changes in the risk situation in a good way, for an extended period of time that eliminates noise in an improved manner. We have chosen to construct the BAB-factor using both 36 months of historical data, and 60 months of historical data to get as robust results as possible. Frazzini and Pedersen further employ some adjustments in their estimation, including a shrinking of the time series estimate of beta (β_t^{TS}) toward the cross-sectional mean (β^{XS}). They

[5] When using a filter similar to Bernt Arne Ødegaard, we determine whether or not to include a security based on its price the last trading day of period $t-1$.

argue that the shrinking factor will diminish the effects of outliers. We have not made the corresponding shrinkage of our estimates.

To be consistent, only securities that fulfill the predefined preconditions in our three different filters will be used for factor calculation- including the betting-against-beta factor. Also, a precondition to calculate the beta is that a security must have monthly returns for all the previous months in question, 36 or 60 months. If requirements are met and betas are estimated for each security, we rank all securities in ascending order on the basis of their estimated beta, and constructs two portfolios. One low-beta portfolio comprised of all the stocks with a beta below the median, and one high-beta portfolio consisting all the stocks with a beta above the median. Weights of the securities in the two portfolios are determined by the ranked betas, with higher weights assigned to the extreme values (i.e. highest weight for the lower-beta securities in the low-beta portfolio and for the higher-beta securities in the high-beta portfolio). The portfolios are rebalanced every month.

The process can be illustrated by letting z denote the nx1 vector of beta ranks $z_i = rank(\beta_{it})$, and $\bar{z} = 1_n' z/n$ the average rank of all the securities, with n being the number of securities and $1_n'$ a vector of ones. Given these definitions, the portfolio weights of the low-beta and high-beta portfolios are:

$$\begin{aligned} W_H &= k(z - \bar{z})^+ \\ W_L &= k(z - \bar{z})^- \end{aligned} \tag{5.4.1}$$

Where x^+ and x^- indicate the positive and negative elements of a vector and k is the normalizing constant that assures that the sum of weights in each portfolio equals one, hence $k = 2/1_n'|z - \bar{z}|$. The BAB factor is a long-short combination of the two portfolios that is long the low-beta portfolio and short-sells the high beta portfolio. Each portfolio is rescaled to have a beta of one at portfolio formation and the resulting factor is therefore market-neutral. The final step to calculate the return of the BAB factor is then given by the equation:

$$R_{t+1}^{BAB} = \frac{1}{\beta_t^L}(R_{t+1}^L - r_f) - \frac{1}{\beta_t^H}(R_{t+1}^H - r_f) \tag{5.4.2}$$

where $R_{t+1}^L = R_{t+1}' W_L, \quad R_{t+1}^H = R_{t+1}' W_H, \quad \beta_t^L = \beta_t' W_L, \quad \beta_t^H = \beta_t' W_H.$

6 Results

In this section the main results from our empirical investigation is presented. We will start by giving some descriptive statistics for the calculated asset pricing factors and their related correlations, before we move on to the sorts approach. For the latter we will examine the returns on sets of deciles formed from sorts on different firm characteristics. Finally, in section 6.4 we will show the results from the cross-sectional

Fama MacBeth (1973) regressions on different asset pricing models.

6.1 Asset pricing factors

Table 4 gives descriptive statistics for the calculated asset pricing factors. The table lists the average percentage monthly return, and in the parenthesis the p-value for a test of difference from zero. The averages from both the HML and the PR1YR-factor appear to be significantly different from zero. Meaning that if you had followed one of these strategies, you would have earned a positive average return for the whole sample period. The PR1YR-factor has the highest average returns of all the factors regardless of the period tested, and it is also significant positive for all the sub-periods on a 5 % level, except for the period 1992-1995 (where it is significant positive on a 10 % level). SMB turns out to be insignificant for all of the sub-periods on a 5 % significance level, but it yields a significant negative average return for the periods from 1992 – 2010 and 2006 – 2010 on a 10 % significance level. The BAB-factor has both negative and positive average returns during the sub-periods, but it is far from significant. Based on this, it seems to be a book-to-market and momentum effect at the Oslo Stock Exchange during our sample period. Also, there is a weak indication of a negative SMB effect. From the correlation overview in the same table we can observe limited correlation between the factors, but we do notice a negative correlation of -0,3 between BAB and PR1YR. We show similar results with the other filter criteria in the appendix section 8.4.

Table 4: Descriptive statistics for asset pricing factors

Average

	SMB	HML	PR1YR	BAB
1992-2010*	-0.54 (0.06)	0.92 (0.00)	2.21 (0.00)	0.01 (0.98)
1992-1995*	0.38 (0.57)	-0.19 (0.77)	1.48 (0.06)	NA
1996-2000	-0.24 (0.63)	0.91 (0.06)	1.52 (0.00)	-0.53 (0.59)
2001-2005	-0.81 (0.15)	2.28 (0.00)	3.44 (0.00)	0.84 (0.67)
2006-2010	-1.23 (0.04)	0.33 (0.52)	2.25 (0.00)	-0.92 (0.36)

*The BAB value are not available in all of the sub-periods due to three years of beta construction.

Correlations

	SMB	HML	PR1YR	BAB
SMB	1			
HML	-0,024	1		
PR1YR	-0,146	0,122	1	
BAB	-0,103	-0,035	-0,310	1

The table describes the calculated asset pricing factors. SMB and HML are the Fama and French (1992) pricing factors. PR1YR is the Carhart (1997) factor. BAB is the betting-against-beta factor recently documented by Frazzini and Pedersen (2013). The table lists the average percentage monthly return, and in the parenthesis the p-value for a test of difference from zero. The table also list an overview of the correlation between the factors.

6.2 Simple portfolio sort based on Market Beta

When the betas are estimated, we rank the numerical values and divide the securities into 5 portfolios based on the ranking. Securities in portfolio 1 are those with the lowest betas, while the ones in portfolio 5 are those with the highest betas. The beta values in portfolio 1 are mainly positive. However, there are some few negative estimated beta values in some months. We have chosen to not exclude the stocks with negative beta estimates based on their rare occurrence. This procedure, from calculations of betas, ranking of securities, and to assigning into portfolios is done through all the possible investment years. Table 5 shows the results for the whole period, calculating average returns of beta sorted portfolios.

Results are shown for the whole time period, although we lose the time spent on creating the beta factor. For that reason the 3-year beta portfolios starts in 1995 and the 5-year beta portfolios start in 1997. Portfolio 1 consists of the stock with lowest beta values. At first glance it looks like there is no relation between betas estimated and returns. Both the mean and median values show a relatively unsystematic distribution of returns during the period. Surprisingly, the results indicate that stocks with high beta values have negative returns for both calculation methods. The sample period used in this study is relatively short, and it would be interesting to examine average returns related to the beta values for a much longer time period. Based on our data, there appears to be no positive relationships between beta estimated and subsequent returns, which is contradictory to CAPM. A possible explanation could be related to recent research done by Frazzini and Pedersen (2013), which suggest that risky high-beta assets require lower risk-adjusted returns. This means that investors are not rewarded efficiently for taking risk because they bid up high-beta assets. Interestingly, we see that the volatility of the stock returns increase with the stocks beta. Both the minimum and maximum values increases related to beta, showing that riskier stocks tend to be more volatile.

Table 5: Beta portfolios 1995(1997) – 2010

Three years of monthly returns

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	0.50	(3.69)	-12.50	1.08	8.82	19	30	39
2	0.50	(4.62)	-19.35	0.69	10.20	19	30	39
3	0.25	(6.11)	-27.38	1.24	13.12	19	30	39
4	0.41	(7.30)	-34.17	1.09	21.18	19	30	39
5	-0.70	(9.69)	-37.54	0.57	26.75	18	29	39

Five years of monthly returns

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	0.40	(3.32)	-13.22	0.51	8.79	14	19	24
2	0.72	(4.29)	-18.95	1.25	11.93	14	19	24
3	0.63	(5.63)	-27.57	1.02	11.87	14	19	24
4	0.43	(6.91)	-27.99	0.79	14.52	14	19	24
5	-1.10	(10.00)	-42.62	0.67	20.84	13	19	25

Returns are percentage monthly returns. The returns are not annualized. Data for stocks listed at the Oslo Stock Exchange during the period 1991-2010. Calculations use the stocks satisfying the "filter" criteria discussed in 4.2. When the portfolios are constructed, we rank the numerical values and divide the securities into 5 portfolios based on the ranking. When dividing by 5 we use a round function for the first 4 portfolios. The fifth portfolio is defined as the sum of the first four portfolios subtracted by the total number. This is why the number of stocks in portfolio 5 can vary with +/- 1 stocks.

6.3 Simple portfolio sorts based on CAPM anomalies

In this section we present returns on sets of deciles formed from sorts on different anomalies. The approach helps us to get a picture of how average returns vary across the spectrum of an anomaly variable. We will start by sorting on firm size and then continue to sort on book-to-market ratio. Finally we sort on momentum.

6.3.1 Size

The size effect is a well known and good documented regularity showing that investments in small companies on average have had a (risk-adjusted) return premium relative to investments in big companies. However, it has been proven that the effect varies with the choice of time period being analyzed. For example, it has been shown that the effect for the most countries was declining and negative after it was first documented by Banz in 1981 and that it later again become on average positive. Taking this into account, we have chosen to split into different sub periods to observe the evolvement of differential returns between small and large companies. But first, to investigate the size effect in Norway, we sort into portfolios based on a company's market value at the end of the previous year. Each year the portfolios are re-balanced. Table 6 shows returns for 5 portfolios sorted on size for the period 1992 – 2010. Portfolio 1 contains the smallest companies and portfolio 5 the largest companies.

Table 6 shows a relatively unsystematic distribution of returns during the period. There is no indication that the small companies have higher returns than the large companies, quite the contrary. Small companies actually have a negative return over the period as opposed to the large companies, which have positive returns. This trend can partly be confirmed by the median values, which almost are monotonically increasing with firm size. In other words, it appears that there has been no size effect in Norway. In panel B of the table we observe that the differential return between small and large companies has been negative also for most sub-periods, and has been more negative over time. The last column of the table shows the results for a test of whether the differential return between the two portfolios is significantly different from zero. Only for the last sub-period (2006-2010) do we find support for a significant negative difference in the returns of small and large companies. Meaning that a SMB-strategy during the financial crises would yield a significant negative return.

Table 6: Monthly returns for portfolios sorted on company value

Panel A shows the monthly percentage returns for 5 portfolios constructed based on market value. The results are for the whole sample period 1992 - 2010. The portfolios are re-balanced at the end of each year. Panel B shows the average monthly return for the portfolios containing the 20 percent smallest firms (portfolio 1) and the 20 percent largest firms (portfolio 5) on the exchange for four sub-periods. The table also show p-values from a test of whether the return difference between the portfolios is zero.

Panel A: Whole sample 1992 - 2010

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-0.25	(7.14)	-33.49	0.14	21.83	18	35	50
2	0.14	(6.78)	-27.14	0.97	21.54	20	34	50
3	-0.02	(7.29)	-30.88	0.72	17.43	20	33	50
4	0.60	(6.62)	-29.45	1.58	13.74	21	35	50
5	0.30	(7.52)	-32.16	1.21	16.76	19	36	51

Panel B: Sub-periods

	Small (Portf. 1)	Large (Portf. 5)	Diff	t-test: diff=0
1992 - 1995	1.60	0.75	0.85	0.53
1996 - 2000	0.17	0.53	-0.37	0.56
2001 - 2005	-0.47	0.17	-0.64	0.39
2006 - 2010	-1.73	-0.13	-1.60	0.03

6.3.2 Book value relative to market value

The relationship between book value and market value is another well know company characteristic that seems to give a systematic pattern in returns across companies. Several studies have found that companies with the highest book value relative to market value have systematically higher risk-adjusted returns than those with lowest book value relative to market value. To investigate whether this phenomenon also is present in Norway, we construct five portfolios in the same manner as the size portfolios.

Table 7 shows the results of this analysis. Portfolio 1 contains the companies with the lowest BE/ME ratio, while portfolio 5 contains the companies with the highest BE/ME ratio. As we can see from the table, there has been a positive differential return in the period: the companies with the highest BE/ME ratio have had the highest returns, and the returns are falling monotonically with lower BE/ME ratio. Portfolio 5 gives on average a return of 1,24 percent per month compared with portfolio 1. In light of this, it appears that there has been a systematic pattern in returns across companies in Norway related to BE/ME. In the table's panel B we show returns for the two extreme portfolios based on BE/ME for four sub-periods. We see that the BE/ME effect has been dominating in most of the periods in our sample (except for the period 1992-1995), and that the effect was highest in the period 2001-2005, where it had a differential return per month of 3,23 percent. The latter is however also the only period that is significant.

Table 7: Monthly returns for portfolios sorted on BE/ME

Panel A shows the monthly percentage returns for 5 portfolios constructed based on Book to Market value (BE/ME). The results are for the whole sample period 1992 - 2010. The portfolios are re-balanced at the end of each year. Panel B shows the average monthly return for the portfolios containing the 20 percent smallest firms (portfolio 1) and the 20 percent largest firms (portfolio 5) on the exchange for four sub-periods. The table also show p-values from a test of whether the return difference between the portfolios is zero.

Panel A: Whole sample 1992 - 2010

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-0.64	(8.47)	-37.50	0.28	18.52	21	35	50
2	0.19	(7.00)	-32.28	1.08	14.00	20	35	50
3	0.28	(6.20)	-30.43	1.17	12.94	20	34	50
4	0.34	(6.46)	-23.37	1.28	15.46	20	34	50
5	0.60	(6.59)	-34.04	1.21	17.32	17	36	51

Panel B: Sub-periods

	Small (Portf. 1)	Large (Portf. 5)	Diff	t-test: diff=0
1992 - 1995	1.04	0.83	-0.21	0.80
1996 - 2000	0.14	0.99	0.85	0.21
2001 - 2005	-1.63	1.60	3.23	0.00
2006 - 2010	-1.61	-0.93	0.67	0.21

6.3.3 Momentum

Jagadeesh and Titman (1993) documented that an investment strategy defined as buying winning stocks the last 3-12 months and selling looser stocks with low return over the same period, gave risk-adjusted returns. The momentum effect has been confirmed in financial markets in several countries, and the profits generated from the momentum strategy can not be explained away stating that high-performance stocks are riskier or that trading costs associated with the strategy will eat up the profits (Chuang & Ho, 2013).

Our table 8 shows monthly returns of portfolios sorted on momentum at Oslo Stock Exchange. We have chosen to show the monthly returns with momentum periods comprising 6, 12, 24, and 36 months, to see if the choice of time period has an effect on the returns. Furthermore, consider the returns estimated with a period of 12 months. Portfolio 1 contains the stocks with the lowest returns the previous 12 months (last month is skipped), while portfolio 5 contains the stocks with the highest return. As we can see, the returns are increasing monotonically with higher momentum. This is also the case for the time period of 6 months. In line with theory the momentum effect is highest with a strategy containing 12 previous months. The table also show that the momentum effect is decreasing when longer time periods are chosen, and that there is an indication of a mean reversion (this is clearly the case when using same filter criteria as Bernt Arne Ødegaard (2009), see appendix 8.7 table 29). This supports prior research on momentum. For example, De Bondt and Thaler (1985) argued that over a 3- to 5-year holding period, stocks that performed poorly over the previous 3- to 5- years would realize higher returns than stocks that performed well over the same time period. Regardless of time period chosen portfolio 1 has a negative average return, meaning that an investment strategy that consist of buying prior losers will yield a negative return for our time period. But there is as mentioned an indication of an increase when using a longer time period. Again looking at the time period of the 12 previous months, the average return is 1,18 percent for portfolio 5. The spread between portfolio 1 and portfolio 5 is 2,64 percent. This means that if you follow the investment strategy, you will on average earn a return of 2,64 percent each month for the whole time period, excluding transactions costs - a distinct momentum effect.

Table 8: Momentum sorted portfolios

5 Portfolios - 6 months

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-1.47	(9.50)	-34.48	0.23	22.55	23	38	53
2	-0.20	(6.58)	-26.11	0.78	13.69	23	38	53
3	0.49	(5.62)	-27.47	0.90	12.91	23	38	53
4	0.62	(5.85)	-26.81	1.46	14.16	23	38	53
5	0.87	(7.17)	-24.98	1.36	19.37	23	39	54

5 Portfolios - 12 months

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-1.46	(9.60)	-38.24	0.13	25.70	22	36	48
2	-0.36	(7.06)	-32.67	0.34	17.38	22	36	48
3	0.49	(5.82)	-28.66	1.00	14.35	22	36	48
4	0.64	(5.57)	-20.17	1.51	13.46	22	36	48
5	1.18	(7.07)	-27.78	1.91	21.70	21	36	49

5 Portfolios - 24 months

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-0.50	(9.26)	-32.53	0.82	25.79	21	32	43
2	0.50	(6.50)	-26.33	0.63	19.12	21	32	43
3	0.78	(5.35)	-21.89	1.27	15.69	21	32	43
4	1.00	(5.32)	-26.67	1.65	12.74	21	32	43
5	0.36	(6.74)	-31.52	1.33	16.38	20	32	44

5 Portfolios - 36 months

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-0.64	(8.68)	-30.34	0.36	26.31	20	30	39
2	0.13	(6.07)	-23.32	0.38	16.72	20	30	39
3	0.71	(5.08)	-24.85	1.37	12.26	20	30	39
4	0.49	(4.91)	-24.13	1.51	9.99	20	30	39
5	0.31	(6.89)	-37.66	1.38	14.78	18	30	40

6.4 Fama MacBeth regression

In the following sections, we will present results from our estimations of the CAPM, Fama French three-factor model, Carharts four-factor model, and one model where we have made certain adjustments compared to the models mentioned. The different models are empirically tested over the period 1992 to 2010. We have chosen to group our securities in four different sorted datasets; 1) 5 portfolios sorted on firm size 2) 5 portfolios sorted on book-to-market 3) 5 portfolios sorted on momentum, and 4) 5 portfolios sorted on market beta. The main reason to break it in two different sorts is that we want to reduce measurement errors, and to hopefully get a dispersion of the market betas. For any model and data set combination, the Black, Jensen and Scholes (1972) time series average absolute pricing error test, and the Fama MacBeth (1973) cross-sectional test are conducted. For all the t-tests in section, the significance level of rejecting null hypothesis is 5 % .

6.4.1 CAPM

We will first start to present the results of our CAPM estimation, since this is considered to be the benchmark model in finance literature. The model is considered to be correct if the intercept is zero, and the slope of the market beta is the expected value of the excess return of market value. In table 9 and 10, panel A shows the results of the CAPM time series regressions for the 5 portfolios sorted on firm size, book-to-market equity, momentum, and market beta during 1992 – 2010. Column two and three in the tables show estimated constant terms, α, with related p-values. α is the measure of abnormal return, or the pricing error of the portfolios. It is the difference in the expected return on the portfolios estimated and its time series average with the expected return predicted by the CAPM. This means that if the CAPM describes expected return and a correct market portfolio proxy is selected, the regression intercepts of all portfolios should be zero. An α which is significantly different from zero therefore indicates a bad specified model. Furthermore, column four and five show estimated market betas, β_i^1, and their related p-values. The final column shows the adjusted R^2. R^2 is the most common goodness of fit statistic. A usual definition is to say that it is the square of the correlation between the values of the dependent variable and the corresponding fitted values from the model. If this correlation is high, the model fits well, while low correlation gives a value close to zero. Adjusted R^2 is a modification to R^2 and takes into account the loss of degrees of freedom associated with adding extra variables. Adjusted R^2 can be used as a decision-making tool for determining whether a given variable should be included in a regression model or not. However, there are problems with the maximization of adjusted R^2 in relation to model selection. Implying that criterion, researchers will typically end up with large models, containing a lot of marginally significant or insignificant variables (Brooks, 2008). The mentioned information above is also adequate for the models coming in the next sections.

If we throw a glance at the results from the estimation, we can see that the absolute values of the average of the intercepts are 0,0022, 0,0034, 0,008, and 0,0042 for portfolios sorted on firm size, book-to-market equity, momentum, and market beta respectively. From the t-test, the null hypothesis is rejected for portfolio 4 sorted on firm size, for portfolio 1 and 5 sorted on book-to-market, for all portfolios sorted on momentum, and for all portfolios sorted on market beta, except portfolio 3. The significant constant terms are an indication of poorly specified models for the mentioned portfolios. Furthermore, looking at the beta values they are all significant regardless of the model chosen. When we sort on firm size, the betas have a good dispersion and range from 0,94 in portfolio 1 to 1,05 in portfolio 3. The dispersion is poorest when sorted on market beta, where it ranges systematically from 0,48 in portfolio 1 to 1,46 in portfolio 5. These are the portfolios with the lowest and highest risk in the tests of the CAPM, which is natural. Adjusted R^2 is lowest for portfolio 1 sorted on market beta with a value of 0,68. The highest adjusted R^2 is for portfolio 2 sorted on book-to-market value on 0,91. Based on the time series regression, it seems like the market factor in the CAPM is not quite able to price portfolios sorted on momentum and book-to-market equity. This may indicate that the CAPM is inadequate to explain the returns in the Norwegian market. Within the framework of a multi-factor model the explanation for this can be that both the momentum and the book-to-market equity characteristics represent risk factors that investors demand compensation for being exposed to, and that this effect is not captured by the market portfolio.

Panel B in the tables shows estimated risk premiums, $\lambda[1]$, for the market factor. These are estimated with the Fama MacBeth (1973) cross-sectional regressions, as described in section 3.4.2. The regressions are run on the monthly excess return of the portfolio on the estimated beta. As before, if the CAPM is true the intercept, α, is zero. A risk factor is said to be priced if the $\lambda[1]$ is significantly different from zero. Results from our tests show that all risk premiums are significantly different from zero, except when we sort on size. However, we can conclude that the market portfolios is a priced risk factor, and indicate that the CAPM might be a inadequate model for the Norwegian stock market based on all the significant constant terms (except for size).

Table 9: Estimation of the CAPM on portfolios sorted on size and book value relative to market value

Panel A shows the results from estimating the CAPM as in equation 3.2.3 for portfolios sorted on size and BE/ME. Firm size is measured as the market capitalization and BE/ME is measured by the ratio between a firms book value relative to market value. Both size- and BE/ME portfolios are equal weighted. For each set of portfolios, columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The two last columns for each set of portfolios show the estimated market beta β_i^1 and associated p-value. Panel B shows the risk premium estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero.

Panel A: Exposure estimates

Size portfolios						*BE/ME portfolios*					
Size	constant	p-value	β_i^1	p-value	R^2_{adj}	BE/ME	constant	p-value	β_i^1	p-value	R^2_{adj}
1 (low MCAP)	-0.003	0.17	0.940	0.00	0.73	1 (low BE/ME)	-0.007	0.00	1.197	0.00	0.85
2	0.000	0.26	0.960	0.00	0.85	2	0.001	0.44	1.024	0.00	0.91
3	-0.001	0.62	1.050	0.00	0.88	3	0.002	0.29	0.886	0.00	0.86
4	0.005	0.00	0.951	0.00	0.87	4	0.002	0.14	0.926	0.00	0.87
5	0.002	0.29	1.045	0.00	0.82	5	0.005	0.02	0.903	0.00	0.79

Panel B: Risk premia estimates

Size portfolios			*BE/ME portfolios*		
Factor	Risk premium	p-value	Factor	Risk premium	p-value
α	0.002	(0.93)	α	0.035	(0.00)
$\lambda[1](er_m^{ew})$	-0.000	(0.99)	$\lambda[1](er_m^{ew})$	-0.034	(0.00)

Table 10: Estimation of the CAPM on portfolios sorted on momentum and beta

Panel A shows the results from estimating the CAPM as in equation 3.2.3 for portfolios sorted on momentum and beta. Both momentum- and beta portfolios are equal weighted. For each set of portfolios, columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The two last columns for each set of portfolios show the estimated market beta β_i^1 and associated p-value. Panel B shows the risk-premium estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factors. If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero.

Panel A: Exposure estimates

Momentum portfolios						*Beta portfolios*					
Momentum	constant	p-value	β_i^1	p-value	R^2_{adj}	Beta	constant	p-value	β_i^1	p-value	R^2_{adj}
1 (low momentum)	-0.014	(0.00)	1.324	(0.00)	0.83	1 (low beta)	0.003	(0.04)	0.476	(0.00)	0.68
2	-0.004	(0.04)	1.010	(0.00)	0.87	2	0.006	(0.00)	0.630	(0.00)	0.76
3	0.005	(0.00)	0.834	(0.00)	0.86	3	0.002	(0.21)	0.879	(0.00)	0.86
4	0.006	(0.00)	0.773	(0.00)	0.81	4	0.005	(0.01)	1.080	(0.00)	0.87
5	0.011	(0.00)	0.955	(0.00)	0.76	5	-0.005	(0.03)	1.455	(0.00)	0.90

Panel B: Risk premia estimates

Momentum portfolios			*Beta portfolios*		
Factor	Risk premium	p-value	Factor	Risk premium	p-value
α	0.042	(0.00)	α	0.013	(0.00)
$\lambda[1](er_m^{ew})$	-0.041	(0.00)	$\lambda[1](er_m^{ew})$	-0.012	(0.03)

6.4.2 Fama French's three-factor model

We move on to the estimation of the three-factor model consisting of the Fama French factors, R_m, SMB and HML. A number of studies have shown that the three-factor model can explain returns in a better way than CAPM, and we want to see if this also applies to the Norwegian market. The results from our estimation are shown in table 11, and in table 31 to 33 in the appendix section 8.8. The concept of the tables is the same as before, the only difference is that we now we will have more factors included.

Looking at the absolute values of the average of the intercepts, we get 0,0016, 0,001, 0,0068, and 0,0032 when we sort our portfolios on firm size, book-to-market equity, momentum, and market beta respectively. If we compare these results to the ones we got from CAPM, we see that the average absolute pricing errors of the Fama French three-factor model are smaller. This might indicate that the Fama French three-factor model outperforms the CAPM. This is consistent with results found in past literature, and is exactly that Fama and French (1992) claimed. Another thing which also is evident from table 11, is that we once more have difficulties to price portfolios sorted on momentum. All portfolios sorted on momentum have significant alphas, and they increase with higher momentum. This is also the case for portfolios sorted on market beta, where there are significant alpha values for portfolio 2, portfolio 4, and portfolio 5. Regardless of the portfolio sorting, the three-factor model has significant exposure to the market factor. Also, we notice that all portfolios have significant exposure to SMB, while two portfolios have exposure to the HML-factor (portfolio 3 and portfolio 4). The latter is a trend in the remaining portfolio sorts as well, with the exception of portfolios sorted on book-to-market equity, which have three significant portfolio exposures to SMB and four to HML. Adjusted R^2 is lowest for portfolio 1 sorted on market beta with a value of 0,69. The highest adjusted R^2 is for portfolio 5 sorted on firm size with a value of 0,94. Although the three-factor model seems to be an improvement compared to the CAPM, there are still some worrying elements especially when sorted on momentum, but also regarding the market beta. Possibly it would be a good idea to include the PR1YR factor in the model as well, to see if it can help us to price the momentum portfolios. This is done in the following section.

Table 12 summarizes the estimates of the risk premiums, λ, and the alphas, α, with associated p-values. The last two columns show the results if we instead estimate the CAPM on the portfolios. The table shows that the SMB-factor is a priced risk factor when we sort on firm size and momentum. Similarly, the HML-factor is a priced risk factor when we sort on momentum and market beta. Not surprisingly, we see that the α is significant when we sort the portfolios on momentum and market beta. Also, we observe that the CAPM has significant α values on all portfolio sorts, besides when we sort on size. The preliminary conclusion based on the estimation of our portfolios is therefore that the three-factor model fits better than CAPM for the Norwegian stock market.

Table 11: A multifactor model for the OSE - Momentum portfolios

Panel A shows the results from estimating the Fama French three-factor model as in equation 3.3.3 for a portfolio sorted on momentum. The momentum portfolio is equal weighted. Columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns show the estimated β_i^k and their associated p-values. Panel B show the risk premiums estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero

Momentum	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	$\beta[3]$	p-value	R^2_{adj}
1 (low momentum)	-0.012	(0.00)	1.315	(0.00)	0.119	(0.05)	-0.108	(0.08)	0.83
2	-0.005	(0.01)	1.016	(0.00)	-0.086	(0.03)	0.065	(0.11)	0.87
3	0.003	(0.03)	0.843	(0.00)	-0.088	(0.01)	0.115	(0.00)	0.87
4	0.004	(0.01)	0.780	(0.00)	-0.100	(0.01)	0.084	(0.03)	0.82
5	0.010	(0.00)	0.956	(0.00)	-0.132	(0.02)	0.002	(0.97)	0.77

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	0.046	(0.00)
$\lambda[1](er_m)$	-0.047	(0.00)
$\lambda[2](SMB)$	-0.072	(0.00)
$\lambda[3](HML)$	-0.088	(0.00)

Table 12: Asset pricing tests for different test assets

	Fama/French				CAPM	
Portfolio		er_m^{ew}	SMB	HML		er_m^{ew}
sort	α	$\lambda[1]$	$\lambda[2]$	$\lambda[3]$	α	$\lambda[1]$
Size (ew)	0.033	-0.032	-0.007	0.022	0.002	-0.000
p-value	0.06	0.08	0.04	0.10	0.93	0.99
BE/ME (ew)	-0.051	0.051	-0.040	0.023	0.035	-0.034
p-value	0.50	0.49	0.31	0.18	0.00	0.00
Momentum (ew)	0.046	-0.047	-0.072	-0.088	0.042	-0.041
p-value	0.00	0.00	0.00	0.00	0.00	0.00
Market beta (ew)	0.056	-0.046	0.021	-0.214	0.013	-0.012
p-value	0.00	0.00	0.30	0.01	0.00	0.03

6.4.3 Carhart's four-factor model

As we saw in the previous section, the three-factor model was an improvement compared to the CAPM. To improve further, we want to try to extend the three-factor model with the additional momentum factor, PR1YR. Carhart's (1997) four-factor model is well established in the financial theory, so we have chosen to rely on the theory and estimate the model to see if it also applies in the Norwegian market. The model consist of the factors R_m, SMB, HML, and PR1YR, and the results of our estimation is shown in table 13, and in table 34 to 36 in appendix section 8.8.

We will concentrate on table 13, and we want to start by looking at the absolute values of the average of the intercepts, as this may give us an indication of the quality of the model. Again we have sorted our portfolios on firm size, book-to-market equity, momentum, and market beta. The results are 0,0014, 0,001, 0,0008, and 0,0026 respectively. This is a clear improvement to the CAPM, but also to the three-factor model, when we base ourselves on absolute values of the average of the intercepts. Looking at the intercepts of each of the portfolios, we see that they all are far from significant, except for portfolio 3 which would have been on a 10 % significance level. This is the case for whatever the sort we use for the regression. Nevertheless, there is still one portfolio (portfolio 5) that has a significant constant term when we sort on market beta. Table 13 shows good diversion of the market factor, and it is significant regardless of how we sort. Furthermore, the estimation shows that portfolio 2 and portfolio 3 has significant exposure to both the SMB and the HML-factor, while all portfolios, besides portfolio 3, have significant exposure to the momentum factor when we sort on momentum. This picture varies to some extent depending on which of the characteristic we sort on. We refer to the appendix for more detailed information regarding these results. Adjusted R^2 is lowest for portfolio 1 when we sort on market beta, with a value of 0,70. The highest adjusted R^2 for this estimation, and for all of our estimations whatever model, is found in portfolio 5 sorted on firm size, with a value of 0,95.

Once again the risk premiums can be seen in an summary table, 14. The table shows that whatever sorting, none of the portfolios give a significant difference from zero when it comes to the SMB, which suggests that this is not a priced risk factor. However, we see that there might be weak evidence that HML and PR1YR can be. HML appears to be a priced risk factor when we sort of market beta, while PR1YR indicates the same thing when we sort on momentum. If we had chosen to use a significance level of 10 %, we would have found two additional significant differences from zero for these factors. Looking at the α we have significance when we sort on firm size, and once again when we sort on market beta. Nevertheless, the four-factor model seems to fit the Norwegian stock market better than both the CAPM and the three-factor model based on the absolute values of the alphas, R^2 and the Fama MacBeth (1973) cross-sectional regression.

Table 13: A multifactor model for the OSE - Momentum portfolios

Panel A shows the results from estimating Carhart's four-factor model as in equation 3.3.5 for a portfolio sorted on momentum. The momentum portfolio is equal weighted. Columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns show the estimated β_i^k and their associated p-values. Panel B show the risk premiums estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero

Momentum	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	$\beta[3]$	p-value	$\beta[4]$	p-value	R^2_{adj}
1 (low momentum)	-0.000	(0.95)	1.000	(0.00)	0.004	(0.92)	-0.052	(0.17)	-0.627	(0.00)	0.94
2	-0.001	(0.65)	0.948	(0.00)	-0.123	(0.00)	0.083	(0.03)	-0.199	(0.00)	0.89
3	0.003	(0.07)	0.849	(0.00)	-0.085	(0.01)	0.113	(0.00)	0.019	(0.51)	0.87
4	0.000	(1.00)	0.859	(0.00)	-0.057	(0.09)	0.064	(0.06)	0.232	(0.00)	0.86
5	0.000	(0.85)	1.150	(0.00)	-0.028	(0.39)	-0.048	(0.14)	0.567	(0.00)	0.92

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	-0.028	(0.30)
$\lambda[1](er_m)$	0.031	(0.27)
$\lambda[2](SMB)$	0.085	(0.13)
$\lambda[3](HML)$	0.127	(0.09)
$\lambda[4](PR1YR)$	0.022	(0.00)

Table 14: Asset pricing tests for different test assets

		Fama/French + PR1YR				CAPM	
Portfolio		er_m^{ew}	SMB	HML	PR1YR		er_m^{ew}
sort	α	$\lambda[1]$	$\lambda[2]$	$\lambda[3]$	$\lambda[4]$	α	$\lambda[1]$
Size (ew)	0.048	-0.052	-0.005	0.063	-0.084	0.002	-0.000
t-value	0.03	0.04	0.15	0.16	0.39	0.93	0.99
BE/ME (ew)	-0.035	0.039	-0.012	0.017	0.082	0.035	-0.034
t-value	0.65	0.61	0.79	0.33	0.20	0.00	0.00
Momentum (ew)	-0.028	0.031	0.085	0.127	0.022	0.042	-0.041
t-value	0.30	0.27	0.13	0.09	0.00	0.00	0.00
Market beta (ew)	0.056	-0.056	0.012	-0.207	-0.034	0.013	-0.012
t-value	0.00	0.00	0.63	0.01	0.10	0.00	0.03

6.4.4 CAPM including BAB

Finally, we have devoted a last section to a model consisting of the CAPM plus the BAB-factor, which comes from a recent research by Frazzini and Pedersen (2013). The BAB-factor is claimed to have a positive average return and the return should be increasing in the ex-ante tightness of constraints and in the spread in betas between high- and low-beta securities. To investigate whether the BAB-factor is a priced risk factor in the Norwegian market, we have constructed a BAB-factor for which we have chosen to use in a regression together with the market factor. Results from this estimation are shown in table 15, and in table 37 to 38 in the appendix section 8.8.

The absolute values of the average of the intercepts are 0,003, 0,003, 0,0086, and 0,0036 for portfolios sorted on firm size, book-to-market equity, momentum, and market beta respectively. The values are higher compared to the other multifactor models, but in line with CAPM. Table 15 shows a poor dispersion of the market factor, not surprisingly, but the factor is significant for all of the portfolios. Portfolio 1, portfolio 2, and portfolio 5 do all have an exposure to the BAB-factor when sorted on market beta. This is not the case when we sort on our other characteristics. In fact it is few portfolios that has an exposure to the factor. The adjusted R^2 is lowest for portfolio 1 when we sort on firm size, with a value of 0,77. The highest adjusted R^2 is found in portfolio 5 sorted on market beta, with a value of 0,91. Consistent with previous tests of the BAB-factor in this paper, this suggests that there are few signs of any BAB effect in the Norwegian market. Moving on to table 16 which summarizes the estimates of the risk premiums and the alphas, we see that the BAB-factor is only significant when we sort on momentum and none of the other characteristics. The model where we sort on momentum is also the only model with significant alpha. Correspondingly, we observe that the CAPM has significant alphas on all portfolios whatever characteristics we chose to sort on, besides when we sort on size. Based on these estimations, we find small to no evidence that there is a betting-against-beta effect, but the model may appear to price the Norwegian market marginally better than CAPM.

Table 15: A multifactor model for the OSE - Beta portfolios

Panel A shows the results from estimating a multifactor model containing the market factor and the BAB-factor for a portfolio sorted on beta. The beta portfolio is equal weighted. Columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns show the estimated β_i^k and their associated p-values. Panel B show the risk premiums estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero

Beta	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	R^2_{adj}
1 (low beta)	0.002	(0.06)	0.266	(0.00)	0.187	(0.00)	0.82
2	0.005	(0.00)	0.537	(0.00)	0.083	(0.00)	0.78
3	0.002	(0.20)	0.891	(0.00)	-0.011	(0.67)	0.86
4	0.005	(0.01)	1.077	(0.00)	0.002	(0.92)	0.87
5	-0.004	(0.05)	1.593	(0.00)	-0.123	(0.00)	0.91

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	0.014	(0.09)
$\lambda[1](er_m)$	-0.013	(0.17)
$\lambda[2](BAB)$	-0.018	(0.61)

Table 16: Asset pricing tests for different test assets

		CAPM + BAB			CAPM
Portfolio		er_m^{ew}	BAB		er_m^{ew}
sort	α	$\lambda[1]$	$\lambda[2]$	α	$\lambda[1]$
Size (ew)	-0.020	0.020	0.053	0.002	-0.000
p-value	0.21	0.24	0.12	0.93	0.99
BE/ME (ew)	0.033	-0.034	-0.054	0.035	-0.034
p-value	0.09	0.09	0.58	0.00	0.00
Momentum (ew)	0.047	-0.046	-0.160	0.042	-0.041
p-value	0.00	0.00	0.00	0.00	0.00
Market beta (ew)	0.014	-0.013	-0.018	0.013	-0.012
p-value	0.09	0.17	0.61	0.00	0.03

7 Conclusion

In this research we document an empirical study of stock pricing at the Oslo Stock Exchange. We have analyzed what factors systematically affect the exchange, using methods of analysis where these factors are allowed to affect different assets differently (cross-sectional analysis). An interesting goal of the work has been to see whether asset-pricing results from other countries, which are widely known in finance theory, carry over to the Norwegian stock market as well. To our knowledge such an extensive empirical analysis of the Oslo Stock Exchange has only been done before by Randi Næs, Johannes A. Skjeltorp and Bernt Arne Ødegaard (2009), using different assumptions.

The results of our paper may be of interest and importance because such factors can be used to set required returns for investments, and to evaluate a stock's contribution to a portfolio. The research has investigated whether those risk factors typically used internationally for such purposes also are relevant in the Norwegian setting. This applies to factors as an overall market factor, and factors related to firm size, book-to-market equity, and momentum. We also include the recently invention of the betting-against-beta factor. Our results document that in addition to the local market, empirically motivated factors related to book-to-market equity, and especially momentum seem to be factors demanding risk compensation at the Oslo Stock Exchange. Unlike the recent research by Frazzini and Pedersen (2013), this paper provides evidence that there is no betting-against-beta effect in the Norwegian market. Based on estimation of different asset pricing models, we have found that Carhart's (1997) standard four-factor model containing the market factor, size-factor, book-to-market factor, and a momentum factor provides a reasonable fit for the cross-section of Norwegian stock returns.

For possible further research we would like to use a longer sample period for our analysis, and it would be valuable to seal our missing data to make the dataset more complete. To test the various models, we would have liked to apply the Generalized Method of Moments method (GMM). By using GMM one can estimate the two steps in Fama Macbeth (1973) regressions simultaneously, thereby accounting for the errors in variables problem. In addition, the GMM method is more robust to time series and distributional properties of the error terms. In terms of our momentum findings it would be interesting to further study this phenomena and to quantify the downside risk. Hongwei Chuang and Hwai-Chung Ho (2014) has found a way to determine whether the price of winning stocks in the momentum strategy reach the level where risk incurred from the falling of prices is imminent. They constructed an implied risk index to quantify the downside risk of a stock and used it to manage the tail risk from the momentum strategy. This method will help to identify those stocks that are less likely to be overpriced and have more momentum left to sustain their trends. The results from their study achieved impressing improvement on the overall performance, but also avoided the big losses suffered from financial crises. A construction of this implied price risk (IPR-factor) would be interesting for further work on the momentum effect at Oslo Stock Exchange.

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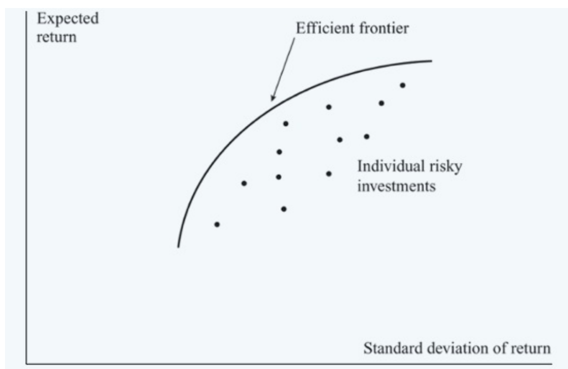
8 Appendix

8.1 Efficient frontier

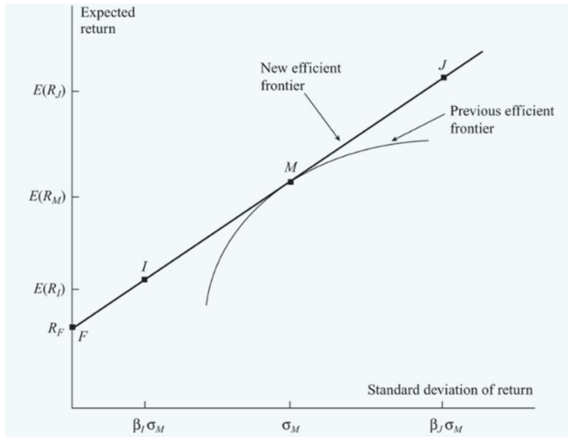
In finance theory it is common to assume that investors are risk-averse. They want to reduce the standard deviation of return while increasing expected return. This is something that can be done by moving as far as possible in a ”northwest” direction in figure 1. If we consider that every possible portfolio is available to the investors, we can obtain what is known as efficient frontier. As illustrated in figure 1, the efficient frontier represents the limit of how far an investor can move in a northwest direction. There is no investment that dominates a point on the efficient frontier in the sense that it has both a higher return and a lower standard deviation of return. The attainable set can be found in the area southeast of the efficient frontier. For any point in this area there is a point on the efficient frontier that has a higher expected return and lower standard deviation of return.

Figure 1



Only risky investment is considered in figure 1. Suppose that we also include a risk-free investment that yields a return of R_F to be combined into a portfolio. This will give us a new efficient frontier, as shown in figure 2. There the risk-free investment is denoted by point F, and there is drawn a tangent from point F to the efficient frontier of risky investments that was developed in figure 1. M becomes the point of tangency, and FJ will end up as our new efficient frontier.

Figure 2



This can be shown by considering that we form an investment I by investing β_I of our funds in the risky portfolio, M, and the remaining $1 - \beta_I$ funds in the risk-free investment F ($0 < \beta_I < 1$). From equation 3.1.1 the expected return from the investment, $E(R_I)$, is then given by:

$$E(R_i) = (1 - \beta_I)R_F + \beta_I E(R_M)$$

and from equation 3.1.2, because the risk-free investment has zero standard deviation, the return R_I has standard deviation of

$$\beta_I \sigma_M$$

where σ_M is the standard deviation of return for portfolio M. This combination of risk and return will correspond to the point labelled I in figure 2. The point I will then be β_I of the way from F to M. By choosing a suitable combination of the investment represented by point F and the investment represented by point M, all points on the line FM can be obtained. The points on this new efficient frontier will dominate all the points on the previous efficient frontier based on a better risk-return combination. The straight line FM is therefore part of the new efficient frontier. By making an assumption that we can both borrow and invest at the risk-free rate of RF, we can create investments beyond M. We can, for example, create the investment represented by the point J in figure 2 where the distance of J from F is β_J times the distance from F ($\beta_J > 1$). To make this happen we borrow β_J of the amount that we have available for investment at rate RF, and invest both original funds and the borrowed funds in the investment represented by point M. The investment will then, after allowing for the interest paid, have an expected return $E(R_J)$ given by

$$E(R_J) = (\beta_J)E(R_M) - (\beta_J - 1)R_F$$

and the standard deviation of the return will be

$$\beta_J \sigma_M$$

The expected risk-return combination will then correspond to point J. This example shows that when risk-free investment is considered, the efficient frontier must be a straight line (Capital Market Line). This means that it should be a linear trade-off between expected return and the standard deviation of returns, as indicated in figure 2. Further, this implies that all investors should choose the same portfolio of risky assets, represented by M (which usually is referred to as the market portfolio). Also, their appetite for risk should therefore reflect a combination of a risky investment with borrowing or lending at the risk-free rate.

8.2 The Capital Assets Pricing Model's assumptions

CAPM assumes investors are risk averse and, when investors are choosing among portfolios, they only care about the mean and variance of their one-period investment return. As a result of this, investors choose mean-variance-efficient portfolios, in the sense that the portfolios minimize the variance of portfolio return, given expected return, and maximize expected return, given variance. Consequently, the Markowitz approach is often called a mean-variance model (French, 2004). Also, all investors have homogeneous beliefs about the risk/reward tradeoffs in the market (Borchert, 2003).

CAPM assumes that all investors can borrow and lend at a risk-free rate, which does not depend on the amount borrowed or lent. Only one risk factor is common to a broad-based market portfolio. This risk factor is the systematic market risk, which drives non-diversifiable volatility. Investors are assumed to hold diversified portfolios, as the market does not reward investors for the bearing of diversifiable risk. In addition there is an assumption about no distortionary taxes or transaction costs (Borchert, 2003). All investors have the same expectations about security rewards, and all investors have identical expectations about security risk. Markets are perfect where each investor is a price-taker who does not believe he can influence price (Rosenberg, 1981).

In short, the CAPM assumptions imply that the market portfolio must be on the minimum variance frontier if the asset market is to clear. This means that the algebraic relation that holds for any minimum variance portfolio must hold for the market portfolio. Another assumption is that short selling is unrestricted, and this assumption is as unrealistic as unrestricted risk-free borrowing and lending (French, 2004).

8.3 Filtering and exclusions

Table 17: Filtering and exclusions

Filtering the dataset using preconditions like Ødegaard

Year-end	Total stocks	Missing stocks	Penny stocks	Micro caps.	Iliquid stocks
1991	143	20	44	0	0
1992	157	11	50	0	2
1993	162	18	37	0	7
1994	173	14	37	0	0
1995	177	14	31	0	4
1996	187	18	23	0	1
1997	236	18	26	0	7
1998	251	15	60	0	0
1999	229	40	46	0	0
2000	226	33	49	0	4
2001	223	28	61	0	0
2002	212	27	83	0	0
2003	187	36	50	0	2
2004	196	17	49	0	3
2005	229	22	39	0	9
2006	235	23	31	0	5
2007	273	23	44	0	7
2008	265	29	109	0	0
2009	241	32	92	0	0

The table provides some descriptive statistics for the sample of equities traded on the Oslo Stock Exchange in the period 1991 to 2010. The first column lists the year. The second column lists the number of stocks available in our dataset with daily prices. The third column lists how many stocks that are missing in our accounting information. The fourth column lists how many stocks that are excluded for having to low stock price. The fifth column lists how many stocks that are excluded regarding market capitalization. The final column lists how many stocks that are excluded based on trading days.

8.4 Asset pricing factors

Table 18: Descriptive statistics for asset pricing factors

Average - With similar assumptions to Ødegaard

	SMB	HML	PR1YR	BAB
1992-2010*	-0.48 (0.10)	0.68 (0.03)	2.09 (0.00)	-0.29 (0.80)
1992-1995*	0.33 (0.68)	-0.10 (0.91)	1.19 (0.09)	2.39 (0.08)
1996-2000	-0.16 (0.75)	0.78 (0.14)	1.42 (0.01)	-0.51 (0.65)
2001-2005	-0.58 (0.27)	1.47 (0.02)	3.50 (0.00)	0.24 (0.94)
2006-2010	-1.26 (0.03)	0.35 (0.50)	2.09 (0.00)	-1.12 (0.33)

*The BAB value are not available in all of the sub-periods due to three years of beta construction.

Correlations

	SMB	HML	PR1YR	BAB
SMB	1			
HML	-0,085	1		
PR1YR	-0,097	0,080	1	
BAB	-0,185	0,056	-0,263	1

The table describes the calculated asset pricing factors. SMB and HML are the Fama and French (1996) pricing factors. PR1YR is the Carhart (1997) factor. BAB is the recently betting-against-beta factor documented by Frazzini and Pedersen (2013). The table lists the average percentage monthly return, and in the parenthesis the p-value for a test of difference from zero. The table also list an overview of the correlation between the factors.

Table 19: Descriptive statistics for asset pricing factors

Average - Without assumptions

	SMB	HML	PR1YR	BAB
1992-2010*	-0.56 (0.05)	0.83 (0.01)	2.28 (0.00)	0.53 (0.48)
1992-1995*	0.49 (0.49)	-0.16 (0.80)	0.82 (0.37)	4.81 (0.00)
1996-2000	-0.37 (0.44)	0.57 (0.30)	1.28 (0.02)	-0.75 (0.46)
2001-2005	-0.74 (0.21)	2.25 (0.00)	4.11 (0.00)	2.02 (0.29)
2006-2010	-1.29 (0.03)	0.28 (0.60)	2.60 (0.00)	-1.12 (0.30)

*The BAB value are not available in all of the sub-periods due to three years of beta construction.

Correlations

	SMB	HML	PR1YR	BAB
SMB	1			
HML	-0,010	1		
PR1YR	-0,229	0,135	1	
BAB	-0,110	-0,036	-0,261	1

The table describes the calculated asset pricing factors. SMB and HML are the Fama and French (1996) pricing factors. PR1YR is the Carhart (1997) factor. BAB is the recently betting-against-beta factor documented by Frazzini and Pedersen (2013). The table lists the average percentage monthly return, and in the parenthesis the p-value for a test of difference from zero. The table also list an overview of the correlation between the factors.

8.5 Simple portfolio sort based on Market Beta

Table 20: Beta portfolios 1995(1997) – 2010

Three years of monthly returns - With similar assumptions to Ødegaard

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	0.46	(3.26)	-12.67	0.90	7.81	15	24	27
2	0.68	(4.35)	-16.97	1.42	9.01	15	24	27
3	0.15	(5.63)	-29.81	0.99	11.40	15	24	27
4	0.47	(6.96)	-33.86	1.17	14.85	15	24	27
5	-1.14	(9.75)	-41.62	0.53	18.75	15	24	28

Five years of monthly returns - With similar assumptions to Ødegaard

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	0.40	(3.32)	-13.22	0.51	8.79	14	19	24
2	0.72	(4.29)	-18.95	1.25	11.93	14	19	24
3	0.63	(5.63)	-27.57	1.02	11.87	14	19	24
4	0.43	(6.91)	-27.99	0.79	14.52	14	19	24
5	-1.10	(10.00)	-42.62	0.67	20.84	13	19	25

Returns are percentage monthly returns. The returns are not annualized. Data for stocks listed at the Oslo Stock Exchange during the period 1991-2010. Calculations use the stocks satisfying the "filter" criteria discussed in 4.2. When the portfolios are constructed, we rank the numerical values and divide the securities into 5 portfolios based on the ranking. When dividing by 5 we use a round function for the first 4 portfolios. The fifth portfolio is defined as the sum of the first four portfolios subtracted by the total number. This is why the number of stocks in portfolio 5 can vary with +/- 1 stocks.

Table 21: Beta portfolios 1995(1997) – 2010

Three years of monthly returns - Without assumptions

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	0.48	(3.65)	-12.50	1.05	7.97	19	30	39
2	0.66	(4.61)	-18.38	1.04	10.21	19	30	39
3	0.22	(6.10)	-27.68	1.36	12.45	19	30	39
4	0.41	(7.44)	-33.06	1.25	19.14	19	30	39
5	-0.75	(9.89)	-37.05	0.74	23.61	18	30	39

Five years of monthly returns - Without assumptions

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	0.46	(3.52)	-12.85	0.73	12.33	16	26	29
2	0.81	(4.73)	-18.77	1.77	12.46	16	26	29
3	0.45	(6.28)	-28.43	1.08	14.51	16	26	29
4	-0.01	(7.88)	-34.70	0.97	21.11	16	26	29
5	-0.99	(10.04)	-38.39	0.87	21.54	15	25	30

Returns are percentage monthly returns. The returns are not annualized. Data for stocks listed at the Oslo Stock Exchange during the period 1991-2010. Calculations use the stocks satisfying the "filter" criteria discussed in 4.2. When the portfolios are constructed, we rank the numerical values and divide the securities into 5 portfolios based on the ranking. When dividing by 5 we use a round function for the first 4 portfolios. The fifth portfolio is defined as the sum of the first four portfolios subtracted by the total number. This is why the number of stocks in portfolio 5 can vary with +/- 1 stocks.

8.6 Fama French portfolios

Table 22: Average returns for the six portfolios used in the FF construction

1992 - 2010

SL -0.54 (8.23)	SM -0.04 (6.85)	SH 0.59 (6.70)
BL 0.04 (7.73)	BM 0.86 (6.83)	BH 0.74 (8.10)

1992 - 1995

SL 1.51 (7.23)	SM 0.95 (6.28)	SH 1.42 (8.51)
BL 1.21 (5.46)	BM 0.61 (6.35)	BH 0.92 (8.39)

1996 - 2000

SL 0.17 (7.13)	SM 0.61 (5.28)	SH 0.79 (4.58)
BL -0.06 (6.90)	BM 1.07 (6.20)	BH 0.87 (6.34)

2001 - 2005

SL -1.62 (10.37)	SM 0.01 (7.38)	SH 1.64 (6.03)
BL 0.13 (7.09)	BM 1.07 (6.93)	BH 1.27 (8.33)

2006 - 2010

SL -1.42 (7.07)	SM -1.33 (7.96)	SH -1.31 (7.42)
BL -0.71 (10.25)	BM 0.50 (7.82)	BH -0.16 (9.25)

The table shows average returns for the six portfolios S/L, S/M, S/H, B/L, B/M and B/H.

Table 23: Average returns for the six portfolios used in the FF construction

1992 - 2010 - With similar assumptions to Ødegaard

SL	SM	SH
-0.38 (7.70)	-0.16 (6.55)	0.48 (6.41)
BL	BM	BH
0.05 (7.76)	0.77 (6.85)	0.55 (8.17)

1992 - 1995 - With similar assumptions to Ødegaard

SL	SM	SH
0.80 (8.45)	1.11 (5.62)	1.09 (9.41)
BL	BM	BH
0.98 (5.26)	0.56 (6.20)	0.49 (8.80)

1996 - 2000 - With similar assumptions to Ødegaard

SL	SM	SH
0.23 (6.66)	0.63 (5.21)	0.75 (4.84)
BL	BM	BH
0.16 (7.10)	0.84 (6.33)	0.81 (6.47)

2001 - 2005 - With similar assumptions to Ødegaard

SL	SM	SH
-1.01 (9.09)	0.11 (6.68)	1.09 (4.63)
BL	BM	BH
0.20 (7.06)	1.02 (6.97)	0.79 (8.29)

2006 - 2010 - With similar assumptions to Ødegaard

SL	SM	SH
-0.97 (6.30)	-2.11 (7.82)	-1.03 (6.62)
BL	BM	BH
-0.80 (10.30)	0.50 (7.82)	-0.04 (9.19)

The table shows average returns for the six portfolios S/L, S/M, S/H, B/L, B/M and B/H.

Table 24: Average returns for the six portfolios used in the FF construction

1992 - 2010 - Without assumptions

SL	SM	SH
-0.56 (8.56)	-0.05 (6.85)	0.52 (6.91)
BL	BM	BH
0.10 (7.69)	0.80 (6.73)	0.68 (8.07)

1992 - 1995 - Without assumptions

SL	SM	SH
1.31 (7.58)	1.34 (6.60)	1.45 (8.90)
BL	BM	BH
1.23 (5.45)	0.62 (6.24)	0.77 (8.51)

1996 - 2000 - Without assumptions

SL	SM	SH
0.60 (7.33)	0.08 (5.10)	0.63 (4.51)
BL	BM	BH
0.18 (6.91)	0.90 (6.23)	0.93 (6.27)

2001 - 2005 - Without assumptions

SL	SM	SH
-1.81 (10.96)	0.23 (7.64)	1.61 (6.21)
BL	BM	BH
0.10 (7.13)	1.00 (6.62)	1.17 (8.16)

2006 - 2010 - Without assumptions

SL	SM	SH
-1.52 (6.97)	-1.40 (7.65)	-1.41 (7.71)
BL	BM	BH
-0.71 (10.11)	0.50 (7.81)	-0.25 (9.27)

The table shows average returns for the six portfolios S/L, S/M, S/H, B/L, B/M and B/H.

8.7 Simple portfolio sorts based on CAPM anomalies

Table 25: Monthly returns for portfolios sorted on company value

Panel A shows the monthly percentage returns for 5 portfolios constructed based on market value. The results are for the whole sample period 1992 - 2010. The portfolios are re-balanced at the end of each year. Panel B shows the average monthly return for the portfolios containing the 20 percent smallest firms (portfolio 1) and the 20 percent largest firms (portfolio 5) on the exchange for four sub-periods. The table also show p-values from a test of whether the return difference between the portfolios is zero.

Panel A: Whole sample 1992 - 2010 - With similar assumptions to Ødegaard

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-0.40	(5.98)	-20.46	-0.06	20.28	12	27	43
2	-0.28	(6.57)	-30.50	0.54	17.08	15	26	43
3	0.06	(6.96)	-32.85	0.81	14.39	16	27	43
4	0.49	(6.71)	-27.26	1.13	18.19	17	27	43
5	0.24	(7.65)	-32.89	1.04	16.54	16	28	43

Panel B: Sub-periods - With similar assumptions to Ødegaard

	Small (Portf. 1)	Large (Portf. 5)	Diff	t-test: diff=0
1992 - 1995	0.91	0.64	0.27	0.84
1996 - 2000	0.19	0.03	-0.30	0.63
2001 - 2005	-0.62	0.00	-0.64	0.37
2006 - 2010	-1.67	-0.06	-1.61	0.06

Table 26: Monthly returns for portfolios sorted on company value

Panel A shows the monthly percentage returns for 5 portfolios constructed based on market value. The results are for the whole sample period 1992 - 2010. The portfolios are re-balanced at the end of each year. Panel B shows the average monthly return for the portfolios containing the 20 percent smallest firms (portfolio 1) and the 20 percent largest firms (portfolio 5) on the exchange for four sub-periods. The table also show p-values from a test of whether the return difference between the portfolios is zero.

Panel A: Whole sample 1992 - 2010 - Without assumptions

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-0.03	(7.04)	-31.58	0.06	17.87	19	38	53
2	-0.05	(6.96)	-23.21	0.65	21.66	24	37	53
3	-0.06	(7.08)	-31.51	0.59	16.43	25	37	53
4	0.53	(6.84)	-29.39	1.53	13.62	25	37	53
5	0.32	(7.45)	-32.16	1.21	16.76	23	38	51

Panel B: Sub-periods - Without assumptions

	Small (Portf. 1)	Large (Portf. 5)	Diff	t-test: diff=0
1992 - 1995	1.70	0.82	0.89	0.50
1996 - 2000	0.65	0.57	0.08	0.89
2001 - 2005	-0.09	0.23	-0.33	0.69
2006 - 2010	-1.87	-0.19	-1.67	0.02

Table 27: Monthly returns for portfolios sorted on BE/ME

Panel A shows the monthly percentage returns for 5 portfolios constructed based on Book to Market value (BE/ME). The results are for the whole sample period 1992 - 2010. The portfolios are re-balanced at the end of each year. Panel B shows the average monthly return for the portfolios containing the 20 percent smallest firms (portfolio 1) and the 20 percent largest firms (portfolio 5) on the exchange for four sub-periods. The table also show p-values from a test of whether the return difference between the portfolios is zero.

Panel A: Whole sample 1992 - 2010 - With similar assumptions to Ødegaard

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-0.74	(8.07)	-33.42	0.36	17.54	16	27	43
2	0.23	(6.59)	-30.38	0.94	13.56	15	27	43
3	0.10	(6.49)	-31.22	0.87	14.11	15	27	43
4	0.24	(6.10)	-23.21	1.11	13.52	16	27	43
5	0.30	(6.05)	-30.92	0.93	18.22	15	28	43

Panel B: Sub-periods - With similar assumptions to Ødegaard

	Small (Portf. 1)	Large (Portf. 5)	Diff	t-test: diff=0
1992 - 1995	0.82	0.20	-0.62	0.47
1996 - 2000	-0.31	1.11	1.42	0.05
2001 - 2005	-1.65	1.00	2.65	0.00
2006 - 2010	-1.34	-1.15	0.19	0.74

Table 28: Monthly returns for portfolios sorted on BE/ME

Panel A shows the monthly percentage returns for 5 portfolios constructed based on Book to Market value (BE/ME). The results are for the whole sample period 1992 - 2010. The portfolios are re-balanced at the end of each year. Panel B shows the average monthly return for the portfolios containing the 20 percent smallest firms (portfolio 1) and the 20 percent largest firms (portfolio 5) on the exchange for four sub-periods. The table also show p-values from a test of whether the return difference between the portfolios is zero.

Panel A: Whole sample 1992 - 2010 - Without assumptions

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-0.69	(8.42)	-36.89	0.24	17.55	24	38	53
2	0.20	(7.04)	-31.95	0.95	14.74	25	37	53
3	0.30	(6.45)	-31.78	1.10	13.89	22	38	53
4	0.39	(6.57)	-23.57	1.23	18.01	23	37	53
5	0.49	(6.36)	-27.79	0.86	18.28	21	38	51

Panel B: Sub-periods - Without assumptions

	Small (Portf. 1)	Large (Portf. 5)	Diff	t-test: diff=0
1992 - 1995	1.09	0.75	-0.34	0.68
1996 - 2000	0.03	1.03	1.00	0.17
2001 - 2005	-1.64	1.35	2.99	0.00
2006 - 2010	-1.66	-1.12	0.54	0.31

Table 29: Momentum sorted portfolios

5 Portfolios - With similar assumptions to Ødegaard: 6 months

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-1.70	(8.98)	-37.33	-0.02	16.71	17	29	42
2	0.11	(5.85)	-24.73	0.69	18.03	17	29	42
3	0.39	(5.25)	-24.95	0.91	13.28	17	29	42
4	0.56	(5.69)	-29.69	1.25	14.73	17	29	42
5	0.68	(6.86)	-27.78	0.84	17.95	17	29	44

5 Portfolios - With similar assumptions to Ødegaard: 12 months

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-1.80	(9.34)	-41.05	0.16	20.92	17	28	40
2	-0.08	(6.32)	-28.66	0.36	18.24	17	28	40
3	0.57	(5.32)	-24.84	1.01	12.45	17	28	40
4	0.56	(5.10)	-18.81	0.94	14.98	17	28	40
5	0.96	(6.86)	-27.90	1.67	18.84	16	28	41

5 Portfolios - With similar assumptions to Ødegaard: 24 months

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-0.74	(8.82)	-36.43	0.45	19.72	16	26	34
2	0.37	(5.87)	-20.18	0.60	21.17	16	26	34
3	1.08	(5.07)	-21.74	1.58	12.93	16	26	34
4	0.84	(5.04)	-25.94	1.52	12.86	16	26	34
5	0.28	(6.57)	-34.62	1.15	16.32	14	26	34

5 Portfolios - With similar assumptions to Ødegaard: 36 months

	Returns					Number of securities		
Portfolio	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	0.43	(3.28)	-13.70	0.77	7.80	15	24	27
2	0.59	(4.49)	-16.74	1.08	10.71	15	24	27
3	0.22	(5.57)	-29.05	1.32	12.89	15	24	27
4	0.47	(6.68)	-32.24	1.14	14.63	15	24	27
5	-1.09	(9.68)	-40.87	0.49	19.86	15	24	28

Table 30: Momentum sorted portfolios

5 Portfolios - Without assumptions: 6 months

Portfolio	Returns					Number of securities		
	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-1.45	(9.94)	-33.88	-0.11	24.68	28	41	54
2	-0.35	(6.78)	-26.22	0.87	13.98	28	41	54
3	0.53	(5.68)	-27.40	1.25	12.87	28	41	54
4	0.60	(5.76)	-26.92	1.28	12.77	28	41	54
5	0.83	(7.06)	-24.58	1.51	19.54	27	40	55

5 Portfolios - Without assumptions: 12 months

Portfolio	Returns					Number of securities		
	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-1.57	(10.22)	-38.57	-0.11	23.57	26	38	50
2	-0.49	(7.21)	-31.95	0.62	15.36	26	38	50
3	0.53	(5.80)	-29.52	0.79	12.30	26	38	50
4	0.69	(5.50)	-20.49	1.54	13.59	26	38	50
5	1.15	(6.95)	-27.60	1.96	20.50	26	38	52

5 Portfolios - Without assumptions: 24 months

Portfolio	Returns					Number of securities		
	Mean	(Std)	Min	Med	Max	Min	Med	Max
1 (Smallest)	-0.81	(9.87)	-39.82	0.97	22.83	23	34	45
2	0.48	(6.76)	-31.01	0.81	18.29	23	34	45
3	0.86	(5.40)	-21.58	1.35	15.17	23	34	45
4	0.99	(5.18)	-25.87	1.55	12.10	23	34	45
5	0.46	(6.70)	-31.61	1.32	17.55	22	34	46

8.8 Fama MacBeth regression

Table 31: A multifactor model for the OSE - Size portfolios

Panel A shows the results from estimating the Fama French three-factor model as in equation 3.3.3 for a portfolios sorted on size. Firm size is measured as the market capitalization, and the portfolio are equal weighted. For the portfolio, columns two and three show the estimated constant with the associated p-value for the portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns show the estimated beta β_i^k and associated p-value. Panel B shows the risk premium estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero.

Size	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	$\beta[3]$	p-value	R^2_{adj}
1 (low MCAP)	-0.001	(0.76)	0.935	(0.00)	0.437	(0.00)	-0.046	(0.37)	0.80
2	0.002	(0.22)	0.958	(0.00)	0.261	(0.00)	-0.019	(0.62)	0.88
3	-0.001	(0.55)	1.056	(0.00)	0.090	(0.02)	0.078	(0.06)	0.88
4	0.003	(0.06)	0.960	(0.00)	-0.283	(0.00)	0.104	(0.00)	0.91
5	-0.001	(0.44)	1.046	(0.00)	-0.629	(0.00)	-0.018	(0.52)	0.94

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	0.033	(0.06)
$\lambda[1](er_m)$	-0.032	(0.08)
$\lambda[2](SMB)$	-0.007	(0.04)
$\lambda[3](HML)$	0.022	(0.10)

Table 32: A multifactor model for the OSE - BE/ME portfolios

Panel A shows the results from estimating the Fama French three-factor model as in equation 3.3.3 for a portfolio sorted on BE/ME. BE/ME is measured by the ratio between a firms book value relative to market value, and the BE/ME portfolios are equal weighted. For the portfolios, columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns for each set of portfolios show the estimated beta β_i^k and associated p-value. Panel B shows the risk premium estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero.

BE/ME	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	$\beta[3]$	p-value	R^2_{adj}
1 (low BE/ME)	-0.002	(0.28)	1.163	(0.00)	0.117	(0.01)	-0.433	(0.00)	0.90
2	0.002	(0.08)	1.009	(0.00)	-0.095	(0.00)	-0.199	(0.00)	0.92
3	0.000	(0.87)	0.889	(0.00)	-0.212	(0.00)	0.028	(0.41)	0.88
4	0.000	(0.79)	0.943	(0.00)	-0.002	(0.96)	0.215	(0.00)	0.89
5	0.001	(0.54)	0.833	(0.00)	0.049	(0.17)	0.472	(0.00)	0.88

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	-0.051	(0.50)
$\lambda[1](er_m)$	0.051	(0.49)
$\lambda[2](SMB)$	-0.040	(0.31)
$\lambda[3](HML)$	0.023	(0.18)

Table 33: A multifactor model for the OSE - Beta portfolios

Panel A shows the results from estimating the Fama French three-factor model as in equation 3.3.3 for a portfolio sorted on beta. The beta portfolio is equal weighted. Columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns show the estimated β_i^k and their associated p-values. Panel B show the risk premiums estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero

Beta	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	$\beta[3]$	p-value	R^2_{adj}
1 (low beta)	0.002	(0.24)	0.497	(0.00)	-0.010	(0.79)	-0.131	(0.00)	0.69
2	0.004	(0.02)	0.640	(0.00)	-0.132	(0.00)	0.083	(0.04)	0.78
3	0.001	(0.73)	0.881	(0.00)	-0.175	(0.00)	0.043	(0.28)	0.87
4	0.004	(0.03)	1.076	(0.00)	-0.105	(0.03)	0.000	(1.00)	0.87
5	-0.005	(0.02)	1.447	(0.00)	-0.130	(0.02)	-0.027	(0.63)	0.90

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	0.056	(0.00)
$\lambda[1](er_m)$	-0.046	(0.00)
$\lambda[2](SMB)$	0.021	(0.30)
$\lambda[3](HML)$	-0.214	(0.01)

Table 34: A multifactor model for the OSE - Size portfolios

Panel A shows the results from estimating Carhart's four-factor model as in equation 3.3.5 for a portfolio sorted on size. The size portfolio is equal weighted. Columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns show the estimated β_i^k and their associated p-values. Panel B show the risk premiums estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero

Size	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	$\beta[3]$	p-value	$\beta[4]$	p-value	R^2_{adj}
1 (low MCAP)	-0.000	(0.93)	0.927	(0.00)	0.433	(0.00)	-0.044	(0.40)	-0.025	(0.57)	0.80
2	0.003	(0.10)	0.941	(0.00)	0.252	(0.00)	-0.015	(0.70)	-0.048	(0.14)	0.88
3	-0.001	(0.68)	1.051	(0.00)	0.088	(0.03)	0.079	(0.05)	-0.015	(0.66)	0.88
4	0.003	(0.10)	0.962	(0.00)	-0.282	(0.00)	0.103	(0.00)	0.005	(0.85)	0.91
5	0.000	(0.86)	1.025	(0.00)	-0.640	(0.00)	-0.013	(0.65)	-0.063	(0.01)	0.95

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	0.048	(0.03)
$\lambda[1](er_m)$	-0.052	(0.04)
$\lambda[2](SMB)$	-0.005	(0.15)
$\lambda[3](HML)$	0.063	(0.16)
$\lambda[4](PR1YR)$	-0.084	(0.39)

Table 35: A multifactor model for the OSE - BE/ME portfolios

Panel A shows the results from estimating Carhart's four-factor model as in equation 3.3.5 for a portfolio sorted on BE/ME. The BE/ME portfolio is equal weighted. Columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns show the estimated β_i^k and their associated p-values. Panel B show the risk premiums estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero.

BE/ME	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	$\beta[3]$	p-value	$\beta[4]$	p-value	R^2_{adj}
1 (low BE/ME)	-0.000	(0.84)	1.132	(0.00)	0.101	(0.02)	-0.425	(0.00)	-0.087	(0.02)	0.90
2	0.002	(0.10)	1.008	(0.00)	-0.096	(0.00)	-0.198	(0.00)	-0.003	(0.92)	0.92
3	0.000	(0.90)	0.889	(0.00)	-0.211	(0.00)	0.028	(0.42)	0.002	(0.94)	0.88
4	0.001	(0.60)	0.936	(0.00)	-0.006	(0.86)	0.217	(0.00)	-0.023	(0.45)	0.87
5	0.002	(0.34)	0.929	(0.00)	0.043	(0.24)	0.475	(0.00)	-0.034	(0.27)	0.88

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	-0.035	(0.65)
$\lambda[1](er_m)$	0.039	(0.61)
$\lambda[2](SMB)$	-0.012	(0.79)
$\lambda[3](HML)$	0.017	(0.33)
$\lambda[4](PR1YR)$	0.082	(0.20)

Table 36: A multifactor model for the OSE - Beta portfolios

Panel A shows the results from estimating Carhart's four-factor model as in equation 3.3.5 for a portfolio sorted on beta. The beta portfolio is equal weighted. Columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns show the estimated β_i^k and their associated p-values. Panel B show the risk premiums estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero

Beta	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	$\beta[3]$	p-value	$\beta[4]$	p-value	R^2_{adj}
1 (low Beta)	0.001	(0.57)	0.511	(0.00)	-0.002	(0.96)	0.123	(0.00)	0.044	(0.06)	0.70
2	0.003	(0.06)	0.649	(0.00)	-0.127	(0.00)	0.078	(0.05)	0.029	(0.37)	0.78
3	-0.001	(0.54)	0.908	(0.00)	-0.160	(0.00)	0.029	(0.46)	0.083	(0.01)	0.87
4	0.005	(0.01)	1.062	(0.00)	-0.112	(0.02)	0.007	(0.89)	-0.042	(0.29)	0.87
5	-0.003	(0.16)	1.415	(0.00)	-0.146	(0.01)	-0.011	(0.84)	-0.097	(0.04)	0.90

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	0.056	(0.00)
$\lambda[1](er_m)$	-0.048	(0.00)
$\lambda[2](SMB)$	0.012	(0.63)
$\lambda[3](HML)$	-0.207	(0.01)
$\lambda[4](PR1YR)$	-0.034	(0.10)

Table 37: A multifactor model for the OSE - Size portfolios

Panel A shows the results from estimating a multifactor model containing the market factor and the BAB-factor for a portfolio sorted on size. The size portfolio is equal weighted. Columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns show the estimated β_i^k and their associated p-values. Panel B show the risk premiums estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero

Size	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	R^2_{adj}
1 (low MCAP)	-0.005	(0.03)	0.862	(0.00)	0.019	(0.52)	0.77
2	-0.000	(0.92)	0.938	(0.00)	0.009	(0.67)	0.88
3	-0.001	(0.71)	1.082	(0.00)	-0.049	(0.03)	0.89
4	0.006	(0.00)	0.934	(0.00)	0.018	(0.41)	0.88
5	0.003	(0.20)	1.031	(0.00)	0.050	(0.07)	0.85

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	-0.020	(0.21)
$\lambda[1](er_m)$	0.020	(0.24)
$\lambda[2](BAB)$	0.053	(0.12)

Table 38: A multifactor model for the OSE - BE/ME portfolios

Panel A shows the results from estimating a multifactor model containing the market factor and the BAB-factor for a portfolio sorted on BE/ME. The BE/ME portfolio is equal weighted. Columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns show the estimated β_i^k and their associated p-values. Panel B show the risk premiums estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero

BE/ME	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	R^2_{adj}
1 (low BE/ME)	-0.006	(0.01)	1.298	(0.00)	-0.054	(0.08)	0.86
2	0.001	(0.46)	1.029	(0.00)	0.003	(0.89)	0.90
3	0.002	(0.23)	0.874	(0.00)	0.028	(0.18)	0.88
4	0.001	(0.42)	0.856	(0.00)	0.043	(0.05)	0.87
5	0.005	(0.01)	0.786	(0.00)	0.031	(0.22)	0.80

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	0.033	(0.09)
$\lambda[1](er_m)$	-0.034	(0.09)
$\lambda[2](BAB)$	-0.054	(0.58)

Table 39: A multifactor model for the OSE - Momentum portfolios

Panel A shows the results from estimating a multifactor model containing the market factor and the BAB-factor for a portfolio sorted on momentum. The momentum portfolio is equal weighted. Columns two and three show the estimated constant with the associated p-value for each portfolio. Constants that are significantly different from zero indicate a wrongly specified model. The remaining columns show the estimated β_i^k and their associated p-values. Panel B show the risk premiums estimated for the intercept and each factor. These risk premiums are estimated with the Fama MacBeth (1973) regression. The regressions are run on the monthly excess return of the portfolio on the estimated factor(s). If the model is true, the intercept, α, is zero. The factor is priced if the, $\lambda[i]$, is significantly different from zero

Momentum	constant	p-value	$\beta[1]$	p-value	$\beta[2]$	p-value	R^2_{adj}
1 (low Momentum)	-0.014	(0.00)	1.368	(0.00)	-0.025	(0.49)	0.84
2	-0.004	(0.01)	0.918	(0.00)	0.072	(0.00)	0.88
3	0.005	(0.00)	0.803	(0.00)	0.028	(0.18)	0.88
4	0.007	(0.00)	0.726	(0.00)	0.020	(0.35)	0.83
5	0.013	(0.00)	1.020	(0.00)	-0.027	(0.40)	0.78

Risk premia	R_m^{ew}	
Factor	premium	p-value
α	0.047	(0.00)
$\lambda[1](er_m)$	-0.046	(0.00)
$\lambda[2](BAB)$	-0.160	(0.00)